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THE ALLOCATION OF PUBLIC GUARANTEED LOANS TO FIRMS DURING COVID-19: CREDIT RISK AND RELATIONSHIP LENDING

by Emilia Bonaccorsi di Patti[*], Roberto Felici[†], Davide Moretti[§] and Francesca Rinaldi[*]

Abstract

Using loan-by-loan data matched with supervisory and borrower balance sheet data, we investigate whether public guarantees supported firms that were already weaker before the pandemic shock or, conversely, borrowers that were low risk but needed liquidity to weather economic uncertainty. We find that government-guaranteed loans were more likely to be granted to borrowers who were safer, more liquidity constrained and for whom the granting bank was a significant lender. The availability of soft information on the borrower was not an important driver of allocation, consistent with the purpose of guarantees, which is to mitigate asymmetric information problems. Evidence from *ex-post* default data one year later shows that borrowers with guaranteed loans were significantly less likely to have repayment problems than those with no guarantee, holding constant the observable *ex-ante* risk. An asymmetric information test based on Chiappori & Salanie (2000) rejects the hypothesis that the allocation of guarantees was affected by large-scale adverse selection.

JEL Classification: G18, G21, E63, H12, H81.

Keywords: relationship lending, bank credit, loan guarantees, COVID-19, credit risk, asymmetric information.

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1. Introduction[1]

During the Covid-19 pandemic governments in many countries deployed exceptional measures to support the provision of liquidity to businesses hit by a sharp drop in revenues. These measures typically included expanded access to government guarantees on loans and legislative moratoria. In Italy, as in other countries adopting similar interventions, banks were involved in the implementation of these programs. As the primary source of credit to firms, banks faced significant demand for moratoria on repayments and were involved in supporting firms in accessing public guarantees on new credit. Government measures, together with expansionary monetary policy, were effective in boosting credit growth. Between March 2020 and the end of March 2021 the flow of loans with a public guarantee surpassed 160 billion and loans that were granted a moratoria totaled 185 billion (for 65 billion of loans borrowers resumed repayments). A large share of these loans were new credit (Cascarino et al. 2022) meeting the needs of small and medium-sized firms (De Mitri et al. 2021).

In normal times public guarantees are aimed at facilitating access to credit, especially by firms that are more opaque, lack credit history or collateral. This channel is particularly important for small firms. Public guarantees encourage credit provision by banks because they reduce both risk and capital requirements by transferring credit risk - partially or entirely - to the government. The drawback of public guarantees is that they can discourage banks from selecting ex ante creditworthy borrowers and from ex post monitoring them. This may, in turn, cause an increase in the riskiness of loans with potentially negative consequences for the stability of banks and for the budget of the government. During the Covid-19 pandemic, eligibility criteria to access public guarantees were made more favorable in many countries and new programs were introduced, usually with a very high guarantee coverage, often reaching 100 percent.

[1] We thank two anonymous referees for useful comments and suggestions and Paolo Emilio Mistrulli for comments on a previous version of the paper. The views expressed do not necessarily represent those of the Bank of Italy, the Eurosystem or their staff. All errors are our responsibility.

In this paper we study how loans with a public guarantee were allocated to borrowers, focusing on two dimensions: pre-pandemic credit risk of borrowers and strength of bank-firm relationships. We analyze loans issued between the beginning of the pandemic in March 2020 and March 2021, a longer period than other analyses on Italian data (e.g. Altavilla et al. 2021, Core & De Marco 2021). In the early phase of the Covid-19 crisis banks faced organizational frictions in processing applications, therefore we consider a full year of data to capture the outcome of the choices of firms and banks rather than the effects of these frictions. As explained below, we also exploit information on subsequent credit quality at the borrower level to extract information on unobservable risk possibly driving allocation.

In regard to credit risk, we test the hypothesis that guarantees were granted more likely to borrowers who were riskier already before the pandemic. There are two main reasons why this could be the case: i) public guarantees were used by banks to shift some of their existing portfolio credit risk to the government, replacing outstanding non-guaranteed exposures with guaranteed loans rather than granting new credit; ii) riskier borrowers had a stronger incentive to apply for cheaper loans exploiting the availability of the new guarantee programs. The opposite might hold if, instead, banks allocated guarantees to safer borrowers. Banks might have prioritized their safest borrowers in providing loans to preserve the franchise value of their portfolio, given the overall high uncertainty in the aftermath of the pandemic outbreak.

As noted by Altavilla et al. (2021), to prevent the first phenomenon government programs excluded the worst borrowers through non-eligibility clauses for firms that already had non-performing loans before the pandemic. Nonetheless, within the pool of eligible borrowers that apply for a guarantee, banks could have still allocated guarantees according to their own relative risk assessment. Testing this hypothesis requires the identification of riskier yet performing firms. This is a challenging task since banks typically do not release their own forward-looking assessment on borrowers' credit risk.

Most studies, as Altavilla et al. (2021), measure credit risk by the presence of arrears or non-performing loans, which are ex post risk variables. Thanks to our data, as explained in more detail below, we measure credit risk by the ex ante probability of default that the bank computes with its own internal models approved by the supervisor.

A second factor that could have played a significant role in allocating guarantees is the strength of bank-firm relationships. Theory and evidence suggest that during hard times banks would support their relationship borrowers to preserve the value of their informational rent. Relationship lending acts as liquidity insurance to borrowers during crises (see for example Sette & Gobbi 2015, Bolton et al. 2016). According to this view, cheap guaranteed loans would be allocated preferably to borrowers with a greater relationship franchise value. A less benign view of relationship banking posits instead that banks might be encouraged to support weak borrowers, evergreening loans of clients they have a close relationship with in the hope that firms will eventually recover. According to this second view, the availability of public guarantees on bank loans would exacerbate the tendency to support zombie firms, leading to an expansion of credit to the weakest relationship borrowers[2] (see Favara et al. 2021). Both views predict that relationship borrowers are more likely to receive guaranteed loans, although they have different efficiency implications.

On the opposite side, as suggested by evidence from Jiménez et al. (2022), the availability of guarantees would allow banks to extend credit to borrowers they know less. The purpose of the guarantees is precisely to overcome the asymmetric information problems that prevent banks from lending when it is difficult to gather good signals on the prospects of a borrower. When credit is in high demand but uncertainty on firms' prospects is high, such as during the pandemic, banks may be more prone to extend loans if they can share the risk with the government. This hypothesis predicts a greater

[2] Acharya et al. (2019) and Blattner et al. (2019) suggest that in the aftermath of the Global Financial Crisis weak European banks directed cheap credit to nonviable firms, keeping them alive.

probability of observing guaranteed loans to borrowers with weaker relationships, or no relationships. Public guarantees overcome information asymmetries and would substitute for strong relationships. We note, nonetheless, that a negative correlation between relationship strength and the allocation of guaranteed credit could be as well the result of firm choice, with firms expanding borrowing from intermediaries they have weaker relationships precisely to diversify their funding sources.

Recent theoretical work suggests that banks may behave differently depending on the strength of their balance sheet, conditional on the pool of borrowers in their portfolios (see Carletti et al. 2023). We investigate heterogeneity in the probability of observing guaranteed loans by bank capitalization. In particular, given that bank capital is costly, banks with low capitalization could be more prone to off-load credit risk and engage in substitution between non-guaranteed and guaranteed loans. They could also have a stronger incentive than high capital banks to exploit the guarantee program to lend to new customers saving on capital absorption.

We base our analysis on bank-firm loan-level data from the Italian module of the AnaCredit database - a euro area harmonized credit register - matched with information on borrowers' balance sheets and supervisory data on bank characteristics. In particular, we estimate the probability that a bank grants a guaranteed loan to a borrower as a function of the riskiness of the borrower and the intensity of the existing relationship. Our data include a rich set of risk measures: banks' assessment of the probability of default of borrowers based on their internal models, accounting loan classification in stages based on international accounting standards (IFRS9), private bureau credit scores. Thanks to the contract level information, we can construct multidimensional measures of the strength of a relationship based on the type of loans, duration and relative importance of the lender for each firm.

Indeed, demand side factors are likely to have been very important in the allocation of guarantees and in the observed subsequent credit growth. Firms facing a bigger liquidity shock due to the collapse in revenues are more likely to have demanded guarantees to support and increase in borrowing. We can control for demand side effects saturating the regressions with firm controls and province-industry fixed effects following the approach suggested by Degryse et al. (2019). Furthermore, we exploit information on all the relationships that each firm had with banks to estimate regressions with firm fixed effects following the approach of Khwaja & Mian (2008) to study the allocation of guarantees and moratoria for the same firm across many banks. The fixed effects approach is not immune from the criticism that if the demand for guarantees is bank-specific we cannot fully identify the supply side effect, but we mitigate this concern because we include many relationship-specific controls.

In the second part of our analysis we study the role of the strength of the bank-firm relationship in sustaining loan growth. We split the sample between firms benefiting from guarantees and firms with no guaranteed loans because the two groups are most likely different as firm self-select into guaranteed loans. The inclusion of firm (or industry*province) fixed effects in the estimation controls for firm demand so that identification is based on differential loan growth across the banks lending to the same firm. These regressions yield information on the impact of the loan guarantee on credit expansion, in a similar vein as Cascarino et al. (2022), and on the benefits of relationships for borrowers that do not resort to the public guarantee programs.

The Covid-19 crisis is a quasi-natural experiment to analyze the allocative effects of relationships because the shock was unanticipated by firms and exogenous with respect to the pre-Covid-19 formation of relationships. The firm fixed effects model controls for matching between banks and firms and allows us to study which relationship characteristics affected the allocation of guarantees exploiting variation across the relationships that each firm has.

A key empirical question to be addressed in any study of guarantees and risk is to what extent unobservable risk drives the allocation of guarantees. We do have detailed information on banks' internal assessment of risk, as well as other measures, but we complement our analysis with evidence based on the ex post credit quality of loans granted during the acute phase of the pandemic. Controlling for observed ex ante riskiness and our full set of relationship and firm-level variables, we assess whether participation in the guarantee programs is associated to systematic differences in the probability that the borrower defaults on at least one loan by March 2022 (a year after the cutoff date of our guarantees allocation sample).[3] We follow the approach proposed by Chiappori & Salanie (2000) in the context of insurance markets to identify adverse selection or moral hazard, which would materialize in a systematically higher than predicted ex post default rate for borrowers that have a higher than predicted probability of obtaining a guaranteed loan. This approach is employed by other studies on credit markets (e.g. Albertazzi et al. 2015).

We contribute to the literature on credit markets during the Covid-19 pandemic by exploring in detail data on relationships for a large sample of Italian firms, including unlisted, small businesses. Furthermore, we improve on other studies by focusing on forward looking measures of credit risk of borrowers and, to our knowledge, are the first to test empirically how observable and unobservable borrower risk influenced the allocation of public guarantees.

Our paper is related to the literature on United States data analyzing the role of relationships in the granting of PPP loans. Such literature finds that relationships with banks have helped firms gain access to PPP (e.g. Amiram & Rabetti 2020, Balyuk et al. 2021, Faulkender et al. 2020, James et al. 2021) but it relies on proxies of relationships, while we employ granular credit data. Balyuk et al. (2021) find that firms with strong bank relationship are more likely to receive PPP loans, but they employ data on firms that access the syndicated loan market, like Li et al. (2020). We

[3] We also consider June, September and December 2022 for robustness purposes because the guaranteed loans were exempt from the reimbursement of capital for the first two years; this may have concealed repayment problems for some time although we argue that pre-Covid fragile firms would have likely emerged regardless the interest-only period.

can focus instead on very large number of firms, mostly small and unlisted, for which access to credit is typically more difficult and more sensitive to cyclical and structural shocks.

Our analysis is close to two recent papers by Jiménez et al. (2022) on Spain and Altavilla et al. (2021) on multiple countries. With respect to the former, we characterize relationship by multiple dimensions (intensity, duration) rather than focusing only on the share of credit provided by the lending bank. The latter assesses the degree of substitution between preexisting loans by guaranteed loans for Italy, France Germany and Spain using the European module of AnaCredit, a dataset that is very similar to ours, analyzing also credit risk employing arrears as their measure of borrowers' credit risk. We consider a richer set of measures of credit risk, and focus also on the relationships' characteristics. Furthermore, we investigate not only guarantees but also moratoria, assessing to what extent the two measures were complementary, which is something none of the above papers does.

Our study is complementary to two other studies on Italy. Core & De Marco (2021) analyze which firms and which bank characteristics explain the probability of accessing to government guarantees in Italy, but they do not analyze the role of pre pandemic bank-firm matching and relationship history.[4] Cascarino et al. (2022) analyze credit register data for Italy to measure the additionality of guaranteed loans with respect to existing credit and find that guaranteed loans, especially those fully guaranteed, generated 0.8 extra credit for each unit of guaranteed loan. Our results are broadly consistent with their findings.

Finally, we contribute to the relationship lending literature. The Covid-19 shock is suitable to test for the benefits of relationship banking because it is an exogenous shock to firm conditions and not to banks' health. To our knowledge only Berger et al. (2022)

[4] We focus on firms that are in AnaCredit to investigate a different question with respect to Core & De Marco (2021), who study which firms had access to guaranteed loans, as we condition on bank-firm relationships associated with at least one outstanding exposure of 25k euro.

focus on the pandemic to analyze how relationship borrowers fared compared to the other borrowers.

Our main results are the following. During the pandemic ex ante riskier borrowers were less likely to receive a guaranteed loan, everything else equal. Borrowers benefiting from moratoria were even less likely than those with no moratoria on outstanding loans. The findings on relationship characteristics suggest that guarantees were a substitute for soft information. In some of our regressions borrowers with close relationships with banks were less likely to get a guaranteed loan. Similarly, longer relationships were less likely to get a guaranteed loan, while new ones were more likely. The coefficient of an overall index of soft information available to the lender is mostly negative but not always statistically significant; for some samples the sign turns positive. The probability of observing a guaranteed loan increases with the pre-existing dependence of the firm on the bank's credit and with the ratio of used to granted overdraft loans in line with Jiménez et al. (2022). New relationships are more likely than old ones to entail a guaranteed loan with a slightly larger effect for riskier firms, which suggests that guarantees helped firms with no prior loans reported, consistent with their function of mitigating credit constraints due to information asymmetries. Bank-firm physical proximity, consistently with other studies on the Covid-19 shock (Branzoli et al. 2021, Core & De Marco 2021), increase the probability of entailing observing a guaranteed loan, most likely because of mobility restrictions during the pandemic favouring banks with larger branch networks.

Public guarantees were effective in increasing lending. Like other studies on the Italian program, firms that have at least one guaranteed loan experienced faster credit growth than those with no guarantee, controlling for firm credit demand. Our findings on the effect of bank-firm relationships on credit growth are ambiguous. For firms with no guaranteed loans, more soft information production is associated with faster credit growth while it is not for firms with guarantees, consistently with guarantees substituting relationship banking. Nonetheless our specific proxy for close relationships is either not significant or has a negative coefficient. Further analysis would be necessary to understand the mechanism behind these apparently conflicting results.

In regard to banks' characteristics, capitalization does not appear to influence the allocation of guarantees. Banks with low capital expand credit relatively more when the borrower has been granted a loan with a public guarantee, likely because these loans have a lower regulatory capital requirement, but the result is not robust to the inclusion of bank fixed effects.

Finally, the results from the asymmetric information test are not consistent with adverse selection in the allocation of public guarantees nor with moral hazard because guarantees are allocated less likely to firms that have a higher than expected ex post default given their ex ante observed characteristics. A limitation of the test is that our ex post default period of observation could be too short, but extending it further would include the effects of the 2022 shock to energy prices on the economy. Moreover, although we find that ex post defaults are lower for recipients of guaranteed loans, controlling for pre-Covid credit risk, further analysis would be necessary to identify a causal effect of the program.

The paper is organized as follows. Section 2 describes the institutional details of government measures in Italy during Covid-19 pandemic. Section 3 describes the data and variables used for the analysis and Section 4 shows our regression specifications for allocation of guarantee and for loan growth. Section 5 presents and discusses the main results. Section 6 investigate bank heterogeneity and Section 7 presents the results of a test for detecting adverse selection and/or moral hazard; the last Section 8 concludes.

2. Government measures to support credit in Italy during Covid-19

After the outbreak of Covid-19 pandemic, the Italian Government enacted several support measures to counteract the consequences for the economy. In March 2020 a wide-ranging package of measures to limit the risk of a tightening in credit supply was implemented to relieve firms on existing debt service and facilitate recourse to new borrowing. The Decree Law 18/2020 introduced a public debt moratorium for small and medium-sized (SMEs) enterprises. Firms in good standing (with no deteriorated debt) were eligible for: (a) the deferment of loans maturing in the subsequent months; (b) the suspension of mortgage loan instalments and lease payments; (c) the freezing of the existing available uncommitted credit facilities (current account overdrafts and loans granted against advances on receivables). Initially envisaged until September 2020, the moratorium was subsequently extended twice, although with some limitations (until June 30, 2021 and until December, 31 2021). In addition to the public moratorium, in March 2020 the Italian banking association and the employers' associations entered into an agreement allowing SMEs to delay the payment of loans instalments due. Although the deadline to apply for the moratoria was extended to the end of March 2021, with a maximum period of suspension of loan payments of 9 months, most firms applied in the first three to six months of the first wave of the pandemic in 2020.

The Decree Law 23/2020 expanded significantly the existing scheme of public guarantees on loans provided by the Central Guarantee Fund ("Fondo Centrale di Garanzia", FCG). This fund had been running smaller scale public guarantee schemes for SMEs since the early 2000s. The measure raised the maximum amount of the guarantees provided by the FCG to each firm from 2.5 million to 5 million and introduced new public guarantee schemes for SMEs. The first new scheme ("Letter M") allows banks to grant to SMEs loans up to 30,000 euro with a 100 per cent coverage and a maturity up to 10 years with no prior screening nor authorization by the FCG. The second group of schemes ("Letter N and C") introduced guarantees on loans to SMEs and Midcap (i.e. firms with up to 500 workers) up to 5 million euro in value, a coverage of 90 per cent and a maturity of up to 6 years. A specific program was designed for loans granted within debt renegotiation or consolidation agreements ("Letter E"), with coverages up to 80 (or 90 per cent if an additional guarantee is provided). For all schemes, the maximum guaranteed amount could not exceed 25 per cent of the borrower's revenues. The Decree Law 73/2021 ("Sostegni bis") extended by 6 months, until December 2021, the possibility of applying for the guarantees provided by FCG. "Letter M" loans could be granted before a formal approval by the FCG, the latter usually based on simplified procedures. The decree does not prevent banks from assessing credit risk of loans applicants with "Letter M" guarantee. Evidence collected by the Bank of Italy[5] indicates that banks applied different approaches to screen potential borrowers, for example fast track procedures for their best clients and more careful evaluation for riskier ones. For the other public guarantee programs banks followed standard procedures to assess the debtors' creditworthiness.

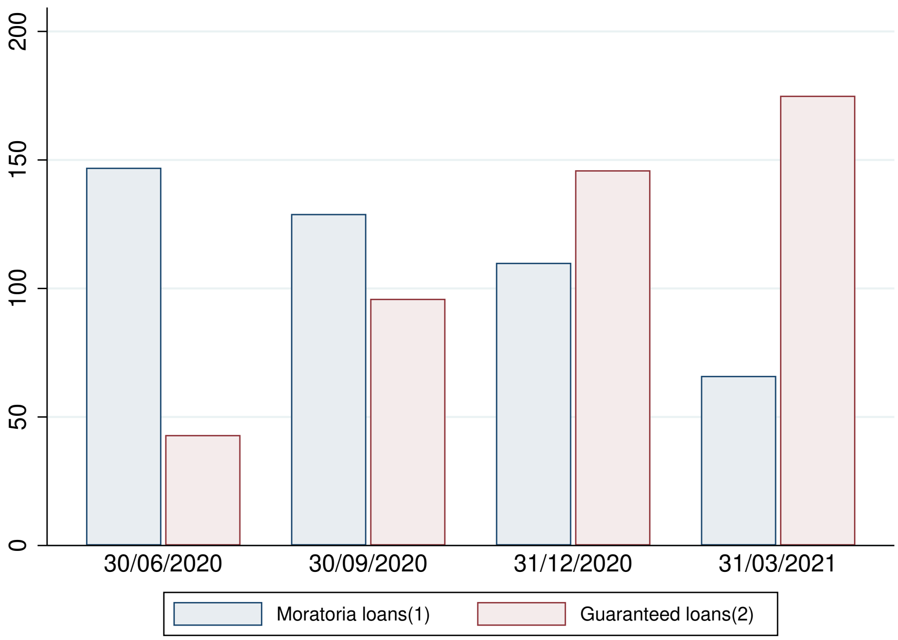
Large firms and SMEs that exhausted the threshold of FCG guarantees could apply for guarantees issued by SACE, the Italian export credit finance agency. These guarantees are available to firms that are not "undertakings in difficulty" under EU Regulations, and whose liabilities were performing as of 29 February 2020.

About two thirds of the new guaranteed loans were granted early during the pandemic (second quarter of 2020) under the "Letter M" scheme (as shown by Cascarino et al. 2022). Nevertheless, the overall amount of these loans is significantly smaller than credit under "Letter N and C" schemes. Guaranteed loans falling under the "Letter N Confidi" and "Renegotiation" schemes have been infrequent. The small "Letter M" loans are likely to be mostly driven by demand than by strategic considerations by banks. The total uptake of guaranteed credit until March 2021 was 175 billion, of which 152 guaranteed by the FCG, whereas loans benefiting from a moratorium reached a peak of around 150 billion in the earliest months after the launch of the public and private programs.

As shown in Figure 1, guaranteed loans increased throughout the entire period while

[5] For more details see: https://www.bancaditalia.it/focus/covid-19/task-force/misure-supporto/scheda-04/index.html (only in Italian).

Figure 1: Loans to firms benefiting from public measures (billion)



Source: Finrep, MCC and SACE. (1) Outstanding amounts (net of expired). Data referring to June 2020 are partially estimated. (2) Cumulated flows of newly originated loans.

moratoria peaked during the first half of 2020 and gradually declined, as health and economic conditions improved. The findings in Albanese & Ciocchetta (2021) and Branzoli et al. (2021) suggest that some of the delay in the issuance of guaranteed loans was the result of organizational frictions. Once banks adapted their processes to the lockdown, the program was fully rolled out and guaranteed loans continued to expand. On the contrary, the moratoria were effective immediately after the approval of the Decree, as they had to be granted upon request by firms. Subsequently, some firms requested an extension while others resumed payments, leading to a gradual decline in the volume of loans under moratoria.

This evidence supports our choice to focus on a longer period than other analyses. Including one year of data allows us to study the allocative choices of banks, if any, abstracting from the effect of these frictions. In the next section we illustrate how we construct our data set.

3. Data and variables

We combine micro-level data from three different sources. The first source is AnaCredit, a granular database containing information on loans collected in a harmonized way across all euro area countries. The second and third sources are Cerved for firms' balance sheet data and Supervisory reports for bank variables, respectively.

AnaCredit collects loan-by-loan information from around 250 resident credit institutions. The data refer to firms whose bank-level exposure is of at least 25,000 euro in granted credit.[6] Loans in AnaCredit account for about 98 per cent of total lending to businesses by Italian banks.[7] The data include the amounts of credit granted and disbursed, the type of loan, the interest rate, the credit quality, whether there are guarantees or real collateral and its allocated protection value. Basic information on each borrowing firm, including size, municipality, province, and industry is available. We collect loan information with a quarterly frequency for the period December 2019 - March 2021 to identify new loans granted during the pandemic. The quarterly frequency is important because we need to identify moratoria, including those granted for a relatively short period, as well as loans with a short maturity.

Loans backed by the credit support schemes or benefiting from the moratorium introduced by the government decrees are identifiable by a special flag assigned by the reporting banks during the pandemic.[8] We conduct our analysis at the bank-firm pair level, hence credit quantities and other information refer to the sum of all contracts referring to a single relationship though we retain information on the number of contracts and their type.

For each bank-firm relationship we construct a dummy variable equal to 1 if the firm receives a loan with a public guarantee under the Covid-19 programs, zero otherwise.

[6] AnaCredit does not include exposures towards sole proprietorships so the smallest firms are under-represented.

[7] A number of small intermediaries are exempted from reporting as provided by AnaCredit Regulation.

[8] The change to the AnaCredit reporting model was applied only at the national level. For more details see Circular n. 297/2017 of the Bank of Italy.

This is our main dependent variable. The variable is set to zero for partial guarantees that were granted on loans benefiting from the legislative moratoria because they were subsidiary to the suspension of installments.[9]

Further, we identify firms receiving small loans under the "Letter M" scheme by combining the publicly available list on the website of the FCG with our data. We extract also credit relationships entailing only a "Letter M" loan and no other type of credit. We employ this information for robustness purposes. These new relationships started during the pandemic possibly because banks could take advantage of the guarantee to expand their customer base without the need to screen. In our dataset we find 363 thousand out of over two million of such loans because most of them are below the reporting threshold of AnaCredit.

We also consider total bank-firm pair loans granted and total disbursed at the beginning and at the end of our sample period, to compute credit growth rates, broken down by type. We are able to distinguish revolving and the like from non-revolving loans. The former tend to be more information intensive and include overdrafts, credit cards, trade receivables and other revolving type of instruments.

An important information available in our data, not considered by most of the other studies on the Covid-19 guarantees, is whether the firms obtained a moratorium on outstanding debt. We create a dummy variable equal to 1 if the specific bank-firm relationship benefited from a public or private Covid-19 moratorium, 0 otherwise, and a similar dummy at the firm level (we employ the latter in our asymmetric information test, see Section 7).

3.1. Risk and Relationship characteristics

For each bank-firm pair observed in December 2019 we calculate the share of the outstanding amount classified in the three stages envisaged by the IFRS9 account-

[9] For further details see Special Section, article 57 of the "Cura Italia" Decree.

ing principles. According to IFRS9, credit exposures must be categorized by banks as performing (stage 1), underperforming (stage 2) or non-performing (stage 3) with the purpose of assessing adequate accounting provisioning against the expected credit losses. We define a borrower's riskiness as the ratio of stage 2 and stage 3 loans to total loans. Since each bank can give its own assessment, the same borrower can be considered more or less risky by different banks. In our analysis we focus on borrowers that are not defaulted so firms with stage 3 exposures are dropped and our credit risk indicator boils down to the ratio of stage 2 loans to total outstanding loans.

A subset of banks also provide information on their borrowers' probability of default (PD) over a one year horizon based on their internal rating (IRB) model validated by the supervisor.[10] These PDs are a crucial input to the calculation of regulatory capital and are very useful in testing for the role of capital management in targeting guarantees as they capture the lender's assessment of credit risk. Banks estimate internal PDs following a "through the cycle (TtC)" approach, i.e. removing the influence of cyclical factors, and adopting a forward-looking assessment of credit risk. On top of using the PDs as risk measures, we compute the variable PD_ante_avg as the mean of the PDs of all banks lending to the same firm. We employ this variable as a proxy of the credit risk of firms establishing a new relationship (there is no pre-pandemic PD calculated by the new lender).

We then construct a rich set of relationship characteristics, in line with the literature on relationship banking. Our purpose is to capture the amount of private/soft information that the bank possesses on its borrowers through repeated and stable interactions with them.

Many studies use the importance of the bank for the firm in terms of share of credit. Others focus on the duration of the relationship. We argue that the first of these variables might capture dependence on the bank/switching costs but not necessarily soft

[10] PDs are available for 23 banks (out of 250) but these banks account for about 75 per cent of relationships and over 90 per cent of the overall loan volume.

information. Similarly, duration is correlated with the production of soft information, but long term loans that are fully collateralized may not be generating much information on the prospects of the business. Therefore, we prefer to consider the number of loan contracts that generate private information on the transactions between the firm and its clients and suppliers, i.e. revolving credit lines, overdrafts and factoring, relative to the total number of contracts (Soft_information). We include factoring among the contracts that generate information because we argue that the lender can monitor the volume of business of the borrower and the structure and number of its business counterparts. Berger & Udell (2006) categorize factoring as a "transactions technology because the underwriting process is based on hard information about the value of a borrowers account receivable". In our context, we focus on the contribution of the overall volume of factoring transactions to the ability to monitor the borrower's business conditions, rather than on the information needed to screen credit quality and approve a single new contract.

The length of the relationship (Duration) is computed using information on the loan contract with the earliest inception date considering all the loans outstanding at the end of 2019 for each bank-firm pair. We take the natural log of this variable to account for a declining marginal effect of duration in terms of knowledge acquired by the bank on the firm. We acknowledge that our variable may underestimate the true length of the relationship because we can go back only to the oldest contract among the ones that are still outstanding.

To identify relationships entailing much soft information we define a dummy variable that is equal to 1 if the relationship is in the top quartile of the distribution of our variable Soft_information and its duration is longer than 3 years, 0 otherwise (Close_rel).

We consider a proxy of physical proximity between the bank and the firm to control for transaction costs, given by the log of the number of branches of bank i operating in the municipality where firm j has its headquarters (Proximity). Proximity is often used as a proxy for access to information on the firm and its local market, assuming that banks that have a stronger presence in a given local market and/or that are physically close to the firm have better knowledge on the firm and its prospects.[11] The rationale for including this variable in addition to our soft information proxies is that during the pandemic physical distance played an important, though different, role. Mobility between municipalities was limited by restrictions and banks that had many branches were more easily accessible.

We also include the share of the firm's total credit outstanding granted by each bank (Bank_share), as it has been used by Altavilla et al. (2021) and Jiménez et al. (2022). This variable captures the importance of the bank to the firm and we expect that firms demand guaranteed loans more often from their main lender. We compute also the ratio of credit disbursed to overdraft credit granted (Used_Overdraft), which is a standard measure of liquidity constraints of firms. In the case of multiple banking, it proxies for the preferred lines of credit from which the firm draws liquidity.

Three other dummy variables control for the presence of collateral:
i) d_FCG_guar_nocovid is equal to 1 if the relationships entails other loans issued under the pre-Covid public guarantee program; ii) d_personal_guarantee is equal to 1 if the firms has posted personal guarantees; iii) d_real_guarantee equal to 1 if the firm has posted real collateral. Prior public guarantees should increase the probability of participation to the Covid19 programs since it signals that both the bank and the firm possess prior knowledge of these programs and how to apply. Instead, we do not have priors on the signs of the effects of the other two variables.

We identify new bank-firm relationships as those that were never reported before March 2020 (New_rel) and new firms as those that were never reported in AnaCredit before March 2020 (New_firm). We include these variables to account for the poten-

[11] This variable does not take into account the functional distance, i.e. the distance between the firm and the center of decisions within the bank, which depends on the organization structure and degree of delegation as pointed out in Stein (2002).

tial effect of the public guarantee programs in reducing information asymmetries and allowing banks to expand their customer base.

Finally, we calculate the number of lenders granting credit to the firm before the pandemic (Number_lenders) to account for the ability to switch between banks.

All the relationship variables are based on pro forma data if a bank disappears as a result of a merger within our sample period. For example, if bank B lends to firm i and bank A acquires bank B within our sample period, the duration of the relationship between firm i and bank A takes into account also the length of the relationship that firm i had with bank B. Similarly, we compute credit growth using pro forma data on loans provided by bank A and bank B to firm i in t-1.

We do not collapse data on loans by banks belonging to the same banking group because soft information is accumulated during the interaction between each firm and the the loan officer of the specific financial institution handling the credit relationship. The top tier holding company management would be many decision-making layers above local loan officers, particularly for the smallest firms.

3.2. Other variables

We match the AnaCredit data with key firms balance sheet variables provided by Cerved, a database including balance sheet information on Italian companies (Ebitda, Leverage, Liquid assets, Sales, Tangible assets and Total asset). We compute standard balance sheet and profitability ratios as defined in Table A18 of the Annex. Cerved computes the Zscore, a measure of credit risk estimated by linear discriminant analysis, considering profitability and other financial indicators as in Altman et al. (1994). In the official publications of the Bank of Italy the Zscores are grouped into four categories (4. risky, 3. vulnerable, 2. solvent, 1. safe). To test our hypotheses we employ a dummy variable Risky equal to 1 if the debtor is classified in the fourth bucket, 0 otherwise.[12]

[12] In our sample 6 per cent of firms are considered safe, 36 solvent, 39 vulnerable and 19 risky.

For firm size we consider a set of dummy variables based on the size classes defined by the European Commission (large=1, medium=2, small=3, micro=4, missing=0) available in AnaCredit. These categories were relevant for eligibility to the different programs (FCG and SACE).

Using the bank identifier from AnaCredit, we match the data with the supervisory data. We include Total assets, Total loans, Loans to non-financial corporations, Non-Performing loans and the Common Equity Tier 1 ratio. We gather these variables at the individual and at the highest consolidated banking group if the bank belongs to a group from the Supervisory reports because capital requirements apply at the consolidated entity level. We focus on the CET1 ratio in a number of tests to explore heterogeneous behavior across banks with respect to the allocation of guarantees.

The definitions of variables are reported in Table A18 in the Annex. The resulting dataset has around 1.5 million observations (bank-firm relationships) referring to 224 banks and just under one million firms. We drop firms that have at least one defaulted exposure as of December 2019 since they do not qualify for access to the public liquidity support measures and remain with 1.3 million observations. Tables with descriptive statistics are in the Annex (Tables A13-A17).

3.3. Descriptive Statistics

We report in Table 1 aggregate figures for loan volumes at the beginning and at the end of the sample period for all firms with no defaulted exposures as of December 2019. The overall volume of credit increases by 9 per cent between December 2019 and March 2021 and the increase is the result of two components: relationships receiving at least one guaranteed loan and relationships of firms not receiving any guaranteed loan. The aggregate data also suggest that firms receiving guaranteed loans reduce their borrowing from other banks. The second row of the table shows that relationships with no guarantee referring to firms receiving a guaranteed loan by another bank experience a credit contraction. This may depend on both supply and demand factors.

Table 1: Aggregate credit by uptake of public guarantees

Firm has a public guarantee	Bank-firm pair has a guarantee	Outstanding credit Dec-19	Outstanding credit Mar-21	Change
No	No	259.3	267.0	3%
Yes	No	110.8	98.7	-11%
Yes	Yes	94.5	142.4	51%
	Total	**464.7**	**508.1**	**9%**

Notes: Data in billion euros. Borrowers that had at least one defaulted loan as of December 2019 are dropped because they are not eligible for guarantees.

The data at the relationship level provide a different picture. Table 2 reports mean growth rates of credit granted and disbursed computed over the bank-firm level dataset, by relationship guarantee status (firm has/has not received at least one guaranteed loan). We note that bank-firm relationships with a public guarantee experience fast growth of credit while those with no guarantee experience a drop, regardless of the firms having received a guarantee or not. The average drop in credit disbursed is larger for firms that received a guaranteed loan (10.4 against 9.0 per cent). This figure is consistent with some substitution occurring between different banks granting guaranteed loans and banks not granting them (see Altavilla et al. 2021, Cascarino et al. 2022). Contrasting the aggregate and average growth for firms not receiving a guaranteed loan, suggests that some very large firms increased their borrowing significantly.

In the full sample (Table A13), that includes also new credit relationships, 36 per cent of relationships have at least one guaranteed loan and 29 per cent loans with moratoria. Our soft information variable takes an average value of 0.45, with a standard deviation of 0.39, meaning that about half of the contracts involved in each relationship are suitable to generate soft information (factoring, revolving and overdraft). On average, a bank typically grants half of the overall borrowing of each firm, but at least a quarter of firms have only one relationship while another quarter has at least 4. Focusing on risk measures, our second set of key variables, the PD is highly skewed with a small

Table 2: Average credit growth by uptake of public guarantees

Firm has a public guarantee	Bank-firm pair has a guarantee	Change in credit granted (1)	N. of obs.	Change in credit disbursed (1)	N. of obs.
No	No	-3.6	456,010	-9.0	393,077
Yes	No	-3.5	307,772	-10.4	287,393
Yes	Yes	23.7	554,722	35.3	538,160
	Total	**7.9**	**1,318,504**	**10.3**	**1,218,630**

Notes: Credit growth is the percentage change between March 2021 and December 2019 for each bank-firm pair for continuing borrowers. Credit growth rates are winsorized at the 5 per cent. (1) Sample mean in percentage points.

number of very risky firms.

Firms with balance sheet data are shown in Table A14. They are on average larger than firms in the full sample, have a lower incidence of guaranteed loans, particularly "Letter M" guarantees, and a lower average PD. The subset of firms with multiple bank relationships includes around 450,000 observations (Table A15). Relationships with at least one guaranteed loan are less than in the full sample (around 27 per cent), and those with "Letter M" guarantees much lower (7 per cent).

In the next section we illustrate our empirical approach and the regression models.

4. Empirical analysis

4.1. Allocation of guarantees

Our main regression model relates the probability that a bank-firm pair includes a Covid-19 guaranteed loan against the baseline of no Covid-19 guaranteed loan. We include only eligible firms, dropping those with at least one defaulted exposure before the activation of the program because they are not eligible. Only SMEs were eligible for the public FCG Covid-19 schemes but later a public guarantee program administered by the government controlled company SACE was approved for larger firms. Therefore, our main sample contains all firms. For robustness purposes we estimate the model with the subsample of SMEs and all results hold so we do not report any of these results for the sake of brevity. We specify a linear probability model as follows:

$$\begin{aligned} prob(guarantee)_{ij} = & \; Relationship_{ij} + Risk_{ij} + Moratoria_{ij} \\ & + FirmCharacteristics_i + BankFE_j + \epsilon_{ij} \end{aligned} \tag{1}$$

We include the dummy Moratoria among the explanatory variables beacause moratoria were granted early during the crisis and upon demand by firms (see Figure 1), hence can be considered largely exogenous with respect to banks' choices on guarantees.

The variable Risk in equation (1) is indexed by ij as our main measures of firm risk can vary across different lenders (the PD and the share of stage 2 loans). The other two measures are defined at the firm level (average PD and the dummy Risky).

The relationship controls are: the ratio of drawn to granted credit (Used_Overdraft), the dummy variables on prior public guarantee loans (d_FCG_guar_nocovid), the presence of personal guarantees on loans from the bank (d_personal_guarantee), if the firm posted real collateral on loans from the bank (d_real_guarantee).

A key issue is how to control for the size of the economic shock from the pandemic, which in turn would affect the demand for guaranteed loans. We follow Degryse et al. (2019) and include a set of industry times province dummy variables to control for industry and province heterogeneity across the local markets where firms have their headquarters.

We add balance sheet controls that may influence the demand and supply of the public guaranteed loans: Ebitda, Leverage, Sales_on_assets, Liquidity, Tangible_on_assets.

We control for firm size with the set of dummy variables described in subsection 3.2. Firms with missing data on size class, typically very small ones, are kept in the sample and considered as the excluded category in the regression. We include the Number_lenders to control for the franchise value of each bank-firm relationship (more relationships presumably reduce the ability to extract rents from the borrower).

We include bank fixed effects to control for any bank-level difference in the propensity to provide loans with public guarantee and other unobservable heterogeneity. For example Branzoli et al. (2021) and Albanese & Ciocchetta (2021) show that prior investment in technology by banks and the size of the branch network were both important determinants of credit supply during the pandemic.

In a second specification we focus on the interaction between moratoria and risk, to understand whether guarantees were granted to riskier firms already benefiting from moratoria. The specification is:

$$\begin{aligned} prob(guarantee)_{ij} &= Relationship_{ij} + Risk_{ij} * Moratoria_{ij} \\ &\quad + FirmCharacteristics_i + BankFE_j + \epsilon_{ij} \end{aligned} \tag{2}$$

A positive coefficient of the interaction term would be consistent with a systematic transfer of ex ante credit risk to the government.

It could also be the case that ex ante riskier firms were also hit more by the pandemic, which would jointly increase their demand for moratoria and for guaranteed loans. In an alternative specification we saturate the regression with firm fixed effects to control for any firm-level factor influencing the demand for loans following Khwaja & Mian (2008). This specification is more robust to unobserved firm characteristics but has the disadvantage of excluding from the estimation firms borrowing from one bank, typically the smaller and more opaque firms which are more likely to demand guarantees. We cannot estimate this model with the dummy Risky based on Zscore and the average PD as these risk measures do not vary across banks for the same firm.

As a caveat, we underline that our empirical analysis is based on outcomes as we neither observe loan applications of firms that get rejected by banks nor have information on the extent to which banks were active in promoting the uptake of the guarantees by their borrowers. Nevertheless, when we investigate the role of bank capitalization by interacting bank CET1 with firm or relationship characteristics we can reasonably argue that we are identifying supply side effects in the allocation of guarantees.

4.2. Loan growth

The purpose of the guarantee program was to provide liquidity to firms hit by the shock.

Relationship strength could be a complement or a substitute of public guarantees in ensuring that firms got the liquidity support they needed. We study the determinants of credit growth comparing firms with and without loans with public guarantees, splitting the sample into the subsample of borrowers who did not receive any guaranteed loans and the subsample of borrowers who did.

We include industry*province fixed effects in the regressions to control for credit demand. We also estimate the model with firm fixed effects, which means comparing the change in credit granted to the same firm across the existing relationships as in Khwaja & Mian (2008). Since we include bank fixed effects, we control for bank-level unobservables affecting credit supply thereby focusing on bank-firm relationship characteristics.

$$\begin{aligned} creditgrowth_{ij} = {} & Relationship_{ij} + Risk_{ij} \\ & + Moratoria_{ij} + FirmFE_i + BankFE_j + \epsilon_{ij} \end{aligned} \tag{3}$$

For the sake of comparison with the literature on the effects of guarantees on credit substitution (Cascarino et al. 2022, Altavilla et al. 2021), we estimate a second regression model replacing credit growth with the measure of loan substitution proposed by Altavilla et al. (2021). The latter paper aims at measuring additionality of the guarantee programs. Our dependent variable is the growth of the non-guaranteed component of credit, with loans with no guarantee computed at the bank-firm pair subtracting the value of the protection from the total outstanding credit disbursed by the bank to the firm.[13] The protection value could be less than 100 per cent, so our measure considers as non-guaranteed credit also the amount of a guaranteed loan that is not covered by the guarantee (e.g. 20 euro out of a 100 euro loan covered by an 80 per cent guarantee). This is slightly different from the measure employed by Altavilla et al. (2021), who distinguish between loans with and without a guarantee and include the entire exposure in both cases. Results are illustrated in the next section.

5. Results

5.1. Allocation of guarantees

The results of our first set of regressions are shown in Table A1. We report results for our two main measures of risk (PD_ante and Share_stage2), without (columns 1 and 2) and with firm-level control variables (columns 3 and 4). When we include firm balance sheet controls the sample is smaller, but main results are unchanged.

In all the regressions shown, riskier borrowers are less likely to receive a guaranteed loan (controlling for industry*province fixed effects). A one standard deviation increase in the PD (0.06) reduces the probability of a guarantee by almost 3 percentage points, which is economically significant but not very large given that the sample mean of the dependent variable is in the 0.28-0.36 range depending on the sample. The coefficient of Share_stage2 is negative and statistically significant. A one standard deviation increase in the variable (0.3) yields a 2 percentage points lower probability of a guarantee, which is very similar to the economic effect of the PD.

The proxy for soft information is not correlated with the likelihood of a guaranteed loan except for the specification shown in column (2) where it has a positive coefficient. The change in the sign is not explained by the different sample as we replicate

[13] Formally we define our measure of credit substitution as in the following formula:

$$subs_{i,j} = -[(granted\_loan_{i,j,t} - prot\_value_{i,j,t}) - granted\_loan_{i,j,t-1}]/granted\_loan_{i,j,t-1}$$

the estimation with the same dataset employed to obtain the results in column (1). Furthermore, our variable identifying close relationships is negatively correlated with guarantees as well but not always statistically significant. In particular, when Close_rel is equal to 1 the probability of having a guaranteed loan is less then 1 percentage points lower.

The effect of duration is negative and not always statistically significant. We note that the magnitude of the coefficient changes with the sample. For banks reporting PDs - typically the larger ones - the effect is bigger, suggesting that for these intermediaries the marginal benefit of soft information is declining faster than for smaller banks.

Overall, these results suggest that guarantees were not allocated preferably to firms whose bank relationships entailed soft information acquisition. Guarantees were actually provided to firms on which the bank had less soft information. Relationships played a role but in a different sense, as the probability of guarantee increases with the importance of the bank for the firm in terms of share of borrowing (Bank_share). This result is consistent with Jiménez et al. (2022). In our interpretation, a large share of borrowing from the bank is capturing the existence of a significant business relationship rather than the amount of soft information on the firm's prospects (captured by our other variables in the regression). Having a significant relationship likely entails knowing personally the loan officer which makes communication with the bank smoother during full or partial lock-down.

Physical proximity between the bank and the firm has a positive and significant effect, as found by other studies on bank behavior during the Covid-19 shock (Branzoli et al. 2021, Core & De Marco 2021). Considering that our regressions include control for a variety of relationships characteristics, we conclude that proximity is capturing a pure physical distance/travel cost effect.

The coefficient of the moratoria dummy is very stable across all of our regressions and shows that relationships with moratoria have a 13-18 percentage higher probability of entailing also a guaranteed loan than those with no moratoria. We interpret this finding as suggesting that firms that were hit more by the Covid-19 shock resorted to both support measures, although many firms applied for new credit to face uncertainty even if they did not have loan repayment issues.

Larger firms have a lower uptake of guarantees, as expected, while for smaller ones the incidence of guaranteed loans is slightly higher than for firms with no size class information. Firms that have already posted real collateral to back an outstanding loan at the same bank are less likely to have a loan with a public guarantee. The opposite holds for firms that posted personal guarantees on previous loans as they are generally riskier.[14] For the sake of brevity, we do not show the coefficients of the other control variables in the results reported (columns 3 and 4) but they are as expected (results are available upon request). In particular, firms with more tangible assets and more liquidity have a lower probability of guarantee.

For robustness purposes, Table A2 reports results from regressions estimated with the firm-level risk metrics. They are similar to our main results shown in Table A1. Riskier firms again have a lower probability of having a guaranteed loan than other firms (not significance if the Zscore measure is used without other firm controls, column 2) and the coefficients or the other key variables are stable.

In Table A3 we report the results of specifications that include an interaction term between PD_ante and Moratoria. The coefficient of the interaction term is always negative and statistically significant. Focusing on column (1), the marginal effect of the PD on the probability of having a guaranteed loan is negative and larger in absolute terms (-0.37 for firms with no moratoria and -0.65 for firms with moratoria). These result is robust across risk measures and samples (see columns 2, 3 and 4).

In Table A4 we test for robustness to the exclusion of "Letter M" loans because we want to focus on the banks' behavior in providing guaranteed loans. "Letter M" loans

[14] For robustness purposes we estimate the specifications in Table A1 on a subsample with no large companies and the results continue to hold.

are very small, fully guaranteed and have a capped interest rate. Many firms were likely to have requested these loans for precautionary liquidity needs. In columns (1) and (2) we consider the sample of bank-firm relationships without "Letter M" loans while in columns (3) and (4) exclude bank-firm pairs with at least one "Letter M" loan. Our main results continue to hold.

Table A5 reports results of a model that includes firm fixed effects. This specification is robust to any firm level unobservable characteristics that may influence the demand for guaranteed loans. The identification is based on the variation across banks lending to the same firms. Typically this approach is employed to focus on supply effects controlling for demand and the matching between banks and firms. The drawback is that the estimation sample is restricted to firms with at least two relationships before the pandemic shock, which excludes smaller firms that borrow from one bank.

Most results are unchanged but we note that the coefficient of the relationship variables are no longer significant. This may reflect less variation in the data once smaller firms, not providing balance sheet data and hence more opaque, are dropped from the sample. The negative relationship between the probability of a guarantee and risk is unchanged. The interaction term between risk and the moratoria dummy remains negative and significant with both risk measures (PD_ante and Share_stage2). We note that the coefficient of the ratio of overdraft used to granted is not always significant. In the full sample firms with a higher used/granted ratio are more likely to have a guaranteed loan, probably because this variable is signalling greater liquidity needs at the firm level which is mostly absorbed by the fixed effect.

The key message from our analysis so far is that firms that are riskier before the shock are less likely to receive a guaranteed loan and even more so if they have also obtained a moratorium on existing debt from the same bank. Relationships associated with greater information acquisition before the pandemic are generally not more likely to participate in the public guarantee scheme.

Our findings focus on pre-pandemic risk because we test the hypothesis that banks use guarantees strategically to reduce the credit risk of their existing portfolio. Clearly, the allocation of guarantees is also the result of the demand by firms, which in turn should be related to the size of the shock hitting them during the pandemic. In our approach we control for the economic impact of the pandemic with industry*province fixed effects. We cannot infer anything on whether the allocation of guarantees reflects the drop in economic activity. To gain some insights on this issue, we study the allocation of guarantees by industry replacing the industry*province fixed effect with the industry-level drop in value added in 2020.[15] We keep the province fixed effects to control for local market heterogeneity. The results, available upon request, show that guarantees were allocated more likely to firms in the industries that suffered the most, fulfilling the purpose of the support measures. At the same time, our results on credit risk and relationship lending continue to hold controlling for the heterogeneity in the shock hitting firms. We are able to identify separately the role of the ex ante risk and the ex post shock (implying a possible increase in credit risk due to the drop in revenues) because the industry average of the ex ante credit risk is not correlated with the size of the shock. In particular, we verify that industry average PDs are not correlated with the drop in the value added.

5.2. New relationships

In this subsection we illustrate the results from regressions investigating the role that public guarantees might have played in the willingness of banks to extend credit to new clients. New clients were more difficult to evaluate during the pandemic due to the tough economic environment and to greater problems in collecting and processing soft – but also hard – information. Thanks to the transfer of risk, the public guarantees are likely to have incentivized banks to accept new clients given the low skin in the game.

[15] We consider the 2020-2019 change in value added at current prices published by the Italian national statistical institute (ISTAT).

This is actually an intended effect of the policy, which allows firms to access liquidity even in the absence of a credit record or an existing credit relationship.

Public guarantees, especially "Letter M" ones, allowed banks to grant loans minimizing the physical interaction and limiting the collection of information about firms to the minimum necessary to process the application and forward it to the FCG (the public agency granting the State guarantee). These loans were small, had a capped interest rate and the guarantee was approved with minimal screening.

We add to our main regression model the variables New_rel, equal to 1 if the relationship was not in existence before March 2020, 0 otherwise.[16] Relationships history controls from AnaCredit are all set to zero. As previously explained, the variable PD_ante_avg is computed averaging the pre-pandemic PDs from other lenders if reported in the dataset. The assumption is that these PDs reflect the available hard information on the riskiness of the firms initiating a new relationship. The variable Risky is instead unrelated to the presence of the firm in AnaCredit and depends mostly on accounting data. As shown in columns (1) of Table A6, New_rel has a positive and highly significant coefficient, with a magnitude of about 29 per cent, meaning that new relationships have a 29 percent higher probability of benefiting from the public guarantee scheme than old ones. When we include observations on banks with no validated internal models for credit risk, the magnitude increases to 43 per cent (see column 2).

We estimate an additional specification by further adding the dummy New_firm, equal to 1 if the firm has no contract with an inception date before March 2020, zero otherwise.[17] The variable has a positive and significant coefficient, suggesting that firms entering the AnaCredit dataset during the pandemic are more likely than others to have a guarantee, consistent with the public scheme allowing access to credit to firms that did not borrow or borrowed so little that they were below the AnaCredit

[16] The results hold also with firm fixed effects but we want to keep single-bank firms since many of the new borrowers probably fall into this category.

[17] This proxy may overestimate new borrowers because a firm might have only new contracts but an old relationship. Nevertheless, we cannot recover from AnaCredit the inception date of the relationship.

threshold of 25k euro (see column 3).

Finally we estimate a similar specification by adding the interaction between the dummy Risky and the dummy New_firm to verify whether the policy was more beneficial in terms of access to credit to riskier firms. Here we show only results with the dummy Risky to measure credit risk. Results are reported in Table A7 (for the full sample and for robustness purposes also for the subsample without "Letter M" loans). The coefficient of the interaction term is positive and statistically significant consistent with the fact that relatively riskier new firms had a slightly higher probability of obtaining the guarantee than safer firms. The level effect remains negative and significant.

5.3. Credit growth

We compare the growth of loans for guaranteed relationships with the one of relationships with no guaranteed loan to shed some light on the role of credit relationships in shielding borrowers from shocks. Credit growth is the change over the entire sample period of credit granted, including unused loan commitments. If strong relationships entail greater support by banks, we should observe that firms with close bank-firm relationships experience faster credit expansion everything else equal. To the extent that guarantees are a substitute for soft information, the role of relationships should differ in the sample of firms benefiting from the guarantees. This is why we estimate separate regressions for the two sets of firms (participating/not participating in the public guarantee scheme).

The results in Table A8 show that for firms with at least one guaranteed loan (columns 1 and 2), credit grows by around 45 per cent more for relationships with at least one guaranteed loan than those with no guarantee, controlling for the ex ante risk level of the debtor and for relationship characteristics (the unconditional difference is 30 percentage points). Close relationships exhibit a slower growth but the economic magnitude of the effect is small.

For firms with no guarantee at all (columns 3 and 4), more soft information is associated with faster credit growth, consistent with a supporting role of bank-firm relationships when franchise value is greater. Nevertheless, the dummy Close_rel has a negative coefficient, which is not consistent with this hypothesis. The magnitude of the coefficient of Close_rel is one order smaller than the effect of Soft_information.

We underscore that credit risk has a negative and significant coefficient only in the sample of firms participating in the program. When a firm has no guarantees a moratorium is associated to faster credit growth but this does not occur for firms with no guarantee (columns 3 and 4).

Since we can only observe the ex post matching between firms and banks and cannot distinguish between faster credit growth due to demand by firms or supply by banks, we estimate a version of the model with firm fixed effects. The fixed effects control for firm unobserved characteristics, including the impact of the pandemic on firm's activity and the change in the demand for credit. The regression captures supply-side effects if firm credit demand is not bank specific or, if there is any specialization across banks, any heterogeneity is adequately controlled for by the bank-firm relationship variables. Even with the firm fixed effects our main results continue to hold (see Table A9).

For the sake of comparison with Altavilla et al. (2021) we replace credit growth with our credit substitution measure in the regression on the dummy Covid_guarantee for the subset of beneficiaries of at least one guaranteed loan. We obtain a positive and statistically significant effect of the guarantee dummy, but slightly lower in magnitude than theirs (results are available upon request). A smaller effect indicates a smaller expansion rate of non-guaranteed loans, i.e. less new credit and more substitution between old loans with new guaranteed loans. We ascribe the different magnitude to the fact that we measure credit growth over a longer period of time than their analysis (February-August 2020), which gives more time for existing loans to expire and be replaced by new guaranteed loans.[18]

6. Bank capitalization, allocation of guarantees and credit growth

In this section we investigate whether the behavior of banks differs depending on their capitalization. The first hypothesis to be tested is that weaker banks would be more willing than strong banks to reduce portfolio risk by substituting existing loans with guaranteed ones. If banks were pursuing portfolio risk reduction - including through regulatory risk weight reduction to save capital - they would be targeting ex ante riskier borrowers in allocating guarantees (see Carletti et al. 2023).

We measure bank capitalization with the Common Equity Tier 1 (CET1) ratio as it is the regulatory requirements definition. Low capital banks are identified by a dummy (d_lowcap) equal to 1 if the CET1 ratio is below the 25th percentile of the distribution (0.13) of capitalization, 0 otherwise. We choose a binary variable capturing low capital banks because the effect of capitalization is likely to be significant only when capital is close the minimum requirement rather than when it is well above it.

In addition to the allocation of guarantees, we study whether guarantees enable relatively faster credit expansion by less capitalized banks, helping disproportionately riskier borrowers of more constrained banks. We estimate a regression model of credit growth with bank fixed effects and an interaction term between the low capital dummy variable and borrower risk. The bank fixed effects are crucial to control for other bank characteristics that influence credit supply.

We cannot estimate this regression using the probability of default at the bank-firm level (PD_ante) because there are too few banks with PD data that are also in the low capital bucket. Hence, we use the firm average of the PDs calculated by other lenders (PD_ante_avg). We consider this as a proxy of the unobserved risk assessment of banks without a validated internal rating model under the assumption that the PDs

[18] Some of the difference could depend on how we define and measure the share of guaranteed loans that is not covered by the public guarantee.

provided by other banks is a good measure of credit risk. We run the regression with the other risk measures as well (Share_stage2 and dummy Risky). The regression model includes bank fixed effects so we do not obtain a linear effect for low CET1 but we ensure that all bank-level factors influencing banks' credit supply are controlled for.

Results, reported in Table A10, show that the coefficients of the interaction between the dummy d_lowcap and the risk measures are not statistically significant. Contrary to Jiménez et al. (2022) we find no evidence of systematic risk shifting behavior by banks in the allocation of public guarantees. A possible explanation is the different institutional design of the public guarantee schemes in the two countries. One of the differences is that in Spain firms were required to pay entry fees while in Italy this was not the case.

In the last set of regressions focusing on bank capitalization we analyze credit growth (see Table A11). We do find that low capitalization banks expand credit more to borrowers that have been granted a loan with a public guarantee than to other borrowers, which is coherent with the very small impact on regulatory capital requirements of these loans thanks to the government guarantee. The effect is 6 percentage points additional credit growth with respect to an average difference in credit growth between relationships with a guarantee and those without it of about 50 percentage points. This difference seems large but the average difference in credit growth between relationships with guarantees and those with no guarantee in the raw data is 26 percentage points (see columns 1 and 2).

The last two columns of the Table A11 reports regressions without bank fixed effects to provide insights on the level effects of bank characteristics. Banks with low CET1 ratio expand credit less than the other banks, on average. Banks with a business focus on corporate lending expand credit more, consistent with theories of bank specialization, while the opposite holds for banks with more NPLs.

7. Adverse selection and moral hazard: Insights from ex post credit quality

Our results reject the hypothesis that the allocation of guarantees was targeted to pre-pandemic riskier borrowers. Yet, it could be possible that our analysis is not considering unobservable risk. In our regressions, based on multiple measures of credit risk, we show that guaranteed loans were allocated more likely to relatively safer borrowers, controlling for industry and local market, based on the internal assessment of credit risk by each bank. The allocation problem involves two layers of information asymmetries, one between the bank and the guarantor (the FCG or SACE) and the other between the bank and the borrower.

Riskier borrowers might have well self-selected into the program. Analogously, banks might have included other information on the quality of the borrower that we do not observe. A systematic role of unobservable risk in the allocation of guaranteed loans would generate a higher ex post default of beneficiaries of guarantees, controlling for observed measures of risk.

We study this possibility by collecting information on the performance of loans after the acute phase of the Covid-19 pandemic, comparing borrowers receiving guaranteed loans with those benefiting from the moratoria and those with neither guarantee nor moratoria.

We add to our main dataset a dummy variable that is equal to 1 if the borrower-bank pair shows at least one defaulted loan between April 2021 and March 2022, 0 otherwise. We consider this a sufficient signal of ex post deterioration but we underline that we do not apply any materiality threshold. This means that even a small past due loan would be flagged as default occurrence in our analysis. For robustness purposes we replicate the exercise considering there more extended periods (June, September and December 2022).

We collapse at the firm level the relationship data and define a new dummy variable (default_post_f) equal to 1 if at least one relationship shows repayment problems because we do not want strategic default to influence our results in the case of multiple bank borrowers. This is a very broad definition that would capture also solvent firms and does not coincide with official statistic on corporate defaulted loans. We underscore that repayment problems for borrower with guaranteed loans may refer to any contract, not necessarily to the one benefiting from the guarantee.

The regression model relates the probability of default of the firm to firm controls and type of support measure, defined by a set of dummy variables for moratoria (yes, no), public guarantee (yes, no), moratoria and guarantee (yes, no). We further distinguish between types of program, i.e. "Letter M" guarantee or other program, by defining the following dummy variables: "Letter M" only (yes, no), "Letter M" and other guarantees (yes, no), only other guarantees (yes, no), with no guarantee as the excluded category. We cannot include the firm fixed effects so we include the full set of balance sheet control variables. Relationship variables are aggregated at the firm level as averages to describe synthetically the structure of the relationships of each borrower. Similarly, we consider averages of the bank controls.

We employ a logit model, which is the standard approach in the literature estimating a default equation, and a linear probability model for the sake of comparison with our main results.

The results of both regressions are not consistent with the hypothesis of adverse selection due to asymmetric information between the borrower and the bank (Table A12, columns 1 and 2). We employ for simplicity the linear probability model coefficients to compute the marginal effects (predicted probability differences) by type of support measures. They represent the conditional difference in the ex post probability of a default occurrence of any of the loans of debtors associated with each category.[19] The

[19] Albeit moratoria were still effective at December 2021, the Supervisory Authorities were encouraging banks to consider any possible sign of credit deterioration when assessing the credit classification in stage 2 or default. For more details see Enria (2020).

marginal effect of the dummy for guaranteed loan is negative, statistically significant and implies a 4 percentage points difference in the ex post probability of default between borrowers with a guaranteed loans and other borrowers (see Figure 2). Such difference is economically significant given the sample average default rate of 4.4 per cent.[20] Figure 2 shows also the magnitude of the marginal effects on the ex post probability of default of the presence of a moratorium and the joint presence of a moratorium and a public guarantee. The firms with moratoria only tend to be marginally riskier than those not participating in any program. Furthermore, borrowers receiving a moratorium and a public guarantee have a slightly higher ex post probability of defaulting on a loan than those with guaranteed loans only.

A caveat in interpreting our results is that the negative coefficient of guarantees in the ex post default regression could also reflects the benefit of the liquidity obtained by firms in the wake of the shock (we showed that credit grows more for these firms).

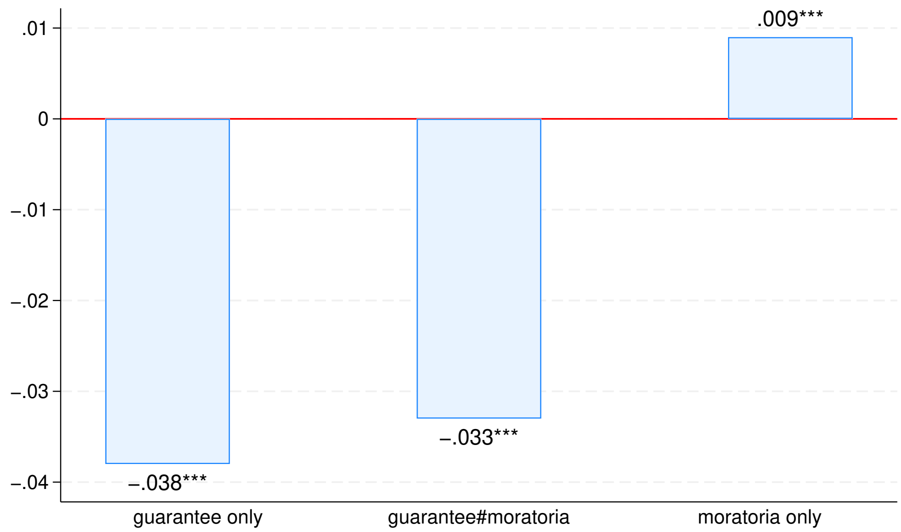
These loans helped covering the loss in revenues at a cheap cost given the low rates charged and were granted with a very favorable reimbursement schedule (interest only period until half of 2022). We cannot draw any conclusion on the impact of the program because the regressions estimated are not suitable to gauge the causal effect.

Asymmetric information between the bank and the guarantor may be more relevant than the one between the firm and the bank, given the incentive structure of the public guarantee. In order to test for the relevance of asymmetric information (and unobservable risk) in the allocation of guarantees we follow the approach proposed by Chiappori & Salanie (2000) for insurance contracts.[21] The analogies with their setting are quite straightforward. While in the insurance market risk is transferred from the insured to the insurer, in the case of public guarantees on loans default risk

[20] The sample averages of our default indicator are: 2.6 per cent for guarantee only, 5.4 per cent for guarantee and moratoria, 8 per cent for moratoria only and 6 per cent for neither moratoria nor guarantee.

[21] See also the contributions on the bank loan market by Stroebel (2016), Crawford et al. (2018), Darmouni (2020), and on the security issuance for example by Benmelech et al. (2012), Albertazzi et al. (2015) and Iannamorelli et al. (2024).

Figure 2: Marginal effects of uptake of different support measures on Probability of Loan Default



Notes: The figure represents the difference between the probability that a borrower defaults on at least one contract of each type of support uptake and the benchmark of non uptake. Default may occur on any loan, not necessarily those benefiting from the support measures. We do not apply any materiality threshold i.e. a minimum loan size. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

is transferred from the bank to the government.

In our context the test is based on the joint estimation of two linear probability models in a seemingly unrelated regression (SURE) design, conditioning on observable firm characteristics. The first equation refers to the probability of observing a public guarantee and the second one to the ex post probability of default on at least one loan by the borrower. A positive (negative) correlation between the error terms of the two regressions means that guarantees are allocated to firms that are more (less) likely to exhibit a defaulted loan. To our knowledge, we are the first to implement the test to study public guarantees on loans.

The test cannot distinguish between adverse selection and moral hazard, yet it provides evidence on the potential role of unobservable risk due to asymmetric information between parties involved. One important difference between the setup of Chiappori & Salanie (2000) is that there are two layers of asymmetric information problems, one between the bank and the firm and the other between the bank and the government, while in insurance markets there is only one asymmetry between the insured and the insurer. Our test cannot distinguish between the source of adverse selection/moral hazard. For example, the firm might apply for the guarantee knowing that it is facing additional risk, unobserved by the bank, or it could be the case that both bank and firm have inside knowledge and the information asymmetry is between them and the guarantor.

The results of the SURE model confirm the general picture described in the previous exercise with the linear probability model and the logit model. Furthermore, the residuals of the two equations in the SURE exhibit a negative correlation of 6 per cent, significant at the 99 per cent level (Table A12, columns 3 and 4). Riskier firms have a lower probability of benefiting from a guarantee, which is not consistent with systematic adverse selection in the allocation of public guarantees by banks. It is inconsistent also with an increase in moral hazard as a result of guarantees, i.e. guaranteed firms taking more risk than similar firms that did not apply/obtain public guarantee. We replicate the asymmetric information test with the original bivariate probit and find a stronger negative correlation of 20 per cent (not shown).

We note that our risk variables generally predict quite well the ex post default. We try changing the end date to June, September 2022 or December 2022. In the earlier part of 2022 many firms were still not paying back principal but only interest on guaranteed loans because of a payment holiday on pre-amortization. This could conceal the inability to service debt of some firms, leading to underestimation of defaults. Extending the period of observation does not change our findings.

As already said, we cannot distinguish between a reduction in ex post default due to the liquidity support provided by the new credit granted under the public guarantee program and a positive selection by banks of their safer borrowers. We can nonetheless derive some indications of the net effect of the two channels. Future analyses could explore in greater detail this issue.

8. Conclusions

We analyze the allocation of liquidity support measures in Italy during Covid-19 pandemic. We use a unique dataset of loan level data that allows to identify each single loans backed by a guarantee within the relevant public guarantees schemes implemented by the Italian government following the outbreak of the pandemic, as well as those loans that benefited from a suspension of payments (legislative or voluntary moratoria).

Compared to the emerging literature on this topic, we focus on the ex ante riskiness of beneficiaries of credit support and on the role that the characteristics of bank-firm relationship have played in the allocation of these measures. Thanks to a special data collection that was enacted in Italy soon after the deployment of the government support measures, we can analyze the interaction between public guarantees and moratoria, two key policy measures adopted by many European countries after the outbreak of the pandemic.

Our results indicate that during the pandemic pre-pandemic riskier borrowers were less likely to receive a guaranteed loan, everything else equal, which suggests that the program was not employed on a large scale by banks to off-load prior credit risk. The study of the interaction between guarantees and moratoria suggests that relationships with moratoria were more likely to have a guaranteed loan than those with no moratoria.

We also find that prior relationships matter only to the extent they are quantitatively important (large share of borrowing by one bank correlates with a higher probability of observing a guaranteed loan by that same bank). The prior existence of information generating contracts did not increase the likelihood of a guaranteed loan; if anything close relationship appear to be weakly negatively correlated with participation to the program. Our evidence suggest that public guarantees were frequently employed in the provision of credit to new clients. Furthermore, firms appearing for the first time in the AnaCredit dataset are more likely than others to have a guarantee, consistent with the public scheme allowing access to credit to firms that did not borrow or borrowed so little that they were below the reporting threshold of 25k euro.

We find no evidence that bank capitalization influenced the allocation of guarantees and only weak evidence that guarantees affected credit expansion by low capitalised banks.

Finally, we include some preliminary evidence that borrowers that later on defaulted on at least one of their loans are those that are less likely to get guaranteed loans, controlling for observable characteristics. Such finding is not consistent with a systematic role of adverse selection in participation to the liquidity support program nor with moral hazard.

References

Acharya, V. V., Eisert, T., Eufinger, C. & Hirsch, C. (2019), 'Whatever it takes: The real effects of unconventional monetary policy', *The Review of Financial Studies* **32**(9), 3366–3411.

Albanese, A. & Ciocchetta, F. (2021), 'Which banks were more effective in supporting credit supply during the pandemic?'.

Albertazzi, U., Eramo, G., Gambacorta, L. & Salleo, C. (2015), 'Asymmetric information in securitization: An empirical assessment', *Journal of Monetary Economics* **71**, 33–49.

Altavilla, C., Ellul, A., Pagano, M., Polo, A. & Vlassopoulos, T. (2021), 'Loan guarantees, bank lending and credit risk reallocation', *Bank Lending and Credit Risk Reallocation (November 14, 2021)* .

Altman, E. I., Marco, G. & Varetto, F. (1994), 'Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the italian experience)', *Journal of banking & finance* **18**(3), 505–529.

Amiram, D. & Rabetti, D. (2020), 'The relevance of relationship lending in times of crisis'.

Balyuk, T., Prabhala, N. & Puri, M. (2021), 'Small bank financing and funding hesitancy in a crisis: Evidence from the paycheck protection program', *Available at SSRN 3717259* .

Benmelech, E., Dlugosz, J. & Ivashina, V. (2012), 'Securitization without adverse selection: The case of clos', *Journal of Financial Economics* **106**(1), 91–113.

Berger, A. N., Bouwman, C. H., Norden, L., Roman, R. A., Udell, G. F. & Wang, T. (2022), 'Is a friend in need a friend indeed? how relationship borrowers fare during the covid-19 crisis', *How Relationship Borrowers Fare during the COVID-19 Crisis (July 1, 2022). Kelley School of Business Research Paper* (2021-01).

Berger, A. N. & Udell, G. F. (2006), 'A more complete conceptual framework for sme finance', *Journal of Banking & Finance* **30**(11), 2945–2966.

Blattner, L., Farinha, L. & Rebelo, F. (2019), 'When losses turn into loans: The cost of undercapitalized banks'.

Bolton, P., Freixas, X., Gambacorta, L. & Mistrulli, P. E. (2016), 'Relationship and transaction lending in a crisis', *The Review of Financial Studies* **29**(10), 2643–2676.

Branzoli, N., Rainone, E. & Supino, I. (2021), 'The role of banks' technology adoption in credit markets during the pandemic', *Available at SSRN 3878254* .

Carletti, E., Leonello, A. & Marquez, R. (2023), 'Loan guarantees, bank underwriting policies and financial stability', *Journal of Financial Economics* **149**(2), 260–295.

Cascarino, G., Gallo, R., Palazzo, F. & Sette, E. (2022), 'Public guarantees and credit additionality during the covid-19 pandemic', *Bank of Italy Temi di Discussione (Working Paper) No* **1369**.

Chiappori, P.-A. & Salanie, B. (2000), 'Testing for asymmetric information in insurance markets', *Journal of political Economy* **108**(1), 56–78.

Core, F. & De Marco, F. (2021), 'Public guarantees for small businesses in italy during covid-19'.

Crawford, G. S., Pavanini, N. & Schivardi, F. (2018), 'Asymmetric information and imperfect competition in lending markets', *American Economic Review* **108**(7), 1659–1701.

Darmouni, O. (2020), 'Informational frictions and the credit crunch', *The Journal of Finance* **75**(4), 2055–2094.

De Mitri, S., De Socio, A., Nigro, V. & Pastorelli, S. (2021), 'Financial support measures and credit to firms during the pandemic', *Bank of Italy Occasional Paper* (665).

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K. & Schepens, G. (2019), 'Identifying credit supply shocks with bank-firm data: Methods and applications', *Journal of Financial Intermediation* **40**, 100813.

Enria, A. (2020), 'Identification and measurement of credit risk in the context of the coronavirus (covid-19) pandemic'. URL https://www.bankingsupervision.europa.eu/press/letterstobanks/shared/pdf/2020/ssm.2020_letter_credit_risk_identification_measurement~734f2a0b84.en.pdf?c839e6212e8a9bf18dc0d26ab0b1cd7f.

Faulkender, M. W., Jackman, R. & Miran, S. (2020), 'The job preservation effects of paycheck protection program loans', *Available at SSRN 3767509* .

Favara, G., Minoiu, C. & Perez-Orive, A. (2021), 'Us zombie firms: How many and how consequential?'.

Iannamorelli, A., Nobili, S., Scalia, A. & Zaccaria, L. (2024), 'Asymmetric information and corporate lending: Evidence from sme bond markets', *Review of Finance* **28**(1), 163–201.

James, C. M., Lu, J. & Sun, Y. (2021), 'Time is money: Real effects of relationship lending: Evidence from community bank lending in the paycheck protection program.', *Available at SSRN 3633339* .

Jiménez, G., Laeven, L., Martinez-Miera, D. & Peydró, J.-L. (2022), 'Public guarantees, relationship lending and bank credit: Evidence from the covid-19 crisis', *Relationship Lending and Bank Credit: Evidence from the COVID-19 Crisis (March 14, 2022)* .

Khwaja, A. I. & Mian, A. (2008), 'Tracing the impact of bank liquidity shocks: Evidence from an emerging market', *American Economic Review* **98**(4), 1413–1442.

Li, L., Strahan, P. E. & Zhang, S. (2020), 'Banks as lenders of first resort: Evidence from the covid-19 crisis', *The Review of Corporate Finance Studies* **9**(3), 472–500.

Sette, E. & Gobbi, G. (2015), 'Relationship lending during a financial crisis', *Journal of the European Economic Association* **13**(3), 453–481.

Stein, J. C. (2002), 'Information production and capital allocation: Decentralized versus hierarchical firms', *The journal of finance* **57**(5), 1891–1921.

Stroebel, J. (2016), 'Asymmetric information about collateral values', *The Journal of Finance* **71**(3), 1071–1112.

Annex

Table A1: Allocation of guarantees and bank-firm level risk measures

	(1) Covid_guarantee	(2) Covid_guarantee	(3) Covid_guarantee	(4) Covid_guarantee
Duration	-0.1004	-0.0825**	-0.0703	-0.0769**
	(0.0598)	(0.0383)	(0.0484)	(0.0331)
Soft_information	0.0223	0.0483***	-0.0100	0.0090
	(0.0203)	(0.0159)	(0.0182)	(0.0151)
Close_rel	-0.0090	-0.0086*	-0.0092	-0.0098**
	(0.0061)	(0.0046)	(0.0057)	(0.0047)
Proximity	0.0039***	0.0041***	0.0027**	0.0027**
	(0.0009)	(0.0010)	(0.0011)	(0.0011)
PD_ante	-0.4690***		-0.4263***	
	(0.0560)		(0.0545)	
Share_stage2		-0.0758***		-0.0636***
		(0.0092)		(0.0110)
Moratoria	0.1830***	0.1583***	0.1571***	0.1334***
	(0.0192)	(0.0179)	(0.0197)	(0.0181)
Bank_share	0.1844***	0.1665***	0.1758***	0.1643***
	(0.0149)	(0.0110)	(0.0149)	(0.0126)
Used_overdraft	0.0898***	0.0753***	0.0629***	0.0567***
	(0.0209)	(0.0129)	(0.0195)	(0.0126)
d_FCG_guar_nocovid	0.0329**	0.0309***	0.0398***	0.0397***
	(0.0129)	(0.0097)	(0.0131)	(0.0104)
d_personal_guarantee	0.0719***	0.0661***	0.0598***	0.0575***
	(0.0029)	(0.0044)	(0.0027)	(0.0034)
d_real_guarantee	-0.0486***	-0.0488***	-0.0222	-0.0238*
	(0.0147)	(0.0105)	(0.0182)	(0.0143)
Firm_size=1	-0.0241**	-0.0202***	-0.0244*	-0.0242***
	(0.0092)	(0.0060)	(0.0117)	(0.0090)
Firm_size=2	0.0075	0.0106	0.0117	0.0122
	(0.0114)	(0.0093)	(0.0109)	(0.0078)
Firm_size=3	0.0074	0.0062	0.0007	0.0003
	(0.0116)	(0.0078)	(0.0102)	(0.0066)
Firm_size=4	0.0341***	0.0292***	0.0276**	0.0244***
	(0.0110)	(0.0086)	(0.0104)	(0.0080)
Number_lenders	0.0048*	0.0026	0.0058**	0.0041***
	(0.0026)	(0.0017)	(0.0021)	(0.0015)
Constant	0.3091**	0.2498***	0.2614***	0.2470***
	(0.1111)	(0.0675)	(0.0913)	(0.0604)
Observations	718316	1047466	351732	481161
R^2	0.141	0.160	0.155	0.166
Adjusted R^2	0.133	0.154	0.140	0.154
Firm_controls	NO	NO	YES	YES
Bank_FE	YES	YES	YES	YES
IndustryProv_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (1) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise controlling for bank-firm level risk measure and several relationship lending variables and firm characteristics. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Firm controls include: Ebitda, Leverage, Sales on assets, Tangible on assets and Liquidity. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A2: Allocation of guarantees and firm level risk measures

	(1) Covid_guarantee	(2) Covid_guarantee	(3) Covid_guarantee	(4) Covid_guarantee
Duration	-0.101**	-0.127***	-0.071*	-0.079**
	(0.048)	(0.040)	(0.038)	(0.037)
Soft_information	0.021	0.024	-0.007	0.003
	(0.017)	(0.017)	(0.016)	(0.016)
Close_rel	-0.010*	-0.011**	-0.009	-0.009
	(0.006)	(0.005)	(0.005)	(0.005)
Proximity	0.004***	0.003***	0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
PD_ante_avg	-0.210***		-0.171***	
	(0.040)		(0.034)	
Risky		-0.009***		-0.033***
		(0.003)		(0.004)
Moratoria	0.162***	0.148***	0.136***	0.135***
	(0.020)	(0.019)	(0.019)	(0.018)
Bank_share	0.170***	0.173***	0.165***	0.168***
	(0.012)	(0.011)	(0.013)	(0.012)
Used_overdraft	0.083***	0.081***	0.059***	0.058***
	(0.016)	(0.015)	(0.015)	(0.013)
d_FCG_guar_nocovid	0.032***	0.041***	0.039***	0.041***
	(0.011)	(0.011)	(0.012)	(0.011)
d_personal_guarantee	0.067***	0.072***	0.055***	0.057***
	(0.004)	(0.005)	(0.003)	(0.003)
d_real_guarantee	-0.047***	-0.038***	-0.023	-0.026*
	(0.012)	(0.013)	(0.016)	(0.015)
Firm_size=1	-0.020**	-0.030***	-0.019*	-0.024***
	(0.008)	(0.007)	(0.010)	(0.009)
Firm_size=2	0.010	0.007	0.014	0.010
	(0.010)	(0.009)	(0.009)	(0.008)
Firm_size=3	0.007	0.002	0.004	-0.001
	(0.010)	(0.008)	(0.009)	(0.007)
Firm_size=4	0.030***	0.026***	0.025***	0.023***
	(0.010)	(0.008)	(0.009)	(0.008)
Number_lenders	0.003*	0.004**	0.004***	0.004**
	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.303***	0.342***	0.243***	0.247***
	(0.085)	(0.070)	(0.069)	(0.067)
Observations	933203	736186	475611	522415
R^2	0.157	0.162	0.168	0.170
Adjusted R^2	0.150	0.154	0.156	0.159
Firm_controls	NO	NO	YES	YES
Bank_FE	YES	YES	YES	YES
IndustryProv_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (1) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid19 guarantee and 0 otherwise controlling for firm level risk measure and several relationship lending variables and firm characteristics. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Firm controls include: Ebitda, Leverage, Sales on assets, Tangible on assets and Liquidity. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A3: Allocation of guarantees, firm riskiness and use of moratoria

	(1) Covid_guarantee	(2) Covid_guarantee	(3) Covid_guarantee	(4) Covid_guarantee
Duration	-0.099	-0.082**	-0.069	-0.076**
	(0.060)	(0.038)	(0.048)	(0.033)
Soft_information	0.022	0.048***	-0.011	0.009
	(0.020)	(0.016)	(0.018)	(0.015)
Close_rel	-0.009	-0.009*	-0.009	-0.010**
	(0.006)	(0.005)	(0.006)	(0.005)
Proximity	0.004***	0.004***	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
PD_ante	-0.370***		-0.314***	
	(0.046)		(0.046)	
Share_stage2		-0.070***		-0.054***
		(0.012)		(0.013)
Bank_share	0.184***	0.167***	0.175***	0.164***
	(0.015)	(0.011)	(0.015)	(0.013)
Used_overdraft	0.089***	0.075***	0.062***	0.057***
	(0.021)	(0.013)	(0.019)	(0.013)
d_FCG_guar_nocovid	0.032**	0.031***	0.040***	0.040***
	(0.013)	(0.010)	(0.013)	(0.010)
d_personal_guarantee	0.072***	0.066***	0.060***	0.057***
	(0.003)	(0.004)	(0.003)	(0.003)
d_real_guarantee	-0.048***	-0.049***	-0.022	-0.024*
	(0.015)	(0.010)	(0.018)	(0.014)
Firm_size=1	-0.024**	-0.020***	-0.025**	-0.024***
	(0.009)	(0.006)	(0.012)	(0.009)
Firm_size=2	0.008	0.011	0.011	0.012
	(0.011)	(0.009)	(0.011)	(0.008)
Firm_size=3	0.007	0.006	0.000	0.000
	(0.012)	(0.008)	(0.010)	(0.007)
Firm_size=4	0.034***	0.029***	0.027**	0.024***
	(0.011)	(0.009)	(0.010)	(0.008)
Number_lenders	0.005*	0.003	0.006**	0.004***
	(0.003)	(0.002)	(0.002)	(0.002)
Moratoria=1	0.191***	0.160***	0.165***	0.136***
	(0.019)	(0.018)	(0.019)	(0.018)
Moratoria=1 × PD_ante	-0.285***		-0.330***	
	(0.045)		(0.073)	
Moratoria=1 × Share_stage2		-0.016		-0.027**
		(0.015)		(0.013)
Constant	0.304**	0.247***	0.258**	0.244***
	(0.111)	(0.067)	(0.091)	(0.060)
Observations	718316	1047466	351732	481161
R^2	0.142	0.160	0.155	0.166
Adjusted R^2	0.133	0.154	0.140	0.155
Firm_controls	NO	NO	YES	YES
Bank_FE	YES	YES	YES	YES
IndustryProv_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (2) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise controlling for bank-firm level risk measure, several relationship lending variables, firm characteristics and the dummy Moratoria. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Firm controls include: Ebitda, Leverage, Sales on assets, Tangible on assets and Liquidity. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A4: Allocation of guarantees, firm riskiness and use of moratoria - "Letter M" loans

	(1)	(2)	(3)	(4)
	Covid_guarantee subsample without Bank-Firm relationship with only "Letter M" loans		Covid_guarantee subsample without Bank-Firm relationship with at least one "Letter M" loans	
Duration	-0.100	-0.082**	-0.075	-0.060
	(0.060)	(0.038)	(0.061)	(0.038)
Soft_information	0.021	0.047***	-0.010	0.011
	(0.020)	(0.016)	(0.027)	(0.021)
Close_rel	-0.009	-0.009*	-0.006	-0.007
	(0.006)	(0.005)	(0.006)	(0.004)
Proximity	0.004***	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
PD_ante	-0.469***		-0.356***	
	(0.056)		(0.043)	
Share_stage2		-0.076***		-0.062***
		(0.009)		(0.009)
Moratoria	0.183***	0.159***	0.183***	0.143***
	(0.019)	(0.018)	(0.030)	(0.026)
Bank_share	0.185***	0.166***	0.080***	0.062***
	(0.015)	(0.011)	(0.008)	(0.007)
Used_overdraft	0.090***	0.075***	0.074**	0.059***
	(0.021)	(0.013)	(0.028)	(0.018)
d_FCG_guar_nocovid	0.033**	0.031***	0.057***	0.053***
	(0.013)	(0.010)	(0.019)	(0.015)
d_personal_guarantee	0.072***	0.066***	0.042***	0.035***
	(0.003)	(0.004)	(0.005)	(0.005)
d_real_guarantee	-0.049***	-0.049***	-0.016	-0.019
	(0.015)	(0.010)	(0.025)	(0.019)
Firm_size=1	-0.024**	-0.020***	0.050**	0.046***
	(0.009)	(0.006)	(0.023)	(0.015)
Firm_size=2	0.008	0.011	0.050*	0.050**
	(0.011)	(0.009)	(0.027)	(0.022)
Firm_size=3	0.008	0.007	0.087***	0.078***
	(0.012)	(0.008)	(0.026)	(0.016)
Firm_size=4	0.034***	0.030***	0.054***	0.045***
	(0.011)	(0.009)	(0.012)	(0.008)
Number_lenders	0.005*	0.003	0.010**	0.007***
	(0.003)	(0.002)	(0.004)	(0.002)
Constant	0.307**	0.248***	0.186	0.149**
	(0.111)	(0.068)	(0.113)	(0.067)
Observations	717971	1046795	617356	903214
R^2	0.141	0.160	0.130	0.142
Adjusted R^2	0.133	0.154	0.120	0.135
Bank_FE	YES	YES	YES	YES
IndustryProv_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (1) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise controlling for bank-firm level risk measure, several relationship lending variables, firm size and the dummy Moratoria. The estimates are carried out for two different subsample of credit relationships: those with only "Letter M" loans and those with at least one "Letter M" loan. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A5: Allocation of guarantees, firm riskiness and use of moratoria – firms with multiple bank relationships

	(1) Covid_guarantee	(2) Covid_guarantee	(3) Covid_guarantee	(4) Covid_guarantee
Duration	-0.004	-0.014	-0.003	-0.013
	(0.049)	(0.040)	(0.049)	(0.040)
Soft_information	-0.013	0.005	-0.014	0.005
	(0.016)	(0.014)	(0.016)	(0.014)
Close_rel	-0.002	-0.004	-0.002	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)
PD_ante	-0.533***		-0.416***	
	(0.029)		(0.032)	
Share_stage2		-0.070***		-0.062***
		(0.009)		(0.011)
Moratoria	0.101***	0.081***	0.111***	0.083***
	(0.011)	(0.009)	(0.011)	(0.009)
Bank_share	0.178***	0.194***	0.177***	0.194***
	(0.010)	(0.012)	(0.009)	(0.012)
Used_overdraft	0.016	0.022***	0.015	0.022***
	(0.012)	(0.008)	(0.012)	(0.008)
Proximity	0.021***	0.014***	0.021***	0.014***
	(0.004)	(0.002)	(0.004)	(0.002)
d_FCG_guar_nocovid	0.026*	0.022**	0.026*	0.022**
	(0.014)	(0.010)	(0.014)	(0.010)
d_personal_guarantee	0.023***	0.031***	0.023***	0.031***
	(0.004)	(0.003)	(0.004)	(0.003)
d_real_guarantee	-0.019	-0.034***	-0.019	-0.034***
	(0.015)	(0.012)	(0.015)	(0.012)
Moratoria=1 × PD_ante			-0.348***	
			(0.053)	
Moratoria=1 × Share_stage2				-0.022**
				(0.009)
Constant	0.216**	0.203***	0.211**	0.200***
	(0.091)	(0.075)	(0.091)	(0.075)
Observations	409044	656627	409044	656627
R^2	0.438	0.411	0.439	0.411
Adjusted R^2	0.118	0.115	0.118	0.115
Bank_FE	YES	YES	YES	YES
Firm_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (2) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise controlling for bank-firm level risk measure, several relationship lending variables and the dummy Moratoria. The estimates are carried out for the sample of firms with multiple bank relationships. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Standard errors double-clustered at bank and firm level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A6: Allocation of guarantees and new relationships

	(1) Covid_guarantee	(2) Covid_guarantee	(3) Covid_guarantee
New_firm			0.335***
			(0.032)
New_rel	0.295***	0.434***	0.330***
	(0.049)	(0.052)	(0.048)
Soft_information	-0.017	-0.026	-0.017
	(0.017)	(0.020)	(0.019)
Close_rel	-0.010*	-0.012*	-0.010*
	(0.006)	(0.006)	(0.006)
PD_ante_avg	-0.111***		
	(0.033)		
Risky		-0.016***	-0.022***
		(0.005)	(0.005)
Moratoria	0.133***	0.137***	0.132***
	(0.020)	(0.020)	(0.020)
Bank_share	0.149***	0.107***	0.141***
	(0.013)	(0.015)	(0.013)
Used_overdraft	0.056***	0.066***	0.059***
	(0.015)	(0.014)	(0.014)
Proximity	0.003**	0.004**	0.003**
	(0.001)	(0.002)	(0.001)
d_FCG_guar_nocovid	0.038***	0.041***	0.038***
	(0.012)	(0.011)	(0.011)
d_personal_guarantee	0.046***	0.036***	0.042***
	(0.004)	(0.007)	(0.006)
d_real_guarantee	-0.017	-0.007	-0.014
	(0.014)	(0.014)	(0.014)
Firm_size=1	-0.024**	-0.077***	-0.037***
	(0.010)	(0.013)	(0.009)
Firm_size=2	0.008	-0.046***	-0.006
	(0.010)	(0.012)	(0.008)
Firm_size=3	-0.001	-0.056***	-0.013**
	(0.009)	(0.011)	(0.007)
Firm_size=4	0.027***	-0.016	0.020**
	(0.009)	(0.011)	(0.008)
Number_lenders	0.003**	0.001	0.003*
	(0.001)	(0.002)	(0.002)
Constant	0.121***	0.197***	0.133***
	(0.029)	(0.035)	(0.030)
Observations	506811	588447	588447
R^2	0.171	0.216	0.227
Adjusted R^2	0.161	0.206	0.218
Firm_controls	YES	YES	YES
Bank_FE	YES	YES	YES
IndustryProv_FE	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (1) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise. The dummy New_rel, equal to 1 if the bank-firm relationship was reported only after march 2020, is included with the aim to test whether the guarantees have facilitated the creation of new bank-firm relationships. Firm controls include: Ebitda, Leverage, Sales on assets, Tangible on assets, Liquidity. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A7: Allocation of guarantees, firm riskiness and new firms

	(1) Covid_guarantee Full sample	(2) Covid_guarantee subsample without Bank-Firm relationship with only "Letter M" loans
New_rel	0.330***	0.330***
	(0.048)	(0.048)
Moratoria	0.133***	0.133***
	(0.020)	(0.020)
Number_lenders	0.003*	0.003*
	(0.002)	(0.002)
Bank_share	0.141***	0.142***
	(0.013)	(0.013)
Used_overdraft	0.059***	0.060***
	(0.014)	(0.014)
Close_rel	-0.010*	-0.010*
	(0.006)	(0.006)
Soft_information	-0.017	-0.018
	(0.019)	(0.019)
Proximity	0.003**	0.003**
	(0.001)	(0.001)
d_FCG_guar_nocovid	0.038***	0.038***
	(0.011)	(0.011)
d_personal_guarantee	0.042***	0.042***
	(0.006)	(0.006)
d_real_guarantee	-0.014	-0.013
	(0.014)	(0.014)
Risky=1	-0.024***	-0.024***
	(0.005)	(0.005)
New_firm=1	0.329***	0.329***
	(0.032)	(0.032)
Risky=1 × New_firm=1	0.045***	0.045***
	(0.009)	(0.009)
Constant	0.133***	0.132***
	(0.030)	(0.030)
Observations	588447	588231
R^2	0.227	0.227
Adjusted R^2	0.218	0.218
Firm_controls	YES	YES
Bank_FE	YES	YES
IndustryProv_FE	YES	YES

Notes: This table reports bank-firm level estimates of the equation (1) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise. An interaction term Risky*New_firm is included with the aim to test whether the guarantees have facilitated the access to credit by riskier firms. Firm controls include: Ebitda, Leverage, Sales on assets, Tangible on assets, Liquidity, Firm_size. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A8: Credit growth and relationship characteristics – firms receiving and not receiving a guaranteed loan

	(1)	(2)	(3)	(4)
	Delta_granted subsample with only recipients firms		Delta_granted subsample with only not-recipients firms	
Covid_guarantee	0.458***	0.447***		
	(0.028)	(0.019)		
Loan_size	-0.023***	-0.052***	-0.010***	-0.023***
	(0.003)	(0.005)	(0.002)	(0.002)
Duration	-0.236**	-0.251***	-0.156**	-0.221***
	(0.100)	(0.059)	(0.068)	(0.041)
Soft_information	0.027	0.019	0.076***	0.070***
	(0.028)	(0.020)	(0.021)	(0.014)
Close_rel	-0.012***	-0.014***	-0.010**	-0.014***
	(0.003)	(0.003)	(0.004)	(0.004)
Bank_share	-0.147***	-0.159***	-0.036***	-0.047***
	(0.019)	(0.014)	(0.004)	(0.004)
Used_overdraft	0.002	0.015	0.021*	0.030***
	(0.017)	(0.012)	(0.012)	(0.008)
Proximity	0.004***	0.004***	0.002	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Moratoria	-0.009	0.016	0.062***	0.081***
	(0.026)	(0.020)	(0.019)	(0.013)
d_FCG_guar_nocovid	-0.050***	-0.042***	-0.049***	-0.045***
	(0.012)	(0.008)	(0.010)	(0.007)
d_personal_guarantee	-0.019	-0.039**	-0.016	-0.024***
	(0.021)	(0.015)	(0.010)	(0.007)
d_real_guarantee	-0.097***	-0.071***	-0.024***	-0.010**
	(0.013)	(0.007)	(0.007)	(0.004)
PD_ante	-0.218***		-0.018	
	(0.037)		(0.043)	
Share_stage2		-0.038***		-0.009
		(0.006)		(0.008)
Constant	0.728***	1.118***	0.336**	0.631***
	(0.171)	(0.130)	(0.127)	(0.072)
Observations	405339	575528	215212	326479
R^2	0.264	0.267	0.084	0.079
Adjusted R^2	0.252	0.258	0.059	0.061
Bank_FE	YES	YES	YES	YES
IndustryProv_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (3) in which the dependent variable is Delta_granted defined as the variation of the granted credit for each relationship in the guarantee allocation period considered (March 2020 - March 2021) controlling for the use of support measures (public guarantees and moratoria), bank-firm level risk measure, several relationship lending variables and firm characteristics. The estimates are carried out for two different subsample of firms: those with only recipients guarantees and those with only not-recipients guarantees. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A9: Credit growth and relationship characteristics – firms receiving and not receiving a guaranteed loan - firms with multiple bank relationships

	(1)	(2)	(3)	(4)
	Delta_granted subsample with only recipients firms		Delta_granted subsample with only not-recipients firms	
Covid_guarantee	0.466***	0.454***		
	(0.016)	(0.014)		
Loan_size	-0.011***	-0.041***	-0.009***	-0.029***
	(0.002)	(0.003)	(0.001)	(0.002)
Duration	-0.112**	-0.140***	-0.063	-0.124***
	(0.046)	(0.029)	(0.041)	(0.027)
Soft_information	0.020	0.020	0.044**	0.042***
	(0.030)	(0.020)	(0.018)	(0.014)
Close_rel	-0.012***	-0.015***	-0.005	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Bank_share	-0.292***	-0.217***	-0.078***	-0.033***
	(0.012)	(0.010)	(0.012)	(0.011)
Used_overdraft	0.027***	0.042***	0.038***	0.044***
	(0.009)	(0.009)	(0.008)	(0.008)
Proximity	-0.005	0.003	-0.001	0.000
	(0.004)	(0.002)	(0.004)	(0.002)
Moratoria	0.002	0.025**	0.054***	0.073***
	(0.013)	(0.012)	(0.011)	(0.010)
d_FCG_guar_nocovid	-0.039***	-0.041***	-0.039***	-0.039***
	(0.012)	(0.008)	(0.010)	(0.008)
d_personal_guarantee	-0.011	-0.021*	-0.030***	-0.036***
	(0.013)	(0.011)	(0.005)	(0.005)
d_real_guarantee	-0.059***	-0.041***	-0.028***	-0.010*
	(0.011)	(0.009)	(0.009)	(0.006)
PD_ante	-0.245***		-0.059**	
	(0.034)		(0.025)	
Share_stage2		-0.029***		-0.013***
		(0.005)		(0.004)
Constant	0.364***	0.756***	0.175*	0.524***
	(0.082)	(0.068)	(0.088)	(0.064)
Observations	249028	401044	93475	145369
R^2	0.535	0.507	0.430	0.426
Adjusted R^2	0.274	0.269	0.059	0.065
Bank_FE	YES	YES	YES	YES
Firm_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (3) in which the dependent variable is Delta_granted defined as the variation of the granted credit for each relationship in the guarantee allocation period considered (March 2020 - March 2021) controlling for the use of support measures (public guarantees and moratoria), bank-firm level risk measure, several relationship lending variables. The estimates are carried out for two different subsample of firms: those with only recipients guarantees and those with only not-recipients guarantees. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Standard errors double-clustered at bank and firm level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A10: Allocation of guarantees and bank capitalization

	(1) Covid_guarantee	(2) Covid_guarantee	(3) Covid_guarantee	(4) Covid_guarantee
PD_ante_avg	-0.210***	-0.168***		
	(0.047)	(0.039)		
d_lowcap=1 × PD_ante_avg	0.007	-0.009		
	(0.070)	(0.058)		
Risky=1			-0.029***	
			(0.004)	
Risky=1 × d_lowcap=1			-0.017	
			(0.012)	
Share_stage2				-0.065***
				(0.013)
d_lowcap=1 × Share_stage2				0.008
				(0.017)
Constant	0.298***	0.236***	0.240***	0.241***
	(0.084)	(0.070)	(0.067)	(0.060)
Observations	933203	475611	522415	481161
R^2	0.156	0.167	0.169	0.165
Adjusted R^2	0.150	0.156	0.159	0.154
Firm_controls	NO	YES	YES	YES
Rel_controls	YES	YES	YES	YES
Bank_FE	YES	YES	YES	YES
IndustryProv_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (1) in which the dependent variable is the dummy Covid_guarantee equal to 1 if the credit relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise exploring the heterogeneity between banks in the allocation of guarantees. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Firm controls include: Ebitda, Leverage, Sales on assets, Tangible on assets, Liquidity, Firm_size. Relationship controls include: Duration, Bank_share, Used_overdraft, Overdraft_share, Soft_information, Close_rel, Proximity, Moratoria, d_FCG_guar_nocovid, d_personal_guarantee, d_real_guarantee, Number_lenders. Standard errors double-clustered at bank and industry*province level. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A11: Credit growth and bank capitalization

	(1) Delta_granted	(2) Delta_granted	(3) Delta_granted	(4) Delta_granted
PD_ante_avg		-0.069***		-0.065***
		(0.019)		(0.005)
Share_stage2	-0.021***		-0.010***	
	(0.006)		(0.002)	
d_lowcap=1			-0.016***	-0.013***
			(0.002)	(0.002)
Covid_guarantee=1	0.399***	0.415***	0.391***	0.410***
	(0.029)	(0.033)	(0.003)	(0.003)
d_lowcap=1 × Covid_guarantee=1	0.062	0.059	0.070***	0.063***
	(0.040)	(0.047)	(0.004)	(0.004)
Bank_size			-0.133***	-0.094***
			(0.005)	(0.005)
NFC_ratio			0.213***	0.244***
			(0.008)	(0.009)
NPL_ratio			-0.086***	-0.113***
			(0.025)	(0.027)
Constant	0.497***	0.459***	0.781***	0.615***
	(0.101)	(0.110)	(0.021)	(0.024)
Observations	902861	804844	888808	795305
R^2	0.238	0.242	0.218	0.222
Adjusted R^2	0.232	0.235	0.212	0.215
Bank_FE	YES	YES	NO	NO
Rel_controls	YES	YES	YES	YES
IndustryProv_FE	YES	YES	YES	YES

Notes: This table reports bank-firm level estimates of the equation (3) in which the dependent variable is Delta_granted defined as the variation of the granted credit for each relationship in the guarantee allocation period considered (March 2020 - March 2021) exploring the heterogeneity between banks in the the effects of the support measures (public guarantees and moratoria) on credit allocation. The new bank-firm relationships born after the outbreak of the pandemic (March 2020) have been dropped. Relationship controls include: Duration, Bank_share, Used_overdraft, Overdraft_share, Soft_information, Close_rel, Proximity, Moratoria, d_FCG_guar_nocovid, d_personal_guarantee, d_real_guarantee, Number_lenders. Standard errors clustered at industry*province and bank level for specification (1) and (2); at industry*province level for specifications (3) and (4). Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. All the definitions of the variables are summarized in table A18.

Table A12: Ex post probability of default: test for asymmetric information

	(1) Logit: marg. effects Dep. var: default_post_f	(2) Linear Prob. Dep. var: default_post_f	(3) Seemingly unrelated reg. Dep. var: p(guarantee)=1	(4) Seemingly unrelated reg. Dep. var: p(default)=1
Covid_guarantee_f	-0.045***	-0.038***		
	(0.001)	(0.001)		
Duration_f	-0.052***	-0.054***	-0.181***	-0.048***
	(0.005)	(0.006)	(0.010)	(0.006)
Bank_share_f	-0.053***	-0.054***	-0.101***	-0.051***
	(0.001)	(0.001)	(0.002)	(0.001)
Soft_information_f	0.015***	0.011***	0.078***	0.008***
	(0.001)	(0.001)	(0.002)	(0.001)
Close_rel_f	-0.007***	-0.007***	0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Proximity_f	0.003***	0.002***	0.005***	0.002***
	(0.000)	(0.000)	(0.001)	(0.000)
Moratoria_f	0.008***	0.009***	0.139***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
d_FCG_guar_nocovid_f	0.014***	0.017***	0.087***	0.014***
	(0.001)	(0.001)	(0.002)	(0.001)
d_personal_guarantee_f	0.018***	0.012***	0.060***	0.010***
	(0.001)	(0.001)	(0.002)	(0.001)
d_real_guarantee_f	0.001	-0.002**	0.024***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
PD_ante_f	0.380***	1.066***	-0.320***	1.077***
	(0.004)	(0.011)	(0.008)	(0.011)
FinM_f	0.006***	0.002**	0.635***	-0.020***
	(0.001)	(0.001)	(0.001)	(0.001)
FinMonly_f	0.009***	0.017***	0.150***	0.011***
	(0.003)	(0.002)	(0.001)	(0.002)
Bank_size_f	0.016***	0.016***	0.036***	0.015***
	(0.002)	(0.002)	(0.003)	(0.002)
d_lowcap_f	-0.003***	-0.004***	0.109***	-0.008***
	(0.001)	(0.001)	(0.002)	(0.001)
NPL_ratio_f	0.268***	0.268***	-0.349***	0.280***
	(0.015)	(0.018)	(0.027)	(0.018)
NFC_ratio_f	-0.067***	-0.082***	-0.097***	-0.078***
	(0.006)	(0.006)	(0.010)	(0.006)
Covid_guarantee_f*Moratoria_f	0.017***	0.005***		
	(0.001)	(0.001)		
Observations	429999	430169	430169	
R^2		0.124		
Correlation coefficient			-0.06***	
Breusch-Pagan test - chi2 (Pr=0.0000)			1570.112	
Industry dummies	YES	YES	YES	YES
Province dummies	YES	YES	YES	YES

Notes: All variables indexed as "_f" are those listed in Table A18 collapsed by firm as described in Section 7. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

TABLE A13: SUMMARY STATISTICS - FULL SAMPLE OF BANK-FIRM RELATIONSHIPS

	count	mean	sd	p25	p50	p75
Covid_guarantee	1356788	.356	.479	0	0	1
Moratoria	1356788	.29	.454	0	0	1
finM	1356788	.2	.4	0	0	0
finMonly	1356788	.00785	.0882	0	0	0
New_rel	1356788	.146	.353	0	0	0
New_firm	1356788	.087	.282	0	0	0
Loan_size	1356788	8.83	5.02	7.61	10.8	12.1
Delta_outstanding	905121	.127	.871	-.347	-.0481	.316
Delta_granted	995384	.093	.451	-.13	0	.221
Bank_share	1310018	.432	.402	.0352	.304	.999
Used_overdraft	1356788	.231	.362	0	0	.468
Duration	1158491	1.99	.0725	1.95	1.95	2.08
Soft_information	1356788	.447	.39	0	.5	.8
Close_rel	1356788	.257	.437	0	0	1
Proximity	1356788	1.13	1.26	0	.693	1.61
d_FCG_guar_nocovid	1356788	.0721	.259	0	0	0
d_personal_guarantee	1356788	.535	.499	0	1	1
d_real_guarantee	1356788	.226	.418	0	0	0
PD_ante	839684	.0293	.0661	.0035	.0105	.0277
PD_ante_avg	1021740	.035	.0931	.00417	.011	.0279
Share_stage2	1236981	.118	.309	0	0	0
Risky	880783	.164	.37	0	0	0
Ebitda	881792	.00596	.0178	.00026	.00097	.00352
Leverage	607321	.5	.299	.258	.532	.741
Sales_to assets	881792	1.23	.905	.641	1.09	1.6
Tangible_on_assets	881792	.24	.255	.0375	.145	.365
Liquidity	881792	.0963	.133	.00915	.0425	.129
Log_total_asset	881792	.597	1.73	-.611	.459	1.66
Firm_size=0	1356788	.332	.471	0	0	1
Firm_size=1	1356788	.0993	.299	0	0	0
Firm_size=2	1356788	.0969	.296	0	0	0
Firm_size=3	1356788	.167	.373	0	0	0
Firm_size=4	1356788	.304	.46	0	0	1
Number_lenders	1356788	3.13	2.97	1	2	4
CET1_ratio	1323214	.141	.032	.132	.139	.147
d_lowcap	1356788	.215	.411	0	0	0
NPL_ratio	1328158	.0898	.0386	.0674	.0877	.0997
NFC_ratio	1328168	.454	.109	.403	.457	.523
Bank_size	1352390	2.39	.52	2.32	2.5	2.63

Notes: The table shows descriptive statistics of the full sample of bank-firm observations, including new relationships.

Table A14: Summary Statistics - Bank-firm relationships of firms with balance sheet data

	count	mean	sd	p25	p50	p75
Covid_guarantee	541273	.284	.451	0	0	1
Moratoria	541273	.325	.468	0	0	1
finM	541273	.0973	.296	0	0	0
finMonly	541273	.000669	.0259	0	0	0
Loan_size	541273	10.5	4.1	10.3	11.6	12.8
Delta_outstanding	422422	.126	.925	-.418	-.0687	.338
Delta_granted	471443	.0917	.472	-.147	0	.213
Bank_share	523131	.38	.36	.0729	.245	.653
Used_overdraft	541273	.225	.354	0	0	.441
Duration	541273	1.99	.0705	1.95	1.95	2.08
Soft_information	541273	.543	.369	.25	.5	1
Close_rel	541273	.311	.463	0	0	1
Proximity	541273	1.16	1.33	0	.693	1.61
d_FCG_guar_nocovid	541273	.107	.309	0	0	0
d_personal_guarantee	541273	.518	.5	0	1	1
d_real_guarantee	541273	.233	.423	0	0	0
PD_ante	364300	.0231	.0538	.00301	.0071	.0201
PD_ante_avg	489356	.029	.0778	.00398	.00988	.0242
Share_stage2	481698	.108	.295	0	0	0
Risky	541033	.15	.357	0	0	0
Ebitda	541273	.00854	.0214	.00044	.00159	.00607
Leverage	541273	.516	.291	.289	.547	.748
Sales_to assets	541273	1.22	.838	.69	1.1	1.57
Tangible_on_assets	541273	.238	.243	.0425	.154	.361
Liquidity	541273	.0879	.119	.00885	.0399	.119
Log_total_asset	541273	1.14	1.68	-.0834	.988	2.21
Firm_size=0	541273	.159	.366	0	0	0
Firm_size=1	541273	.167	.373	0	0	0
Firm_size=2	541273	.167	.373	0	0	0
Firm_size=3	541273	.258	.438	0	0	1
Firm_size=4	541273	.249	.432	0	0	0
Number_lenders	541273	4.42	3.58	2	3	6
CET1_ratio	529459	.14	.0267	.132	.139	.147
d_lowcap	541273	.221	.415	0	0	0
NPL_ratio	531669	.0885	.0381	.0651	.0877	.0997
NFC_ratio	531670	.456	.112	.412	.457	.523
Bank_size	539989	2.41	.486	2.34	2.51	2.63

Notes: The table shows descriptive statistics of the sample of bank-firm observations relating to firms with balance sheet data and excluding new relationships.

Table A15: Summary Statistics - Only firms with multiple relationships

	count	mean	sd	p25	p50	p75
Covid_guarantee	456265	.266	.442	0	0	1
Moratoria	456265	.332	.471	0	0	1
finM	456265	.0668	.25	0	0	0
finMonly	456265	.000353	.0188	0	0	0
Loan_size	456265	10.7	4.05	10.4	11.8	13
Delta_outstanding	357533	.109	.917	-.434	-.077	.317
Delta_granted	396785	.0845	.471	-.154	0	.198
Bank_share	449610	.279	.278	.0558	.184	.431
Used_overdraft	456265	.231	.355	0	0	.463
Duration	456265	1.99	.0702	1.95	1.95	2.08
Soft_information	456265	.555	.365	.273	.5	1
Close_rel	456265	.315	.464	0	0	1
Proximity	456265	1.09	1.29	0	.693	1.61
d_FCG_guar_nocovid	456265	.114	.318	0	0	0
d_personal_guarantee	456265	.495	.5	0	0	1
d_real_guarantee	456265	.222	.416	0	0	0
PD_ante	306412	.0229	.0532	.003	.00698	.0201
PD_ante_avg	431468	.0296	.0802	.0041	.0101	.0245
Share_stage2	408340	.106	.291	0	0	0
Risky	456195	.147	.354	0	0	0
Ebitda	456265	.00975	.0228	.00059	.00204	.00749
Leverage	456265	.53	.277	.324	.563	.75
Sales_to assets	456265	1.23	.796	.729	1.11	1.56
Tangible_on_assets	456265	.234	.232	.0467	.16	.356
Liquidity	456265	.0802	.108	.00843	.0372	.109
Log_total_asset	456265	1.39	1.62	.198	1.24	2.41
Firm_size=0	456265	.0963	.295	0	0	0
Firm_size=1	456265	.186	.389	0	0	0
Firm_size=2	456265	.186	.389	0	0	0
Firm_size=3	456265	.291	.454	0	0	1
Firm_size=4	456265	.24	.427	0	0	0
Number_lenders	456265	5.06	3.55	3	4	6
CET1_ratio	445510	.139	.0259	.132	.139	.147
d_lowcap	456265	.232	.422	0	0	0
NPL_ratio	447452	.0883	.0385	.0636	.0877	.0997
NFC_ratio	447453	.457	.115	.413	.457	.524
Bank_size	455068	2.4	.504	2.34	2.51	2.63

Notes: The table shows descriptive statistics of the sample of bank-firm observations relating to firms with multiple lenders and excluding new relationships.

Table A16: Summary Statistics - Only firms with no guaranteed loan

	count	mean	sd	p25	p50	p75
Covid_guarantee	484118	0	0	0	0	0
Moratoria	484118	.224	.417	0	0	0
finM	484118	0	0	0	0	0
finMonly	484118	0	0	0	0	0
Loan_size	484118	9.69	4.37	9.74	11	12.2
Delta_outstanding	328287	-.111	.72	-.47	-.139	0
Delta_granted	385037	-.0466	.341	-.182	-.0192	0
Bank_share	446999	.621	.402	.201	.77	1
Used_overdraft	484118	.207	.353	0	0	.324
Duration	484118	2	.0762	1.95	1.95	2.08
Soft_information	484118	.504	.403	0	.5	1
Close_rel	484118	.308	.462	0	0	1
Proximity	484118	1.16	1.26	0	.693	1.61
d_FCG_guar_nocovid	484118	.0523	.223	0	0	0
d_personal_guarantee	484118	.57	.495	0	1	1
d_real_guarantee	484118	.316	.465	0	0	1
PD_ante	296402	.0305	.0771	.00256	.0069	.0209
PD_ante_avg	366541	.0414	.12	.00321	.00822	.024
Share_stage2	412792	.142	.34	0	0	0
Risky	293183	.149	.356	0	0	0
Ebitda	293887	.00731	.0219	.00025	.00107	.00384
Leverage	200162	.42	.322	.123	.389	.679
Sales_to assets	293887	1.08	.937	.348	.946	1.51
Tangible_on_assets	293887	.28	.293	.0373	.166	.446
Liquidity	293887	.114	.146	.00984	.0542	.164
Log_total_asset	293887	.751	1.74	-.396	.594	1.68
Firm_size=0	484118	.409	.492	0	0	1
Firm_size=1	484118	.0993	.299	0	0	0
Firm_size=2	484118	.079	.27	0	0	0
Firm_size=3	484118	.136	.342	0	0	0
Firm_size=4	484118	.278	.448	0	0	1
Number_lenders	484118	2.47	2.69	1	2	3
CET1_ratio	472946	.142	.0284	.132	.139	.147
d_lowcap	484118	.205	.404	0	0	0
NPL_ratio	474780	.0901	.0393	.0674	.0877	.101
NFC_ratio	474784	.458	.112	.413	.457	.524
Bank_size	482903	2.38	.509	2.3	2.5	2.57

Notes: The table shows descriptive statistics of the sample of bank-firm observations relating only to firms with no guaranteed loan and excluding new relationships.

Table A17: Summary Statistics - Only firms with at least one guaranteed loan

	count	mean	sd	p25	p50	p75
Covid_guarantee	674373	.525	.499	0	1	1
Moratoria	674373	.418	.493	0	0	1
finM	674373	.266	.442	0	0	1
finMonly	674373	.00219	.0467	0	0	0
Loan_size	674373	10.8	3.09	10.4	11.3	12.4
Delta_outstanding	576834	.262	.919	-.274	.012	.537
Delta_granted	610347	.181	.488	-.0853	.00817	.417
Bank_share	664722	.434	.361	.114	.328	.763
Used_overdraft	674373	.316	.388	0	0	.703
Duration	674373	1.99	.0695	1.95	1.95	2.08
Soft_information	674373	.537	.346	.333	.5	.969
Close_rel	674373	.296	.457	0	0	1
Proximity	674373	1.11	1.24	0	.693	1.61
d_FCG_guar_nocovid	674373	.108	.31	0	0	0
d_personal_guarantee	674373	.666	.472	0	1	1
d_real_guarantee	674373	.228	.419	0	0	0
PD_ante	451533	.0266	.0556	.0039	.0105	.0258
PD_ante_avg	598578	.0303	.0668	.00522	.0126	.0298
Share_stage2	635104	.119	.304	0	0	0
Risky	472126	.178	.382	0	0	0
Ebitda	472260	.00579	.0158	.00034	.00112	.00398
Leverage	341111	.572	.254	.398	.607	.768
Sales_to assets	472260	1.24	.793	.735	1.11	1.57
Tangible_on_assets	472260	.229	.233	.0425	.149	.348
Liquidity	472260	.0727	.103	.00725	.0321	.0954
Log_total_asset	472260	.76	1.63	-.431	.609	1.83
Firm_size=0	674373	.219	.414	0	0	0
Firm_size=1	674373	.12	.326	0	0	0
Firm_size=2	674373	.127	.333	0	0	0
Firm_size=3	674373	.208	.406	0	0	0
Firm_size=4	674373	.325	.469	0	0	1
Number_lenders	674373	3.88	3.16	2	3	5
CET1_ratio	661742	.14	.0258	.132	.139	.147
d_lowcap	674373	.221	.415	0	0	0
NPL_ratio	664139	.0894	.0372	.0663	.0877	.0997
NFC_ratio	664139	.453	.104	.396	.457	.523
Bank_size	673197	2.41	.458	2.34	2.54	2.63

Notes: The table shows descriptive statistics of the sample of bank-firm observations relating only to firms with at least one guaranteed loan and excluding new relationships.

Table A18: Variables employed in the estimates

	DEFINITION	SOURCE
CHARACTERISTICS OF THE RELATIONSHIP		
Covid_guarantee	Dummy equal to 1 if the relationship includes at least one loan benefiting from a Covid guarantee and 0 otherwise	AnaCredit
Moratoria	Dummy equal to 1 if the relationship includes at least one loan benefiting from a Covid moratorium and 0 otherwise	AnaCredit
FinM	Dummy equal to 1 if the relationship includes at least one loan benefiting from a guarantee as in the "Letter M" scheme and 0 otherwise	Fondo Centrale di Garanzia
FinMonly	Dummy equal to 1 if the relationship includes only loans benefiting from Guarantees as in the "Letter M" scheme and 0 otherwise	Fondo Centrale di Garanzia
New_rel	Dummy equal to 1 if the relationship was reported only after march 2020 and not reported as of december 2019	AnaCredit
New_firm	Dummy equal to 1 if the firm is reported as having only relationships started after march 2020 and no relationships as of december 2019	AnaCredit
Loan_size	The logarithm of outstanding credit	AnaCredit
Delta_outstanding	For each relationship the variation of the outstanding credit in the observation period	AnaCredit
Delta_granted	For each relationship the variation of the granted credit in the observation period	AnaCredit
Duration	The logarithm of the number of years the bank-firm relationship lasted before the pandemic	AnaCredit
Bank_share	For each relationship the share of the firm's total credit outstanding by each bank	AnaCredit
Used_overdraft	For each relationship the ratio of used to granted overdraft loans	AnaCredit
Soft_information	The number of revolving credit lines, overdrafts and factoring to the number of total contracts that form the bank-firm relationship	AnaCredit
Close_rel	Dummy equal to 1 if the relationships' duration is longer than 3 years and the related Soft_information variable is in the highest quartile of the overall distribution.	AnaCredit
Proximity	For each bank-firm relationship the log number of branches of the bank operating in the municipality where the firm has its headquarters	Official bank register
d_FCG_guar_nocovid	Dummy equal to 1 if the firm had a loan with a guarantee from the FCG before the Covid shock from that bank	AnaCredit
d_personal_guarantee	Dummy equal to 1 if the firm posted personal guarantees on loans from the bank and 0 otherwise	AnaCredit
d_real_guarantee	Dummy equal to 1 if the firm posted real collateral on loans from the bank and 0 otherwise	AnaCredit
PD_ante	Ex ante firm probability of default assigned by the bank	AnaCredit
PD_ante_avg	Ex ante firm average probability of default among the banks that have granted credit	AnaCredit
Share_stage2	For each bank firm relationship the share of the outstanding amount classified in stage 2 according to the IFRS9 accounting principles	AnaCredit
Number_lenders	Number of lenders granting credit to the firm	AnaCredit
FIRM'S CHARACTERISTICS (as of December 2019)		
Risky	Dummy equal to 1 if the Credit risk Zscore of the firm is in the fourth bucket of the aggregation used in the official publications of the Bank of Italy (4. risky, 3. vulnerable, 2. solvent, 1. safe)	Cerved
Ebitda	Earnings Before Interest Tax Depreciation Amortization of the firm	Cerved
Leverage	Leverage of the firm	Cerved
Sales_on_assets	The ratio between sales and assets of the firm	Cerved
Tangible_on_assets	The share of tangible assets over total assets of the firm	Cerved
Liquidity	The ratio between liquid assets as reported in the firm's balance sheet and total assets	Cerved
Firm_size	Classification of firms by size in accordance with the Annex to Commission Reccomendation 2003-361-EC (N/A=0, large=1, medium=2, small=3, micro=4)	AnaCredit
BANK'S CHARACTERISTICS (as of December 2019)		
CET 1 ratio	Common Equity Tier 1 ratio at consolidated level for banks belonging to groups	Supervisory Report
d_lowcap	Dummy equal to 1 if the CET1 ratio of the bank is below the 25th percentile of the capitalization distribution	Supervisory Report
NPL_ratio	Non-performing loans over total loans of the bank	Supervisory Report
NFC_ratio	Loans to non-financial corporations over total loans of the bank	Supervisory Report
Bank_size	Logarithm of the total assets of the bank	Supervisory Report

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ANDINI M., M. BOLDRINI, E. CIANI, G. DE BLASIO, A. D'IGNAZIO and A. PALADINI, *Machine learning in the service of policy targeting: the case of public credit guarantees,* Journal of Economic Behavior & Organization, v. 198, pp. 434-475, **WP 1206 (February 2019).**

ANGELICO C., J. MARCUCCI, M. MICCOLI and F. QUARTA, *Can we measure inflation expectations using twitter?,* Journal of Econometrics, v. 228, 2, pp. 259-277, **WP 1318 (February 2021).**

BARTOCCI A., A. NOTARPIETRO and M. PISANI, *Covid-19 shock and fiscal-monetary policy mix in a monetary union,* Economic challenges for Europe after the pandemic, Springer Proceedings in Business and Economics, Berlin-Heidelberg, Springer, **WP 1313 (December 2020).**

BOTTERO M., C. MINOIU, J. PEYDRÒ, A. POLO, A. PRESBITERO and E. SETTE, *Expansionary yet different: credit supply and real effects of negative interest rate policy,* Journal of Financial Economics, v. 146, 2, pp. 754-778, **WP 1269 (March 2020).**

BRONZINI R., A. D'IGNAZIO and D. REVELLI, *Financial structure and bank relationships of Italian multinational firms,* Journal of Multinational Financial Management, v. 66, Article 100762, **WP 1326 (March 2021).**

CANTELMO A., *Rare disasters, the natural interest rate and monetary policy,* Oxford Bulletin of Economics and Statistics, v. 84, 3, pp. 473-496, **WP 1309 (December 2020).**

CARRIERO A., F. CORSELLO and M. MARCELLINO, *The global component of inflation volatility,* Journal of Applied Econometrics, v. 37, 4, pp. 700-721, **WP 1170 (May 2018).**

CIAPANNA E. and G. ROVIGATTI, *The grocery trolley race in times of Covid-19. Evidence from Italy,* Italian Economic Journal / Rivista italiana degli economisti, v. 8, 2, pp. 471-498, **WP 1341 (June 2021).**

CONTI A. M., A. NOBILI and F. M. SIGNORETTI, *Bank capital requirement shocks: a narrative perspective,* European Economic Review, v.151, Article 104254, **WP 1199 (November 2018).**

FAIELLA I. and A. MISTRETTA, *The net zero challenge for firms' competitiveness,* Environmental and Resource Economics, v. 83, pp. 85-113, **WP 1259 (February 2020).**

FERRIANI F. and G. VERONESE, *Hedging and investment trade-offs in the U.S. oil industry,* Energy Economics, v. 106, Article 105736, **WP 1211 (March 2019).**

GUISO L., A. POZZI, A. TSOY, L. GAMBACORTA and P. E. MISTRULLI, *The cost of steering in financial markets: evidence from the mortgage market,* Journal of Financial Economics, v.143, 3, pp. 1209-1226, **WP 1252 (December 2019).**

LAMORGESE A. and D. PELLEGRINO, *Loss aversion in housing appraisal: evidence from Italian homeowners,* Journal of Housing Economics, v. 56, Article 101826, **WP 1248 (November 2019).**

LI F., T. MÄKINEN, A. MERCATANTI and A. SILVESTRINI, *Causal analysis of central bank holdings of corporate bonds under interference,* Economic Modelling, v.113, Article 105873, **WP 1300 (November 2020).**

LOBERTO M, A. LUCIANI and M. PANGALLO, *What do online listings tell us about the housing market?,* International Journal of Central Banking, v. 18, 4, pp. 325-377, **WP 1171 (April 2018).**

MIRENDA L., M. SAURO and L. RIZZICA, *The economic effects of mafia: firm level evidence,* American Economic Review, vol. 112, 8, pp. 2748-2773, **WP 1235 (October 2019).**

MOCETTI S., G. ROMA and E. RUBOLINO, *Knocking on parents' doors: regulation and intergenerational mobility,* Journal of Human Resources, v. 57, 2, pp. 525-554, **WP 1182 (July 2018).**

PERICOLI M. and M. TABOGA, *Nearly exact Bayesian estimation of non-linear no-arbitrage term-structure models,* Journal of Financial Econometrics, v. 20, 5, pp. 807-838, **WP 1189 (September 2018).**

ROSSI P. and D. SCALISE, *Financial development and growth in European regions,* Journal of Regional Science, v. 62, 2, pp. 389-411, **WP 1246 (November 2019).**

SCHIVARDI F., E. SETTE and G. TABELLINI, *Credit misallocation during the European financial crisis,* Economic Journal, v. 132, 641, pp. 391-423, **WP 1139 (September 2017).**

TABOGA M., *Cross-country differences in the size of venture capital financing rounds: a machine learning approach,* Empirical Economics, v. 62, 3, pp. 991-1012, **WP 1243 (November 2019).**

2023

APRIGLIANO V., S. EMILIOZZI, G. GUAITOLI, A. LUCIANI, J. MARCUCCI and L. MONTEFORTE, *The power of text-based indicators in forecasting Italian economic activity,* International Journal of Forecasting, v. 39, 2, pp. 791-808, **WP 1321 (March 2021).**

BALTRUNAITE A., G. BOVINI and S. MOCETTI, *Managerial talent and managerial practices: are they complements?,* Journal of Corporate Finance, v. 79, Article 102348, **WP 1335 (April 2021).**

BARTOCCI A., A. NOTARPIETRO and M. PISANI, *Non-standard monetary policy measures in non-normal times,* International Finance, v. 26, 1, pp. 19-35, **WP 1251 (November 2019).**

CAPPELLETTI G. and P. E. MISTRULLI, *The role of credit lines and multiple lending in financial contagion and systemic events,* Journal of Financial Stability, v. 67, Article 101141, **WP 1123 (June 2017).**

CECI D. and A. SILVESTRINI, *Nowcasting the state of the Italian economy: the role of financial markets,* Journal of Forecasting, v. 42, 7, pp. 1569-1593, **WP 1362 (February 2022).**

CIAPANNA E, S. MOCETTI and A. NOTARPIETRO, *The macroeconomic effects of structural reforms: an empirical and model-based approach,* Economic Policy, v. 38, 114, pp. 243-285, **WP 1303 (November 2020).**

CORNELI F., *Sovereign debt maturity structure and its costs,* International Tax and Public Finance, v. 31, 1, pp. 262-297, **WP 1196 (November 2018).**

DAURICH D, S. DI ADDARIO and R. SAGGIO, *The macroeconomic effects of structural reforms: an empirical and model-based approach,* Review of Economic Studies, v. 90, 6, pp. 2880–2942, **WP 1390 (November 2022).**

DI ADDARIO S., P. KLINE, R. SAGGIO and M. SØLVSTEN, *The effects of partial employment protection reforms: evidence from Italy,* Journal of Econometrics,v. 233, 2, pp. 340-374, **WP 1374 (June 2022).**

FERRARI A. and V. NISPI LANDI, *Toward a green economy: the role of central bank's asset purchases,* International Journal of Central Banking, v. 19, 5, pp. 287-340, **WP 1358 (February 2022).**

FERRIANI F., *Issuing bonds during the Covid-19 pandemic: was there an ESG premium?,* International Review of Financial Analysis, v. 88, Article 102653, **WP 1392 (November 2022).**

GIORDANO C., *Revisiting the real exchange rate misalignment-economic growth nexus via the across-sector misallocation channel,* Review of International Economics, v. 31, 4, pp. 1329-1384, **WP 1385 (October 2022).**

GUGLIELMINETTI E., M. LOBERTO and A. MISTRETTA, *The impact of COVID-19 on the European short-term rental market,* Empirica, v. 50, 3, pp. 585-623, **WP 1379 (July 2022).**

LILLA F., *Volatility bursts: a discrete-time option model with multiple volatility components,* Journal of Financial Econometrics, v. 21, 3, pp. 678-713, **WP 1336 (June 2021).**

LOBERTO M., *Foreclosures and house prices,* Italian Economic Journal / Rivista italiana degli economisti, v. 9, 1, pp. 397-424, **WP 1325 (March 2021).**

LOMBARDI M. J., M. RIGGI and E. VIVIANO, *Worker's bargaining power and the Phillips curve: a micro-macro analysis, and wages,* Journal of the European Economic Association, v. 21, 5, pp. 1905–1943, **WP 1302 (November 2020).**

MODENA F., S. PEREDA-FERNANDEZ and G. M. TANZI, *On the design of grant assignment rules,* Politica economica/Journal of Economic Policy, v. 1/2023, pp. 3-40, **WP 1307 (December 2020).**

NERI S., *Long-term inflation expectations and monetary policy in the Euro Area before the pandemic*, European Economic Review, v. 154, Article 104426, **WP 1357 (December 2021).**

ORAME A., *Bank lending and the European debt crisis: evidence from a new survey*, International Journal of Central Banking, v. 19, 1, pp. 243-300, **WP 1279 (June 2020).**

RIZZICA L., G. ROMA and G. ROVIGATTI, *The effects of shop opening hours deregulation: evidence from Italy,* The Journal of Law and Economics, v. 66, 1, pp. 21-52, **WP 1281 (June 2020).**

TANZI G. M., *Scars of youth non-employment and labour market conditions,* Italian Economic Journal / Rivista italiana degli economisti, v. 9, 2, pp. 475-499, **WP 1312 (December 2020).**

2024

BALTRUNAITE A. and E. KARMAZIENE, *Fast tracks to boardrooms: director supply and board appointments,* Journal of Corporate Finance, v. 88, Article 102642, **WP 1278 (June 2020).**

BENCHIMOL J. and L. PALUMBO, *Sanctions and Russian Online Prices,* Journal of Economic Behavior & Organization, v. 225, pp. 483-521, **WP 1468 (October 2024).**

BRANZOLI N., R. GALLO, A. ILARI and D. PORTIOLI, *Central banks' corporate asset purchase programmes and risk-taking by bond funds in the aftermath of market stress,* Journal of Financial Stability, v. 72, Article 101261, **WP 1404 (March 2023).**

BRANZOLI N., E. RAINONE and I. SUPINO, *The role of banks' technology adoption in credit markets during the pandemic,* Journal of Financial Stability, v. 71, Article 101230, **WP 1406 (March 2023).**

BUONO I, F. CORNELI and E. DI STEFANO, *Capital inflows to emerging countries and their sensitivity to the global financial cycle,* International Finance, v. 27,2, pp. 17-34, **WP 1262 (February 2020).**

DEL PRETE S, G. PAPINI and M. TONELLO, *Gender quotas, board diversity and spillover effects. Evidence from Italian banks,* Journal of Economic Behavior & Organization, v. 221, pp. 148-173, **WP 1395 (December 2022).**

De Marchi R. and A. Moro, *Forecasting fiscal crises in emerging markets and low-income countries with machine learning models,* Open Economies Review. v. 35, 1, pp. 189-213, **WP 1405 (March 2023).**

Ferrari A. and V. Nispi Landi, *Whatever it takes to save the planet? Central banks and unconventional green policy,* Macroeconomic Dynamics, v. 28, 2, pp. 299-324, **WP 1320 (February 2021).**

Flaccadoro M., *Exchange rate pass-through in small, open, commodity-exporting economies: lessons from Canada,* Journal of International Economics, v. 148, Article 103885, **WP 1368 (May 2022).**

Gautier E., C. Conflitti, R. Faber, B. Fabo, L. Fadejeva, V. Jouvanceau, J.-O. Menz, T. Messner, P. Petroulas, P. Roldan-Blanco, F. Rumler, S. Santoro, E. Wieland and H. Zimmer, *New facts on consumer price rigidity in the euro area,* American Economic Journal: Macroeconomics, v. 16, 4, pp. 386-431, **WP 1375 (July 2022).**

Lattanzio S., *Schools and the transmission of Sars-Cov-2: evidence from Italy,* Economics & Human Biology, v. 52, Article 101342, **WP 1453 (February 2023).**

Moro A. and V. Nispi Landi, *The external financial spillovers of CBDCs,* Journal of Economic Dynamics and Control, v. 159, Article 104801, **WP 1416 (July 2023).**

Porreca E. and A. Rosolia, *Immigration and unemployment. Do natives get it right?,* Journal of Economic Behavior & Organization, v. 225, pp. 522–540, **WP 1273 (April 2020).**

Rainone E., *Real-time identification and high frequency analysis of deposits outflows,* Journal of Financial Econometrics, v. 22, 4, pp. 868–907, **WP 1319 (December 2017).**

Zaghini A., *Unconventional Green,* Journal of Corporate Finance, v. 85, Article 102556, **WP 1453 (April 2024).**

FORTHCOMING

Baltrunaite A., M. Cannella, S. Mocetti and G. Roma, *Board composition and performance of state-owned enterprises: quasi experimental evidence,* The Journal of Law, Economics, and Organization, **WP 1328 (April 2021).**

Benvenuti M. and S. Del Prete, *The evolution of banking competition in italian credit markets using a profit elasticity approach,* Italian Economic Journal / Rivista italiana degli economisti, **WP 1237 (October 2019).**

Ciani E., A. Grompone and E. Olivieri, *Jobs for the long-term unemployed: place-based policies in depressed areas,* Italian Economic Journal / Rivista italiana degli economisti, **WP 1249 (November 2019).**

Cuciniello V. and N. Di Iasio, *Determinants of the credit cycle: a flow analysis of the extensive margin,* Journal of Money, Credit and Banking, **WP 1266 (March 2020).**

Cuciniello V., C. Michelacci and L. Paciello, *subsidizing business entry in competitive credit markets,* Journal of Political Economy, **WP 1424 (October 2023).**

Flaccadoro M., *Exchange rate pass-through in small, open, commodity-exporting economies: lessons from Canada,* Journal of International Economics, **WP 1365 (April 2022).**

Loschiavo D., F. Tullio and A. di Salvatore, *Measuring households' financial fragilities: an analysis at the intersection of income, financial wealth, and debt,* Review of Income and Wealth, **WP 1452 (April 2024).**

Michelangeli V. and E. Viviano, *Can internet banking affect households' participation in financial markets and financial awarness?,* Journal of Money, Credit and Banking, **WP 1329 (April 2021).**

Mistretta A., *Synchronization vs transmission: the effect of the German slowdown on the Italian business cycle,* International Journal of Central Banking, **WP 1346 (October 2021).**

Moro A., *Optimal policies in a small open economy with an environmental externality and shallow foreign exchange markets,* Portuguese Economic Journal, **WP 1348 (October 2021).**

Rainone E., *Reservation rates in interbank money markets,* Journal of Money, Credit and Banking, **WP 1160 (February 2021).**

Ropele T., Y. Gorodnichenko and O. Coibion, *Inflation expectations and misallocation of resources: evidence from Italy,* American Economic Review: Insights, **WP 1437 (December 2023).**

Rosolia A., *Do firms act on their inflation expectations? Another look at Italian firms,* Journal of Political Economy Macroeconomics, **WP 1353 (October 2021).**