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Cyril Couaillier, Marco Lo Duca,
Alessio Reghezza, Costanza Rodriguez d'Acri

Caution: do not cross! Capital buffers and lending in Covid-19 times

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Abstract

While regulatory capital buffers are expected to be drawn to absorb losses and meet credit demand during crises, this paper shows that banks were unwilling to do so during the pandemic. To the contrary, banks engaged in forms of pro-cyclical behaviour to preserve capital ratios. By employing granular data from the credit register of the European System of Central Banks, we isolate credit supply effects and find that banks with little headroom above regulatory buffers reduced their lending relative to other banks, also when controlling for a broad range of pandemic support measures. Firms' inability to reallocate their credit needs to less constrained banks had real economic effects, as their headcount went down, although state guarantee schemes acted as partial mitigants. These findings point to some unintended effects of the capital framework which may create incentives for pro-cyclical behaviour by banks during downturns. They also shed light on the interactions between fiscal and prudential policies which took place during the pandemic.

JEL classification: E61; G01; G18; G21

Keywords: Coronavirus; Macroprudential policy; MDA distance; Bank lending; Buffer usability; Credit register

Non-technical summary

The Basel III capital framework provides the foundations for the prudential supervision of banks (BCBS, 2011). Its goal is to reduce the pro-cyclical effects of the banking system on the economic cycle, namely to limit bank risk-taking and excessive credit growth in good times and credit supply contractions during periods of economic distress. To this aim, the framework envisages that bank capital is built up during economic upturns and then employed to absorb losses and meet credit demand during economic downturns and crises. The deep economic recession, the economic uncertainty, the prospect of serious deterioration in bank asset quality and profitability caused by the Covid-19 pandemic provided a first test of the capital framework. By analysing euro area banks' behaviour during the pandemic, this paper investigates banks' willingness (or unwillingness) to make use of capital buffers, as envisaged by Basel III.

Banks in the euro area entered the Covid-19 pandemic with relatively strong capital ratios (Enria, 2020), however, most of this capital was held in the form of prudential regulatory buffers. These buffers sit on top of minimum capital requirements and constitute the combined buffer requirement (CBR). 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 et al. 2017). However, banks' willingness or ability to draw down the CBR may be limited by a several factors, including limitations to distributions (according to the Maximum Distributable Amount – MDA – mechanism), market pressure and stigma. Ultimately, impediments to the use of buffers can negatively affect lending supply to the real economy when most needed, thereby causing pro-cyclical amplification.

In this paper, we investigate empirically whether banks closer to the MDA trigger take adjustment actions curtailing their lending to NFCs during the pandemic in comparison to banks further away from the MDA. This research question is of primary importance for policy makers as it points to possible unintended distortions in the capital framework and possible pro-cyclical effects during downturns (Behn et al., 2020).

We employ loan-level data to exploit multiple bank relationships, thus controlling for credit demand effects (Khwaja and Mian, 2008). We also match our datasets with bank- and loan-level information on banks' features including reliance on central bank funding, payment moratoria and government guaranteed loans. In this way we isolate credit supply effects triggered by the proximity to the MDA from other bank specific features and from pandemic-related support measures which also have an impact on lending. We apply sample matching strategies to convey robust results and ensure that results are not driven by other possible explanations.

The results of our analysis show that proximity to the MDA trigger results in lower lending to NFCs. Specifically, we find that proximity to the MDA reduces lending by about 3.5% to NFCs during the pandemic. We also find that lower lending from banks in proximity of the MDA trigger resulted in credit constraints to firms exposed to these banks as lost loans were not fully replaced. In particular, firms that prior to the pandemic received most of their borrowing from banks closer to the MDA trigger 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 proximity to the MDA trigger as firms receiving loans covered by government schemes counter off the lending impairments caused by banks in proximity of the MDA trigger.

Beyond contributing to different strands of the academic literature on banking, these findings inform the current debate on the appropriateness of the capital buffer framework and support discussions on how to improve its design. They also shed some light on the fiscal and prudential policies' interactions which took place during the pandemic.

1 Introduction

The Basel III capital framework provides the foundations for the prudential supervision of banks (BCBS, 2011). Its goal is to reduce the pro-cyclical effects of the banking system on the economic cycle, namely to limit bank risk-taking and excessive credit growth in good times and credit supply contractions during periods of economic distress. To this aim, the framework envisages that bank capital is built up during economic upturns and then employed (i.e. by allowing temporary declines in capital ratios) to absorb losses and meet credit demand during economic downturns and crises. The deep economic recession and the economic uncertainty caused by the Covid-19 pandemic provided a first test of the Basel III capital framework. By analysing euro area banks' behaviour during the pandemic, this paper investigates banks' willingness (or unwillingness) to make use of capital buffers, as envisaged by Basel III.

The rapid spread of Covid-19 worldwide confronted policymakers not only with a major public health problem but also with the prospect of a serious economic and financial crisis. While prompt and forceful policy actions assuaged the worst economic effects of the pandemic,[2] restrictions on personal mobility and nonessential business operations strongly affected business profits, causing a surge in 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. Therefore, in this paper we exploit the exogenous economic shock caused the Covid-19 pandemic to assess banks' behaviour and their willingness to use regulatory capital in periods of severe economic distress.

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

[2] 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, March 2020).

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), counter cyclical buffer (CCyB), systemic risk buffer (SyRB) and 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 et al. 2017). 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).

[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 (Enria, 2020; BIS, 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 (Drehmann et al., 2020; Baker and Wurgler, 2015). This can lead to higher funding costs and/or have negative implications for bank credit ratings (Claessens et al., 2018). Third, banks' willingness to draw down buffers depends on the expected reaction of supervisory

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

authorities (Borio et al., 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.[4] Additionally, 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. Finally, other regulatory requirements such as the leverage ratio or the Minimum Requirement for own funds and Eligible Liabilities (MREL) constrain the usability of buffers if they are more binding than risk-based requirements (BoP, 2020). For the above reasons, banks tend to keep capital targets above the CBR (Couaillier, 2020; Behn et al., 2020) by holding excess capital (or management buffers).[5]

Bank unwillingness to draw down buffers can negatively affect lending supply to the real economy when most needed. In this paper, we investigate empirically whether banks closer to the MDA trigger take adjustment actions to preserve capital ratios, curtailing their lending to non-financial corporations (NFCs) during the pandemic in comparison to banks further away from the MDA trigger. This research question is of primary importance for policy makers as it points to possible unintended effects of the capital framework and possible pro-cyclical behaviour of banks during downturns (Behn et al., 2020).

Our analysis offers a comprehensive assessment of the effect of proximity to the MDA trigger on bank credit supply adjustments following the pandemic outbreak. Specifically, we answer the following questions: Did banks closer to the MDA trigger 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 MDA trigger? We rely on granular loan-level data to address these questions.

Several empirical challenges must be overcome to estimate the effect of proximity to

[4]When approaching the MDA trigger, 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).

[5]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.

the MDA trigger 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 relationship *via* the inclusion of industry-location-size fixed effects to control for the heterogeneity in credit demand across firms (Degryse et al., 2019). Second, it necessitates isolating bank credit supply from pandemic-related measures: most notably, government guarantee and moratoria schemes. 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 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 et al. (2020) show that in the absence of TLTRO III lending to firms would have been 3 percentage points lower. Additionally, Martinez-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 MDA trigger, thereby ensuring that results are not endogenous, i.e. driven by weaker balance sheets for banks closer to the MDA trigger point.

To preview our findings, proximity to the MDA trigger results in lower lending to NFCs. Specifically, we find that proximity to the MDA reduces lending by about 3.5% to NFCs during the pandemic. We also find that lower lending from banks in proximity of the MDA trigger resulted in credit constraints for firms exposed to these banks as lost loans were not fully replaced. In particular, firms that prior to the pandemic received most of their borrowing from banks closer to the MDA trigger 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 MDA trigger. In particular, firms receiving loans covered by government schemes counter off the lending impairments caused by banks in proximity of the MDA trigger.

Our paper provides a solid contribution to the extant literature in several respects. First, we add to the long-standing empirical literature on bank capitalisation and lending (Bernanke and Lown, 1991; Berger and Udell, 1995; Peek and Rosengren, 1997; Gambacorta and Mistrulli, 2004; Berrospide and Edge, 2010).[6] While these papers investigate the absolute level of capital ratios, we investigate the impact of the *closeness to regulatory buffers*.

Our paper also 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, 2019; Gropp et al., 2019; De Jonghe et al., 2020), structural buffers (Reghezza et al., 2020; Behn and Schramm, 2020; Degryse et al., 2020) and dynamic capital requirements (Aiyar et al., 2014; Auer and Ongena, 2016; Jimenez et al., 2017; Basten, 2019) on bank lending. While this literature largely focuses on the impact of changes in capital requirements, we contribute by investigate 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.

We also differ from the previous literature in terms of data granularity. Earlier studies apply aggregate (Hancock et al., 1995; Lown and Morgan, 2006) or bank-level data (Peek and Rosengren, 2000). However, bank-level data may be prone to endogeneity issues due

[6]For the theoretical literature we refer to Diamond and Rajan (2000), Bolton and Freixas (2006), Van de 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 et al., 2011; Behn et al., 2016; Fraisse et al., 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 (among the few exceptions, Altavilla et al., 2020), 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 MDA trigger 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.

Finally, we contribute to the policy-oriented debate on the effectiveness of the buffer framework (FSB, 2020; BIS, 2021; IMF, 2021) by providing empirical evidence of how banks in proximity of the MDA trigger point fared at the onset of the pandemic.

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 MDA trigger 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 health emergency were in proximity of the MDA trigger, adjust their balance sheet after the shock. We use loan-level data as they allow 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 multiple bank-firm relationships to control for firm credit demand, hence firms that borrow from multiple banks and within-firm comparisons across banks at different distance to the MDA trigger. However, one shortcoming of the Khwaja and Mian (2008) econometric identification strategy is the exclusion of single-bank lending relationships 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, we follow the approach by Popov and Van 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.[7] The industry clusters are based on 2-digit NACE codes. The location clusters are based on 5-digit postal code for the largest countries in the sample while for the smallest (Cyprus, Estonia, Lativa, Lithuania, Luxembourg, Malta, Slovakia and Slovenia) on the firm's country headquarter. For size, we take the definition given in *AnaCredit* which distinguishes between large, medium, small and micro enterprises.[8] The inclusion of ILS fixed effects allows us to

[7]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

[8]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

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

$$\Delta Log(loans)_{i,k} = \alpha_k + \beta Low.D2MDA_i + \tau X_i' + \delta Z_i + \gamma_j + \epsilon_{i,k} \quad (1)$$

where the dependent variable is the change in the logarithm of loans from bank i to firm k around the pandemic. Following, Betrand et al. (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.[9] In equation (1), Low.D2MDA 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 MDA trigger below the first quartile of the distribution, 0 otherwise.[10] β is our coefficient of interest as it indicates whether a given bank in proximity of the MDA trigger lends less following the shock in comparison to banks with more sizeable MDA 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),[11] 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 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

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

[9] 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. However, in unreported tests 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.

[10] In a robustness check in Section 5 we test a different computation of the dummy variable Low.D2MDA

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

sheet activities-to-total assets (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-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, two additional variables capturing the percentage share of loans from the bank that are subject to government moratoria (S.MORA) and guarantees (S.GUAR), the ratio of dividend planned in 2019 but not paid in 2020-to-risk weighted assets (DIVIDEND.REST) and the lag of the take up of other forbearance measures (L.FORBEARANCE).[12] α identifies firm (or ILS) fixed-effects employed to capture heterogeneity in credit demand across firms and to account for the possibility that firm demand was already impaired prior to the pandemic. 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 (Jimenez 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.D2MDA banks) and the control groups (High.D2MDA banks). Figure 3 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 MDA trigger (our treatment group) and the control group over time (2019Q1-2020Q4). As noticeable and although the trends between the two groups appear to move similarly in the pre-treatment period, banks with

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

sizeable MDA headroom showcase stronger lending following the escalation of the virus.[13]

[Insert Figure 3 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 MDA trigger 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 MDA trigger 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 MDA trigger 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 MDA trigger 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 MDA trigger 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 propensity score matching (PSM) approach (Rosenbaum and Rubin, 1983) which, by pairing each bank with a control unit, allows us to control for banks with similar characteristics as well as to mitigate the concerns that our results are driven by bank specific-attributes. In the spirit of Bersch et al. (2020), we

[13] While both groups increase lending during the pandemic, Figure 3 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 MDA trigger from support measures.

allow treated banks to be matched with at least one and up to three control banks, whilst both treated and control banks are discarded from the analysis if proper matching is not found (Heckman et al. 1997).[14] Figure 4 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 Table 1 Here]

[Insert Figure 4 Here]

2.2 Firm-level analysis

In this section, we empirically investigate whether firms more exposed to banks in proximity of the MDA trigger prior to the pandemic outbreak manage to raise funds from banks with greater MDA headroom to replace the lost lending. We also look at whether prudential buffers have interacted with the fiscal support measures introduced after the pandemic. Theoretically, a reduction in credit supply from those banks in proximity of the MDA trigger would not be contractionary at the firm-level if: (i) banks further away from it pick up the slack and/or (ii) the government offers credit risk protection *via* guaranteed schemes which help capital constrained banks. 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 MDA trigger point may struggle to replace existing sources of financing with alternative ones or to establish new credit relationships during turbulent times. In

[14] 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 0.01 (Dehejia and Wahba, 2002)

addition, banks in proximity to the MDA trigger may leverage on guaranteed credit to reduce their credit risk exposure reducing the guarantees' effectiveness in providing credit to constrained firms (Altavilla et al., 2021). Since, on average, firm exposure to banks with limited MDA headroom prior to the pandemic is sizeable (Figure 5), we delve into this question by following Behn et al. (2016) and adopting the following econometric identification strategy:

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

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 MDA trigger prior to the pandemic, 0 otherwise. Specifically, we define as exposed those firms that prior to the pandemic have more than 25% (first quartile) of their credit originating from more vulnerable banks, i.e. those in proximity of the MDA trigger. 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 MDA headroom, while σ indicates whether guarantees schemes have been effective in providing more credit to firms constrained by banks in proximity of the MDA trigger. 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).

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

In the spirit of Jimenez et al. (2017), in equation (3), we look at whether exposed firms' headcounts is affected during the pandemic as this can have repercussions on firms' performance and, more broadly, on the level of unemployment and economic output.[15] If firms did not manage to raise funds from banks with greater MDA headroom and/or through guaranteed schemes, they may have been forced the to cut the number of employees.

[Insert Figure 5 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 operations database. Bank-level data is matched with loan-level information that is taken 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.[16] *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.[17] 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

[15] 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.

[16] *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

[17] 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.

consistency across countries.

3.1 Descriptive statistics

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.

[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 MDA trigger. As mentioned in the explanation of equation (1), banks considered as treated have a distance to the MDA below 2.6% (first quartile of the distance to the MDA distribution). For graphical purposes, in Figure 6 we report the distribution of the distance to the MDA trigger.[18]

[Insert Table 3 Here]

[Insert Figure 6 Here]

4 Results

4.1 Loan-level results

Table 4 reports the results from estimating equation (1). The Table is divided in 4 columns. Columns 1 and 3 report the results of Khwaja and Mian (2008) approach for the matched and unmatched sample whilst columns 2 and 4 report the results of the Degryse et al. (2019) approach for the matched and unmatched sample. The dataset is collapsed into pre- (2019Q2-2019Q4) and post-event (2020Q2-2020Q4) averages as in Betrand et al. (2004).

The dummy Low.D2MDA is our coefficient of interest as it indicates whether proximity to the MDA results in weaker credit supply at the onset of the pandemic. The first column of Table 4 shows that banks closer to the MDA trigger 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. Notwithstanding the smaller sample in the matched analysis, the variable of interest (Low.D2MDA) retains sign in-line with the unmatched sample providing robustness to the unmatched sample results. In addition, the magnitude of the coefficient is improved in the matched sample which suggests 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

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

relationships in our estimation. The coefficients reported in columns 3 and 4 of Table 4 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.

These results show that proximity of the MDA trigger encourages banks to react to the distressed period followed by the health emergency by reducing outstanding loans to NFCs. The loan-level analysis developed in this section confirms that the credit curtailment can be attributed to a reduction in credit supply and is not instead driven by firm demand. Moreover, the consistency of the results in the matched and unmatched sample certifies that our results are not driven by differences in bank-specific characteristics between banks in proximity of the MDA trigger and banks farther away from it.

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; Fraisse et al., 2019; Gropp et al., 2019). A negative and statistically significant link is also displayed between MKT FUNDING/TA and the change in bank lending. In particular, a 1 pp increase in MKT FUNDING/TA leads to about 0.4% (column 1) decrease 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 NIM 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 et al., 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).

[Insert Table 4 Here]

4.2 Firm-level results

In this section, we analyse whether the proximity to the MDA trigger entails credit rationing at the firm level. In practise, this will depend on (i) the extent to which other banks, not close to the MDA trigger, are able or willing to pick up the slack and/or (ii) the effectiveness of government guaranteed schemes in helping capital constrained banks. 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 smaller MDA headroom. 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.[19]

Results to these questions are reported in Table 5. 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).

By looking at credit from the firms' perspective, e.g. through their borrowing, we find that firms exposed to banks in proximity of the MDA trigger exhibit about 2.6% lower borrowing after the pandemic outbreak than firms exposed to banks with additional capital on top of the MDA trigger. The economic effect is not negligible given the saturation of the model as firms' borrowing capability has been highly impacted by government guarantees and payment moratoria (Core and De Marco, 2021). In our empirical setting, by including ILS fixed effects and controlling for guarantees and moratoria, firms'

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

lower borrowing capability can be attributed to differences in banks' distance to the MDA trigger.

The interaction term in column 2 provides useful insights on the relationship between proximity to the MDA trigger and government guarantees. The single coefficient *Exp.Firm* is still negative and statistically significant (at the 1% level) indicating substitution impediments for those firms that prior to the health emergency borrowed mostly from banks closer to the MDA and that were not able to replace outstanding borrowing with guaranteed credit. 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 MDA on firms' borrowing capability. *Ceteris paribus*, firms receiving loans pledged by government schemes were able to substitute for the lack of borrowing coming from vulnerable banks, as confirmed by the insignificance of an F-test for joint significance testing the sum of the single ($Exp.Firm$) and double coefficient ($Exp.Firm \times S.GUAR$). 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 MDA constrained banks, this is likely to have negative repercussions at the firm level through lower employment, investments and growth. Table 5 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 0.8% in comparison to firms borrowing from MDA 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 5 Here]

5 Robustness checks

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 — for example, in anticipation of the adverse effects of the spread of the virus, or for some non identified bank-specific reasons. 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 6, 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.D2MDA 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) further supporting the validity of our baseline estimation and the selection of the difference-in-difference econometric strategy.

[Insert Table 6 Here]

5.2 Alternative definition of the treatment variable

In the baseline specification, we defined as *treated* banks with a distance to MDA trigger below the fist quartile of the distance to the MDA trigger distribution and as *control* those banks with a distance to the MDA trigger 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.D2MDA in order to consider only the first and last quartile of the distance to the MDA distribution, i.e. omitting the banks in the middle of the distribution. Specifically, for this test the dummy Low.D2MDA takes the value 1 for banks with an average pre-pandemic (2019Q3-Q4) distance to the MDA trigger below the first quartile of the distance to the MDA trigger distribution (as in the baseline specification in equation (1)) while it takes the value 0 only for banks with a distance to MDA trigger above the third quartile of distance to MDA trigger distribution.

The results from this test are reported in Table 7. 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.D2MDA) 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 MDA trigger 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 MDA trigger above the last quartile.

[Insert Table 7 Here]

5.3 Continuous distance to the MDA trigger

As a third robustness check, we replace our dummy variable of interest (Low.D2MDA) with the lag of the distance to the MDA, expressed as a continuous variable (labelled L.Dist.MDA). One advantage of the continuous variable over the dummy variable is that it allows for a better estimation of the intensity of the effect of the distance to the MDA trigger on changes in bank lending supply. On the contrary, the dummy variable groups banks according to a specific threshold determined by their distance to the MDA trigger. However, in our empirical setting, the dummy variable 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 MDA trigger because of weaker balance sheets. Second, it allows for non-linearity in the estimation of the distance to the MDA and bank lending supply. This method is employed also by other studies in the banking literature (see, amongst others, Heider et al., 2019)

Nevertheless, the results displayed in Table 8 (columns 1 and 2) show a positive and statistically significant (at the 1% level) relationship between the distance to the MDA trigger and bank lending supply. Specifically, a 1 pp increase in the distance to the MDA trigger 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. This test further corroborates our baseline findings suggesting that the distance to MDA trigger is a pivotal determinant for bank lending decision following a major systemic event.

[Insert Table 8 Here]

5.4 Matching by CET1 ratio

As a fourth robustness check, we change our matching strategy by replacing the OCR with the CET1 ratio.[20] In the matching strategy employed throughout the paper, we constrain the OCR between the treated and control group to be similar (either by using it in the matching strategy or controlling for it in the regressions) 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 MDA trigger. To control for this possibility we use the CET1 ratio as a control variable in the matching strategy, replacing the OCR. Matching by the CET1 ratio creates a matched

[20] In unreported tests, we employ different matching techniques to control for the reliability of our results. Specifically, we use - instead of the nearest neighbours matching - the radius matching. In addition, we also limit the number of nearest neighbours (3 in the baseline specification) to 1 and 2 control units to be matched with treated banks. Finally, we use other calipers calibrations. The results hold up well in the face of these additional checks and are available upon request.

group of banks that are similar in terms of capital ratios but differ only in respect to their distance to the MDA trigger.

The results of this test are reported in Table 9. In columns 1 and 3 of Table 9 we report the estimate of the unmatched sample where we replace the OCR with the lag of the CET1 ratio as a control variable in the estimation. As shown, the results have sign, magnitude and statistical significance in line with the baseline findings further corroborating their validity. In columns 2 and 4, we apply the aforementioned matching strategy. Notwithstanding the large loss of observations in the matched sample which indicates a smaller group of banks having similar CET1 ratio but, at the same time, different distance to the MDA trigger, the results hold up well, further validating our baseline analysis and suggesting, again, that the distance to the MDA trigger is an important determinant for bank lending decision during a systemic shock.

[Insert Table 9 Here]

6 Conclusion

In this paper we ask whether the Basel III capital framework creates unintended incentives for banks to behave pro-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 MDA trigger 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. The pro-cyclical behaviour of banks in proximity of the MDA trigger resulted in credit constraints for firms mostly exposed to them as they were unable to fully replace the curtailed loans.

While several factors can explain the identified behaviour of banks in proximity of the MDA trigger during the pandemic, it remains difficult to pin down a single mechanism triggering banks' balance sheet adjustments. First, banks may want to avoid restrictions to distributions triggered by the MDA mechanism when banks dip into the CBR. Second, beyond the stigmas associated with the MDA mechanism, banks may want to avoid operating within the CBR as this could be perceived as a sign of weakness, leading to market pressures and/or rating downgrades. Third, banks prefer to stay out of close supervisory scrutiny. Lastly, other minimum regulatory requirements (e.g. leverage ratio or MREL) might be more binding than risk based requirements, thereby making the CBR at least partially unusable. Cursory evidence on the relationship between contingent convertible bonds prices and MDA headroom immediately after the pandemic outbreak suggests that Coco prices dropped more for banks closer to the MDA trigger (Figure 6).[21] While this could indeed indicate a role for the MDA trigger and market stigmas, the identification of the specific factors causing banks' adjustments is left for future research.

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

References

Acharya, V. V., Le, H. T., Shin, H. S. (2017). Bank capital and dividend externalities. *The Review of Financial Studies*, 30, 988-1018. https://doi.org/10.1093/rfs/hhw096

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, 3366-3411. https://doi.org/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, 368-382. https://doi.org/10.1016/j.jfineco.2014.05.003

Altavilla, C., Barbiero, F., Boucinha, M., Burlon, L. (2020). The great lockdown: Pandemic response policies and bank lending conditions. *CEPR Discussion Paper No. DP15298*, Centre for Economic Policy Research.

Altavilla, C., Boucinha, M., Peydro, J. L., Smets, F. (2020) Banking supervision, monetary policy and risk-taking: big data evidence from 15 credit registers, *ECB Working Paper No 2349*.

Altavilla, C. Ellul, A., Pagano, M., Polo, A., Vlassopoulos, T. 2021. Loan guarantees, bank lending and credi risk reallocation. *CEPR Working Paper DP16727*, Centre for Economic Policy Research.

Auer, R. and Ongena, S. (2016). The countercyclical capital buffer and the composition of bank lending. *BIS Working Papers No. 593.*, Bank for International Settlements.

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, 315-320. 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, 453-495. https://doi.org/10.1093/rof/rfz009

BCBS. (2011). Basel III: A global regulatory framework for more resilient banks and banking systems. *Basel Committee on Banking Supervision*, Bank for International Settlements.

Behn M., Haselmann, R., Wachtel, P. (2016). Procyclical capital regulation and lending. *The Journal of Finance*, 71, 919-956. https://doi.org/10.1111/jofi.12368

Behn, M., Schramm, A. (2020). The impact of G-SIB identification on bank lending: Evidence from syndicated loans. *ECB Working Paper Series No. 2479*, European Central Bank. doi:10.2866/784184

Behn, M. Rancoita, E., Rodriguez d'Acri, C. (2020). Macroprudential capital buffers - objectives and usability. *Macroprudential Bulletin No. 11*, European Central Bank.

Berger, A. N., Udell, F. G. (1994). Did risk-based capital allocate bank credit and cause a "credit crunch" in the United States? *Journal of Money, Credit and Banking*, 26, 585-628. https://doi.org/10.2307/2077994

Bernanke, B. S., Lown, C. S., Friedman, B. M. (1991). The credit crunch. *Brookings Papers on Economic Activity*, 205-247. https://doi.org/10.2307/2534592

Berrospide, J. M., Edge, R. M. (2010). The effect of bank capital on lending: What do we know, and what does it mean? *International Journal of Central Banking*, 6, 5-54.

Berrospide, J. M., Edge, R. M. (2019). The effect of bank capital buffers on bank lending and firm activity: What can we learn from five year of stress-test results? *Finance and Economics Discussion Series 2019-050*, Board of Governors of the Federal Reserve System. https://doi.org/10.17016/FEDS.2019.050

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, 101521. https://doi.org/10.1016/j.jcorpfin.2019.101521

Bertrand, M., Duflo, E., Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119, 249-275. https://doi.org/10.1162/003355304772839588

BIS. (2020). Basel Committee meets; discusses impact of Covid-19; reiterates guidance on buffers. *Press Release Basel Committee on Banking Supervision*, 17 June 2020, Bank for International Settlements. Available at: https://www.bis.org/press/p200617.htm.

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.* Bank for International Settlements.

Bolton, P., Freixas, X. (2006). Corporate finance and the monetary transmission mechanism. *The Review of Financial Studies*, 19, 829-870. https://doi.org/10.1093/rfs/hhl002

BoP. (2020). Interaction betweeen regulatory minimum requirements and capital buffers. *Financial Stability Report*, June 2020, Banco de Portugal.

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

Borsuk, M., Budnik, K., Volk, M. (2020). Buffer use and lending impact. *Macroprudential Bulletin No. 11*, European Central Bank.

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

Core, F., De Marco, F. (2021). Public guarantees for small businesses in Italy during Covid-19. *CEPR Discussion Paper No. DP15799*, Centre for Economic Policy Research..

Cornett, M. M., McNutt, J. J., Strahan, P. E., Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, 101, 297-312. https://doi.org/10.1016/j.jfineco.2011.03.001.

Couaillier, C. (2020). What are banks' actual capital targets? Lessons for policymakers. Available at: https://ssrn.com/abstract=3899288.

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

Degryse, H., Mariathasan, M., Tang, T. H. (2020). GSIB status and corporate lending: An international analysis. *CEPR Discussion Paper N. 15564*, Centre for Economic Policy Research.

Dehejia, R. H., Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics*, 84, 151-161. https://doi.org/10.1162/003465302317331982

De Jonghe, O., Dewachter, H., Ongena, S. (2020). Bank capital (requirements) and credit supply: Evidence from pillar 2 decisions. *Journal of Corporate Finance*, 60, 101518. https://doi.org/10.1016/j.jcorpfin.2019.101518

Diamond, W. D., Rajan, R. (2002). A theory of bank capital. *The Journal of Finance*, 55, 2431-2465. https://doi.org/10.1111/0022-1082.00296

Disyatat, P. (2011). The bank lending channel revisited. *Journal of Money, Credit and Banking*, 43, 711-734. https://doi.org/10.1111/j.1538-4616.2011.00394.x

Donald, S. G., Lang, K. (2007). Inference with difference-in-differences and other panel data. *The Review of Economics and Statistics*, 89, 221-233.https://doi.org/10.1162/rest.89.2.221

Drehmann, M., Fara, M., Tarashev, N., Tsatsaronis, K. (2020). Buffering Covid-19 losses - The role of prudential policy. *BIS Bulletin No. 9*, Bank for International Settlement.

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* , November 2020, European Central Bank.

Enria, A. (2021). Introductory statement. Speech at the Press Conference on the Supervisory Review and Evaluation Process, 28 January 2021. Available at: https://www.bankingsupervision.europa.eu/press/speeches/date/2021/html/ssm.sp210128~78f262dd04.en.html

FED. (2020). Statement on the Use of Capital and Liquidity Buffers. *Joint Release*, Board of Governors of the Federal Reserve System Federal Deposit Insurance Corporation Office of the Comptroller of the Currency.

Fraisse, H., Le, M., Thesmar, D. (2019). The real effects of bank capital requirements. *Management Science*, 66, 5-23. https://doi.org/10.1287/mnsc.2018.3222

FSB. (2020). Covid-19 pandemic: Financial stability implications and policy measures taken. *Report submitted to the G20 finance ministers and governors*. Financial Stability Board.

Gambacorta, L., Mistrulli, P. E. (2004). Does bank capital affect lending behaviour? *Journal of Financial Intermediation*, 13, 436-457. https://doi.org/10.1016/j.jfi.2004.06.001

Gambacorta, L., Shin, H. S. (2018). Why bank capital matters for monetary policy? *Journal of Financial Intermediation*, 35, 17-29. https://doi.org/10.1016/j.jfi.2016.09.005

Gersbach, H., Rochet, J. C. (2017). Capital regulation and credit fluctuations. *Journal of Monetary Economics*, 90, 113-124. https://doi.org/10.1016/j.jmoneco.2017.05.008

Gropp, R., Monsk, T., Ongena, S., Wix, C. (2019). Banks response to higher capital requirements: Evidence from a quasi-natural experiment. *The Review of Financial Studies*, 32, 266-299. https://doi.org/10.1093/rfs/hhy052

Hancock, D., Laing, A. J., Wilcox, J. A. (1995). Bank capital shocks: Dynamic effects on securities, loans, and capital. *Journal of Banking and Finance*, 19, 661-677. https://doi.org/10.1016/0378-4266(94)00147-U

Heckman, J. J., Ichimura, H., Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64, 605-654. https://doi.org/10.2307/2971733

Heider, F., Saidi, F., Schepens, G. (2019). Life below zero: Bank lending under negative policy rates. *The Review of Financial Studies*, 32, 3278-3761. https://doi.org/10.1093/rfs/hhz016

Imbens, G. W., Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47, 5-86. DOI:10.1257/jel.47.1.5

IMF. (2021). Covid-19: How will european bank fare? *Departmental Paper No. 2021/008*. International Monetary Fund.

Jimenez, G., Ongena, S., Peydro, 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, 2126-2177. https://doi.org/10.1086/694289

Jimenez, G., Mian, A., Peydro, J. L., Saurina, J. (2020). The real effects of the bank lending channel. *Journal of Monetary Economics*, 115, 162-179. https://doi.org/10.1016/j.jmoneco.2019.06.002.

Khwaja, A. I., Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98, 1413-42.DOI:10.1257/aer.98.4.1413

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, 1575-1597. https://www.jstor.org/stable/3839114

Martinez-Miera, D., Sanchez, V. R. (2021). Impact of dividend distribution restriction on the flow of credit to non-financial corporations in Spain. *Banco de Espana Working Paper*, No 07/21.

Molyneux, P., Reghezza, A., Xie, R. (2021). Bank margins and profits in a world of negative rates. *Journal of Banking and Finance*, 107, 105613.

Peek, J., Rosengren, E. S. (1997). The international transmission of financial shocks: The case of Japan. *American Economic Review*, 87, 495-505. https://www.jstor.org/stable/2951360

Peek, J., Rosengren, E. S. (2000). Collateral damage: Effects of the Japanese bank crisis on real activity in the United States. *American Economic Review*, 90, 30-45. DOI:10.1257/aer.90.1.30

Petersen, M. A. (2009) Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22, 435-480. https://doi.org/10.1093/rfs/hhn053

Popov, A., Van Horen, N. (2015). Exporting sovereign stress: Evidence from syndicated bank lending during the euro area sovereign debt crisis. *Review of Finance*, 19, 1825-1866. https://doi.org/10.1093/rof/rfu046.

Puri, M., Rocholl, J., Steffen, S. (2011). Global retail lending in the aftermatch of the US financial crisis; Distinguishing between supply and demand effects. *Journal of Financial Economics*, 100, 556-578. https://doi.org/10.1016/j.jfineco.2010.12.001.

Reghezza, A., Rodriguez d'Acri, C., Spaggiari, M., Cappelletti, G. (2020). Compositional effects of O-SII capital buffers and the role of monetary policy. *ECB Working Paper Series No 2440*, European Central Bank. doi:10.2866/897417.

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

SSM. (2021). ECB banking supervision provides temporary capital and operational relief in reaction to coronavirus. *Press Release Single Supervisory Mechanism*, 12 March 2020, available at: https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200312~43351ac3ac.en.html

Svoronos, J. P., Vrbaski, R. (2020). Banks' dividends in Covid-19 times. *FSI Briefs No. 6*, Financial Stability Institute, Bank for International Settlements.

Van den Heuvel, S. J. (2008). The welfare cost of bank capital requirements. *Journal of Monetary Economics*, 55, 298-320. https://doi.org/10.1016/j.jmoneco.2007.12.001.

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

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.

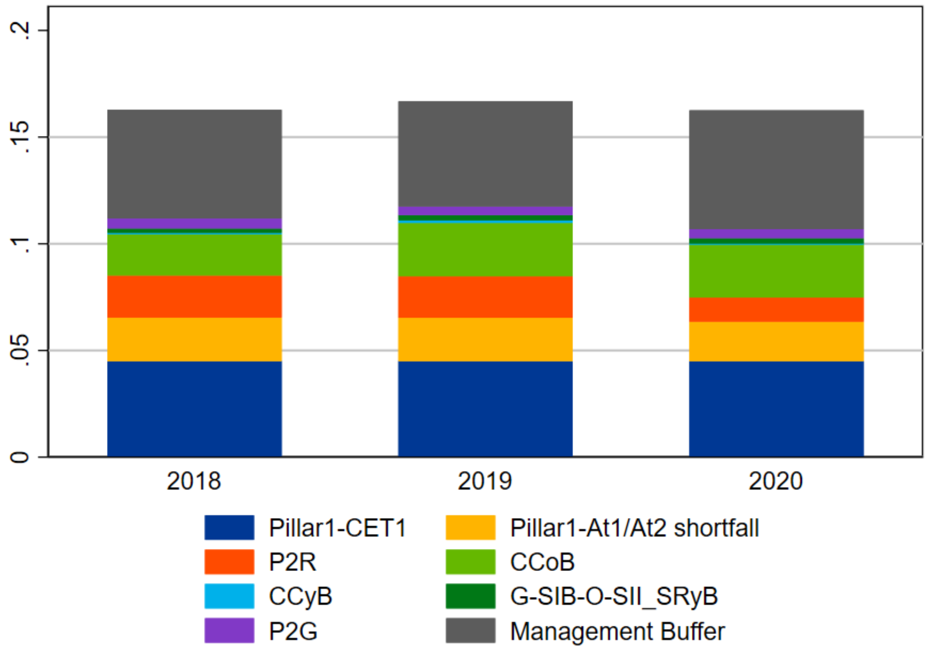

Figure 2. Capital stack

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.

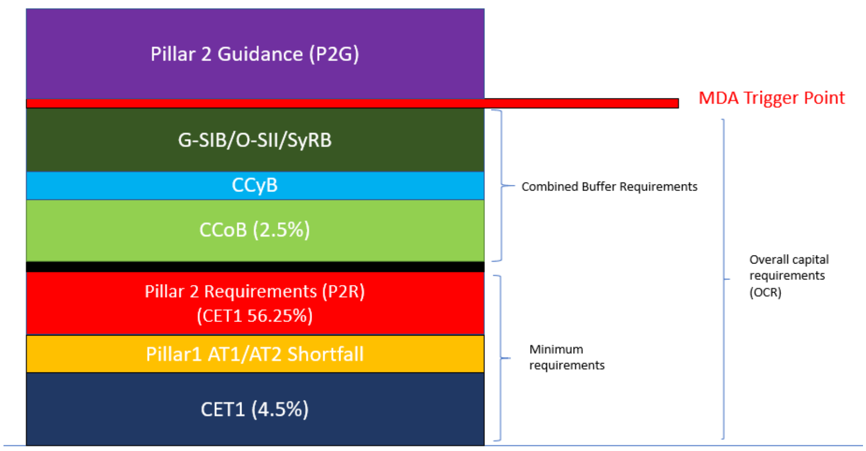

Figure 3. Lending by treated group over 2019Q1-2020Q4

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 MDA trigger (our treatment group) and the control group over time (2019Q1-2020Q4). Low.D2MDA indicates banks with an average distance to the MDA in 2019Q2-Q4 below the first quartile of the distance to the MDA distribution (treated group and blue solid line), whilst High.D2MDA refers to banks with an average distance to the MDA in 2019Q2-Q4 above the first quartile of the distance to the MDA 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.

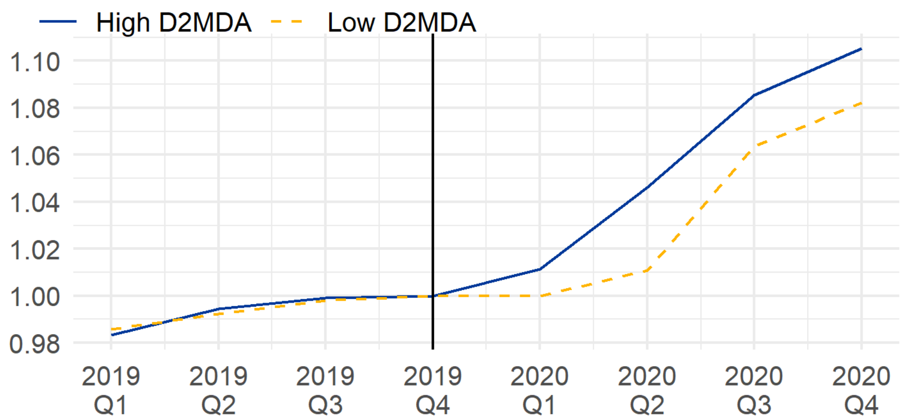

Figure 4. Pscore before and after matching (loan-level analysis)

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.

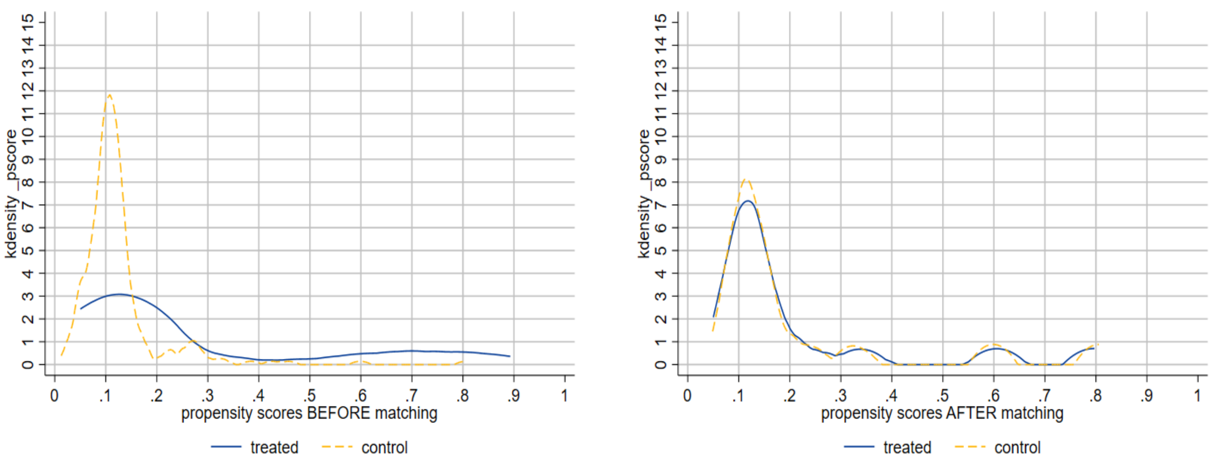

Figure 5. Pre-pandemic outstanding share NFCs borrowing by country

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 (2019Q2-Q4), had an average distance to the MDA trigger below the first quartile of the distance to the MDA trigger distribution. Share non-exposed firms (reported in yellow) indicates the average share of total NFC borrowing from banks that, prior to the pandemic (2019Q2-Q4), had an average distance to the MDA trigger above the first quartile of the distance to the MDA trigger distribution.

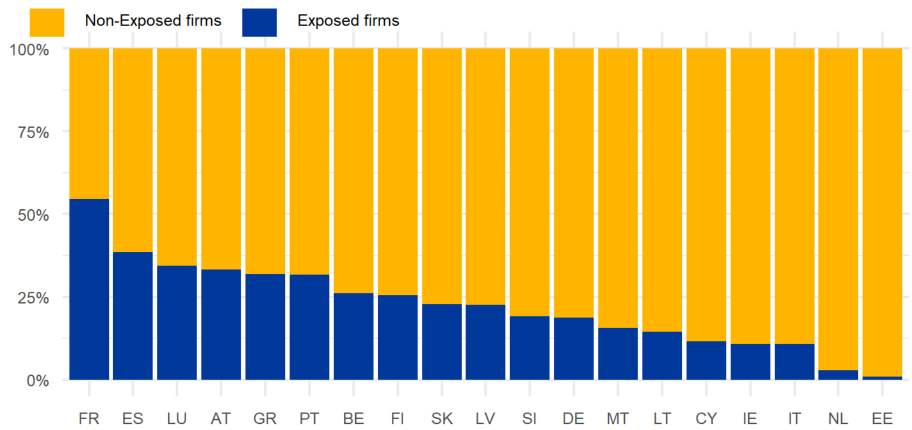

Figure 6. Histogram distance to the MDA

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

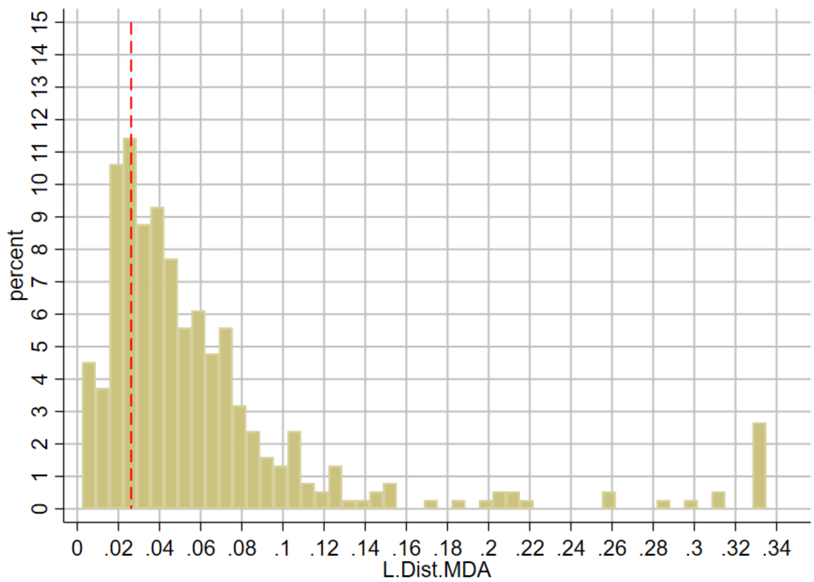

Figure 7. Scatter plot CoCo bond prices and bank distance to MDA trigger point

This figure shows the relationship between the average distance to the MDA trigger 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 MDA trigger. The yellow line represents the fitted values coming from a linear regression model between distance to the MDA trigger and CoCo bond price drop. The grey shaded area indicates confidence interval at the 95% level.

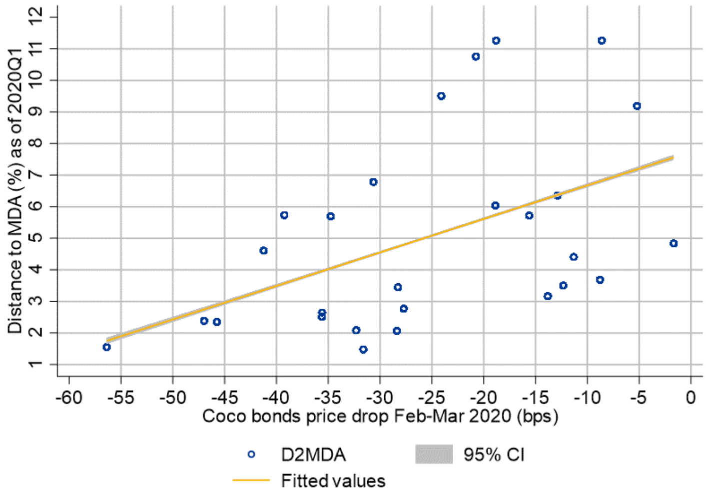

Table 1: Pretreatment bank characteristics

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 (Section 2.1), whilst Panel B reports desciptive statistics for the matched sample. The PSM applies a logit model and one-to-three nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01. Low.D2MDA indicates banks with an average distance to the MDA trigger in 2019Q3-Q4 below the first quartile of the distance to the MDA trigger distribution, whilst High.D2MDA refers to banks with an average distance to the MDA trigger in 2019Q3-Q4 above the first quartile of the distance to the MDA trigger distribution. Welch t-test displays the t-statistics coming from the differences between Low.D2MDA and High.D2MDA. 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.D2MDA	**Low.D2MDA**	**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.D2MDA	**Low.D2MDA**	**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.D2MDA indicates banks with an average distance to the MDA trigger in 2019Q3-Q4 below the first quartile of the distance to the MDA trigger distribution, whilst High.D2MDA refers to banks with an average distance to the MDA trigger in 2019Q3-Q4 above the first quartile of the distance to the MDA trigger 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-three nearest neighbour, imposing a tolerance level on the maximum propensity score distance (caliper) between the control and the treatment group equals to 0.01.

	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.D2MDA	5,301,688	0.422	0.494	0.000	0.000	1.000	1.000
L.Dist.MDA	5,301,688	0.062	0.065	0.002	0.026	0.072	0.334
Exp.Firm	5,301,688	0.422	0.494	0.000	0.000	1.000	1.000
			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.D2MDA is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the MDA trigger below the first quartile of the distance to MDA trigger distribution. L.Dist.MDA is the lag of the distance to the MDA trigger. 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. 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.D2MDA is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the MDA trigger below the first quartile of the distance to MDA trigger 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.D2MDA	-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: 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 MDA trigger 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 6: 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.D2MDA is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the MDA trigger below the first quartile of the distance to MDA trigger 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.D2MDA	-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 7: Redefinition of the variable of interest: Low.D2MDA

This table shows the results of robustness redefining the Low.D2MDA variable that takes the value 0 only for banks with a distance to MDA trigger above the last quartile of the distance to the MDA trigger 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.D2MDA is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the MDA trigger below the first quartile of the distance to MDA trigger 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.D2MDA	-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 8: 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.MDA is the pre-event average of the distance to the MDA trigger 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. MDA	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 9: Alternative Matching Approach

This table shows the results of robustness replacing the OCR in the matching strategy 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.D2MDA is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the MDA trigger below the first quartile of the distance to MDA trigger 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 ILS FE	Matched ILS FE
	(1)	(2)	(3)	(4)
Low.D2MDA	-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 MDA trigger	Low.D2MDA	Dummy variable equal to 1 if a bank, in the quarter prior to the pandemic (2019Q4) has a distance to the MDA trigger 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 MDA trigger point, 0 otherwise	AnaCredit and authors' calculation
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 B. Correlation Matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Low.D2MDA	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.D2MDA is a dummy variable that takes the value 1 if a bank has a pre-pandemic distance to the MDA trigger below the first quartile of the distance to MDA trigger 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.

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Cyril Couaillier
European Central Bank, Frankfurt am Main, Germany; email: Cyril.Couaillier@ecb.europa.eu

Marco Lo Duca
European Central Bank, Frankfurt am Main, Germany; email: marco.lo_duca@ecb.europa.eu

Alessio Reghezza
European Central Bank, Frankfurt am Main, Germany; Bangor University, Bangor, United Kingdom;
email: Alessio.Reghezza@ecb.europa.eu

Costanza Rodriguez d'Acri
European Central Bank, Frankfurt am Main, Germany; email: Costanza.Rodriguez@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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