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Abstract

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JEL Classification: G21, G28

Keywords: Public guarantees, Covid-19, Liquidity constraints, Information technology, Lending relationships

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Information Technology and Credit: Evidence from Public Guarantees

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February 16, 2023

Abstract

This paper investigates whether banks' information technology (IT) can substitute for local branch presence in the provision of small business credit. Our identification strategy relies on loan-level data and the unique institutional features of the Italian public guarantee scheme during Covid-19. Despite the availability of online applications and low screening incentives, small business lending remains local, even for first-time borrowers. However, IT partly mitigates the impact of local branch presence: banks with better IT provide more, cheaper and faster guaranteed loans and lend more in areas where they have no bank branches, especially to first-time borrowers.

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1 Introduction

A large literature argues that small business lending is local because it requires "soft" information gathered through close interactions between banks and potential borrowers (Petersen and Rajan, 1994; Degryse and Ongena, 2005). However, advancements in information technology (IT) in recent decades have challenged this notion and allowed banks to reach more distant customers (Petersen and Rajan, 2002; Granja et al., 2022). Moreover, generous government guarantees on private bank loans to small businesses issued during Covid-19 reduced the need to screen prospective borrowers.[1] Covid-19 also accelerated the adoption of digital technologies from both banks and firms (Kwan et al., 2021; Saka et al., 2022).

In this paper, we study the role of banks' IT and local branch presence in the supply of credit to small businesses. We do so in the context of the Covid-19 guarantee program in Italy. Despite the exceptional nature of the program, which limits how the results generalize to non-guaranteed lending, its unique institutional characteristics make it ideal to investigate whether physical proximity still matters for small business lending. First, credit risk is mostly absorbed by the government and applications were filed online (via email or bank websites). Second, 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 fixed-effects, exploiting the fact that firms obtain guaranteed loans from multiple banks.

We first describe the program and its targeting. On April 8^{th}, 2020 the government introduced a public guarantee of 90% for loans up 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. By August 2020, Italian banks issued one million government guaranteed loans to around 900,000 small businesses for an aggregate amount of €79 billion, 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, i.e. young

[1]These programs targeted SMEs because small firms, unlike large corporations, have limited access to capital markets and credit lines to draw upon and therefore rely more heavily on bank funding (Li et al., 2020; Acharya et al., 2021; Chodorow-Reich et al., 2020).

firms with less cash-on-hand, were more likely to receive guaranteed loans.[2] Importantly, the effect of firm risk (Altman et al. (2012) z-score) is non-monotonic: firms in the middle of the risk distribution are 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 are on average less financially constrained (Altavilla et al., 2021).

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] The variation in loan conditions is mostly explained by supply 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×industry fixed-effects.[4] Motivated by the results of the variance decomposition, we then investigate which bank characteristics can explain such credit outcomes. We find that, conditional on other bank characteristics and firm fixed-effects, banks with better IT systems, as proxied by the Google Playstore review rating on their mobile banking app or spending in IT (He et al., 2021), supply more credit. High IT banks make 25% more guaranteed loans as a fraction of total loans, charge rates that are 14-24% lower and process guaranteed loans almost twice as fast compared to banks with low quality IT.[5]

Given the importance of bank IT in a context of online loan applications, one may question the relevance of the bank branch network for the allocation of credit over this period. Moreover, the low incentives to screen borrowers because of large government guarantees make close interactions between banks and borrowers to acquire soft information less important (Petersen

[2]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.

[3]This is a good approximation of processing time as long as the approval date of the guarantee by the FG is not correlated with bank unobserved heterogeneity, as we show in Table A1 in the Online Appendix.

[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]We validate the rating on the mobile banking app as a measure of the quality of bank IT by showing that it is correlated with the number of digital services offered by the bank, including online lending facility to corporate clients from the confidential Regional Bank Lending Survey (Arnaudo et al., 2022).

and Rajan, 1994; Degryse and Ongena, 2005). In a way, since government guaranteed loans are cheap, online and available to all with little credit risk, they provide the perfect setting to test whether small business lending is still local.

First of all, we find that guaranteed lending remained local: 50% of loans are issued within 1km from a branch of the bank issuing the loan, and 90% within 10km. As a result, provinces where a given bank has at least one branch are more than twice as likely to have guaranteed loans issued by that bank, compared to provinces where the bank has no branches. The effect is weaker for banks with better IT, as these are 30% more likely to issue guaranteed loans in provinces where they have no branches, compared to low IT banks. Banks with better IT are better able to reach customers that are not "close" to their branches, similar to what is found for FinTech lenders in the context of PPP loans (Erel and Liebersohn, 2021). However, because even banks with good quality IT lend more locally, guaranteed lending overall remains local.

Second, to reconcile the evidence with the institutional factors that should make guaranteed lending less local (i.e., online applications and low incentives to screen borrowers), we investigate the role played by existing bank-firm relationships. Since regular small business lending is local, if borrowers obtain guaranteed loans from their relationship banks, then guaranteed lending would also be local. While we cannot observe pre-existing bank-firm relationships, we know whether firms have pre-existing bank debt: we single-out firms without any financial debt outstanding in 2019 who obtained a guaranteed loan in 2020 (i.e., first-time borrowers in 2020). These firms cannot borrow from local banks because of pre-existing relationships since they had no existing relationship to begin with.

We find that first-time borrowers still go to local banks: the average distance between banks and first-time borrowers is the same as that of borrowers with existing debt. The average result hides heterogeneity depending on IT quality of the bank with which the match is formed. When a first-time borrower borrows from a bank with better IT, then the distance is larger than when a pre-existing borrower borrows from the same bank. Moreover, high IT banks lend more to first-time borrowers, in terms of share of total loans issued, in provinces where they have no branches. Taken together, these results tell us that, despite the inherent local nature of guaranteed lending, banks with better quality IT were able to reach more distant customers in areas where they do not have branches, more so when these do not have pre-existing relationships with other banks.

Lastly, we investigate why first-time borrowers borrow from local banks. We find that, in provinces where the share of guaranteed loans granted to local existing borrowers is one percentage point higher, the share of guaranteed loans granted to local first-time borrowers is 0.5 percentage points higher. This result is consistent with the role played by geographically concentrated social networks (Bailey et al., 2018): first-time borrowers gather information about guaranteed loans from other local entrepreneurs and hence are more likely to borrow from local banks in provinces where lending is already more local. While these province-level results should be interpreted with caution because there are other factors that may determine the extent of local borrowing, we find that the effect of existing borrowers' networks is concentrated in areas where bank branches are more difficult to reach because of high branch dispersion. This evidence suggests that peer networks matter more in areas where proximity to bank branches is lower.

This paper contributes to the nascent literature on IT and financial intermediation. D'Andrea and Limodio (2021), D'Andrea et al. (2022) and Mazet-Sonilhac (2022) show that high-speed internet improves banking efficiency and credit supply; Timmer and Pierri (2021) show that banks with higher IT adoption have lower non performing loans during the global financial crisis and Ahnert et al. (2021) find that bank IT helps spurring entrepreneurship. In the context of Covid-19, Kwan et al. (2021) show that banks with better IT increased their web traffic and supplied more Paycheck Protection Program (PPP) loans. We find that bank IT helps with the provision of credit and allows banks to reach more distant customers, substituting for the role of local interactions via branches but only up to some extent: small business lending remains overwhelmingly local even in a setting where screening with soft information is not needed due to high government guarantees.

We also join the burgeoning literature studying the impact of the Covid-19 pandemic on banks and corporates. Covid-19 led to the largest increase in demand for credit ever observed (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 countries most severely affected by the potential future rise in NPLs due to its high share of SMEs (Carletti et al., 2020).

Finally, we contribute to the literature on the effects of public credit guarantees (Brown and Earle, 2017; Mullins and Toro, 2017; Bachas et al., 2021; Barrot et al., 2019; Gonzalez-Uribe and Wang, 2020). Many recent studies have analyzed the PPP and its impact on employment and publicly listed firms (Balyuk et al., 2020; Chetty et al., 2020). Granja et al. (2020) find significant lender heterogeneity in the allocation of PPP loans. Erel and Liebersohn (2021) find that FinTech lenders lent more in areas less served by traditional banks. In Europe, there is evidence that, at least partly, guaranteed lending in 2020 replaced existing, non-guaranteed lending (Altavilla et al., 2021; Cascarino et al., 2021). Our results also suggest 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 channelled 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 the data used in the empirical analysis. Section 3 presents some stylized facts and descriptive evidence about which firms and banks participated in the guarantee program. Section 4 shows the role of bank IT and local banking markets in explaining credit conditions and allocation of guaranteed loans. Finally, Section 5 concludes.

2 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. 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.

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.[6] The guarantees were also greatly expanded in scope and coverage. First of all, the maximum guarantee coverage was increased from 80% to 90% and eligible loan size went from €2.5 to €5 million. 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.[7] All guaranteed 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.

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.[8] First, the firm needs to file a standard loan application with a bank of its choice. Then,

[6]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.

[7]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.

[8]The applicant must be either a bank or a financial intermediary (e.g., leasing and factoring companies) registered and regulated by the Bank of Italy. Thus, differently from the PPP program, this requirement

the bank has to verify the firm eligibility for the scheme through a scoring system software provided by the FG 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 that they are eligible to receive 100% government guaranteed loans. Over this period, since bank branches were hard to reach due to 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.

Other European countries, such as Germany, France, Spain and the UK have introduced similar measures. 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). 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.

2.2 Data

Loan level data on the universe of guaranteed loans are publicly available in Italy.[9] 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

excludes fintech and P2P lending companies (but not online banks) from issuing guaranteed loans.

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

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).[10] 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. Doing so allows us to recover the names of about 120 lenders that extended 95% of total guaranteed credit and match them 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 104 banks that account for 93% of the guaranteed credit extended by the 120 banks we were able to match. 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. The 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.[11] We also show that the rating on the mobile banking app is correlated with

[10]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.

[11]IT expenses and amortization are reported by Italian banks under the IFRS9 accounting standard, which

the number of digital services offered by the bank from the Regional Bank Lending Survey.[12] Panel A of Figure 2a shows a scatter plot between the app rating (i.e. the number of stars on Google Playstore) and the number of digital services offered by each individual bank (on a scale from 1 to 6): banks with a better rated mobile app are also more likely to offer more digital services to their clients. Moreover, we also show in Panel B of Figure 2 that banks that offer online lending facilities are three times more likely (73% vs 27%) to have a high mobile app rating with 4 stars or more. Lastly, it is important to note that, while we focus on banks' IT capabilities, none of the lenders in our sample are FinTech or non-banks. In order to access the FG, the intermediary must be regulated by Bank of Italy. The average lender in the sample has 188 branches and thus a strong physical presence.

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 720,000 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 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.

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

[12] We thank Davide Arnaudo and Paola Rossi from Bank of Italy for providing such correlations.

[13] Within the sample of 720,000 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, and we also match 43% of unlimited liability companies.

3 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.

3.1 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. Partially guaranteed loans are much larger than fully guaranteed loans (€370,000 vs. €20,000 on average), and carry a higher interest rate (2.8% vs 1.1% on average).

It is worth emphasizing that the guarantee program for SMEs in Italy was large even before Covid (Figure 3): 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 4 further reveals that volume of guaranteed lending is concentrated in the 90% guarantee program (€61 billion) and that 100% guaranteed 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 4).[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*).[15] There are however large differences in the take-up rate across geographic areas. While in some provinces the take-up rate is as

[14]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.

[15]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.

low as 7%, in other areas it increases to 26%. Figure A2 in the Online Appendix 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).[16] As one might expect, there are also significant difference in the take-up rate across different sectors (Figure A3 in the Online Appendix). 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.[17]

3.2 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.[18] Most firms are rather small and young, with median assets around five million euros and an age of five years since the incorporation date. Two thirds of firms have no existing financial debt as of 2019, i.e. they do not borrow from banks or other financial intermediaries at all. While striking, this is in line with aggregate survey statistics from the euro-area and the UK.[19] 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:

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

[16] This is not the case in normal times (see Figure A4 in the Online Appendix).

[17] 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.

[18] 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.

[19] According to the Survey on the Access to Finance of Enterprises (SAFE) about 50% of firms in the EU say that bank loans are not an important source of funding because they do not need them.

where 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 $\mu_{p,s}$ is a set of province×4-digit sector fixed-effects to control for local demand conditions.[20]

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 25% of the mean uptake rate.[21] Naturally, larger firms seek partially guaranteed loans more than small firms, since these loans can be as large €5 million. We also find that younger firms are more likely to obtain a fully guaranteed loan and that firms with no existing financial debt are less likely to borrow. 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).

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.

[20] 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.

[21] 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.

3.3 Which banks issue guaranteed loans?

We conclude the section on the descriptive evidence by showing the characteristics 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 100 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 by regressing the share of guaranteed loans over total bank lending in 2019Q4 on $HighAppRating_b$, 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).[22] We also include as controls bank size, capitalization, the quality of the loan portfolio (NPL), profitability and interbank funding.[23] 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

[22] 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 A2 in the Online Appendix).

[23] 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.

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.

4 Bank IT and local banking markets

4.1 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.[24]

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 the bank effectively hands out the loan to the borrower.[25] As such, loan processing times measure the ability of a bank to disburse guaranteed 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. 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

[24] 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).

[25] This measure of processing time is a good proxy for banks' ability to disburse guaranteed loans as long as the FG approval date is not correlated with bank characteristics (i.e. as long as the FG is not approving some bank's applications before others). In this respect, we show that the actual approval date of the guarantee by the FG does not correlate with banks' unobserved heterogeneity (see Table A1 in the Online Appendix).

Panel A of Figure 5 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.[26] Banks with highly rated apps also charge lower rates on average than banks with low-rated apps (Panel B of Figure 5).

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 A2 in the Online Appendix 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 A3). As such, variation at the province and sector level is likely to capture a significant part of demand heterogeneity. Formally, we regress, the interest rate or processing time at loan level on a set of bank and province×sector fixed-effects that proxy for supply and demand heterogeneity, respectively.

Table 4 reports the R^2 statistics 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 with 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.

[26] 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 Figure A5 in the Online Appendix 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.

4.2 Bank IT and credit supply

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

While informative, the cross-sectional results at bank level (Table 3) 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:

$$\mathrm{Y}_{f,b,t} = \beta_1 HighAppRating_b + \gamma' X_b + \mu_f + \lambda_t + \epsilon_{f,b,t} \tag{2}$$

where $Y_{f,b,t}$ is either the interest rate or the processing time of a loan made by bank b to firm f, approved on date t by the FG. X_b is a vector of bank controls, measured as of 2019Q4, including: 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. 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 day fixed-effects for the calendar date in which the guaranteed loan was approved by the FG (λ_t).[27] 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. This is true only for partially guaranteed loans (column 3), where rates are decided by the bank, and not for fully guaranteed loans (up to €30,000) whose rates have an interest rate cap (column 2). Partially guaranteed loans issued by banks with highly rated app carry an interest rate which is 67 basis points lower (24% compared to the mean) than banks with low rated apps. Since we control for size and other bank characteristics, this result is not simply explained by traditional balance sheet factors that

[27]The calendar date when the loan was approved 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.

may be correlated with IT. Importantly, the coefficient remains large and positive (14% compared to the mean) once we include firm fixed-effects, restricting the sample to borrowers with at least two partially guaranteed loans (column 4), suggesting that province×4-digit industry fixed-effects already capture most of the variation in credit demand.[28] We also find that loans to borrowers in areas where banks have no branches are not priced differently and the effect of bank IT is stable if we control for the bank branch location (columns 5-6). Moreover, banks with highly 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. Loans issued in areas where banks have no branches have lower processing times, but the effect of bank IT remains stable when controlling for branch location.

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 (this field is scarcely populated in 2019), while in Table A4 we use the share of IT amortization over total operating costs, which is a measure of past investment in IT, and find similar results. These items are reported under the breakdown of "other administrative expenses" which is mandatory under the new IFRS9 accounting disclosure. 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.

Deposit growth. After the Covid-19 outbreak, bank deposits have grown substantially, in large part because of precautionary motives (Levine et al., 2021). In Italy, total deposits went up by €165 billion in 2020, an increase of 10.5% with respect to December 2019 (ABI, 2021). Given the limitations to mobility, it is plausible to think that banks with better IT were more likely to receive larger inflows of deposits. If that is the case, these banks may have increased the supply of loans more than other banks not because it was easier for them to

[28]Since firms are allowed to obtain only one fully guaranteed loan, but multiple partially guaranteed loans, we include firm fixed-effects only when studying the latter group.

process loan applications but simply because they had more liquidity available. To address this concern, we first show that deposit growth is not significantly associated with the quality of bank IT (column 1 in Table A6 in the Online Appendix). We then include deposit growth as an additional control in all our specifications and find that the coefficient on bank IT is unchanged (columns 2-5 in Table A6).

Robustness to alternative fixed-effects. In columns (1)-(3) of Tables 5 and 6 we control for local demand using province×sector fixed-effects. We can enrich these fixed-effects by making them time-varying and including an additional dummy interactions based on firm characteristics such as size (dummies for quartiles of total assets) and risk (medium and high-risk). Doing so reduces the sample size, as it excludes firms for which financial accounts are not available, but it allows to have more stringent controls for time-varying credit demand. The results are virtually unchanged, as we show in Tables A7 and A8 in the Online Appendix.

Overall, the evidence presented in Tables 3, 5 and 6 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.

4.3 Local banking markets and bank IT

Ample evidence shows that small business lending is local because it relies on "soft" information that can only be acquired through close interactions between borrowers and lenders (Petersen and Rajan, 1994; Berger and Udell, 1995; Degryse and Ongena, 2005). Close lending relationships are valuable because banks shield their existing customers from negative shocks during crisis times (Bolton et al., 2016; Beck et al., 2018), especially in areas where they own at least one branch (Cortés and Strahan, 2017). However, advancements in IT may challenge the role of the local branch network (Petersen and Rajan, 2002), allowing banks to lend to more distant customers (Granja et al., 2022; D'Andrea et al., 2022; Mazet-Sonilhac, 2022).

Our setting provides an ideal testing ground to see whether bank IT can substitute the role of soft information: applications were filed online and the generous guarantee coverage reduces bank incentives to screen borrowers, so the role of local bank interactions should be especially muted over this period. Our key hypothesis is that banks with better IT should lend less "locally".

First of all, summary statistics (Panel A of Table 1) show that guaranteed lending is local: the average distance between firm headquarter and the branch of the bank that issued the loan is 3km. The entire distribution is concentrated: 50% of loans are issued within 1km (14% are made with the bank whose branch is the closest to the firm among all possible bank branches) and 90% within 10km.[29] Thus, despite the presence of online loan applications, small business lending remained local. In part, this may be due to pre-existing lending relationships which we examine in the next section.

To test the hypothesis that banks with better IT lend less to local firms we create a balanced panel of all pairwise combinations of banks b and provinces p (107 provinces for 104 banks) and we run the following regression:

$$Lending_{b,p} = \beta_1 NoBranch_{b,p} + \beta_2 NoBranch_{b,p} \times HighAppRating_b + \mu_p + \mu_b + \varepsilon_{b,p} \quad (3)$$

where $Lending_{b,p}$ is a dummy equal to one if bank b lends in province p, 0 otherwise, $NoBranch_{b,p}$ is a dummy equal to one if bank b has no branches in province p in 2019, μ_p and μ_b are province and bank fixed-effects. We observe guaranteed loans in 32% of all potential bank-province pairs and no branches in the majority of cases (85%). Thus there are a number of provinces where banks lend but have no branches. Our hypothesis is that $\beta_2 > 0$, i.e. banks with better IT are more likely to lend in provinces where the bank has no branches. The results are shown in Table 7.

First of all, we find that provinces where a given bank has no branches are more than twice

[29] To calculate the distance between banks and firms we first obtained the geocoded address of firms' headquarters from Orbis, then we manually geocoded the addresses as of all bank branches in Italy (the list is publicly available on the Bank of Italy website), and then calculated the distance using the formula of Vincenty (1975).

less likely (50 percentage points less, i.e. 156% compared to the mean) to have guaranteed loans compared to provinces where the bank has branches: this result underscores that guaranteed credit between banks and firms remains local. Moreover, banks with better IT are 4.9 percentage points (15%) more likely to issue guaranteed loans in total (column 1) compared to low IT banks, consistent with the evidence in Tables 3, 5 and 6 that bank IT stimulates credit supply. But where are banks with better IT more likely to lend? They are 30% more likely to lend in provinces where they do not have a bank branch and 10% less likely to lend in provinces where they own branches compared to low IT banks (column 2). Thus, banks with better IT lend in provinces that cannot be reached by traditional, branch-based small business lending. These results hold as we control for province and bank fixed-effects (columns 3-4) and importantly they are not just an effect of size (i.e. large banks have better IT and larger networks): controlling for the interaction of $NoBranch_{b,p}$ with the log of bank total assets, which is positive and significant, reduces the effect of bank IT in provinces with no branches but $\widehat{\beta_2}$ is still large and positive (column 5).

Robustness: Log(credit). The results in Table 7, where the dependent variable is a dummy equal to one if the bank makes at least one loan in the province, could be driven by outliers where banks make few loans in provinces where they do not own branches. To address this concern, we show in Table A9 in the Online Appendix that results are similar if we replace the dummy with the log of the total amount of guaranteed credit. We find that the total volume of lending is four times higher in provinces where the bank has branches, compared to where it does not. However, this effect is 15% weaker for high IT banks. Furthermore, in line with our results in Table 3, we find that high IT banks lend more on average, as the coefficient on $HighAppRating_b$ is positive and significant.

4.4 First time borrowers and local credit

A striking result from the previous section is that, even with some heterogeneity depending on bank IT, most firms still borrow from local banks: the coefficient on $NoBranch_{b,p}$ in Table 7 is negative and much larger than the one on the interaction $NoBranch_{b,p} \times HighAppRating_b$. This is surprising in light of the online nature of guaranteed loans in 2020 and low screening incentives: small businesses are not restricted to apply to local banks. A potential explanation is the role played by existing relationships: since small business lending is local, if firms apply for guaranteed loans with their existing banks, guaranteed lending will remain local.

To distinguish the role of local bank networks from that of existing relationships we now focus on firms with no outstanding debt in 2019 which still obtained a guaranteed loan (i.e. first-time borrowers in 2020). If these firms also borrow from local banks then something else, other than existing relationships, can account for the role of local banking networks. Given that banks with better IT are more likely to lend in provinces where they do not own branches, the difference in local lending of first-time borrowers may also depend on whether these banks lend more to first-time borrowers.

We test whether first-time borrowers in 2020 borrow from local banks like firms with pre-existing relationships and whether local borrowing depends on the characteristics of banks with which the match is formed. Formally, we run the following test at loan level:

$$\begin{aligned} Log(Distance)_{b,f,p,s} = {} & \beta_1 ZeroDebt_f + \beta_2 ZeroDebt_f \times HighAppRating_b + \\ & + \mu_{p,s} + \lambda_m + \mu_b + \varepsilon_{b,f,p,s} \end{aligned} \tag{4}$$

where $Log(Distance)_{b,f,p,s}$ is the logarithm of the distance ('as the crow flies') between the headquarter of firm f and the closest branch of bank b that issued the guaranteed loan to the firm. $ZeroDebt_f$ is a dummy equal to one if the firm had no previous financial debt in 2019, 0 otherwise. Given that the sample is restricted to firms who obtained a guaranteed loan in 2020, we refer to firms with no financial debt in 2019 as first-time borrowers. There are many potential first-time borrowers in the data: over two thirds of firms in Orbis have no financial debt in 2019 and, out of these, 24% obtained a guaranteed loan (compared to 38% of firms with debt outstanding). We include day, province-sector and bank fixed-effects to absorb unobserved demand and supply heterogeneity. The results are presented in Panel A of Table 8.

We find that first-time borrowers on average do not borrow from more distant banks: the coefficient on $ZeroDebt_f$ is small and statistically insignificant. Since the average distance for guaranteed loans is 3km and 50% of loans are issued within 1km from the bank branch, this means that first-time borrowers also borrow from local banks. There is however strong heterogeneity depending on the type of bank with which the match is formed: when first-time borrowers borrow from banks with better IT, distance widens by 3% compared to borrowers with pre-existing relationships that borrow from the same high IT bank. Conversely, when first-time borrowers borrow from banks with low quality IT, these are closer than those existing borrowers borrow from. Once more, this is not just an effect of bank size, since first-time borrowers have more distant loans from high IT banks even considering that these may be larger banks, with a widespread branch network (column 4). Moreover, we also include fixed effects for the interactions of the province and industry of the firm, thus ruling out that our results are driven by first-time borrowers being located in historically under-served provinces or active in industries that rely less on external finance.

We also find, in Panel B of Table 8, that banks with better IT lend 16% more, as a share of loans issued, to first-time borrowers in provinces where they do not own bank branches relative to banks with low quality IT. Together with the results from Table 7, we conclude that high IT banks are able to reach more distant customers in areas where they do not have branches, especially when these are first-time borrowers. Finally, we again fail to ascribe the effect of IT to bank size, as we do not find that bigger banks lend more to first-time borrowers, compared to smaller banks, in provinces where they do not have branches.

4.5 Local borrower networks

We have shown that small business lending is local even for first-time borrowers, so it cannot be explained by existing relationships only. Why do first-time borrowers still borrow from local banks then?

In this section we provide a potential explanation based on insights from the social network literature. Bailey et al. (2018) show that, despite the presence of online social media, most social networks are geographically concentrated. For example, for the average county in the US, 62.8% of all friendship links are to individuals living within 100 miles. We thus hypothesize that, within local social networks, entrepreneurs who already borrow from local banks will share information about government guaranteed loans with other small business owners who never borrowed before. We thus expect that where local businesses with existing relationships rely more on local banks, also first-time borrowers will.

On average, the share of local borrowing in a province is around 0.86, but there is significant variation, as the 5^{th} percentile is around 0.71 and the 95^{th} percentile is 0.94. Table 9 shows that the shares of local guaranteed loans granted to existing and first-time borrowers are positively correlated: a one percentage point increase in the share of local borrowing by existing borrowers increases local borrowing from first-time borrowers by 0.5 percentage points. The correlation is robust to the inclusion of a wide array of province characteristics, such as local economic development, the share of firms in manufacturing, the concentration of the local banking sector and the strength of the pandemic. The results are also remarkably stable if we include dummies for the five main macro-areas.

We also control for supply-side factors such as the density of the local branch network, calculated as the standard deviation among all bank branches' coordinates in a province (i.e. the standard distance as defined in Bachi, 1962), and the average distance between firms' headquarters and the closest bank branch. We find that where bank branches are more dispersed (i.e. the standard distance is high), conditional on firm location (i.e. controlling for average minimum distance between firms and bank branches) the share of local guaranteed loans granted to first-time borrowers is lower, suggesting that first-time borrowers find it harder to borrow locally where bank branches are harder to reach.

While these province-level results should be interpreted with caution because there are many other unobserved factors that may determine the extent of local borrowing, in columns (4)-(5) of Table 9 we find that the effect of existing borrowers' networks is concentrated in areas with above the median branch dispersion, i.e. where bank branches are more difficult to reach conditional on a given firm location. In areas where bank branch network are more dense, the effect of existing borrowers' local share is smaller and not statistically significant. These results therefore suggest that peer networks matter more in areas where proximity to bank branches is lower, consistent with a role of informational networks among peers.

5 Conclusion

Several countries worldwide introduced credit guarantees to support small businesses affected by the Covid-19 pandemic, contributing to a large expansion in total bank 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 and controlling for demand exploiting multiple lending relationships.

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. However, banks' pre-existing geographical footprints are an important determinant of the geographical distribution of guaranteed lending. Bank IT partly mitigates the effect of local branches, as banks with good digital infrastructure were better able to reach customers outside their traditional lending markets, more so for first-time borrowers. In other words, differences in bank IT capabilities play an important role in directing such policy stimulus. Policy makers should keep the heterogeneity within the banking system in mind when designing policies that are meant to address firm liquidity shortages during a crisis.

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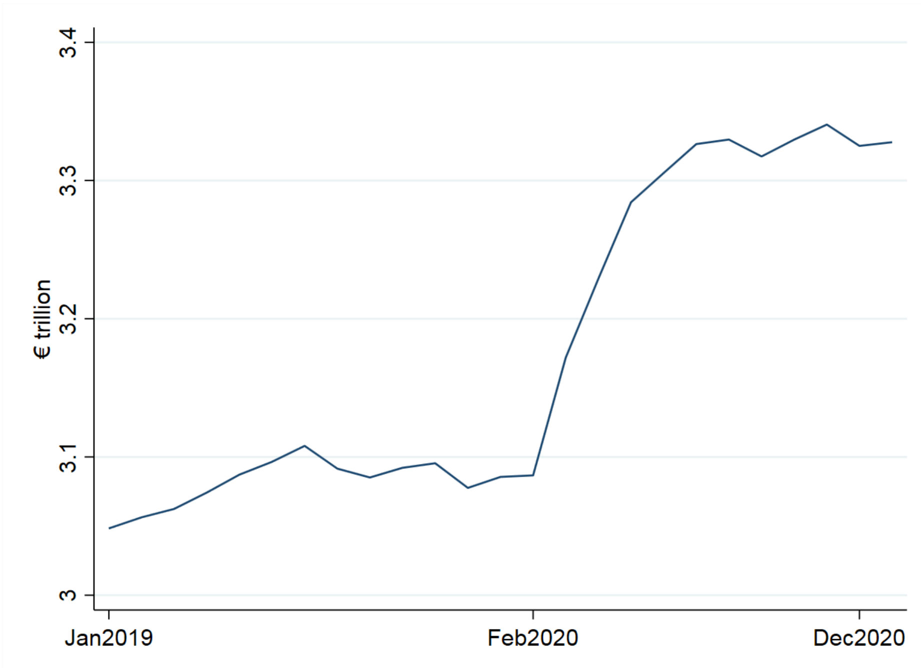
Figure 1: Total Credit to non-financial firms in the Eurozone

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

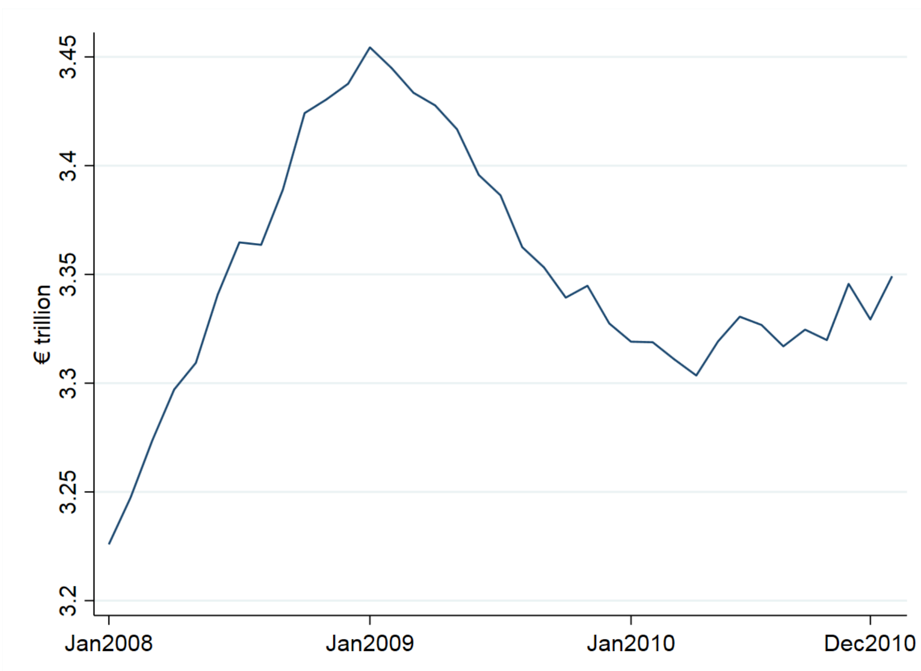
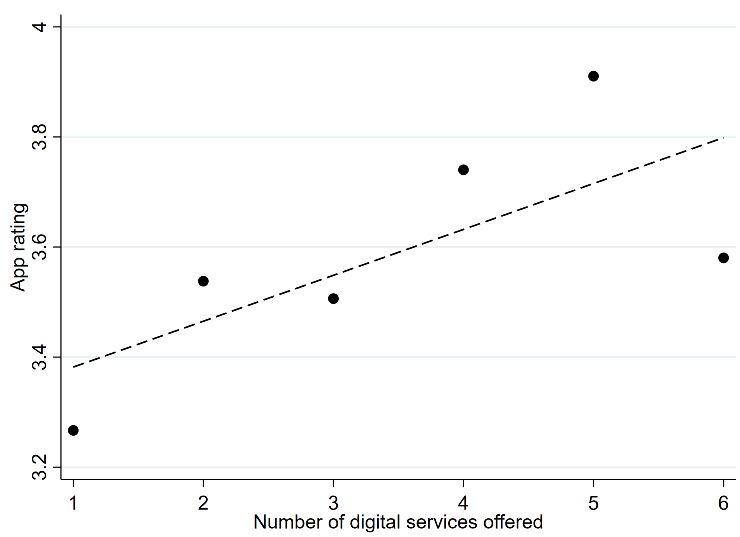


Figure 2: Mobile app rating and digital services

In panel A we report the binned scatter plot of the number of digital services offered by Italian banks and the rating of their mobile banking apps on Google Playstore. In panel B we report a bar chart of the fraction of banks with high (4+ stars) app ratings depending on whether banks offer online lending facilities (e.g., mortgages, consumer credit, business loans). Data are from the *Regional Bank Lending Survey* of the Bank of Italy, 2019 wave.

(a) Panel A. Number of digital services



(b) Panel B. Online lending

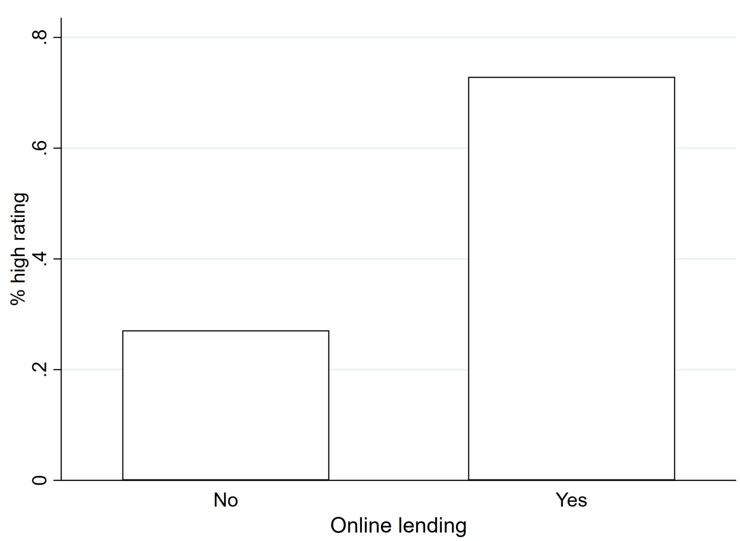


Figure 3: Public guaranteed credit in Italy, 2013-2020

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).

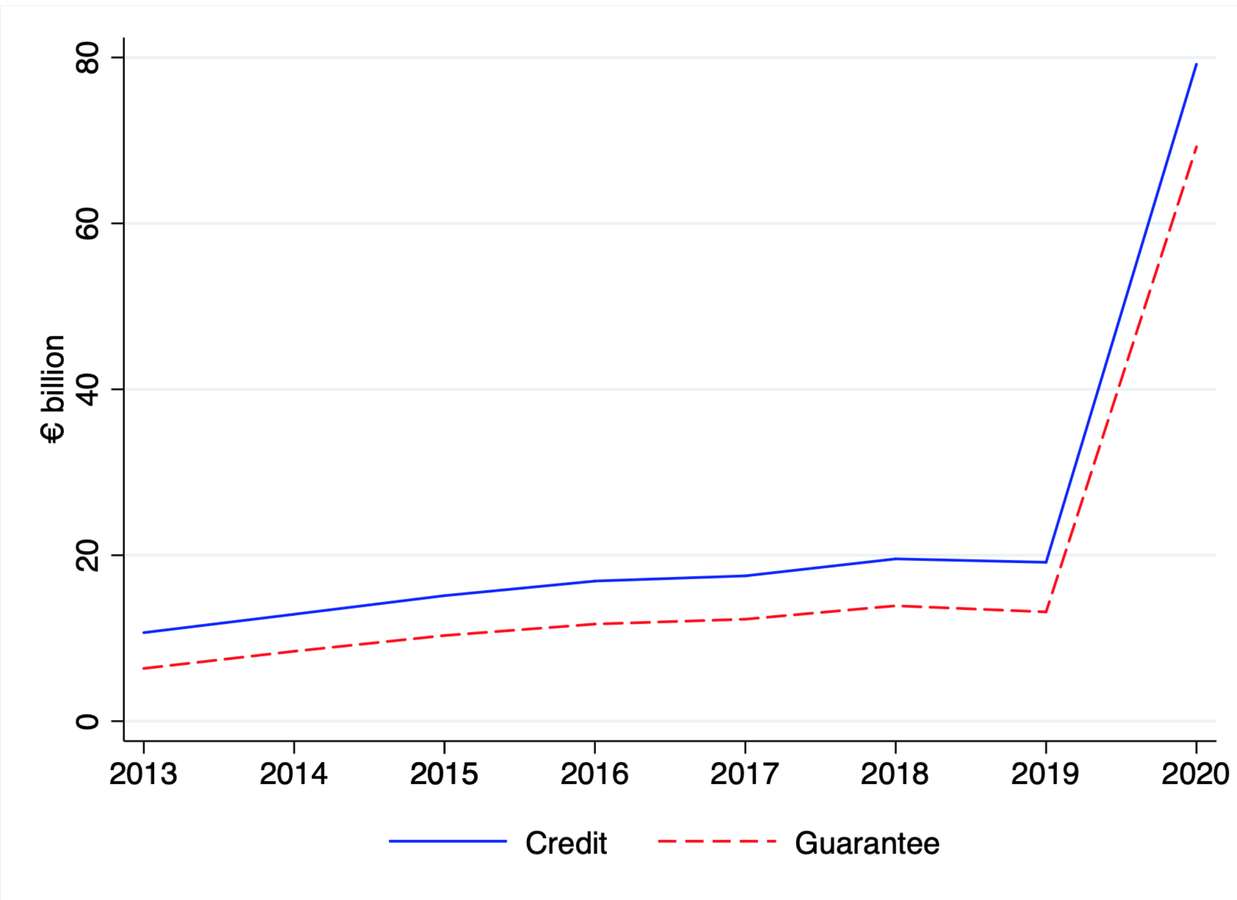
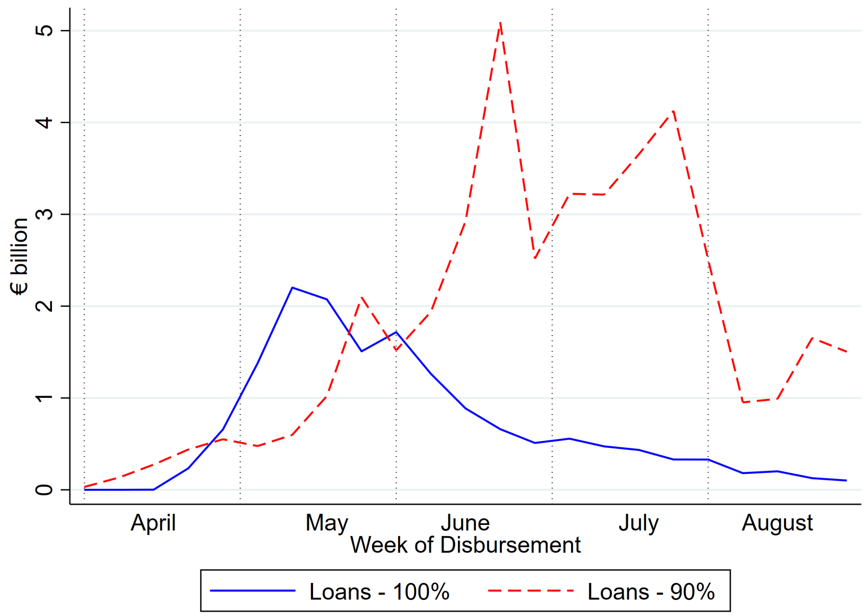


Figure 4: Public guaranteed credit in Italy in 2020

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

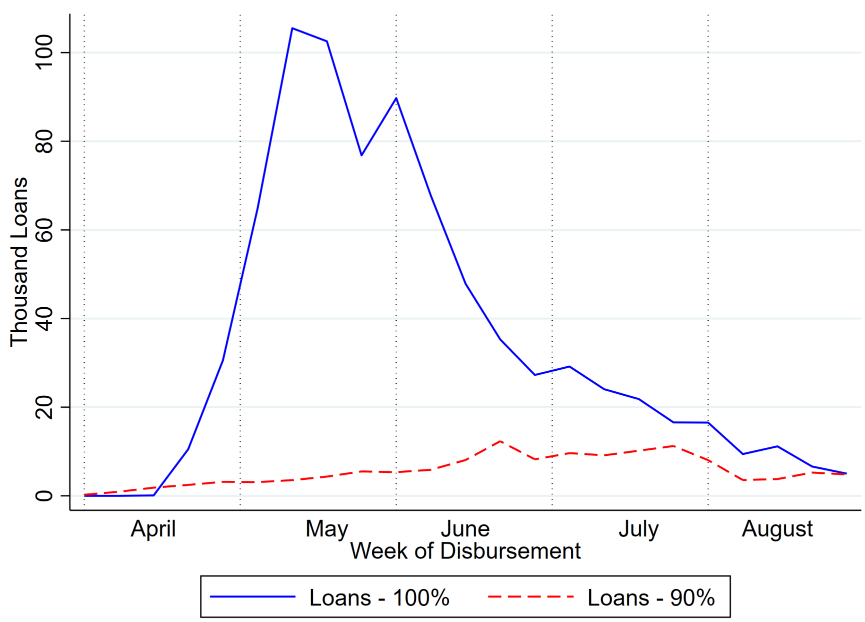
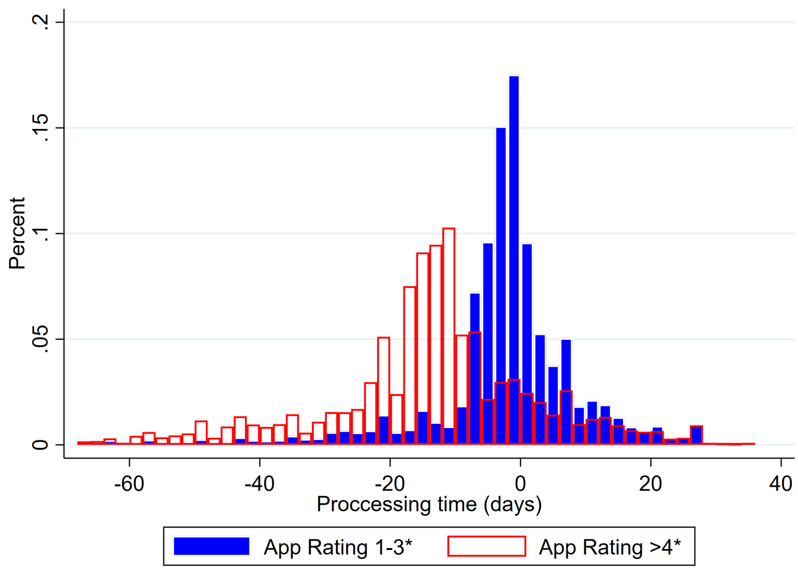


Figure 5: Loan rates and processing times by bank IT

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

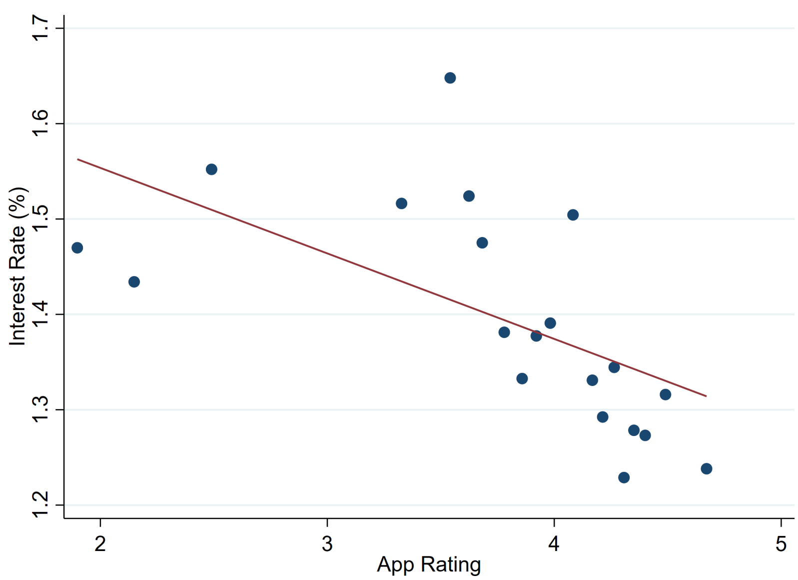


Table 1: **Summary statistics**

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. Panel D reports bank-province characteristics.

	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 Processing Time (days)	359954	-10.483	16.216	-45.000	-7.000	10.000
100% Guarantee Distance (km)	185155	2.717	9.524	0.104	0.804	9.126
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 Processing Time (days)	37998	11.418	12.897	-5.000	9.000	36.000
90% Guarantee Distance (km)	84797	3.621	10.285	0.139	1.289	12.419
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
ZeroDebt	720404	0.680	0.466	0.000	1.000	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
Panel D: Bank-Province level						
Lending=1	11556	0.321	0.467	0.000	0.000	1.000
Log(Lending)	11556	4.334	6.523	0.000	0.000	16.905
NoBranch	11556	0.858	0.350	0.000	1.000	1.000
Loan Share(first-time borrowers)	2690	0.455	0.362	0.000	0.471	1.000

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 variable is a dummy equal to one if the firm obtained a guaranteed loan after April 2020 under different types of programs (90% or 100%), 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). ZeroDebt is a dummy equal to one if the firm reports no financial debt as of December 2019. Standard errors clustered at 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)	-0.004	-0.045***	0.044***
	(0.004)	(0.004)	(0.002)
Log(Age)	-0.024***	-0.025***	0.002***
	(0.002)	(0.002)	(0.001)
Cash/Assets	-0.070***	-0.063***	-0.014***
	(0.003)	(0.002)	(0.001)
ZeroDebt	-0.105***	-0.061***	-0.076***
	(0.004)	(0.003)	(0.002)
Medium risk	0.068***	0.058***	0.024***
	(0.002)	(0.002)	(0.002)
High risk	-0.002	0.003	-0.006***
	(0.002)	(0.002)	(0.001)
Province×Industry FE	Yes	Yes	Yes
Observations	720404	662126	556219
R^2	0.171	0.159	0.185

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

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 from regressions of loan conditions on demand and supply factors. The unit of observation is a loan. 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
Province×Industry FE	Yes	No	Yes	Yes	No	Yes
Bank FE	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 (2). 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 %			
	(1)	(2)	(3)	(4)	(5)	(6)
HighAppRating	-0.182***	-0.083	-0.670***	-0.404***		-0.405***
	(0.055)	(0.066)	(0.193)	(0.132)		(0.132)
NoBranch					-0.098	-0.122
					(0.130)	(0.135)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Province×Industry FE	Yes	Yes	Yes	-	-	-
Firm FE	No	No	No	Yes	Yes	Yes
Observations	850874	745489	105385	103487	103487	103487
R^2	0.237	0.318	0.411	0.653	0.651	0.653

Table 6: **Bank heterogeneity: processing 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 processing 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.

	Processing Time (days)					
	All	100%	90 %			
	(1)	(2)	(3)	(4)	(5)	(6)
HighAppRating	-8.387***	-8.088***	-4.238***	-3.460***		-3.457***
	(1.632)	(1.855)	(0.592)	(0.961)		(0.961)
NoBranch					-2.788*	-2.729*
					(1.666)	(1.640)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Province×Industry FE	Yes	Yes	Yes	-	-	-
Firm FE	No	No	No	Yes	Yes	Yes
Observations	397952	359954	37998	28108	28108	28108
R^2	0.446	0.470	0.405	0.765	0.763	0.765

Table 7: **Local banking markets and bank IT**

This table reports the estimates corresponding to the regression in equation (3). The unit of observation is a bank-province. The dependent variable is a dummy lending equal to one if bank b issues guaranteed loans in province p, 0 otherwise. 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. NoBranch is a dummy variable equal to one if bank b has no branches in province p. 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 province level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Probability of lending				
	(1)	(2)	(3)	(4)	(5)
HighAppRating	0.049***	-0.034***	-0.035***		
	(0.007)	(0.012)	(0.013)		
NoBranch	-0.501***	-0.540***	-0.494***	-0.495***	-0.917***
	(0.013)	(0.013)	(0.018)	(0.023)	(0.031)
NoBranch×HighAppRating		0.101***	0.103***	0.099***	0.059***
		(0.014)	(0.014)	(0.027)	(0.017)
NoBranch×Log(Assets)					0.329***
					(0.010)
Bank controls	Yes	Yes	Yes	-	-
Province FE	No	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes	Yes
Observations	11128	11128	11128	11128	11128
R^2	0.433	0.435	0.475	0.531	0.556

Table 8: **First-time borrowers, bank IT and local credit**

In Panel A, the unit of observation is a loan. The dependent variable is the logarithm of the distance (in km) between the firm and the closest branch of the bank that issued the loan. ZeroDebt is a dummy equal to one if the borrowing firm reports no financial debt in 2019, 0 otherwise. 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 bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. Fixed effects for the bank, the interaction of province and industry (4-digit) of the firm, and day of approval of the loan are added. Standard errors clustered at the firm level in parentheses. In Panel B, the unit of observation is a bank-province. The dependent variable is the share of the loan issued to first-time borrowers by bank *b* in province *p*. NoBranch is a dummy variable equal to one if bank *b* has no branches in province *p*. Standard errors clustered at the province level in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Panel A. Loan (bank-firm) level	Log(Distance)			
	(1)	(2)	(3)	(4)
ZeroDebt	-0.010	-0.008	-0.025**	-0.027***
	(0.008)	(0.008)	(0.010)	(0.010)
ZeroDebt×HighAppRating			0.035**	0.029**
			(0.014)	(0.014)
ZeroDebt×Log(Bank Assets)				0.032***
				(0.009)
Bank Controls	Yes	-	-	-
Firm controls	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Province×Industry FE	Yes	Yes	Yes	Yes
Observations	209765	209765	209765	209765
R^2	0.269	0.290	0.290	0.290

Panel B. Bank-province level	Loan share (First-time borrowers)			
	(1)	(2)	(3)	(4)
NoBranch×HighAppRating	0.074***	0.072***	0.059*	0.061*
	(0.026)	(0.027)	(0.031)	(0.031)
NoBranch	-0.021	-0.032*	-0.033*	-0.032*
	(0.018)	(0.018)	(0.019)	(0.018)
HighAppRating	0.009	0.003		
	(0.010)	(0.011)		
Nobranch×Log(Bank Assets)				-0.023
				(0.023)
Bank controls	Yes	Yes	-	-
Bank FE	No	No	Yes	Yes
Province FE	No	Yes	Yes	Yes
Observations	2690	2690	2690	2690
R^2	0.016	0.088	0.181	0.181

Table 9: **First-time borrowers and network effects**

The unit of observation is a province. The dependent variable is the share of local guaranteed loans granted to first-time borrowers (i.e. borrowers with guaranteed loans in 2020 but no financial debt in 2019). Existing borrowers' local share is the share of local guaranteed loans granted to existing borrowers (i.e. borrowers with guaranteed loans in 2020 and financial debt in 2019). All province characteristics are dated 2019 and have been normalized to have a mean of 0 and a standard deviation of 1. Branch dispersion is the standard distance (Bachi, 1962), i.e. the standard deviation of longitude and latitude coordinates among all bank branches in a province. Branch-firm distance is the average distance between the closest bank branch and each firm's headquarter address in the province. Macro-area fixed-effects are five dummies for NUTS1 regions in Italy: North-West, North-East, Center, South and Islands (Sicily and Sardinia). Robust standard errors in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

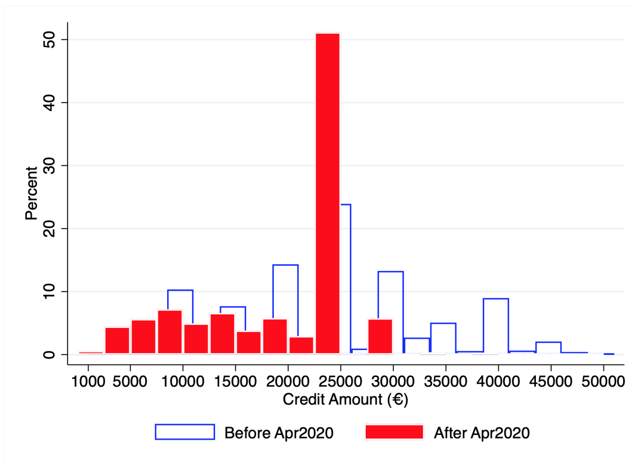
	First-time borrowers' local share				
	(1)	(2)	(3)	(4)	(5)
				Branch Dispersion	
				Low	High
Existing borrowers' local share	0.458**	0.571***	0.570***	0.223	0.551**
	(0.175)	(0.160)	(0.160)	(0.179)	(0.230)
Branch Dispersion		-0.024***	-0.022***		
		(0.008)	(0.008)		
Branch-firm distance		0.024	0.023	-0.020	0.032
		(0.033)	(0.036)	(0.036)	(0.075)
SME share of sales		0.016	0.016	0.019*	0.010
		(0.010)	(0.011)	(0.011)	(0.022)
Share of firms in manufacturing		0.003	0.007	-0.002	0.014
		(0.008)	(0.008)	(0.009)	(0.013)
HHI of bank branches		0.018*	0.012	-0.006	0.002
		(0.010)	(0.011)	(0.019)	(0.011)
Household w/o DSL		-0.001	0.000	-0.018	0.017
		(0.011)	(0.011)	(0.014)	(0.018)
COVID cases per capita		-0.004	-0.014*	-0.006	-0.009
		(0.008)	(0.008)	(0.008)	(0.019)
GDP per capita (000)		-0.018	0.000	0.006	-0.014
		(0.017)	(0.021)	(0.015)	(0.045)
Log(Population)		0.018**	0.010	0.006	-0.010
		(0.008)	(0.010)	(0.010)	(0.023)
Fixed effects					
Geographic area	No	No	Yes	Yes	Yes
Observations	107	107	107	53	54
R^2	0.195	0.380	0.430	0.363	0.525

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 between January 2019 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 2019 - August 2020



(b) Panel B. April - August 2020

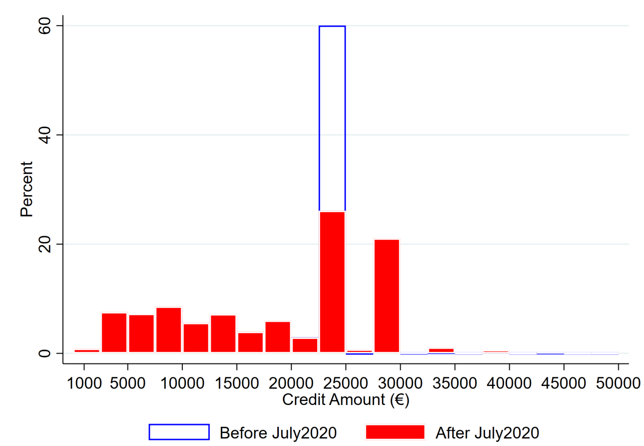


Figure A2: Guarantees, Excess deaths and Closed firms by Province

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 0.4.

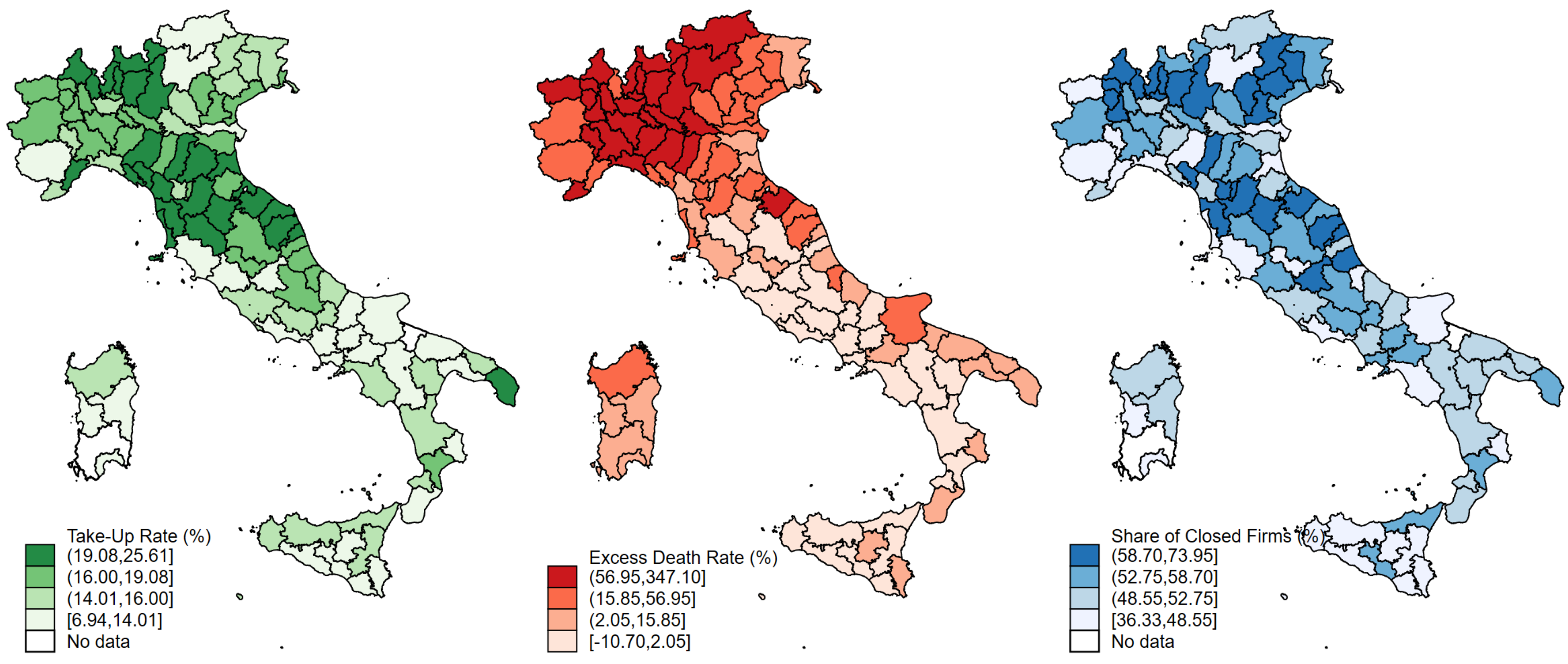


Figure A3: Guarantee by Sector

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.

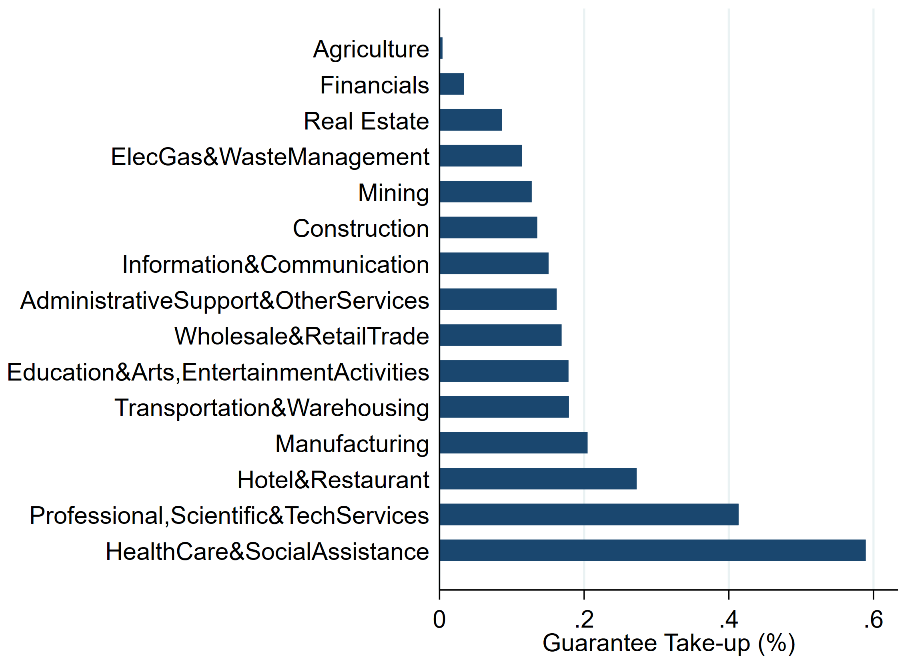


Figure A4: Guarantee Uptake in 2018-19

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).

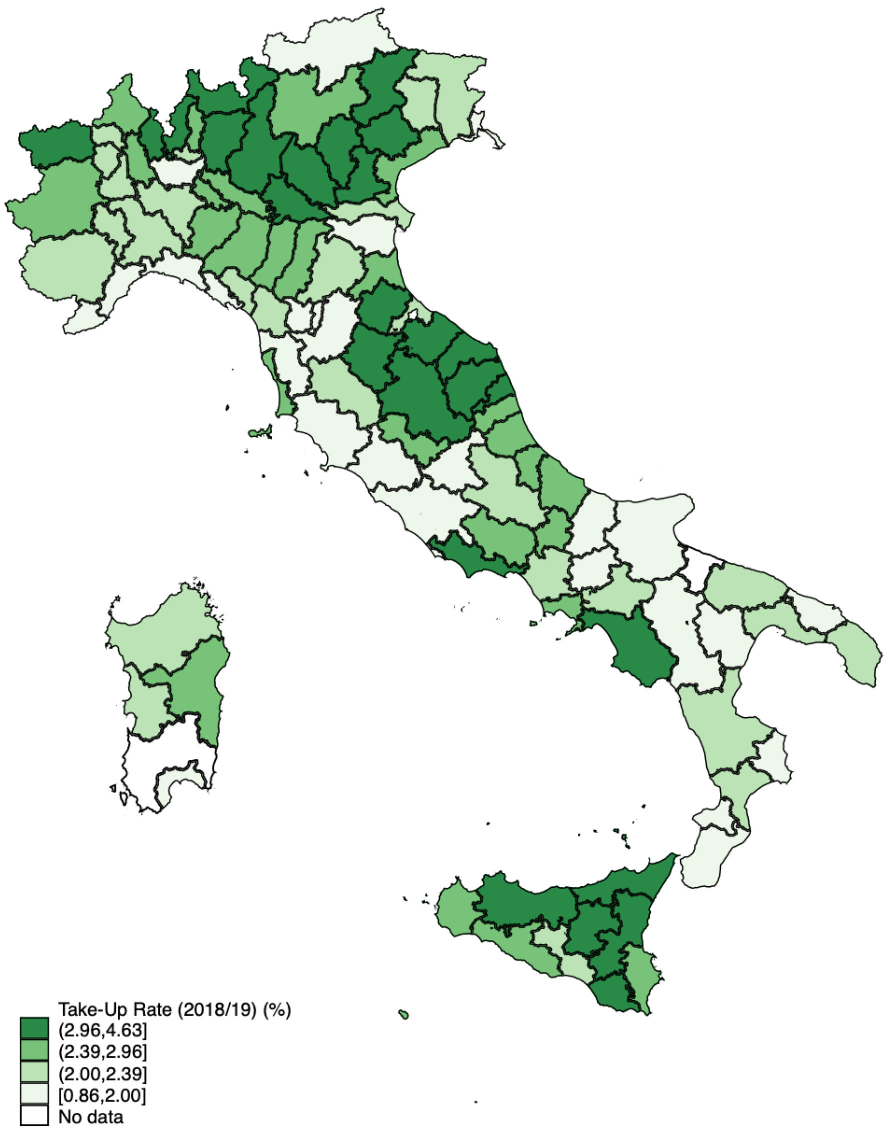


Figure A5: Processing times by bank size

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.

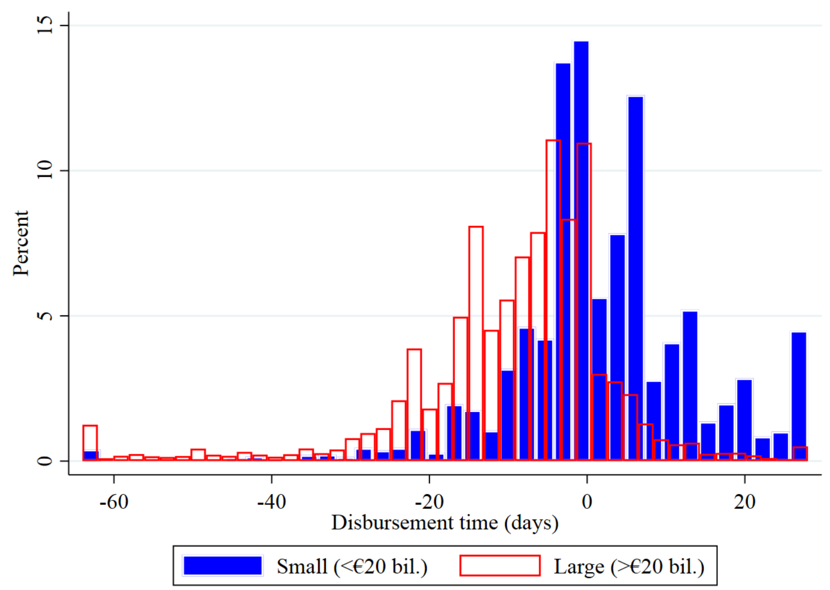


Table A1: **Bank Heterogeneity: Date of approval**

The unit of observation is at the loan level. The dependent variable is the date of approval by the FG of the loans taken under the public guarantee program after April 2020. Fixed effects for the interaction of province and sector (4-digit) and the bank are added.

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

Table A2: **Which banks issue guaranteed loans: robustness (IT expenses and amortization)**

The unit of observation is at the bank level. 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 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. 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)
Bank Controls	Yes	Yes	Yes
Observations	104	104	104
R^2	0.289	0.658	0.184
	All	100%	90%
	(1)	(2)	(3)
IT Amortization (%)	0.351***	0.036*	0.314***
	(0.096)	(0.019)	(0.083)
Bank Controls	Yes	Yes	Yes
Observations	104	104	104
R^2	0.413	0.603	0.313

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

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is at the loan level. 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	All
	(1)	(2)	(3)	(4)	(5)
IT Expenses (%)	-7.123***	-7.293***	-1.605*	-1.253*	-1.247*
	(0.916)	(0.940)	(0.637)	(0.632)	(0.630)
NoBranch					-3.834*
					(1.692)
Observations	397952	359954	37998	28108	28108
R^2	0.453	0.497	0.403	0.771	0.771
	Interest Rate (%)				
	All	100%	90%	All	All
	(1)	(2)	(3)	(4)	(5)
IT Expenses (%)	-0.056**	-0.060**	-0.159*	-0.057	-0.057
	(0.028)	(0.030)	(0.089)	(0.056)	(0.056)
NoBranch					0.035
					(0.153)
Bank controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Province×Industry FE	Yes	Yes	Yes	-	-
Firm FE	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	103487
R^2	0.248	0.294	0.449	0.685	0.685

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

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is at the loan level. 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	All
	(1)	(2)	(3)	(4)	(5)
IT Amortization (%)	-4.193***	-4.171***	-2.519***	-1.780**	-1.773**
	(1.111)	(1.175)	(0.606)	(0.585)	(0.585)
NoBranch					-2.149
					(1.612)
Observations	397952	359954	37998	28108	28108
R^2	0.416	0.446	0.403	0.765	0.757
	Interest Rate (%)				
	All	100%	90%	All	All
	(1)	(2)	(3)	(4)	(5)
IT Amortization (%)	-0.049	-0.016	-0.235	-0.111	-0.111
	(0.051)	(0.029)	(0.274)	(0.164)	(0.164)
NoBranch					-0.095
					(0.127)
Bank controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Province×Industry FE	Yes	Yes	Yes	-	-
Firm FE	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	103487
R^2	0.223	0.277	0.414	0.649	0.649

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

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is at the loan level. 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	All
	(1)	(2)	(3)	(4)	(5)
Playstore rating	-2.950	-2.037	-4.809***	-4.297***	-4.294***
	(2.443)	(2.695)	(0.736)	(0.683)	(0.683)
NoBranch					-2.710*
					(1.575)
Observations	397952	359954	37998	28108	28108
R^2	0.421	0.444	0.409	0.766	0.766
	Interest Rate (%)				
	All	100%	90%	All	All
	(1)	(2)	(3)	(4)	(5)
Playstore rating	-0.071	0.019	-0.459*	-0.399***	-0.399***
	(0.077)	(0.081)	(0.252)	(0.145)	(0.145)
NoBranch					-0.113
					(0.142)
Bank controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Province×Industry FE	Yes	Yes	Yes	-	-
Firm FE	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	103487
R^2	0.233	0.309	0.406	0.653	0.653

Table A6: **Robustness: deposits growth**

The unit of observation is at the bank level in columns (1)-(2) and at the loan level in columns (3)-(4). The dependent variables are: the chage in the logarithm of deposits between 2020 and 2019; the share of lending under the public guarantee program after April 2020 over the total amount of lending as of 2019Q4; the processing time, in days, and the interest rate, in percentage, of the loans taken under the public guarantee program after April 2020. 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. In columns 1 ans 2, observations are weighted by the bank's total assets as of 2019Q4. Standard errors robust to heteroskedasticity (columns 1 and 2) and clustered at the bank level (columns 3 and 4) in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	ΔLog(Deposits)	Share of loans	Processing time	Interest rate
	(1)	(2)	(3)	(4)
HighAppRating	0.062	1.010***	-6.608***	-0.182***
	(0.058)	(0.379)	(1.956)	(0.054)
ΔLog(Deposits)		0.276*	-3.234**	-0.012
		(0.146)	(1.956)	(0.054)
Bank controls	Yes	Yes	Yes	Yes
Day FE	-	-	Yes	Yes
Province$\times$Industry FE	-	-	Yes	Yes
Observations	104	104	394340	841636
R^2	0.261	0.442	0.453	0.239

Table A7: **Bank Heterogeneity: Robustness Interest Rate (Fixed effects)**

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. 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, industry (4-digit), size (quartile dummies for total assets) and risk (medium and high-risk) bins 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 (%)					
	All		100%		90%	
	(1)	(2)	(3)	(4)	(5)	(6)
HighAppRating	-0.258***	-0.294***	-0.085	-0.085	-0.653***	-0.632***
	(0.060)	(0.062)	(0.066)	(0.065)	(0.138)	(0.140)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Date of Approval	Yes	Yes	Yes	Yes	Yes	Yes
Province×Industry×Month×Risk	Yes	No	Yes	No	Yes	No
Province×Industry×Month×Size	No	Yes	No	Yes	No	Yes
Observations	181426	212176	107918	105313	60498	60985
R^2	0.523	0.414	0.450	0.459	0.617	0.615

Table A8: **Bank Heterogeneity: Robustness Processing Times (Fixed effects)**

The unit of observation is a loan. The sample is limited to loans with known processing times. The dependent variable is the processing 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. 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, industry (4-digit),size (quartile dummies for total assets) and risk (medium and high-risk) bins 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)					
	All		100%		90%	
	(1)	(2)	(3)	(4)	(5)	(6)
HighAppRating	-5.453***	-5.660***	-5.555***	-5.691***	-4.442***	-4.532***
	(0.969)	(0.868)	(1.070)	(1.116)	(0.674)	(0.678)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Date of Approval	Yes	Yes	Yes	Yes	Yes	Yes
Province×Industry×Month×Risk	Yes	No	Yes	No	Yes	No
Province×Industry×Month×Size	No	Yes	No	Yes	No	Yes
Observations	70957	68355	45204	43805	20010	20511
R^2	0.565	0.632	0.554	0.560	0.643	0.628

Table A9: **Guaranteed lending, local banking markets and IT**

This table reports the estimates corresponding to the regression in equation (3). The unit of observation is at the bank-province level. The dependent variable is the logarithm of the volume of guaranteed lending by bank b in province p, 0 otherwise. 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. NoBranch is a dummy variable equal to one if bank b has no branches in province p. 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 province level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Log(Lending)				
	(1)	(2)	(3)	(4)	(5)
HighAppRating	0.534***	-0.571***	-0.587***		
	(0.091)	(0.164)	(0.168)		
NoBranch	-9.959***	-10.471***	-9.870***	-9.726***	-15.077***
	(0.168)	(0.163)	(0.205)	(0.261)	(0.370)
NoBranch×HighAppRating		1.353***	1.369***	1.444***	0.924***
		(0.175)	(0.173)	(0.325)	(0.193)
NoBranch×Log(Assets)					4.169***
					(0.150)
Bank controls	Yes	Yes	Yes	-	-
Province FE	No	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes	Yes
Observations	11128	11128	11128	11128	11128
R^2	0.621	0.623	0.656	0.694	0.715