Caution: Do Not Cross! Distance to Regulatory Capital Buffers and Lending in Covid-19 Times

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Abstract[1]

While banks are expected to draw down regulatory capital buffers in case of need during a crisis, we find that banks kept at safe distance from regulatory buffers during the pandemic by pro-cyclically reducing corporate lending. By exploiting granular credit register data, we show that banks with little headroom above their buffers reduced credit supply and that this behavior was amplified for banks that entered the crisis with larger un-drawn credit lines. Affected firms were unable to fully re-balance their borrowing needs to other banks and responded to the credit shock by reducing their headcount, although public guarantees mitigated banks' procyclical behaviour and its real effect at firm level. These findings raise concerns that the capital buffers introduced by Basel III may not be as countercyclical as intended.

JEL classification: E61; G01; G18; G21

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1 Introduction

Left to their own devices, banks tend to reduce capital ratios during an expansion and try to increase them in crisis times by cutting credit to the real economy when it is most needed. This procyclical behaviour came to the fore very clearly during the Great Financial Crisis (GFC) promting regulators to make bank capital more countercyclical and to reduce the risk of a credit crunch during a crisis. This became one of the main goals of the Basel III capital framework, which provides the foundations for the prudential supervision of banks since the GFC (BCBS (2011)). For this purpose, Basel III introduced *capital buffers*, i.e. capital requirements that banks must meet in normal times but on which they can draw in case of need, typically a financial crisis, to absorb losses without rationing credit. The objective is for banks to enter a crisis with adequate capital ratios, but to be able to consume it during the crisis without regulatory constrain while providing credit to the real economy.

The deep economic recession and the uncertainty caused by the Covid-19 pandemic provides the first opportunity to investigate banks' willingness to draw on those buffers when facing a major systemic crisis. Restrictions on personal mobility and nonessential business operations strongly affected business revenues, causing a surge in firms' liquidity needs. At the same time, those containment measures caused a major global economic contraction. As such, banks faced simultaneously a surge in credit demand and the prospect of serious deterioration in asset quality and profitability, a typical case calling for the use of the regulatory buffers. Morever, the ECB Banking Supervision explicitly reminded banks at the beginning of the pandemic that regulatory buffers should be used.[2] While from an aggregate perspective the euro area banking system was able to meet credit demand (ECB (2021)), this outcome reflects general equilibrium effects, including the impact of support policies, and does not say much about the functioning of the Basel III capital buffer framework.

[2] See "ECB Banking Supervision provides temporary capital and operational relief in reaction to coronavirus"

In this paper, we investigate empirically whether banks with little capital above regulatory buffer reduced corporate lending compared to other banks to avoid dipping in their buffers. We resort to granular confidential credit register data and, by exploiting banks' heterogeneity and the exogenous economic shock caused by pandemic, we assess banks' behaviour and their willingness to use capital buffers in periods of severe economic distress, as envisaged by Basel III. Furthermore, we also look at some bank-specific factors that can amplify or weaken buffer usability as well as at the implications of banks' unwillingness to use capital buffers on individual firms' borrowing capacity and quantify the impact of the resulting firms' borrowing constraints on employment. Finally, we also analyse the role of government guarantees in offsetting banks' unwillingness to use buffers for banks and the resulting credit constraints to firms.

Banks in the euro area entered the Covid-19 pandemic with on average strong capital ratios (Enria (2020)). Most of this capital was raised to meet capital requirements (Figure 1): the minimum requirements that banks must meet at all times and the combined buffer requirements (thereafter CBR). The latter capital buffers sit on top of minimum capital requirements and, in the European framework, consist of the capital conservation buffer (CCoB), the countercyclical buffer (CCyB), the systemic risk buffer (SyRB) and the buffers for systemically important banks (Figure 2).[3] The CBR abets banks to absorb losses while continuing to provide key financial services during distressed periods, thus mitigating negative externalities related to credit rationing and asset fire sales that could harm the economy (Acharya, Eisert, Eufinger, and Hirsch (2019)). Indeed, whereas minimum capital requirements must be met on an ongoing basis, the CBR can, in principle, be drawn down when needed during severe downturns or financial crises. Consequently, capital ratios may dip into the CBR in order to: (i) cushion the materialisation of losses (i.e. the numerator of the capital ratio) and; (ii) allow for increases in risk-weighted assets (i.e. the denominator of the capital ratio).

[3]These are buffers for Globally Systemically Important Banks (G-SIBs) and Other Systemically Important Intermediaries (O-SIIs), which are systemic domestic banks

[Insert Figure 1 Here]

[Insert Figure 2 Here]

While prudential authorities made clear at the beginning of the pandemic that banks were expected to use the CBR in case of need (BIS (2020); Enria (2020); FSB (2020)), banks' willingness or ability to draw down buffers may be limited by a number of factors. First, dipping into the CBR triggers restrictions on dividend distributions, bonuses and coupon payments according to the Maximum Distributable Amount (MDA) mechanism (Svoronos and Vrbaski (2020)). Although European supervisors encouraged the suspension of dividend payouts during the Covid-19 pandemic, banks may still want to avoid breaching the MDA trigger in order to distribute dividends as soon as the ban is lifted. Second, dipping into the CBR could provide a negative signal to the market in respect to bank's solvency (Baker and Wurgler (2015); Drehmann, Fara, Tarashev, and Tsatsaronis (2020)). This can lead to higher funding costs and/or have negative implications for bank credit ratings (Claessens, Law, and Wang (2018)). Cursory evidence on the relationship between contingent convertible (Coco) bonds prices and CBR headroom immediately after the pandemic outbreak suggests that Coco bond prices dropped more for banks closer to the CBR (Figure 3).[4] Third, banks' willingness to draw down buffers depends on the expected reaction of supervisory authorities (Borio, Farag, and Tarashev (2020)). If banks expect heightened scrutiny because of a breach of the CBR (EBA (2021)), it is unlikely that banks will make use of it.[5] Finally, banks might be uncertain about the time they will be given to replenish capital buffers. Such concerns may be more relevant when profitability is low or access to capital markets is constrained. For the above reasons, banks tend to keep capital targets above the CBR (Behn and Schramm (2021); Couaillier (2021)) by

[4] We collect CoCo bond prices from Thompson Eikon. The sample involves 27 SSM supervised banks, accounting for existing data availability constraints.

[5] When approaching the CBR, a bank must inform the supervisor of a *Capital Conservation Plan* describing how it intends to replenish its buffer. Should the supervisor disagree with the plan, it can require the institution to increase capital in a specified period and lower the MDA (Article 142 of CRD IV).

holding excess capital (or management buffers).[6]

[Insert Figure 3 Here]

Our analysis offers a comprehensive assessment of the effect of proximity to the CBR on bank credit supply adjustments following the pandemic outbreak. Specifically, we answer the following questions: Did banks closer to the CBR curtail their lending in comparison to banks further away from it? Did firms most exposed to these banks experience a contraction in credit? Did government guaranteed schemes ameliorated the negative effect coming from banks' proximity to the CBR?

Several empirical challenges must be overcome to estimate the effect of proximity to the CBR on lending behaviour during the Covid-19 pandemic. First, it requires accounting for the large surge in credit demand from firms for emergency liquidity needs during the pandemic. In this respect, we rely on granular loan-level data taken from the analytical credit register (*AnaCredit*) of the European System of Central Banks. In particular, we exploit a difference-in-differences (DiD) framework with multiple bank relationships and firm fixed effects (Khwaja and Mian (2008)) as well as single-bank relationships *via* the inclusion of industry-location-size fixed effects to control for the heterogeneity in credit demand across firms (Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019)). Second, it necessitates isolating bank credit supply from pandemic-related measures: most notably, government guarantee and moratoria schemes as well as restrictions on dividends distribution. Indeed, prompt and forceful policy actions assuaged the worst economic effects of the pandemic.[7] Government guarantees on new loans helped firms obtaining bank loans to roll over liquidity and working capital needs while debt service moratoria have also been widely introduced to mitigate the liquidity concerns of households

[6]Bank management buffers (or excess capital) support banks' credit ratings and business model strategies, but, more importantly for this paper, they insulate banks from the supervisory interventions which are triggered when regulatory capital requirements are breached.

[7]Monetary policy ensured accommodative financing conditions overall and for banks. Fiscal policy provided support to household and firms via tax credit, direct transfers, job support schemes, debt moratoria and loan guarantees (ECB (2020)). Prudential authorities also adopted a number of measures to allow banks to operate with more flexibility during the pandemic (SSM (2020)).

and firms. To control for the confounding effect of these measures on bank lending, we match *AnaCredit* with bank-firm level information on payment moratoria and government guarantees. Third, we account for monetary and prudential measures by including unconventional monetary policy (TLTRO III) and the ECB recommendation on dividend distribution in our empirical strategy. Altavilla, Barbiero, Boucinha, and Burlon (2020) show that in the absence of TLTRO III lending to firms would have been 3 percentage points lower. Additionally, Martínez-Miera and Vegas (2021) find that banks extended significantly more credit to non-financial corporations after the entry into force of the recommendation. We also use propensity score matching (PSM) estimations to select banks that share similar characteristics but differing in terms of their proximity to the CBR, thereby ensuring that results are not endogenous, i.e. driven by weaker balance sheets for banks closer to the CBR.

To preview our findings, proximity to the CBR resulted in lower corporate lending. Specifically, we find that proximity to the CBR reduced lending by about 3.5% to firms during the pandemic. We also find that banks with smaller capital headroom on top of capital buffers were more likely to grant loans pledged by government guarantees to economize on risk weights and loss provisioning and, consequently, to avoid approaching the CBR. We show that undrawn credit line balances prior to the pandemic exacerbated buffer usability constraints as large credit line drawdowns that occurred during the pandemic pushed banks closer to the CBR to further cut corporate lending supply to maintain the distance to capital buffer requirements. Additionally, we document that lower lending from banks in proximity of the CBR resulted in credit constraints for firms exposed to these banks as lost loans were not fully replaced. Specifically, firms that prior to the pandemic received large part of their borrowing from banks closer to the CBR experienced about 2.5% lower borrowing during the pandemic in comparison to firms that borrowed mostly from other banks. We document that this lack of perfect credit substitution led to firms cutting down their headcounts by close to 1% in comparison to other firms. Finally, we show that government guarantees ameliorated the negative effect caused by the proximity to the CBR. In particular, firms receiving loans covered by government schemes counter off the lending impairments caused by banks in proximity of the CBR.

Our paper provides a solid contribution to the extant literature in several respects. First, it contributes to a growing literature studying the effect of capital requirements on bank lending. Various papers look at the effect of bank-specific capital surcharges (Berrospide and Edge (2010), Gropp, Mosk, Ongena, and Wix (2019), De Jonghe, Dewachter, and Ongena (2020)), structural buffers (Degryse, Mariathasan, and Tang (2020), Behn and Schramm (2021), Cappelletti, Reghezza, Rodriguez d'Acri, and Spaggiari (2022)) and dynamic capital requirements (Aiyar, Calomiris, Hooley, Korniyenko, and Wieladek (2014), Jiménez, Ongena, Peydró, and Saurina (2017), Basten (2020), Auer and Ongena (2022)) on bank lending. While this literature largely focuses on the impact of changes in capital requirements, we contribute by investigating the *usability of buffers in crisis time*, i.e. a key feature of the Basel III regulatory framework. Should banks not consider these buffers as usable, achieving the countercyclical objective of the framework would be very difficult. In this regard, we contribute to the policy-oriented debate on the effectiveness of the buffer framework (FSB (2020), Aiyar et al. (2021), BIS (2021)) and possible impediments to the counter-cyclical objective of the Basel III framework.

Second, we add to the long-standing empirical literature on bank capitalisation and lending (Bernanke and Lown (1991), Berger and Udell (1994), Rosengren and Peek (1997), Gambacorta and Mistrulli (2004), Berrospide and Edge (2010)).[8] While these papers investigate the absolute level of capital ratios, we investigate the impact of the *closeness to regulatory buffers*.

We also differ from the previous literature in terms of data granularity. Earlier studies apply aggregate (Hancock, Laing, and Wilcox (1995), Lown and Morgan (2006)) or bank-level data (Rosengren and Peek (1997)). However, bank-level data may be prone to endogeneity issues due

[8]For the theoretical literature we refer to Diamond and Rajan (2000), Bolton and Freixas (2000), Van den Heuvel (2008), Gersbach and Rochet (2017) among others.

to the omission of firm-level variables. Addressing this problem requires *perforce* bank lending and firm borrowing to be considered jointly. This allows to control for firm credit demand. Undeniably, a perennial challenge when examining the effect of bank capital requirements on lending is to disentangle supply from demand. Similarly to more recent studies (Puri, Rocholl, and Steffen (2011), Behn, Haselmann, and Wachtel (2016), Fraisse, Lé, and Thesmar (2020)) we combine loan-level and firm-level analyses. However, while papers using loan-level analysis are mostly based on single country setting as they rely on national central bank credit registers, we add to the relevant literature by resorting to *AnaCredit*, the analytical credit register of the European System of Central Banks which allows us to exploit million of loans in a multi-country setting. Furthermore, we overcome an additional econometric identification challenge that emerges when analysing the impact of Covid-19 on bank lending behaviour. This arises from the necessity to disentangle the effect of a bank's distance to the CBR on lending from the effect of the post-pandemic fiscal support packages (notably payment moratoria and loan guarantees). In this paper, by collecting unique data on loan protections we are able to control for pandemic-related fiscal support measures, further mitigating omitted variable bias concerns.

The rest of the paper is organised as follow. Section 2 describes the econometric identification. Section 3 introduces our data and descriptive statistics. Section 4 presents the results. Section 5 presents a number of robustness checks and Section 6 concludes.

2 Econometric Identification

This paper exploits differences in the distance to the CBR prior to the pandemic to investigate whether and to what extent banks adjust their balance sheets after its outbreak. We employ loan-level data, thus controlling for heterogeneity in credit demand, to investigate whether bank lending is affected by a smaller capital headroom above the CBR. The strict exogeneity of the Covid-19 shock naturally lends itself to a DiD research design.

2.1 Bank-firm level analysis

To shed light on bank lending behaviour in response to the pandemic, we start by examining whether and how banks, whose capital ratios prior to the Covid-19 crisis were in proximity of the CBR, adjust their balance sheet after the shock. We use loan-level data to disentangle credit supply from credit demand.

For identification purposes, we follow two distinct approaches. First and in the spirit of Khwaja and Mian (2008) we exploit firm with multiple bank relationships to control for firm credit demand with firm-level fixed effects. As such, we compare how much credit a given firm received from multiple banks at different distance to the CBR. However, one shortcoming of the Khwaja and Mian (2008) econometric identification strategy is the exclusion of single-bank firm which are absorbed by firm fixed effects. Since the majority of single-bank relationships involve small and medium enterprises (SMEs) which are predominant in most European countries, this biases the sample of firms. To tackle this issue, we follow the approach by Popov and Horen (2015), Acharya et al. (2019), Degryse et al. (2019) and construct firm industry-location-size (ILS) fixed effects. To classify the industrial sectors, we follow the Statistical Classification of Economic Activities in the European Community (NACE Rev.2) code.[9] The industry clusters are based on 2-digit NACE codes. The location clusters on the postal code of the firm's country headquarter.[10] For size, we take the definition given in *AnaCredit* which distinguishes between large, medium, small and micro enterprises.[11] The inclusion of ILS fixed effects instead of firm

[9]NACE Rev. 2 classification is based on a hierarchical structure, which consists of first level sections (alphabetical code), second level divisions (2-digit numerical code), third level groups (3-digit numerical code and fourth level classes (4-digit numerical code). Refer to https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

[10]For countries with more than 20 million inhabitants (Germany, France, Italy, Spain) we use the first two digits of the postal code; for countries between 5 and 20 millions; we consier countries with less than 5 millions inhabitants as a single location. In the online Appendix, we also run a robustness check where we build our location size by using the 5-digit post code for all countries in the sample.

[11]The classification of firm size in *AnaCredit* is based on the EU Commission standard whereby a large firm employs more than 250 employees; has an annual turnover greater than EUR 50 million; and annual balance sheet greater than EUR 43 million. A medium firm employs less than 250 but more than 50 employees, has an annual turnover not exceeding EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million. A small firm employs fewer than 50 persons and has an annual turnover and/or annual balance sheet total that does not exceed EUR 10 million. Finally, a micro firm employs fewer than 10 persons and whose annual turnover and/or annual balance sheet total does not exceed EUR 2 million

fixed effects allows us to retain more than 1.3 million additional single bank-firm relationships in our estimation. Our econometric identification relies on the following DiD specification:

$$\Delta Log(loans)_{i,k} = \alpha_k + \beta Low.D2Buffer_i + \tau X_i' + \delta Z_{i,k} + \gamma_j + \epsilon_{i,k} \tag{1}$$

where the dependent variable is the change in the logarithm of loans from bank i to firm k around the pandemic. Following, Bertrand, Duflo, and Mullainathan (2004) we collapse the quarterly data into pre (2019Q3-Q4)- and post (2020Q3-Q4)-event (Covid-19) averages to avoid issues of serial correlation, hence we consider one observation per firm-bank relationship.[12] In equation (1), Low.D2Buffer is our dummy variable of interest which is equal to 1 if a bank, prior to the pandemic (2019Q3-Q4), has an average distance to the CBR below the first quartile of the distribution, 0 otherwise.[13] β is our coefficient of interest as it indicates whether a given bank in proximity of the CBR lends less following the shock in comparison to banks with more sizeable CBR headroom. To control for possible heterogeneity among banks, we specify a vector X that includes averaged lagged bank control variables, thus taking into account bank-specific factors that might potentially affect the dependent variable. Specifically, we introduce the overall capital requirement (L.OCR),[14] the logarithm of bank total assets (L.TA.log), the risk-weight density (L.RW), the ratio of debt securities-to-total assets (L.MKT FUNDING/TA), the net interest margins (L.NIM) the ratio of non-performing loans-to-gross loans (L.NPLs), the ratio of corporate forbearance-to-outstanding loans (L.FORBEARANCE), the ratio of cash and financial assets held for trading-to-total assets (L.LIQUID/TA), the share of non-interest income-to-operating income (L.DIVERS), the ratio of off balance sheet activities-to-total assets

[12] The decision to collapse the dataset into pre (2019Q3-Q4) and post (2020Q3-Q4)-event averages is also aimed at avoiding that our results are driven by the credit surge that occurred in 2020Q2, hence immediately after the pandemic. In the online Appendix we also collapsed the quarterly data into pre (2019Q1-2020Q1 and 2019Q2-2019Q4)- and post(2020Q2-2020Q4). The results are in line to the collapsing strategy used throughout the paper.

[13] In a robustness check in Section 5 we test a different computation of the dummy variable Low.D2Buffer

[14] The OCR is the sum of minimum requirements and the combined buffer requirement, the CBR.

(L.OFF BS), the ratio of credit exposures-to-total assets (L.LOAN/TA), the cost-to-income ratio (L.CIR) and the ratio of provisions-to-total assets (L.PROVISION/TA). Z is a vector of bank and bank-firm policy control variables included to account for the unconventional monetary policies as well as the fiscal measures adopted in reaction to the pandemic. Specifically, we add the ratio of targeted longer term refinancing operations (TLTROs III)-to-total assets, the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets (DIVIDEND.REST) (both variables at bank level) and two additional variables capturing the percentage of post-event credit from bank i to firm k that are subject to government moratoria (S.MORA) and guarantees (S.GUAR) that are computed at the bank-firm level.[15] α identifies firm (or ILS) fixed-effects employed to control for firm credit demand. γ reflects country fixed effects based on banks' headquarter which absorb the different intensities of the spread of the pandemic between countries. Standard errors are double clustered at the bank and firm level (Jiménez et al. (2017)).

The DiD approach requires that several assumptions hold. First, assignment of the treatment has to be exogenous. In a nutshell, the shock should affect the outcome variables and not vice versa. Arguably, in our empirical setting, meeting this assumption is reasonable as the Covid-19 pandemic was indeed an unanticipated exogenous "shock" to the economy. Second and according to Bertrand et al. (2004) and Imbens and Wooldridge (2009), the DiD approach is only valid under the so-called "parallel trend assumption" whereby changes in the outcome variable prior to the shock would be the same in both the treatment (Low.D2Buffer banks) and the control groups (High.D2Buffer banks). Figure 4 shows the normalised trends of the average bank-firm level logarithmic change in lending for the group of banks that were in proximity of the CBR (our treatment group) and the control group over time (2019Q1-2020Q4). The two trends were virtually the same before the Covid outbreak. However, banks with sizeable CBR

[15] Table A in the Appendix provides a definition of the variables used in the paper and the respective sources.

headroom showcase stronger lending following the start of the pandemic.[16]

[Insert Figure 4 Here]

Third, the control group must constitute a valid counterfactual for the treatment, i.e. banks in the control group should share similar characteristics with treated banks. On the one hand, banks closer to the CBR may suffer from weaker balance sheets and, for instance, poorer profitability and/or deteriorated asset quality than banks further away from it. Additionally, banks closer to the CBR could exploit - more than other banks - the exceptional measures undertaken by policy makers as a reaction to the pandemic outbreak. On the other hand, it is also plausible that larger banks lie closer to the CBR as they adopt capital management strategies to limit the amount of profitless excess capital.

In order to address this endogeneity concern, Panel A of Table 1 shows the pre-treatment mean values of the covariates employed in equation (1). We use the Welch's test to test for mean differences between the two groups. As shown, banks closer to the CBR in the collapsed quarters prior to the pandemic have, on average, higher risk weight density, are less profitable, hold greater amount of legacy assets (although lower provisions), have lower capital requirements and engage more in off-balance sheet activities than banks further away from it. Moreover, banks in proximity of the CBR appear to have resorted more to TLTRO III uptakes during the pandemic. Although equation (1) is saturated with bank and policy-specific control variables, we complement the baseline regression by using the PSM approach (Rosenbaum and Rubin (1983)) which, by pairing each bank with a control unit, allows us to get pre-Covid comparable control and treatment groups, mitigating the concerns that our results are driven by bank

[16] While both groups increase lending during the pandemic, Figure 4 only shows unconditional lending developments and thus does not allow to control for the heterogeneity in credit demand across firms as well as for the simultaneity of fiscal and monetary policy measures deployed as a reaction to the pandemic. Therefore the need to rely on granular data and loan-level econometric analysis to disentangle the distance to the CBR from support measures.

specific-attributes. In the spirit of Bersch, Degryse, Kick, and Stein (2020), we allow treated banks to be matched with the nearest control banks, whilst both treated and control banks are discarded from the analysis if proper matching is not found (Heckman, Ichimura, and Todd (1997)).[17] Figure 5 plots the density curves of the treatment and the control groups before and after the PSM. After matching, the two density curves almost overlap. Additionally, Panel B of Table 1 presents the corresponding result of the two-sample Welch t-test after the PSM. There are no statistically significant differences between the treatment and the control groups post matching indicating that the PSM acts as an accurate balancing mechanism. In fact, the number of control group banks diminish by 206 (from 282 to 76), whilst 18 treated banks are dropped from the analysis in the absence of a well suited matching.

[Insert Figure 5 Here]

[Insert Table 1 Here]

We also investigate two factors that could interact with banks willingness to provide credit. First, we interact the treatment dummy with the ratio of pre-pandemic credit lines to total assets ($L.CRLINES/TA$). Indeed, those credit lines constitute a risk of negative shock on banks' capital: while capital requirements are low for un-drawn credit lines, they substantially increase once the line is actually drawn and becomes an outstanding credit. As such, banks with low headroom above the CBR should be even less willing to grant new credit when they are largely exposed to credit lines. Second, we investigate whether public credit guarantee schemes mitigated the impact of banks' unwillingness to use buffers on their credit supply. As public credit guarantees are considered very safe, they considerably reduce credit risk and ultimately the risk weight attached to a loan. Granting such loans instead of un-guaranteed loans limits the increase in Risk-Weighted Assets and thus the decline in the capital ratio. As such, banks

[17] The counterfactual is created via a logit model and we apply one-to-one nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equalling to 0.3 (Dehejia and Wahba (2002)). In the online Appendix, we employ an additional PSM matching strategy based on the coarsened exact matching algorithm (see Iacus, King, and Porro (2012)).

close to the CBR should be particularly tempted to provide guaranteed loans to preserve their capital ratio and thus their headroom over the CBR.

2.2 Firm-level analysis

In this section, we investigate whether the unwillingness to use buffers from banks with low distance to the CBR resulted in lower credit at the firm level. Two factors may mitigate this impact: if (i) banks further away from the CBR pick up the slack and/or if (ii) the government offers credit risk protection *via* guaranteed schemes which help banks close to the CBR to lend. If this is the case, there will be no effect on total credit supply to the real economy but a mere redistribution of market shares across banks and/or more government intervention. In practise, however, firms exposed to banks in proximity of the CBR point may struggle to replace existing sources of financing with alternative ones or to establish new credit relationships during turbulent times. Since, on average, firm exposure to banks with limited CBR headroom prior to the pandemic is sizeable (Figure 6), we delve into this question by following Behn et al. (2016) and adopting the following econometric identification strategy:

$$\begin{aligned}\Delta Log(borrowing)_k = \alpha_{ils} + \beta Exp.Firm_k + \lambda S.GUAR_k + \sigma Exp.Firm_k * S.GUAR_k \\ + \tau X_i + \delta Z_i + \gamma_j + \epsilon_k \qquad (2)\end{aligned}$$

The dependent variable is the change in the logarithm of a firm's total bank loans over the pandemic shock. α identifies ILS fixed effects that we use to control for heterogeneity in credit demand across firms. $Exp.Firm$ is a dummy variable indicating whether a firm is exposed to a bank in proximity of the CBR prior to the pandemic, 0 otherwise. Specifically, we define as exposed those firms that prior to the pandemic have more than 25% of their credit originating from more vulnerable banks, i.e. those in proximity of the CBR. In equation (2), our interest lies in the β and σ coefficients. β captures whether firms' borrowing from vulnerable banks that did not receive loans pledged by government guaranteed schemes is impaired in comparison to firms connected to banks with greater CBR headroom, while σ indicates whether guarantees schemes have been effective in providing more credit to firms constrained by banks in proximity of the CBR. The vectors X and Z are weighted averages (weighting each bank value by its loan volume to firm k prior to the shock over total bank loans taken by this firm) of the same bank and policy-control variables as adopted in equation (1).

$$\Delta Log(N.emplo)_k = \alpha_{ils} + \beta Exp.Firm_k + \lambda S.GUAR_k + \sigma Exp.Firm_k * S.GUAR_k + \tau X_i + \delta Z_i + \gamma_j + \epsilon_k \tag{3}$$

In the spirit of Jiménez et al. (2017), in equation (3), we look at whether exposed firms' head-counts is affected during the pandemic as this can have repercussions on firms' performance and, more broadly, on the level of unemployment and economic output.[18] If firms did not manage to raise funds from banks with greater CBR headroom and/or through guaranteed schemes, they may have been forced the to cut the number of employees.

[Insert Figure 6 Here]

3 Data

Our analysis relies on datasets collected from multiple sources. First, we construct a bank-level dataset by combining information from several supervisory sources. Bank-level balance sheet as well as capital stack (Pillar 1 and 2) and buffer requirements data are gathered from ECB Supervisory Statistics, while TLTRO take-up information is drawn from the ECB market

[18]We rely on the available firm-level data in AnaCredit for this exercise as matching external database providers with Anacredit would greatly reduce the coverage of firms in the sample.

operations database. Bank-level data is matched with loan-level information from *AnaCredit*, the credit register of the European System of Central Banks which contains information on all individual bank loans to firms above €25,000 in the euro area.[19] *AnaCredit* encompasses information on key bank and borrower characteristics such as credit volume, firm location, firm size and firm sector. Our initial dataset (pre-collapse) contains roughly 30 million loans in the euro area. Importantly, *AnaCredit* collects unique data on the protection received for each loan contract which allows us to identify whether the loan is subject to a public guarantee.[20] Furthermore, by using information on loan maturity dates at origination and checking whether these are extended following the pandemic outbreak, we are also able to identify which loan is benefitting from a payment moratoria. The data are collected by the European Central Bank from the national central banks of the Eurosystem in a harmonised manner to ensure consistency across countries.

Table 2 reports the number of banks by country, matching strategy and treatment status. As expected, Germany showcases the greatest number of banks for both samples (matched and unmatched). Notwithstanding sample size differences, the number of banks appears to be well distributed after matching suggesting that the PSM did not alter the sample composition but rather it scaled down the number of banks withing each country to find proper comparables (the only exception being the Netherlands and Slovenia for which the number of control group banks after matching dropped by 13 and 4, respectively). While the reduction of treated banks following the application of the PSM strategy is marginal, the numbers of non-suitable banks in the control group is quite large (205) indicating the appropriateness of complementing the baseline regression with a more comparable sample of banks.

[19] *AnaCredit* stands for analytical credit datasets. Additional documentation can be found here: https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html

[20] COVID guaranteed loans have been identified by using registry information (e.g. LEIs and RIAD codes) of the promotional lenders charged with this task in each country (for example, ICO in Spain, KFW in Germany, BPI in France and SACE/Fondo di Garanzia in Italy). In addition to the registry information of the guarantor, the starting date of the public guarantee scheme has also been used as an identifying device.

[Insert Table 2 Here]

Table 3 and Panel A reports the descriptive statistics of the variables employed. On average, lending increases immediately after the pandemic outbreak by 12.4%. This is likely driven by monetary and prudential policy actions that ameliorated the worst economic effects of the pandemic by ensuring accomodative financing condition overall and for banks as well as by fiscal measures that enabled the transmission of supporting funding conditions to the economy. For instance, TLTROs uptake (TLTRO.III) as well as the bank-firm share of loans under guarantee schemes weighted by total loans (S.GUAR) is not negligible as shown by mean and standard deviation of Table 3 and Panel C. Similarly, firm borrowing increase largely during the pandemic (by 33.5%) confirming the large surge in credit demand from firms for emergency liquidity needs. Panel B of Table 3 outlines the variable of interest, namely the distance to the CBR. As mentioned in the explanation of equation (1), banks considered as treated have a distance to the CBR below 2.6% (first quartile of the distance to the CBR distribution). For graphical purposes, in Figure 7 we report the distribution of the distance to the CBR.[21]

[Insert Table 3 Here]

[Insert Figure 7 Here]

4 Results

4.1 Bank-firm level results

4.1.1 Baseline results

Table 4 reports the results from estimating equation (1). The Table is divided in 4 columns. Columns 1 and 2 report the results of Khwaja and Mian (2008) approach for the matched and unmatched sample whilst columns 3 and 4 report the results of the Degryse et al. (2019)

[21] Table B in the Appendix provides a pairwise correlation matrix for all the right-hand side variables of equation (1).

approach for the matched and unmatched sample. The dataset is collapsed into pre- (2019Q3-2019Q4) and post-event (2020Q3-2020Q4) averages.

The dummy Low.D2Buffer is our coefficient of interest as it indicates whether proximity to the CBR results in weaker credit supply at the onset of the pandemic. The first column of Table 4 shows that banks closer to the CBR contract their lending supply by 3.5% after the pandemic outbreak compared to the control group. This specification includes firm fixed effects which control for firm credit demand. The second column of Table 4 displays the results for the matched sample which addresses the concerns that differences in bank-specific characteristics may drive the results. The coefficient of interest (Low.D2Buffer) remains significantly negative and increases, suggesting a contraction of about 9.2%. In columns 3 and 4, we replace firm fixed effect with ILS fixed effects to allow the inclusion of single-bank relationships which are mostly determined by SMEs. ILS allow us to retain more than 1.3 million single-bank relationships in our estimation. The coefficients have sign and statistical significance in line with the firm FE regressions. As in the firm FE econometric specification, we find a stronger effect in the matched sample. In particular, we find a contraction in bank lending supply by about 3.4% - 8.9% in the unmatched and matched sample, respectively. Overall, these results show that banks close to the CBR tend to contract corporate lending supply in stress time, suggesting they are unwilling to use those buffer, contrary to the intention of the Basel III framework.

Among the bank-specific controls, we document an inverse relationship between the OCR and the change in bank lending during the pandemic. Specifically, a 1 pp increase in the OCR is associated to a contraction of lending supply of 4.2% (column 1). This result is in line with a large literature suggesting a negative relationship between capital requirements and bank lending (see, amongst others, Behn et al. (2016), Gropp et al. (2019), Fraisse et al. (2020)). A negative and statistically significant link is also displayed between $MKTFUNDING/TA$ and the change in bank lending. In particular, a 1 pp increase in $MKTFUNDING/TA$ leads to about 0.4% (column 1) increase in lending supply during the pandemic. Banks relying on non-deposit sources of funds may have an increased sensitivity to the exceptional monetary policy tools implemented against the pandemic, thus being able to exploit favourable financing conditions and extend more credit than banks relying more on deposits as a source of funding (Disyatat (2011)). We also document a positive relation between the net interest marging and the change in bank lending during the shock. Particularly, a 1 pp increase in NIM increases lending supply by about 6.12% (column 1) suggesting that more profitable banks provide more credit during the pandemic (Molyneux, Reghezza, and Xie (2019)). As expected, we find a positive and strongly statistically significant (at the 1% level) relationship between the share of loans under government guaranteed schemes ($S.GUAR$) and the change in bank lending supply. A 1 pp increase in the share of guaranteed loans results in about 1.5% increase in bank lending supply (column 1). Conversely, banks putting loans in moratorium were logically less willing to extend more credit to the borrowing firm.

[Insert Table 4 Here]

4.1.2 Interactions with pre-pandemic credit line balances

In Table 4, we find that proximity to the CBR results in lower lending to NFCs during the pandemic. This reaction could be amplified by undrawn credit line balances prior to the pandemic. Indeed, when faced with a major liquidity shocks, firms are expected to draw on their credit lines, turning off-balance-sheet, low risk-weight, credit lines into on-balance-sheet, high risk-weight, loans, thus increasing banks' Risk Weighted Assets and, mechanically, reducing their capital ratio and thus their headroom over the CBR. Figure 8 shows that banks actually experienced a surge in draw-down of existing credit facilities following the pandemic outbreak, which is confirmed also by other studies (see, amongst others, Acharya et al. (2019); Li, Strahan, and Zhang (2020)). Anticipating these developments, banks close to the CBR and with large unwdrawn credit lines at the outbreak of the COVID-19 pandemic may have been even less willing to extend new credit to firms to preserve their capital ratios. To test for this proposition, we interact our variable of interest (*Low.D2Buffer*), with the pre-pandemic ratio of existing credit line balances to total assets (*L.CR LINES/TA*).

The results reported in Table 7 show that large amounts of credit line balances prior to the pandemic exacerbates usability constraints during downturns. Specifically, a 1 pp increase in the pre-pandemic ratio of existing credit line balances to total assets leads to a 0.56%-0.87% lower lending for banks closer to the CBR. This evidence is in line with a recent paper by Greenwald, Krainer, and Paul (2020) that find that banks with lower pre-crisis capital buffers restricted their term lending supply to a greater degree in response to drawdowns on their credit lines.

[Insert Figure 8 Here]

[Insert Table 7 Here]

4.1.3 Interactions with government guarantees

A growing body of research (see, for instance, Altavilla, Ellul, Pagano, Polo, and Vlassopoulos (2021)) documents that credit guarantee schemes supported firm's liquidity needs by preserving banks' incentives to lend as the credit risk is transferred to a guarantor (the public sector). Moreover, credit benefiting from public guarantees have typically very low risk weights, thus a negligigle negative impact on banks' capital ratio. As such, CBR constrained banks may be more likely to extend guarantees on loans in order to meet credit demand while limiting increases in risk weights and loss provisioning which could affect their distance to CBR. Therefore in this section we answer two distinct questions: 1) Are banks in proximity of the CBR more likely to grant loans partly or fully pledged by government guarantees? and, 2) Did guaranteed loans ameliorate buffer usability constraints on lending supply to NFCs? To answer this question, we use a probit regression model specified as follow:

$$E[Guarantees_{ik}|Low.D2Buffer_i, X_i, Z_i] = \Phi(Low.D2Buffer_i, X_i, Z_i) \quad (4)$$

where *Guarantees* is a binary variable computed at the bank-firm level that takes the value 1 if bank i has granted a loan to firm k which is partially or fully pledged by government guarantees, and 0 otherwise. Low.D2Buffer is our variable of interest as defined in equation (1). A positive coefficient of the Low.D2Buffer variable indicates that banks closer to the CBR are more likely to grant guaranteed loans. For the sake of consistency, we introduce the same set of regressors as well as the same PSM matching strategy as employed in equation (1).

The results reported in Table 5 confirm our hypothesis. The Low.D2Buffer coefficient is positive and statistically significant at the 1% level indicating that banks with smaller capital headroom on top of capital requirements have a greater likelihood to grant loans pledged by government guarantees to economize on risk weights and loss provisioning, i.e. exploiting guarantees schemes in order to avoid approaching the CBR.

Second, we look at whether government guarantee schemes ameliorated credit supply constraints coming from banks in proximity of the CBR as shown in Table 4. For this exercise, we follow the econometric identification strategy used in equation (1) and interact our dummy variable of interest (*Low.D2Buffer*), with the dummy *Guarantees* as specified in equation (4). The results reported in Table 6 are important in two key respects. First, the magnitude of the single dummy (*Low.D2Buffer*) is larger than in the baseline regressions reported in Table 4 suggesting that banks with little headroom on top of the CBR and that did not extend guaranteed loans contracted even more their lending supply. Second, the interaction term (*Low.D2Buffer* x *Guarantees*) is positive and, in most cases, statistically significant implying that public guarantee schemes helped banks in proximity of the CBR to keep up lending. The sum of the single

$Low.D2Buffer$ and the interaction term are insignificantly positive, meaning that credit guarantees were successful in offsetting the negative credit shock due to banks' unwillingness to use their buffers.

This result is of pivotal importance for policy-makers as bank loan guarantees can be especially helpful for capital constrained banks to sustain bank lending during downturns.

[Insert Table 5 Here]

[Insert Table 6 Here]

4.2 Firm-level results

In this section, we analyse whether the proximity to the CBR entails credit rationing at the firm level. In practise, this will depend on (i) the extent to which other banks, not close to the CBR, are able or willing to pick up the slack and/or (ii) the effectiveness of government guaranteed schemes in helping capital constrained banks and maintain their credit supply. To analyse the occurrence of this substitution, we use the dummy *Exp.Firm* as in equation 2 that is equal to one if a firm receives more than 25% of credit prior to the pandemic by banks with low headroom above the CBR. To investigate whether prudential buffers have interacted with the fiscal support measures introduced after the pandemic we use the interaction term $Exp.Firm \times S.GUAR$. The inclusion of ILS allows us to control for heterogeneity in credit demand across firms.[22]

Results to these questions are reported in Table 8. Columns 1 and 2 display the results of the dummy *Exp.Firm* (column 1) and the interaction term $Exp.Firm \times S.GUAR$ (column 2). Firms exposed to banks in proximity of the CBR exhibit about 2.5% lower borrowing after the pandemic outbreak than other firms. This suggests that those firms were not able to fully

[22] In this econometric exercise the inclusion of firm fixed effects is not possible as they would absorb the dummy variables of interest (*Exp.Firm*).

compensate the negative credit supply shock from their usual lenders by contacting other banks.

The interaction term in column 2 provides useful insights on the relationship between proximity to the CBR and government guarantees. The single coefficient *Exp.Firm* is still negative and statistically significant (at the 1% level). However, we find a positive and statistically significant (at the 1% level) effect of government guarantees in mitigating the negative effect of proximity to the CBR on firms' borrowing capability. The two coefficients offset each other, meaning that, *ceteris paribus*, firms linked to banks close to the CBR did not suffer from a negative credit supply shocks when their banks were able to grant them guaranteed credit. This result highlights both the negative aggregate effects originating from localised credit supply constraints and the positive effects of guaranteed credit in mitigating capital buffers usability constrains.

Since firms are unable to substitute funding from CBR constrained banks, this is likely to have negative repercussions at the firm level through lower employment, investments and growth. Table 8 and column 1 reports the results when we regress the dummy variable of interest (*Exp.Firm*) on the logarithmic change in the number of employees. As shown, impediments to credit substitution results in firms reducing headcounts by about 0.8% in comparison to firms borrowing from CBR unconstrained banks. The interaction term $Exp.Firm \times S.GUAR$ is statistically insignificant (column 2) indicating that guaranteed loans did not affect the number of employees during the pandemic.

[Insert Table 8 Here]

5 Robustness checks

We run a series of robustness checks to strengthen our results.

5.1 Placebo test

When using a DiD estimation approach it is important to eliminate the possibility that the identified behaviour on the dependent variable of interest might have already emerged prior to the shock. In practise we need to ensure that bank lending in the treatment group had not already diverged prior to the pandemic. This would invalidate our choice of DiD estimation. To do so, *placebo* exercises can be set up in which the data is tricked to think that a shock occurs at an earlier date. If the estimated coefficients on the 'false' Covid shock are not statistically significant, we can be more confident that our baseline coefficient is capturing a genuine shock.

In Table 9, we report the results from estimates in which we limit our time dimension to the pre-Covid period (2019Q1-Q4), collapsing the quarterly data into pre- (2019Q1-Q2) and post (2019Q3-Q4)-'fake' event averages. The coefficient of the Low.D2Buffer variable is negative in almost all specifications but the magnitude of the coefficient smaller and, most importantly, it is not statistically significant in any of the econometric specifications (matched/unmatched sample and firm/ILS fixed effects), supporting the validity of our baseline estimation and the selection of the difference-in-difference econometric strategy.

[Insert Table 9 Here]

5.2 Alternative definition of the treatment variable

In the baseline specification, we defined as *treated* banks with a distance to CBR below the fist quartile of the distance to the CBR distribution and as *control* those banks with a distance to the CBR above the first quartile. In this set up, we allow some banks to be considered as controls even though they lay slightly above the first quartile. Therefore, in this section, we provide a variation to the baseline specification by redefining the dummy Low.D2Buffer in order to consider only the first and last quartile of the distance to the CBR distribution, i.e. omitting the banks in the middle of the distribution. Specifically, for this test the dummy Low.D2Buffer takes the value 1 for banks with an average pre-pandemic (2019Q3-Q4) distance to the CBR below the first quartile of the distance to the CBR distribution (as in the baseline specification in equation (1)) while it takes the value 0 only for banks with a distance to CBR above the third quartile of distance to CBR distribution.

The results from this test are reported in Table 10. Although dropping banks between the first and third quartile results in a lower number of banks, firms and observations that enter into the estimation, we find that sign and statistical significance of the dummy variable of interest (Low.D2Buffer) is in line with the baseline findings of Table 4. In addition, we find - in the majority of the specifications - a stronger magnitude of the coefficients of interest in the unmatched sample. Specifically, banks in proximity of the CBR contract lending supply by about 4.9% - 7.5% in the specification including firm fixed effects and about 5.6% - 4.2% in the specification which account for the inclusion of single-bank relationships via ILS fixed effects in comparison with banks with a distance to the CBR above the last quartile.

[Insert Table 10 Here]

5.3 Continuous distance to the CBR

As a third robustness check, we replace our dummy variable of interest (Low.D2Buffer) with continuous the distance to the CBR (labelled L.Dist.CBR). Using a dummy specification has two main advantages compared to the continuous variable. First and most important, it allows to apply sample matching strategies (in our case the PSM). This ensures that our results are not endogenous, i.e. not driven by banks that are close to the CBR because of weaker balance sheets. Second, it allows for non-linearity in the estimation of the distance to the CBR and bank lending supply. This method is employed also by other studies in the banking literature (see, amongst others, Gropp et al. (2019) Heider, Saidi, and Schepens (2019)). However, using a continuous specification is a useful robusness check as this allows for a better estimation of the intensity of the effect of the distance to the CBR on changes in bank lending supply, and makes the result less dependent on a threshold.

The results displayed in Table 11 (columns 1 and 2) show a positive and statistically significant (at the 1% level in column 1) relationship between the distance to the CBR and bank lending supply. Specifically, a 1 pp increase in the distance to the CBR is associated to about 0.6% higher lending in the specification with firm fixed effects and about 0.3% when single-bank relationships are included via ILS fixed effects, although not statistically significant.

[Insert Table 11 Here]

5.4 Controlling and matching by CET1 ratio

Next, we replace the OCR with the CET1 ratio among the control variables and in the PSM. In the matching strategy employed throughout the paper, we constrain the OCR between the treated and control group to be similar while allowing the CET1 ratio to vary. While it is important in the empirical strategy to control for differences in terms of bank capital requirements, we may face the possibility that our results are driven by lower levels of CET1 ratio and not necessarily by the proximity to the CBR. Matching by the CET1 ratio creates control and treatment groups that have similar capital ratios but differing in their distance to the CBR (implicitly they have different OCR). The results are reported in Table 12. Signs, magnitudes and statistical significance are in line with the baseline findings further corroborating their validity.

Finally, in the online Appendix, we employ an additional PSM matching strategy based on the coarsened exact matching algorithm proposed by Iacus et al. (2012)). Results are, again, very similar to the PSM strategy employed througout the paper.

[Insert Table 12 Here]

6 Conclusion

In this paper we ask whether the capital buffer introduced in Basel III are successful is making banks act counter-cyclically when confronted with a situation of widespread economic distress, as the one generated by the Covid-19 pandemic. We approach the issue empirically by investigating how banks that prior to the pandemic outbreak maintained a lower buffer on top of regulatory requirements adjusted their balance sheets when compared to other banks.

We find robust evidence that banks proximity to the CBR results in lower lending supply during the Covid-19 pandemic. The results hold when controlling for a number of possible alternative explanations (e.g. credit demand, bank solvency, asset quality, etc) and when controlling for a broad range of pandemic policy support measures. It is amplified for banks with large undrawn credit lines at the outbreak of the Covid-19 pandemic. The pro-cyclical behaviour of banks in proximity of the CBR resulted in credit constraints for firms mostly exposed to them as they were unable to fully replace the curtailed loans. Credit guarantee schemes were instrumental in offsetting the negative credit supply shock due to banks' unwillingness to use buffers.

An important research and policy question regards the drivers of this behavior. Among the list of suspects, unwillingness to face restrictions on capital distribution and fear of market stigma for consuming capital appear as promising candidates. This is left for further research.

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. doi: 10.1093/rfs/hhz005

Aiyar, S., Calomiris, C. W., Hooley, J., Korniyenko, Y., & Wieladek, T. (2014). The international transmission of bank capital requirements: Evidence from the UK. *Journal of Financial Economics*, *113*(3), 368-382. doi: 10.1016/j.jfineco.2014.05

Aiyar, S., Mitra, S., Mineshima, A., Jobst, A. A., Dao, M. C., & Pradhan, M. (2021). *COVID-19: How Will European Banks Fare?* (IMF Departmental Papers / Policy Papers No. 2021/008). International Monetary Fund.

Altavilla, C., Barbiero, F., Boucinha, M., & Burlon, L. (2020). *The great lockdown: pandemic response policies and bank lending conditions* (Working Paper Series No. 2465). European Central Bank.

Altavilla, C., Ellul, A., Pagano, M., Polo, A., & Vlassopoulos, T. (2021). *Loan Guarantees, Bank Lending and Credit Risk Reallocation* (CSEF Working Papers No. 629). Centre for Studies in Economics and Finance (CSEF), University of Naples, Italy.

Auer, R., & Ongena, S. (2022). The countercyclical capital buffer and the composition of bank lending. *Journal of Financial Intermediation*, *In Press*.

Baker, M., & Wurgler, J. (2015). Do strict capital requirements raise the cost of capital? bank regulation, capital structure, and the low-risk anomaly. *American Economic Review*, *105*(5), 315-20. doi: 10.1257/aer.p20151092

Basten, C. (2020). Higher Bank Capital Requirements and Mortgage Pricing: Evidence from the Counter-Cyclical Capital Buffer. *Review of Finance*, *24*(2), 453-495.

BCBS. (2011). *Basel iii: A global regulatory framework for more resilient banks and banking systems* (Tech. Rep.). Bank for International Settlements.

Behn, M., Haselmann, R., & Wachtel, P. (2016). Procyclical Capital Regulation and Lending. *Journal of Finance*, *71*(2), 919-956.

Behn, M., & Schramm, A. (2021). The impact of G-SIB identification on bank lending: evidence from syndicated loans. *Journal of Financial Stability*, *57*(December), 100930.

Berger, A. N., & Udell, G. F. (1994). Did risk-based capital allocate bank credit and cause a "credit crunch" in the united states? *Journal of Money, Credit and Banking*, *26*(3), 585–628.

Bernanke, B. S., & Lown, C. S. (1991). The Credit Crunch. *Brookings Papers on Economic Activity*, *22*(2), 205-248.

Berrospide, J. M., & Edge, R. M. (2010). The Effects of Bank Capital on Lending: What Do We Know, and What Does It Mean? *International Journal of Central Banking*, *6*(34), 1-50.

Bersch, J., Degryse, H., Kick, T., & Stein, I. (2020). The real effects of bank distress: Evidence from bank bailouts in Germany. *Journal of Corporate Finance*, *60*(C). doi: 10.1016/j.jcorpfin.2019.1

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics*, *119*(1), 249-275.

BIS. (2020). *Basel committee meets; discusses impact of covid-19; reiterates guidance on buffers* (Bank for International Settlements press release). Bank for International Settlements.

BIS. (2021). *Evaluating the effectiveness of basel iii during covid-19 and beyond.* (Speech by Pablo Hernández de Cos Chairman of the Basel Committee on Banking Supervision and Governor of the Bank of Spain)

Bolton, P., & Freixas, X. (2000). Corporate finance and the monetary transmission mechanism. *The Review of Financial Studies*, *19*(3), 829–870.

Borio, C., Farag, M., & Tarashev, N. (2020). *Post-crisis international financial regulatory reforms: a primer* (BIS Working Papers No. 859). Bank for International Settlements.

Cappelletti, G., Reghezza, A., Rodriguez d'Acri, C., & Spaggiari, M. (2022). Compositional effects of bank capital buffers and interactions with monetary policy. *Journal of Banking and Finance*, *140*(July), 106530.

Claessens, S., Law, A., & Wang, T. (2018). *How do credit ratings affect bank lending under capital constraints?* (BIS Working Papers No. 747). Bank for International Settlements.

Couaillier, C. (2021). *What are banks' actual capital targets?* (Working Paper Series No. 2618). European Central Bank.

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*(C). doi: 10.1016/j.jfi.2019.01.004

Degryse, H., Mariathasan, M., & Tang, T. H. (2020). *GSIB status and corporate lending: An international analysis* (CEPR Discussion Papers No. 15564). C.E.P.R. Discussion Papers.

Dehejia, R. H., & Wahba, S. (2002). Propensity Score-Matching Methods For Nonexperimental Causal Studies. *The Review of Economics and Statistics*, *84*(1), 151-161.

De Jonghe, O., Dewachter, H., & Ongena, S. (2020). Bank capital (requirements) and credit supply: Evidence from pillar 2 decisions. *Journal of Corporate Finance*, *60*(February), 101518. doi: 10.1016/j.jcorpfin.2019.1

Diamond, D. W., & Rajan, R. G. (2000). A theory of bank capital. *The Journal of Finance*, *55*(6), 2431–2465.

Disyatat, P. (2011). The Bank Lending Channel Revisited. *Journal of Money, Credit and Banking*, *43*(4), 711-734. doi: 10.1111/j.1538-4616.2011.

Drehmann, M., Fara, M., Tarashev, N., & Tsatsaronis, K. (2020). *Buffering covid-19 losses - the role of prudential policy* (Vol. 9; BIS Bulletin). Bank for International Settlements.

EBA. (2021). *Draft revised guidelines on recovery plan indicators under article 9 of directive 2014/59/eu/.* (Consultation paper). European Banking Authority.

ECB. (2020). *Financial stability consideration arising from the interaction of coronavirus-related* *policy measures* (Financial Stability Review). European Central Bank.

ECB. (2021). *Supporting economic recovery and the resilience of the banking sector amid pandemic-related vulnerabilities* (Vol. 2; Financial Stability Review). European Central Bank.

Enria, A. (2020). *Introductory statement. speech at the press conference on the supervisory review and evaluation process* (Vol. 2; Speech). Single Supervisory Mechanism.

Fraisse, H., Lé, M., & Thesmar, D. (2020). The Real Effects of Bank Capital Requirements. *Management Science*, *66*(1), 5-23. doi: 10.1287/mnsc.2018.3222

FSB. (2020). *Covid-19 pandemic: Financial stability implications and policy measures taken* (Report). Financial Stability Board.

Gambacorta, L., & Mistrulli, P. E. (2004). Does bank capital affect lending behavior? *Journal of Financial Intermediation*, *13*(4), 436-457.

Gersbach, H., & Rochet, J.-C. (2017). Capital regulation and credit fluctuations. *Journal of Monetary Economics*, *90*(C), 113-124. doi: 10.1016/j.jmoneco.2017.05

Greenwald, D. L., Krainer, J., & Paul, P. (2020). *The Credit Line Channel* (Working Paper Series No. 2020-26). Federal Reserve Bank of San Francisco. doi: 10.24148/wp2020-26

Gropp, R., Mosk, T., Ongena, S., & Wix, C. (2019). Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment. *The Review of Financial Studies*, *32*(1), 266-299.

Hancock, D., Laing, A. J., & Wilcox, J. A. (1995). Bank capital shocks: Dynamic effects on securities, loans, and capital. *Journal of Banking & Finance*, *19*(3-4), 661-677.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies*, *64*(4), 605-654.

Heider, F., Saidi, F., & Schepens, G. (2019). Life below Zero: Bank Lending under Negative Policy Rates. *The Review of Financial Studies*, *32*(10), 3728-3761.

Iacus, S., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, *20*(1), 1-24.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature*, *47*(1), 5-86.

Jiménez, G., Ongena, S., Peydró, J.-L., & Saurina, J. (2017). Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments. *Journal of Political Economy*, *125*(6), 2126-2177. doi: 10.1086/694289

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. *Review of Corporate Finance Studies*, *9*(3), 472-500.

Lown, C., & Morgan, D. P. (2006). The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey. *Journal of Money, Credit and Banking*, *38*(6), 1575-1597. doi: 10.1353/mcb.2006.0086

Martínez-Miera, D., & Vegas, R. (2021). Impact of the dividend distribution restriction on the flow of credit to non-financial corporations in Spain. *Economic Bulletin*(1/2021), 1-17.

Molyneux, P., Reghezza, A., & Xie, R. (2019). Bank margins and profits in a world of negative rates. *Journal of Banking & Finance*, *107*(C), 1-1. doi: 10.1016/j.jbankfin.2019.1

Popov, A., & Horen, N. V. (2015). Exporting Sovereign Stress: Evidence from Syndicated Bank Lending during the Euro Area Sovereign Debt Crisis. *Review of Finance*, *19*(5), 1825-1866.

Puri, M., Rocholl, J., & Steffen, S. (2011). Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics*, *100*(3), 556-578.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41-55. doi: 10.1093/biomet/70.1.41

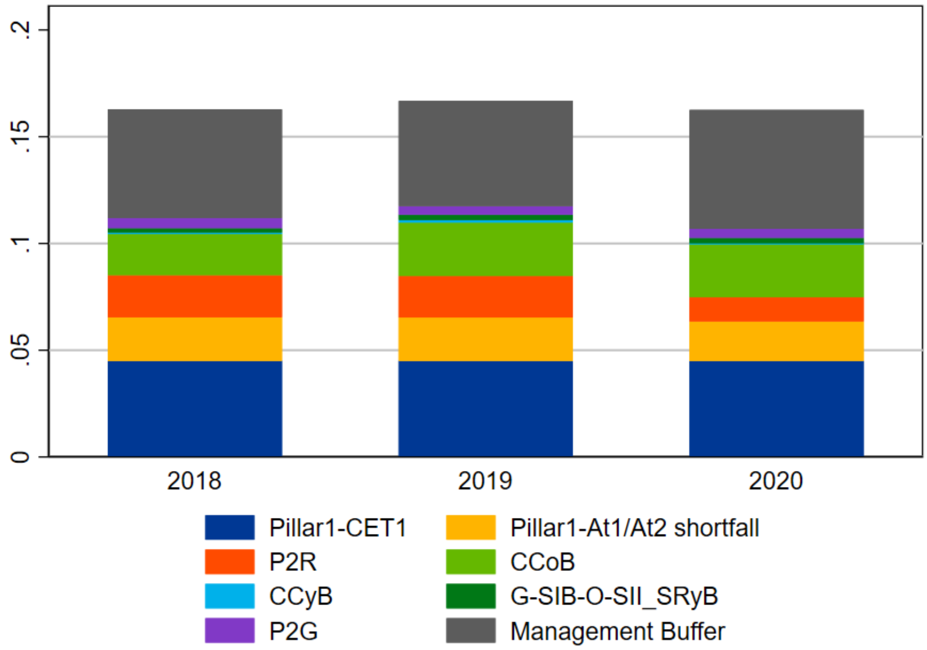
Rosengren, E. S., & Peek, J. (1997). Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States. *American Economic Review*, *90*(1), 30-45.

SSM. (2020). *Ecb banking supervision provides temporary capital and operational relief in reaction to coronavirus* (Press Release). Single Supervisory Mechanism.

Svoronos, J.-P., & Vrbaski, R. (2020). *Banks' dividends in covid-19 times* (Vol. 6; FSI Briefs). Bank for International Settlements.

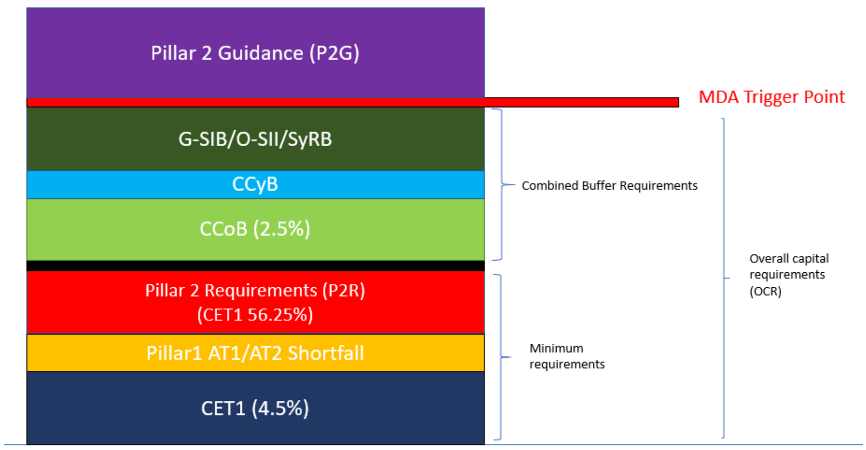
Van den Heuvel, S. J. (2008). The welfare cost of bank capital requirements. *Journal of Monetary Economics*, *55*(2), 298-320.

Figure 1: Evolution of bank CET1 capital ratios and their components



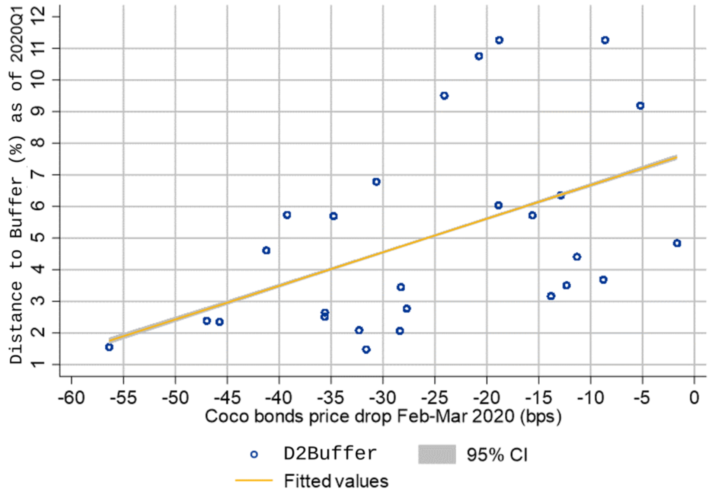
Note: This figure shows the evolution of bank capital ratios divided by components for the sample of euro area significant and less significant banks used throughout the paper over 2018-2020. Capital stack is represented as a percentage of risk-weighted assets (y axis). The decline in P2R in 2020 stems from a change in the composition of capital that can be used to fulfil this requirement. The thinness of the dark green section of the bar, representing the O-SII, G-SIBs and SRyB buffer, is due to the lack of such buffer requirements for some banks in the sample.

Figure 2: Capital stack



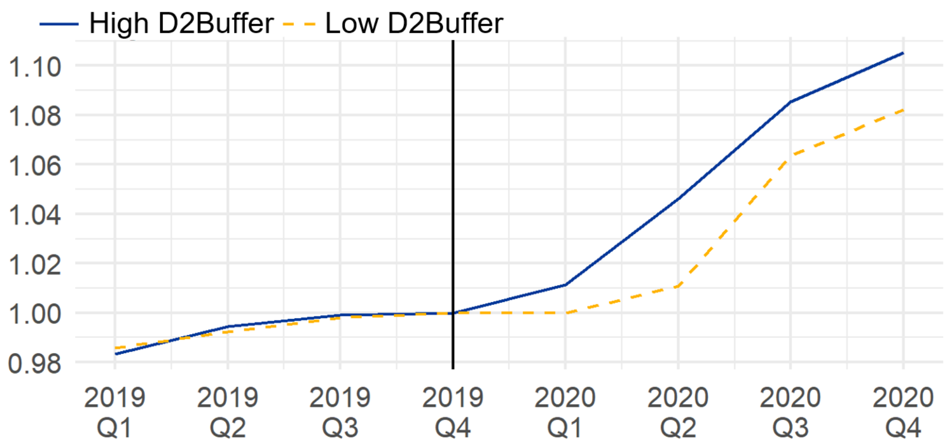
Note: This figure shows Pillar 1 and Pillar 2 CET1 capital requirements along with the combined buffer requirement. The red horizontal line indicates the MDA trigger point below which supervisory actions apply.

Figure 3: Scatter plot CoCo bond prices and bank distance to CBR



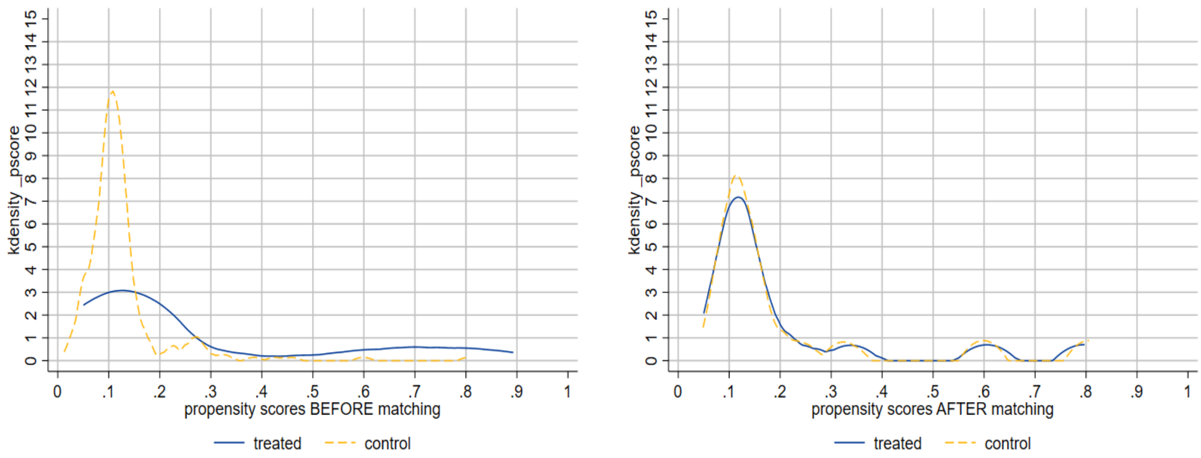
Note: This figure shows the relationship between the average distance to the CBR in 2019Q2-Q4 (y-axis) and contingent convertible bonds price drop (x-axix) measured in basis points over February-March 2020. The price drop is computed as the difference between the highest price registered in February 2020 against the lowest price registered in March 2020. The blue dots indicate bank distance to the CBR. The yellow line represents the fitted values coming from a linear regression model between distance to the CBR and CoCo bond price drop. The grey shaded area indicates confidence interval at the 95% level.

Figure 4: Lending by treated group over 2019Q1-2020Q4



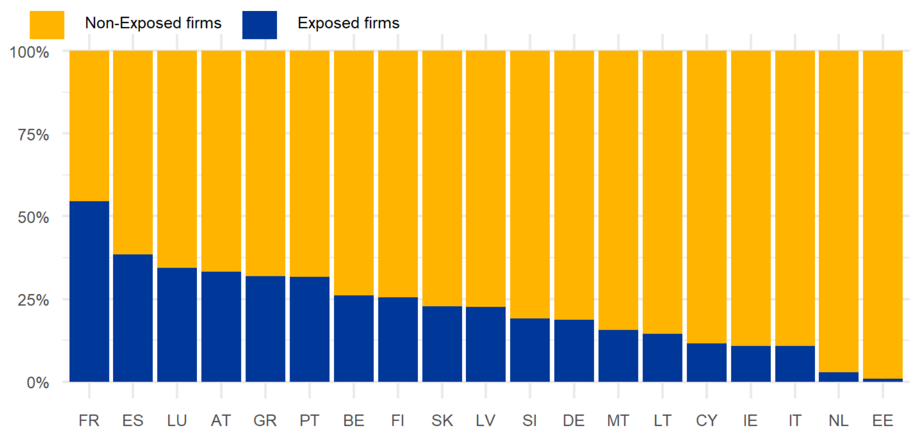
Note: This figure shows the normalised trends of the average bank-firm level logarithmic change in lending for the group of banks that were in proximity of the CBR (our treatment group) and the control group over time (2019Q1-2020Q4). Low.D2Buffer indicates banks with an average distance to the CBR in 2019Q3-Q4 below the first quartile of the distance to the CBR distribution (treated group and blue solid line), whilst High.D2Buffer refers to banks with an average distance to the CBR in 2019Q3-Q4 above the first quartile of the distance to the CBR distribution (control group and dashed yellow line). Trends are normalised such that both variables take value 1 in 2019Q4. The black solid vertical line reveals the Covid-19 shock.

Figure 5: Pscore before and after matching



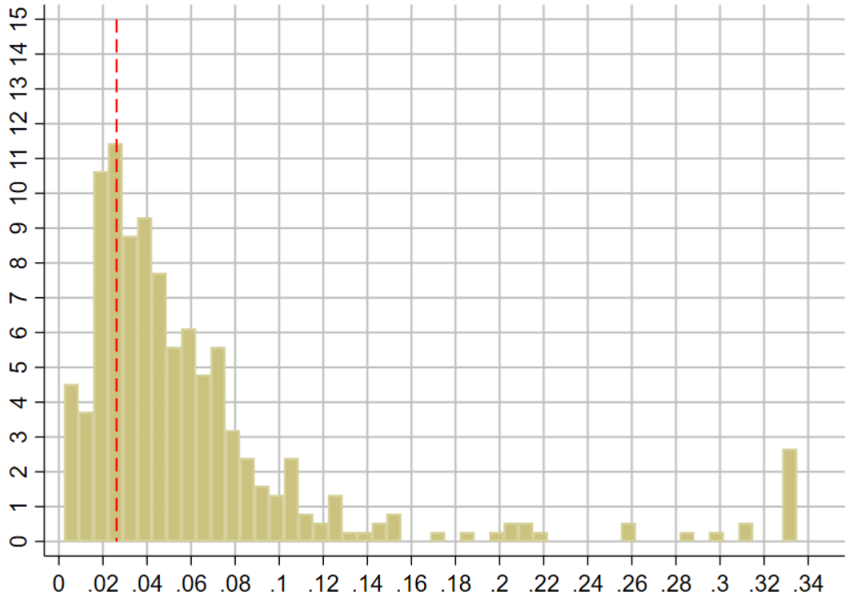
Note: This figure displays Kernel density function of propensity scores between the control (yellow dashed line) and treatment group (blue solid line) before (left) and after (right) the application of the propensity score matching approach.

Figure 6: Pre-pandemic outstanding share NFCs borrowing by country



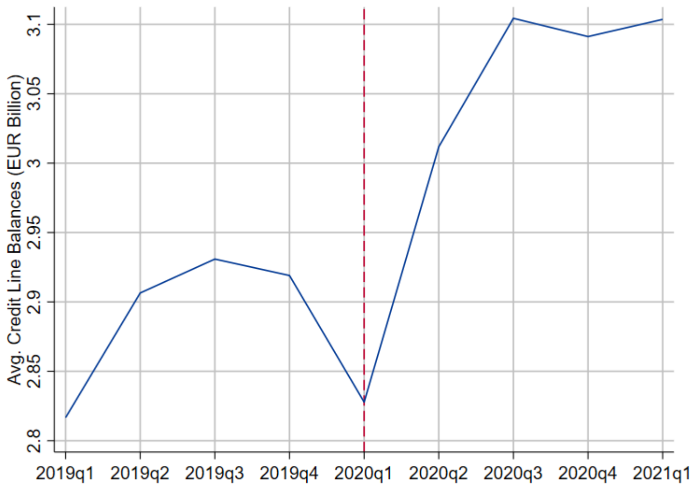
Note: This figure displays the average share of total NFC borrowing by country. Share exposed firms (reported in blue) refers to average share of total NFC borrowing from banks that, prior to the pandemic (2019Q3-Q4), had an average distance to the CBR below the first quartile of the distance to the CBR distribution. Share non-exposed firms (reported in yellow) indicates the average share of total NFC borrowing from banks that, prior to the pandemic (2019Q3-Q4), had an average distance to the CBR above the first quartile of the distance to the CBR distribution.

Figure 7: Pre-Histogram distance to the CBR



Note: This figure shows the distribution of the average distance to the CBR in 2019Q3-2019Q4. The y axis displays the percentage while the x axis the lag of the distance to the CBR. The red dashed vertical line indicates the first quartile of the distance to the CBR distribution.

Figure 8: Average credit line balances over 2019Q1-2021Q1



Note: This figure shows the average credit line balances (in billion of euro) over the period 2019Q1-2021Q1. The dashed red vertical line represents the start of the Covid-19 pandemic.

Table 1: Pretreatment bank characteristics

This table shows bank-specific characteristics, averaged for the pretreatment period (2019Q3-Q4), for the control and the treatment group. The table is divided in two panels. Panel A reports descriptive statistics for the unmatched sample of bank covariates employed the loan-level analysis (2.1), whilst Panel B reports desciptive statistics for the matched sample. The PSM applies a logit model and one-to-one nearest neighbour. Low.D2Buffer indicates banks with an average distance to the CBR in 2019Q3-Q4 below the first quartile of the distance to the CBR distribution, whilst High.D2Buffer refers to banks with an average distance to the CBR in 2019Q3-Q4 above the first quartile of the distance to the CBR distribution. Welch t-test displays the t-statistics coming from the differences between Low.D2Buffer and High.D2Buffer. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	High.D2Buffer	**Low.D2Buffer**	**Welch test**
Panel A: Pre-PSM			
L.OCR	0.118	0.113	1.92*
L.TA.log	22.96	22.884	0.33
L.RWA/TA	0.49	0.531	-2.35**
L.MKT FUNDING/TA	0.059	0.068	-0.7
L.NIM	0.015	0.016	-1.72*
L.NPL	0.031	0.063	-3.88***
L.LIQUID/TA	0.121	0.121	-0.02
L.DIVERS	0.385	0.388	-0.1
L.OFF BS	0.144	0.168	-1.85*
L.LOAN/TA	0.819	0.811	0.58
L.CIR	0.706	0.778	-1.56
L.PROVISION/TA	0.007	0.005	2.52**
TLTRO.III	0.031	0.043	-1.83*
DIVIDEND.REST	0.001	0	0.99
L.FORBEARANCE	0.035	0.036	-0.12
Panel B: Post-PSM			
	High.D2Buffer	**Low.D2Buffer**	**Welch test**
L.OCR	0.114	0.113	0.53
L.TA.log	23.367	23.173	0.66
L.RWA/TA	0.503	0.511	-0.36
L.MKT FUNDING/TA	0.088	0.075	0.72
L.NIM	0.016	0.016	0.08
L.NPL	0.055	0.058	-0.3
L.LIQUID/TA	0.114	0.126	-0.65
L.DIVERS	0.369	0.376	-0.26
L.OFF BS	0.179	0.183	-0.18
L.LOAN/TA	0.836	0.818	1.04
L.CIR	0.71	0.713	-0.06
L.PROVISION/TA	0.005	0.005	-0.54
TLTRO.III	0.049	0.046	0.4
DIVIDEND.REST	0.001	0	0.81
L.FORBEARANCE	0.032	0.035	-0.45

Table 2: Number of banks by country, by treatment and by matching status

This table reports the number of banks by country, by treatment as well as by matching status. Low.D2Buffer indicates banks with an average distance to the CBR in 2019Q3-Q4 below the first quartile of the distance to the CBR distribution, whilst High.D2Buffer refers to banks with an average distance to the CBR in 2019Q3-Q4 above the first quartile of the distance to the CBR distribution. Unmatched sample refers to the pre-PSM sample whilst matched sample indicates the post-PSM. The PSM applies a logit model and one-to-one nearest neighbour.

	Control (unmatched)	Treated (unmatched)	Control (Matched)	Treated (Matched)
AT	45	11	5	6
BE	9	1	3	1
CY	3	2	2	2
DE	85	22	17	18
EE	8	1	2	0
ES	20	8	4	7
FI	9	3	5	3
FR	7	6	3	6
GR	3	4	3	3
IE	10	1	2	1
IT	21	13	18	11
LT	4	1	1	1
LU	13	1	1	1
LV	9	5	1	3
MT	6	2	4	2
NL	13	1	0	1
PT	10	4	4	4
SI	4	5	0	4
SK	3	3	1	2
Total	282	94	76	76

Table 3: Summary statistics

This table displays summary descriptive statistics of the variables used

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
			Panel A: Endogenous Variables				
ΔLog (loans)	3,359,757	0.124	0.626	−1.128	−0.161	0.392	1.985
ΔLog (borrowing)	1,038,853	0.335	0.825	−1.232	−0.134	0.739	2.488
ΔLog (N.emplo)	1,038,853	−0.008	0.201	−0.693	0.000	0.000	0.624
			Panel B: Variables of Interest				
Low.D2Buffer	5,301,688	0.422	0.494	0.000	0.000	1.000	1.000
L.Dist.CBR	5,301,688	0.062	0.065	0.002	0.026	0.072	0.334
Exp.Firm	5,301,688	0.250	0.500	0.000	0.000	1.000	1.000
Guarantees	5,301,688	0.332	0.471	0.000	0.000	1.000	1.000
L. CR LINES/TA	5,282,982	0.150	0.052	0.040	0.120	0.191	0.285
			Panel C: Control variables				
L.OCR	5,301,688	0.105	0.011	0.070	0.097	0.111	0.485
L.TA.log	5,291,458	26.323	1.383	19.424	25.614	27.240	27.240
L.RWA/TA	5,291,458	0.388	0.117	0.156	0.283	0.449	0.811
L.MKT FUNDING/TA	5,291,456	0.147	0.096	0.000	0.090	0.218	0.422
L.NIM	5,259,679	0.013	0.007	0.001	0.010	0.016	0.033
L.NPL	5,277,218	0.045	0.043	0.001	0.023	0.048	0.260
L.LIQUID/TA	5,291,458	0.188	0.134	0.006	0.091	0.248	0.482
L.DIVERS	5,259,679	0.485	0.182	−0.128	0.350	0.605	0.966
L.OFF BS	5,288,863	0.247	0.093	−0.001	0.169	0.336	0.452
L.LOAN/TA	5,291,458	0.786	0.088	0.399	0.758	0.845	0.967
L.CIR	5,253,107	0.696	0.222	0.246	0.601	0.761	2.402
L.PROVISION/TA	5,287,075	0.006	0.004	0.00003	0.004	0.008	0.027
TLTRO.III	5,259,636	0.055	0.049	0.000	0.011	0.095	0.161
S.MORA	4,700,501	0.005	0.062	0.000	0.000	0.000	1.000
S.GUAR	4,700,501	0.157	0.320	0.000	0.000	0.000	1.000
DIVIDEND.REST	5,301,688	0.002	0.003	−0.0005	0.000	0.003	0.024
L.FORBEARANCE	5,244,999	0.028	0.028	0.001	0.009	0.041	0.157

Note: Δ Log (loans) is the change in bank-firm lending in logarithm. Δ Log (borrowing) is the change in the logarithm of a firm's total borrowing. ΔLog (N.emplo) is the logarithmic change in the number of employees at the firm level. Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution. L.Dist.CBR is the lag of the distance to the CBR. Exp.Firm is a dummy variable that takes the value 1 for firms that prior to the pandemic have more than 25% of their credit originating from vulnerable banks. Guarantees is a binary variable computed at the bank-firm level that takes the value 1 if bank i has granted a loan to firm k which is partially of fully pledged by government guarantees. L.CR LINES/TA is the lag of the undrawn credit lines-to-total assets ratio. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs.

Table 4: Baseline regressions

This table shows the results of the DiD loan-level panel regressions as in equation (1). The quarterly data is collapsed into pre- and post-event averages. Δ Log (loans) is the change in bank-firm lending in logarithm. Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. The PSM matched sample is created via logit model and one-to-one nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01. Standard errors are clustered at bank and firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Δ Log (loans)			
	Unmatched Firm FE	Matched Firm FE	Unmatched ILS FE	Matched ILS FE
	(1)	(2)	(3)	(4)
Low.D2Buffer	-0.0355***	-0.0926***	-0.0344*	-0.0892***
	(0.0116)	(0.0153)	(0.0192)	(0.0328)
L.OCR	-4.177***	-1.776***	-3.307***	-0.7316
	(0.5429)	(0.4166)	(0.6625)	(0.7151)
L.TA.log	-0.0048	-0.0091*	-0.0159**	-0.0160**
	(0.0055)	(0.0049)	(0.0071)	(0.0067)
L.RWA/TA	-0.0252	-0.1394*	-0.0375	-0.1751
	(0.0883)	(0.0841)	(0.1089)	(0.1408)
L.MKT FUNDING/TA	0.3844***	0.9188***	0.2268**	0.6822***
	(0.0916)	(0.0993)	(0.1016)	(0.1417)
L.NIM	6.123***	12.32***	6.591**	8.673***
	(1.715)	(1.738)	(2.600)	(2.760)
L.NPL	0.5487**	0.3989*	0.5492	0.8535**
	(0.2312)	(0.2182)	(0.3686)	(0.3551)
L.LIQUID/TA	0.1104	-0.2054	0.2596	-0.3074
	(0.0976)	(0.1944)	(0.1606)	(0.2766)
L.DIVERS	0.2353***	0.1514**	0.2283**	0.1316
	(0.0625)	(0.0655)	(0.0960)	(0.1028)
L.OFF BS	-0.0537	0.0270	-0.0345	0.1508
	(0.0715)	(0.0780)	(0.0997)	(0.1462)
L.LOAN/TA	-0.3495*	-0.1298	-0.2605	-0.3650
	(0.1820)	(0.1452)	(0.2757)	(0.3117)
L.CIR	0.0199	0.0572	0.0241	0.0364
	(0.0254)	(0.0474)	(0.0405)	(0.0618)
L.PROVISION/TA	-8.450***	-12.40***	-5.074**	-12.29***
	(1.585)	(2.062)	(2.040)	(3.213)
TLTRO.III	-0.1955	-0.4023**	0.1515	-0.1968
	(0.1482)	(0.1816)	(0.2491)	(0.2929)
S.MORA	-0.0827***	-0.0860***	-0.0601***	-0.0474***
	(0.0127)	(0.0180)	(0.0135)	(0.0159)
S.GUAR	1.463***	1.489***	1.522***	1.570***
	(0.0460)	(0.0670)	(0.0511)	(0.0856)
DIVIDEND.REST	-0.8782	1.401	-2.050	3.841
	(1.791)	(3.673)	(2.172)	(4.458)
L.FORBEARANCE	-0.1414	-0.0334	-0.1984	-0.5436
	(0.1274)	(0.2861)	(0.1991)	(0.4308)
Fixed-effects				
Firm	Yes	Yes		
Bank country	Yes	Yes	Yes	Yes
ILS			Yes	Yes
Fit statistics				
Observations	978,055	417,343	2,348,622	1,348,854
R^2	0.70033	0.71066	0.33407	0.31016
Within R^2	0.24896	0.23271	0.21111	0.19100

Table 5: Probit regressions

This table shows the results of the probit specification performed on the bank-firm level panel dataset. The quarterly data is collapsed into pre- and post-event averages. Guarantees is a binary variable computed at the bank-firm level that takes the value 1 if bank i has granted a loan to firm k which is partially of fully pledged by government guarantees. L.Dist.CBR is the pre-event average of the distance to the CBR expressed as a continuous variable. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. Robust standard errors reported in parentheses. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Guarantees	
	Unmatched	matched
	(1)	(2)
Low.D2Buffer	0.2116***	0.7750***
	(0.0017)	(0.0036)
L.OCR	-21.3805***	-31.5500***
	(0.1087)	(0.2266)
L.TA.log	0.2327***	0.2071***
	(0.0011)	(0.0022)
L.RWA/TA	-0.4057***	-2.7285***
	(0.0145)	(0.0320)
L.MKT FUNDING/TA	-3.5300***	-5.1317***
	(0.0168)	(0.0349)
L.NIM	61.4604***	82.9930***
	(0.2669)	(0.4834)
L.NPL	-2.4378***	-0.5165***
	(0.0308)	(0.0431)
L.LIQUID/TA	-2.1486***	-0.5061***
	(0.0199)	(0.0374)
L.DIVERS	2.0040***	1.5175***
	(0.0101)	(0.0190)
L.OFF BS	0.4659***	1.5965***
	(0.0132)	(0.0246)
L.LOAN/TA	0.8876***	3.3256***
	(0.0243)	(0.0448)
L.CIR	0.5907***	1.6473***
	(0.0054)	(0.0098)
L.PROVISION/TA	10.3650***	28.5251***
	(0.2434)	(0.5553)
TLTRO.III	5.4795***	8.9714***
	(0.0282)	(0.0440)
S.MORA	-0.1407***	-0.4441***
	(0.0129)	(0.0185)
DIVIDEND.REST	-37.440***	-84.8631***
	(0.2398)	(0.8788)
L.FORBEARANCE	-1.0847***	-3.6340***
	(0.0369)	(0.0659)
Fit statistics		
Observations	4,596,381	2,849,786
Wald chi2	1022695.38	537103.76
Pseudo R^2	0.1680	0.2322

Table 6: Interactions with government guarantee schemes

This table shows the results of the DiD loan-level panel regressions. The quarterly data is collapsed into pre- and post-event averages. Δ Log (loans) is the change in bank-firm lending in logarithm. Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution, and 0 otherwise. Guarantees is a dummy variable that takes the value 1 if a bank has granted a loan to a firm that is covered by government guarantees, and 0 otherwise. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. The PSM matched sample is created via logit model and one-to-one nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01. Standard errors are clustered at bank and firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Δ Log (loans)			
	Unmatched Firm FE	Matched Firm FE	Unmatched ILS FE	Matched ILS FE
	(1)	(2)	(3)	(4)
Low.D2Buffer	-0.0768***	-0.1020***	-0.0712**	-0.1137***
	(0.0155)	(0.0159)	(0.0284)	(0.0337)
Guarantees	0.6763***	0.6243***	0.7194***	0.6065***
	(0.0168)	(0.0184)	(0.0339)	(0.0302)
Low.D2Buffer × Guarantees	0.1308***	0.1394***	0.1177	0.2395***
	(0.0441)	(0.0527)	(0.0871)	(0.0918)
L.OCR	-4.4098***	-1.3524**	-3.4389**	-0.1793
	(0.6267)	(0.5492)	(0.8202)	(0.8193)
L.TA.log	-0.0073	-0.0148***	-0.0157*	-0.0190***
	(0.0067)	(0.0056)	(0.0082)	(0.0077)
L.RWA/TA	-0.0879	-0.2143**	-0.0833	-0.2048
	(0.0968)	(0.0923)	(0.1224)	(0.1454)
L.MKT FUNDING/TA	0.3397***	0.9770***	0.2262**	0.7073***
	(0.0957)	(0.1056)	(0.1038)	(0.1429)
L.NIM	6.3300***	17.0295***	6.5965***	11.8506***
	(1.5671)	(1.8677)	(2.6310)	(2.6877)
L.NPL	1.1719***	0.6434***	1.0591***	0.9506**
	(0.2607)	(0.2131)	(0.4071)	(0.3834)
L.LIQUID/TA	0.0335	-0.0813	0.1879	-0.0904
	(0.0881)	(0.2243)	(0.1837)	(0.3135)
L.DIVERS	0.3141***	0.2179***	0.3015***	0.1883*
	(0.0707)	(0.0636)	(0.1038)	(0.0995)
L.OFF BS	-0.0055	0.0895	0.0176	0.1845
	(0.0888)	(0.0761)	(0.1122)	(0.1438)
L.LOAN/TA	-0.4764***	0.0344	-0.3162	-0.1374
	(0.1804)	(0.1739)	(0.2864)	(0.3313)
L.CIR	0.0019	0.0331	0.0209	0.0040
	(0.0249)	(0.0531)	(0.0420)	(0.0646)
L.PROVISION/TA	-5.4126***	-12.0844***	-2.7090	-10.2621***
	(2.3311)	(2.3627)	(2.8345)	(3.0363)
TLTRO.III	0.2163	-0.4211**	0.1102	-0.2240
	(0.1732)	(0.2060)	(0.2787)	(0.3022)
S.MORA	-0.0669***	-0.0791***	-0.0668***	-0.0614
	(0.0194)	(0.0251)	(0.0202)	(0.0287)
DIVIDEND.REST	-4.6655**	-0.5842	-3.7617	1.0005
	(1.8353)	(4.0323)	(2.5018)	(4.5370)
L.FORBEARANCE	-0.3196**	0.1621	-0.3446	-0.4064
	(0.1384)	(0.3119)	(0.2094)	(0.4370)
Fixed-effects				
Firm	Yes	Yes		
Bank country	Yes	Yes	Yes	Yes
ILS			Yes	Yes
Fit statistics				
Observations	978,055	417,343	2,348,622	1,348,854
R^2	0.6963	0.4591	0.3231	0.2911
Within R^2	0.2388	0.2327	0.1971	0.1755

Table 7: Interactions with undrawn credit line balances

This table shows the results of the DiD loan-level panel regressions. The quarterly data is collapsed into pre- and post-event averages. Δ Log (loans) is the change in bank-firm lending in logarithm. Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution, and 0 otherwise. L.CR LINES/TA is the lag of the undrawn credit lines-to-total assets ratio. L.OCR is the lag of the Overall Capital Requirement ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. The PSM matched sample is created via logit model and one-to-one nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01. Standard errors are clustered at bank and firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Δ Log (loans)			
	Unmatched Firm FE	Matched Firm FE	Unmatched ILS FE	Matched ILS FE
	(1)	(2)	(3)	(4)
Low.D2Buffer	0.0547	-0.0013	0.0702*	0.0521
	(0.0345)	(0.0317)	(0.0414)	(0.0510)
L.CR LINES/TA	0.3749**	0.5286***	0.4835**	0.8616***
	(0.0153)	(0.1162)	(0.1968)	(0.1502)
Low.D2Buffer × L.CR LINES/TA	-0.6294***	-0.5690***	-0.7298***	-0.8749***
	(0.2215)	(0.1777)	(0.2580)	(0.2613)
L.OCR	-3.1161***	-0.8535	-2.1365***	0.2273
	(0.5908)	(0.5595)	(0.7198)	(0.7863)
L.TA.log	-0.0060	-0.0050	-0.0177**	-0.0122**
	(0.0050)	(0.0046)	(0.0071)	(0.0057)
L.RWA/TA	-0.0211	-0.0805	-0.0466	-0.1183
	(0.0836)	(0.0800)	(0.0983)	(0.1160)
L.MKT FUNDING/TA	0.3788***	0.9516***	0.2184***	0.6328***
	(0.0835)	(0.0925)	(0.0797)	(0.1199)
L.NIM	5.4383***	11.8985***	5.8819**	8.1619***
	(1.5859)	(1.7481)	(2.3091)	(2.5355)
L.NPL	0.5058***	0.3810**	0.4987	0.7890***
	(0.2365)	(0.1776)	(0.3237)	(0.2397)
L.LIQUID/TA	0.1229	-0.1530	0.2490*	-0.1460
	(0.0926)	(0.1853)	(0.1493)	(0.2332)
L.DIVERS	0.1804***	0.0844	0.1699**	0.0510
	(0.0529)	(0.0625)	(0.0815)	(0.0958)
L.LOAN/TA	-0.2074	0.0901	-0.1396	-0.0096
	(0.1894)	(0.1513)	(0.2561)	(0.2315)
L.CIR	0.0396	0.0762*	0.0457	0.0570
	(0.0266)	(0.0445)	(0.0396)	(0.0517)
L.PROVISION/TA	-9.2161***	-13.5915***	-5.8703***	-11.2147***
	(1.5528)	(2.3627)	(1.8767)	(2.7071)
TLTRO.III	-0.4445***	-0.5811***	-0.1281	-0.3647
	(0.1544)	(0.1764)	(0.2415)	(0.2700)
S.MORA	-0.0784***	-0.0805***	-0.0574***	-0.0474***
	(0.0112)	(0.0183)	(0.0129)	(0.0153)
S.GUAR	1.4616***	1.4934***	1.5213***	1.5751***
	(0.0459)	(0.0668)	(0.0517)	(0.0840)
DIVIDEND.REST	-0.1372	2.3667	-1.6071	3.4262
	(1.7270)	(3.6601)	(2.097)	(4.0203)
L.FORBEARANCE	-0.1915	-0.0806	-0.2884	-0.5442
	(0.1260)	(0.2460)	(0.2006)	(0.3511)
Fixed-effects				
Firm	Yes	Yes		
Bank country	Yes	Yes	Yes	Yes
ILS			Yes	Yes
Fit statistics				
Observations	978,055	417,343	2,348,622	1,348,854
R^2	0.7006	0.4720	0.3168	0.3301
Within R^2	0.4895	0.2335	0.2115	0.1916

Table 8: Firm-level regressions

This table shows the results of the firm-level panel regressions as in equation (2) and equation (3). The quarterly data is collapsed into pre- and post-event averages. Δ Log (borrowing) is the change in firm borrowing in logarithm. ΔLog (N.employees) is the logarithmic change in the number of employees at the firm level. Exp.Firm. Exp.Firm is a dummy variable equal to 1 for firms that prior to the pandemic have more than 25% of their credit originating from banks closer to the CBR point, 0 otherwise. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. Standard errors are clustered at firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	ΔLog(borrowing)	ΔLog(borrowing)	Δlog(N.emplo)	Δlog(N.emplo)
	(1)	(2)	(3)	(4)
Exp.Firm	-0.0254***	-0.0301***	-0.0076***	-0.0071***
	(0.0030)	(0.0034)	(0.0011)	(0.0013)
Exp.Firm × S.GUAR		0.0297***		-0.0033
		(0.0088)		(0.0024)
L.OCR	-0.3340*	-0.3176*	0.1348**	0.1330**
	(0.1851)	(0.1852)	(0.0608)	(0.0615)
L.TA.log	-0.0562***	-0.0561***	0.0024***	0.0024***
	(0.0017)	(0.0017)	(0.0004)	(0.0005)
L.RWA/TA	-0.1692***	-0.1656***	-0.0060	-0.0064
	(0.0222)	(0.0220)	(0.0064)	(0.0064)
L.MKT FUNDING/TA	0.9039***	0.9021***	0.0796***	0.0798***
	(0.0263)	(0.0262)	(0.0055)	(0.0055)
L.NIM	9.792***	9.782***	0.1460	0.1472
	(0.4175)	(0.4167)	(0.0903)	(0.0902)
L.NPL	0.3773***	0.3769***	-0.1125***	-0.1125***
	(0.0623)	(0.0623)	(0.0118)	(0.0118)
L.LIQUID/TA	0.2969***	0.3028***	-0.1065***	-0.1071***
	(0.0352)	(0.0352)	(0.0121)	(0.0120)
L.DIVERS	0.0843***	0.0875***	0.0432***	0.0428***
	(0.0175)	(0.0176)	(0.0059)	(0.0060)
L.OFF BS	0.2031***	0.2051***	-0.0432***	-0.0435***
	(0.0296)	(0.0296)	(0.0045)	(0.0045)
L.LOAN/TA	-0.5540***	-0.5484***	-0.0730***	-0.0736***
	(0.0513)	(0.0514)	(0.0108)	(0.0107)
L.CIR	0.0100	0.0114	-0.0061**	-0.0063**
	(0.0140)	(0.0141)	(0.0025)	(0.0026)
L.PROVISION/TA	-0.0282	-0.0039	-0.2468***	-0.2495***
	(0.4762)	(0.4751)	(0.0876)	(0.0873)
TLTRO.III	0.5156***	0.5104***	-0.0426***	-0.0421***
	(0.0535)	(0.0536)	(0.0121)	(0.0122)
S.MORA	-0.0913***	-0.0908***	-0.0230***	-0.0231***
	(0.0083)	(0.0083)	(0.0039)	(0.0039)
S.GUAR	2.050***	2.036***	-0.0065***	-0.0050***
	(0.0071)	(0.0078)	(0.0012)	(0.0014)
DIVIDEND.REST	-2.287***	-2.377***	-1.048***	-1.038***
	(0.4589)	(0.4612)	(0.1157)	(0.1163)
L.FORBEARANCE	-1.047***	-1.057***	0.0345***	0.0356***
	(0.0597)	(0.0598)	(0.0130)	(0.0133)
Fixed-effects				
ILS	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,038,844	1,038,844	1,038,844	1,038,844
R^2	0.42228	0.42229	0.10642	0.10642
Within R^2	0.27938	0.27940	0.00189	0.00189

Table 9: Placebo test

This table shows the results of the placebo test. The quarterly data is collapsed into pre- and post-event averages. Δ Log (loans) is the change in bank-firm lending in logarithm. Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. The PSM matched sample is created via logit model and one-to-one nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01. Standard errors are clustered at bank and firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Δ Log (loans)			
	Unmatched Firm FE	Matched Firm FE	Unmatched ILS FE	Matched ILS FE
	(1)	(2)	(3)	(4)
Low.D2Buffer	-0.0048	-0.0218	0.0111	1.33×10^{-5}
	(0.0101)	(0.0169)	(0.0146)	(0.0262)
L.OCR	-0.0180	-1.043	0.9577	0.1247
	(0.4909)	(0.7928)	(0.6519)	(1.015)
L.TA.log	-0.0164***	-0.0132	-0.0116*	0.0010
	(0.0049)	(0.0081)	(0.0069)	(0.0126)
L.RWA/TA	-0.2554***	-0.2807***	-0.0908	-0.0080
	(0.0799)	(0.0801)	(0.1095)	(0.1246)
L.MKT FUNDING/TA	0.3113***	0.4458***	0.3343***	0.3482**
	(0.0733)	(0.1064)	(0.1023)	(0.1571)
L.NIM	3.352***	4.116**	3.375*	2.414
	(1.271)	(2.004)	(1.802)	(2.488)
L.NPL	0.2000	0.0942	-0.2442	-0.5857
	(0.1951)	(0.3758)	(0.3230)	(0.5618)
L.LIQUID/TA	0.4996***	0.3726***	0.7479***	0.6478***
	(0.0763)	(0.0674)	(0.0917)	(0.1090)
L.DIVERS	0.3509***	0.3387***	0.3648***	0.3684***
	(0.0446)	(0.0496)	(0.0725)	(0.0850)
L.OFF BS	-0.0847	-0.1346	-0.3373***	-0.4667**
	(0.0814)	(0.1251)	(0.1202)	(0.1800)
L.LOAN/TA	0.7522***	0.3990**	0.8913***	0.6224**
	(0.1148)	(0.1990)	(0.1227)	(0.3038)
L.CIR	-0.0639	-0.0563	-0.0337	-0.0333
	(0.0463)	(0.0810)	(0.0590)	(0.1203)
L.PROVISION/TA	0.7747	4.246***	1.794	3.184
	(1.816)	(1.526)	(2.243)	(2.715)
L.FORBEARANCE	-0.0942	-0.0094	0.1967	0.1175
	(0.1630)	(0.2077)	(0.2181)	(0.3154)
Fixed-effects				
Firm	Yes	Yes		
Bank country	Yes	Yes	Yes	Yes
ILS			Yes	Yes
Fit statistics				
Observations	1,004,489	389,662	2,295,397	1,302,733
R^2	0.64099	0.68361	0.13829	0.13435
Within R^2	0.03637	0.05305	0.04411	0.05890

Table 10: Redefinition of the variable of interest: Low.D2Buffer

This table shows the results of robustness redefining the Low.D2Buffer variable that takes the value 0 only for banks with a distance to CBR above the last quartile of the distance to the CBR distribution. The quarterly data is collapsed into pre- and post-event averages. Δ Log (loans) is the change in bank-firm lending in logarithm. Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. The PSM matched sample is created via logit model and one-to-one nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01. Standard errors are clustered at bank and firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Δ Log (loans)			
	Unmatched Firm FE	Matched Firm FE	Unmatched IĽS FE	Matched IĽS FE
	(1)	(2)	(3)	(4)
Low.D2Buffer	-0.0491***	-0.0752***	-0.0568**	-0.0425**
	(0.0183)	(0.0254)	(0.0237)	(0.0169)
L.OCR	-2.727***	-1.663	-1.255	-1.985**
	(0.8697)	(1.349)	(1.046)	(0.7980)
L.TA.log	-0.0006	0.0266***	-0.0034	0.0153*
	(0.0068)	(0.0083)	(0.0080)	(0.0081)
L.RWA/TA	-0.2368**	-0.1819	-0.1871	-0.4918***
	(0.1192)	(0.2251)	(0.1349)	(0.1387)
L.MKT FUNDING/TA	0.8858***	-0.0664	0.6025***	-0.7551***
	(0.0942)	(0.2408)	(0.1285)	(0.2286)
L.NIM	9.788***	2.890	5.311*	1.236
	(2.619)	(4.179)	(2.913)	(2.464)
L.NPL	-1.010**	0.6514*	-0.2007	1.496***
	(0.4684)	(0.3616)	(0.5723)	(0.3281)
L.LIQUID/TA	-0.5041**	-0.9437***	-0.2919	-1.223***
	(0.2155)	(0.2943)	(0.2212)	(0.1997)
L.DIVERS	0.1786*	-0.0495	0.1295	-0.2352***
	(0.1068)	(0.1672)	(0.1130)	(0.0884)
L.OFF BS	-0.2703**	0.0973	-0.1133	0.2824
	(0.1176)	(0.1977)	(0.1365)	(0.1955)
L.LOAN/TA	-0.0951	-0.7983**	0.0468	-1.241***
	(0.1984)	(0.3145)	(0.2481)	(0.2332)
L.CIR	0.0997	0.0999**	0.0651	0.0024
	(0.0626)	(0.0476)	(0.0722)	(0.0326)
L.PROVISION/TA	-11.74***	-8.511**	-9.842***	-1.671
	(2.380)	(3.398)	(3.303)	(2.283)
TLTRO.III	-0.6156***	0.0647	-0.2953	0.1941
	(0.2168)	(0.2459)	(0.2358)	(0.2065)
S.MORA	-0.0404**	-0.0449	-0.0333	-0.0449*
	(0.0187)	(0.0343)	(0.0202)	(0.0235)
S.GUAR	1.453***	1.726***	1.644***	1.896***
	(0.0973)	(0.0385)	(0.0973)	(0.0660)
DIVIDEND.REST	14.16**	39.45***	8.551	15.30*
	(7.009)	(14.11)	(7.989)	(8.993)
L.FORBEARANCE	-0.4306	-0.2049	-1.017**	0.5321
	(0.3492)	(0.6329)	(0.4466)	(0.4224)
Fixed-effects				
Firm	Yes	Yes		
Bank country	Yes	Yes	Yes	Yes
ILS			Yes	Yes
Fit statistics				
Observations	214,867	64,532	1,052,407	478,172
R^2	0.74402	0.77924	0.36500	0.39334
Within R^2	0.26928	0.31886	0.22421	0.24088

Table 11: Continuous specification

This table shows the results of the continuous specification performed on the loan-level panel dataset. The quarterly data is collapsed into pre- and post-event averages. Δ Log (loans) is the change in bank-firm lending in logarithm. L.Dist.CBR is the pre-event average of the distance to the CBR expressed as a continuous variable. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. Standard errors are clustered at bank and firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Δ Log (loans)	
	Unmatched Firm FE	Unmatched Firm FE
	(1)	(2)
L.Dist. CBR	0.5777***	0.2723
	(0.1817)	(0.2302)
L.OCR	-4.166***	-3.374***
	(0.5015)	(0.6701)
L.TA.log	-0.0021	-0.0126*
	(0.0055)	(0.0071)
L.RWA/TA	0.0499	0.0505
	(0.0773)	(0.0902)
L.MKT FUNDING/TA	0.3701***	0.1907*
	(0.0865)	(0.1110)
L.NIM	5.298***	5.696**
	(1.652)	(2.645)
L.NPL	0.5488**	0.5155
	(0.2238)	(0.3657)
L.LIQUID/TA	0.1585	0.2708
	(0.1215)	(0.1879)
L.DIVERS	0.2204***	0.2003*
	(0.0643)	(0.1047)
L.OFF BS	-0.0574	-0.0740
	(0.0811)	(0.1142)
L.LOAN/TA	-0.3671*	-0.2933
	(0.2114)	(0.3281)
L.CIR	0.0134	0.0148
	(0.0265)	(0.0450)
L.PROVISION/TA	-7.002***	-3.590*
	(1.452)	(2.041)
TLTRO.III	-0.0989	0.2272
	(0.1445)	(0.2609)
S.MORA	-0.0861***	-0.0603***
	(0.0124)	(0.0137)
S.GUAR	1.459***	1.520***
	(0.0462)	(0.0512)
DIVIDEND.REST	-1.610	-2.403
	(1.911)	(2.419)
L.FORBEARANCE	-0.1456	-0.2059
	(0.1273)	(0.2050)
Fixed-effects		
Firm	Yes	
Bank country	Yes	Yes
ILS		Yes
Fit statistics		
Observations	978,055	2,348,622
R^2	0.70029	0.33392
Within R^2	0.24886	0.21093

Table 12: Controlling for CET1 ratio

This table shows the results of robustness replacing the OCR in the set of control and matching variables with the CET1 ratio. The quarterly data is collapsed into pre- and post-event averages. Δ Log (loans) is the change in bank-firm lending in logarithm. Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution. L.CET1 is the lag of the common equity tier1 ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs. The PSM matched sample is created via logit model and one-to-one nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01. Standard errors are clustered at bank and firm level. *, **, *** indicate statistical significance of 1%, 5% and 10% respectively.

	Dependent variable: Δ Log (loans)			
	Unmatched Firm FE	Matched Firm FE	Unmatched IĿS FE	Matched IĿS FE
	(1)	(2)	(3)	(4)
Low.D2Buffer	-0.0541***	-0.0760***	-0.0536**	-0.1070***
	(0.0164)	(0.0183)	(0.0248)	(0.0297)
L.CET1	-0.2506	-10.10***	-0.4558	-9.871***
	(0.2510)	(1.948)	(0.3358)	(1.828)
L.TA.log	-0.0045	-0.0365**	-0.0171**	-0.0071
	(0.0064)	(0.0167)	(0.0075)	(0.0157)
L.RWA/TA	-0.0870	-0.9576***	-0.0829	-0.7624***
	(0.0949)	(0.1940)	(0.1151)	(0.2101)
L.MKT FUNDING/TA	0.3380***	-0.7189***	0.1932*	-1.013***
	(0.1043)	(0.2650)	(0.1134)	(0.3023)
L.NIM	6.749***	16.72***	7.144***	10.97**
	(1.850)	(4.741)	(2.745)	(4.337)
L.NPL	0.3836	-1.056*	0.4050	-0.3548
	(0.2891)	(0.5528)	(0.4416)	(0.5539)
L.LIQUID/TA	-0.0853	-0.7473*	0.0734	-0.6332
	(0.1287)	(0.4247)	(0.1814)	(0.4981)
L.DIVERS	0.2585***	-0.4626**	0.2437**	-0.3238*
	(0.0749)	(0.1768)	(0.1080)	(0.1882)
L.OFF BS	0.1484*	0.4496**	0.1237	0.3000
	(0.0812)	(0.2217)	(0.1112)	(0.2529)
L.LOAN/TA	-0.4259*	-0.5769	-0.3531	-0.0842
	(0.2171)	(0.6023)	(0.2991)	(0.6996)
L.CIR	0.0631**	-0.0893	0.0501	-0.0905
	(0.0284)	(0.0802)	(0.0468)	(0.0891)
L.PROVISION/TA	-9.418***	-12.09***	-5.790**	-10.98***
	(2.045)	(3.058)	(2.481)	(4.136)
TLTRO.III	-0.5944***	0.9168	-0.1583	1.293**
	(0.1642)	(0.5856)	(0.2446)	(0.6343)
S.MORA	-0.0830***	-0.0801***	-0.0588***	-0.0139
	(0.0142)	(0.0298)	(0.0125)	(0.0096)
S.GUAR	1.465***	1.387***	1.525***	1.473***
	(0.0463)	(0.0803)	(0.0511)	(0.0917)
DIVIDEND.REST	1.754	-8.451	-0.5038	-26.62**
	(2.241)	(13.80)	(2.460)	(12.74)
L.FORBEARANCE	-0.3865**	0.4363	-0.4057	0.2647
	(0.1641)	(0.4078)	(0.2474)	(0.5269)
Fixed-effects				
Firm	Yes	Yes		
Bank country	Yes	Yes	Yes	Yes
ILS			Yes	Yes
Fit statistics				
Observations	978,055	100,910	2,348,622	391,809
R^2	0.69950	0.74358	0.33346	0.36103
Within R^2	0.24687	0.27568	0.21039	0.23226

Appendix A

Table A. Variables, label, definitions and sources.

Variable	Label	Definition	Source
Dependent variable			
Lending	Δ Log (loans)	Change in the logarithm of loans from bank i to firm k	AnaCredit
Borrowing	Δ Log (borrowing)	Change in the logarithm of a firm's total bank loans	AnaCredit
Employment	Δlog (N.emplo)	Change in the logarithm of a firm's total number of employees	Anacredit
Variable of interest			
Distance to CBR	Low.D2Buffer	Dummy variable equal to 1 if a bank, in the quarter prior to the pandemic (2019Q4) has a distance to the CBR point below the first quartile of the distribution, 0 otherwise	ECB Supervisory Statistics and authors' calculations
Exposed firms	Exp.Firm	Dummy variable equal to 1 for firms that prior to the pandemic have more than 25% of their credit originating from banks closer to the CBR point, 0 otherwise	AnaCredit and authors' calculation
Dummy Guarantees	Guarantees	Binary variable computed at the bank-firm level that takes the value 1 if bank i has granted a loan to firm k which is partially of fully pledged by government guarantees	AnaCredit and authors' calculation
Credit line balances	CR LINES/TA	The ratio of credit lines balances-to-total assets	ECB Supervisory Statistics and authors' calculations
Bank control variables			
Overall capital requirements	OCR	Sum of minimum requirements and the combined buffer requirements	ECB Supervisory Statistics
Bank size	TA.log	Logarithm of bank total assets	ECB Supervisory Statistics and authors' calculations
Risk weight density	RW	The ratio of risk-weighted assets-to-total assets	ECB Supervisory Statistics and authors' calculations
Funding structure	MKT FUNDING_TA	The ratio of debt securities issued-to-total assets	ECB Supervisory Statistics and authors' calculations
Net interest margin	NIM	The ratio of interest earning assets minus interest bearing liabilities-to-total assets ratio	ECB Supervisory Statistics and authors' calculations
Non-performing loans	NPLs	The ratio of non-performing loans-to-gross loans	ECB Supervisory Statistics and authors' calculations
Liquidity	LIQUID/TA	The ratio of cash and financial assets held for trading-to-total assets	ECB Supervisory Statistics and authors' calculations
Income stream	DIVERS	The ratio of non-interest income-to-operating income	ECB Supervisory Statistics and authors' calculations
Off-balance sheet	OFF BS	The ratio of off balance sheet activities-to-total assets	ECB Supervisory Statistics and authors' calculations
Asset composition	LOAN/TA	The ratio of all credit exposure-to-total assets	ECB Supervisory Statistics and authors' calculations
Operating efficiency	CIR	The ratio of operating expenses-to-operating income	ECB Supervisory Statistics and authors' calculations
Provisions	PROVISION/TA	The ratio of provisions-to-total assets	ECB Supervisory Statistics and authors' calculations
Policy control variables			
TLTRO III	TLTROs III	The ratio of targeted longer term refinancing operations-to-total assets	ECB Market Operations Database
Moratoria	Sh_Mora	Bank-firm level share of loans from the bank that are subjected to debt moratoria	AnaCredit
Guarantees	Sh_Guara	Bank-firm level share of loans from the bank that are subject to government guarantees	AnaCredit
Dividend suspension	DIVIDEND.REST	The ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets	Supervisory Data
Forbearance	FORBEARANCE	The ratio of forbearance take up measure-to-NFC outstanding loans	Supervisory Data

Table 13: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Low.D2Buffer	1															
L.OCR	-0.073	1														
L.TA.log	-0.018	-0.229	1													
TLTRO.III	0.105	-0.155	0.333	1												
L.LOAN/TA	-0.030	-0.248	0.049	0.162	1											
L.CIR	0.092	-0.025	-0.095	-0.007	-0.227	1										
L.DIVERS	0.005	0.145	-0.027	-0.056	-0.462	0.058	1									
DIVIDEND.REST	-0.038	-0.049	0.356	0.076	-0.051	-0.123	-0.002	1								
L.FORBEARANCE	0.007	-0.050	-0.104	-0.085	0.024	0.014	0.097	-0.040	1							
L.LIQUID/TA	0.001	0.266	0.018	-0.203	-0.871	0.083	0.429	0.109	-0.023	1						
L.MKT FUNDING/TA	0.036	-0.078	0.445	0.264	0.106	-0.114	-0.113	0.220	-0.062	-0.050	1					
L.NIM	0.088	0.004	-0.254	-0.026	0.151	-0.118	-0.434	-0.107	-0.044	-0.231	-0.305	1				
L.NPL	0.260	0.098	-0.143	0.246	-0.175	0.107	0.019	-0.063	0.009	0.046	-0.109	0.321	1			
L.OFF BS	0.095	-0.241	0.456	0.213	-0.019	-0.005	0.135	0.175	-0.017	0.090	0.031	-0.123	-0.122	1		
L.PROVISION/TA	-0.115	-0.226	0.117	-0.028	0.210	0.152	-0.054	-0.055	0.057	-0.269	-0.139	-0.054	-0.145	0.049	1	
L.RWA/TA	0.111	-0.048	-0.395	-0.058	0.038	0.038	-0.045	-0.132	0.125	-0.204	-0.369	0.543	0.291	0.053	0.074	1

Note: Low.D2Buffer is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the CBR below the first quartile of the distance to CBR distribution. L.OCR is the lag of the Overall Capital Requirement Ratio. L.TA.log is the lag of the logarithm of bank total assets. L.RW is the lag of risk weight assets-to-total assets ratio. L.MKT FUNDING/TA is the lag of the debt securities-to-total asset ratio. L.NIM is the lag of the net interest margins. L.NPLs in the lag of the non-performing loans-to-total loans ratio. L.LIQUID/TA is the lag of the ratio of cash and financial assets held for trading-to-total assets. L.DIVERS is the lag of the ratio of non-interest income-to-operating income. L.OFF BS is the lag of the ratio of off-balance sheet activities-to-total assets. L.LOAN/TA is the lag of the credit exposures-to-total assets ratio. L.CIR is the lag of the cost-to-income ratio. L.PROVISION/TA is the lag of the ratio of provisions-to-total assets. TLTRO.III is the ratio of targeted long term refinancing operations III-to-total assets. Sh_Mora is the bank-firm share of loans under moratorium. Sh_Guara is the bank-firm share of loans under government guarantee schemes. DIVIDEND.REST is the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets. L.FORBEARANCE is the lag of the ratio of forbearance measures-to-outstanding loans to NFCs.