Pandemic Lending:

The Unintended Effects of Model-based Regulation

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Abstract

Does model-based bank regulation constrain lending when it matters the most? Using an extensive loan-level supervisory dataset on credit exposures of Euro Area banks, we document that during the Covid-19 pandemic, banks using their own (internal-rating based or IRB) models to measure credit risk, decreased their on-balance sheet credit exposures, especially lending, to Non-Financial Corporations more than banks using standard (fixed risk-weights) models to the same borrower. Lower capitalised IRB banks reduced their exposures more towards borrowers absorbing more regulatory capital and borrowers in the economic sectors most affected by the pandemic.

Keywords: Banks; Supervision; Lending; Credit Rationing;

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"Thanks to the reforms conducted after the 2008 financial crisis, banks are capitalised and resilient enough to act as shock absorbers to businesses hit by the Covid-19 pandemic. But we are only at the very early stages of the recovery. It is our responsibility, as co-legislators, to ensure that banks have the necessary flexibility to continue providing the easiest access possible to funding for our citizens and companies". Zdravko Marić, Deputy Prime Minister and Minister of Finance of Croatia (Council of the European Union, press release, 24 June 2020, 14:00)

1 Introduction

Bank lending behaviour is inherently pro-cyclical (Gorton and He, 2008). During upswings of the business cycle, banks tend to overestimate the creditworthiness of their borrowers, resulting in possibly an *excessive* credit expansion, while they swiftly contract their credit supply during downturns. This feature may become critical when the economy is hit by an exogenous shock as the Covid-19 pandemic.

Various factors contribute to amplify the cyclicality of banks' lending. In particular, previous researchers have emphasised and analysed the role of accounting rules, financial innovation and model-based capital regulation. For example, accounting standards and an ex-ante approach to provisioning requirements yield to a situation where banks provision "too little" during booms while they are forced to quickly increase provisioning during recessions, constraining new lending and magnifying the credit cycle (Laeven and Majnoni, 2003; Saurina, 2009). Financial innovation and in particular securitization activities also amplify the cyclicality of banks' lending: securitization enables banks to sell illiquid assets and generate cash-flows that, in times of economic growth, can be used to boost new loans resulting in an increase in the credit supply (Loutskina and Strahan, 2009; Brunnermeier and Sannikov, 2014).

Model-based regulation for the calculation of capital requirements was the most important change in banking regulation introduced by the Basel II agreement. In contrast with the "one-size-fits-all" approach of Basel I agreement, the Basel II and successive amendments provided banks with the choice of using either the Standardised Approach (SA) or the Internal Ratings-Based (IRB) approach to calculate the minimum capital requirements. The SA approach entails a simpler methodology, whereby risk-weights (i.e., pre-determined by the supervisory authorities) are assigned to different categories of borrowers (e.g., banks, corporate, retail, etc). The IRB is a more sophisticated approach relying on banks' own (internal) models to calculate loan-specific risk-weights. Specifically, banks are allowed to use their own models, which have been *ex-ante* scrutinized and authorized by the supervisory authority, to estimate the credit risk parameters (such as probability of default and loss given default) that feed the regulatory formulas used to calculate risk weights and thus the minimum level of regulatory capital.

The rationale behind model-based regulation is to increase the risk sensitivity of capital requirements. At the same time, it has the potential to exacerbate business cycle fluctuations if banks using internal models respond more dynamically to changes in capital charges by adjusting their lending. During upswings of the business cycle, the favourable economic conditions result in low probability of default of borrowers and in low risk weights, while the credit risk parameters inevitably deteriorate during recessions, forcing banks to hold higher capital against their loan portfolio or to deleverage, ultimately worsening the initial downturn. In other words, IRB models may increase the risk of a credit crunch during bad times (see, Goodhart et al., 2004; Gordy and Howells, 2006, for a discussion of the pro-cyclical features of Basel). We focus our analysis on this aspect and provide empirical evidence that model-based regulation can indeed yield to lower credit granted by banks during a major external shock, like the Covid-19 pandemic.

This leads to the following question: Does model-based regulation generate a decline in credit supply at a time of crisis? Our paper addresses this question by exploiting the Covid-19 pandemic that provides us a *quasi natural* experiment setting since (i) Covid-19 is an exogenous shock and orthogonal to bank behaviour; (b) it is reasonable to expect that Covid-19 had a different impact (in terms of capital charges) on IRB and SA banks.

Our main result is that IRB banks have reduced On-Balance Sheet credit exposures, especially loans, to Non-Financial Corporations (NFCs) relative to SA banks in the aftermath of March 2020. Next, we further validate our results by providing evidence that the decrease in loans can be ascribed to a reduction in credit supply. We exploit a proprietary loan-level dataset on bank's large exposures, including virtually all bank-firm relationships either greater than €300 million or weighting more than 10% of banks' eligible capital. We can control for any demand shock by exploiting multiple bank-firm relationships (same firms borrowing at the same time from banks using different regulatory approaches). The results of the analysis further support the notion that

IRB banks have systematically reduced their exposures to large corporations more than SA banks after March 2020. Finally, we constrain our analysis to the sample of IRB banks and identify the determinants of the decrease in loan exposure for banks differently affected by the shock. We show that lower capitalised IRB banks decreased more their lending relative to more capitalized IRB banks. Exposure was reduced more towards borrowers for which credit risk mitigation was limited and for borrowers belonging to the industrial sectors most affected by the pandemic.

Our analysis is based on granular supervisory data covering a large sample of 250 Euro area banks (of which 70 banks using IRB models). As of end of 2019, banks in our sample have an overall asset size of 23.3 trillion (19.8 trillion for the 71 IRB banks), provide loans to the economy for 15.3 trillion (13 trillion from IRB banks) and loans to NFC for 5.3 trillion (4.6 trillion from IRB banks).

Our identification strategy relies on a Difference-in-Differences (DiD) setting around the time in which the Covid-19 pandemic erupted. First, we compare the lending behaviour of IRB and large SA banks. We analyse this with a bank-level analysis and with a loan-level analysis. In the latter, we are able to exploit multiple lending relationships of the same borrower to banks using different regulatory arrangements, therefore controlling for demand shock. Second, we focus only on IRB banks and we compare the lending behaviour of IRB banks with different amount of capital. Low capitalised banks are forced to reduce lending in a pandemic scenario, while higher capitalised IRB banks have the option to cover credit losses using their capital.

Our paper contributes to the vast literature analysing the relationship between bank regulation and bank lending (Bridges et al., 2014; Aiyar et al., 2014a,b; De Marco and Wieladek, 2015; Mésonnier and Monks, 2015; Jiménez et al., 2017; Acharya et al., 2018; Gropp et al., 2019; Cortés et al., 2020; Fraisse et al., 2020; De Jonghe et al., 2020a). Most of the analyses in this literature use as an identification device the shock caused by a regulatory increase in the minimum capital requirements. Capital requirements increments have been found to be followed by a reduction in corporate and household lending (Bridges et al., 2014; Aiyar et al., 2014a; De Marco and Wieladek, 2015) and cross-border lending (Aiyar et al., 2014b) in the UK. By contrast, the introduction of counter-cyclical capital buffers in Spain smoothed the credit supply cycles, sustaining lending to firms and employment in crisis periods (Jiménez et al., 2017). Banks participating in the European

Banking Authority capital exercise of 2011 reacted to higher capital requirements by reducing lending, rather than issuing new equity (Mésonnier and Monks, 2015; Gropp et al., 2019). In the same spirit, there is evidence of a decrease in corporate lending of French and Belgian banks as a result of higher capital requirements set by regulators (Fraisse et al., 2020; De Jonghe et al., 2020a). Higher capital requirements induced by stress-tests are also reported affecting banks' willingness to supply credit (Acharya et al., 2018; Cortés et al., 2020). The analyses reported in this paper substantially support the negative relationship between capital requirements and lending. However, we analyse the impact of capital regulation in the context of the models used for the evaluation of the risk-weighted assets. We show that banks following different regulatory approaches adjust differently their credit supply in response to a shock. These adjustments are directly related to the capital absorbed by the individual exposures, and suggest that model-based regulation induces a *quasi mechanic* reallocation of capital when confronted with significant exogenous shocks.

Our paper is also related to the few previous papers investigating the role played by model-based regulation (Behn, Haselmann and Vig, 2016; Behn, Haselmann and Wachtel, 2016; Bruno et al., 2017). Behn, Haselmann and Vig (2016) show the inaccuracy of model-based risk estimates that systematically under-predict actual default rates, and that both default rates and loss rates are higher for loans that were originated under the model-based approach. Exploiting an exogenous shock to credit risk in the German economy, Behn, Haselmann and Wachtel (2016) show the procyclical effect induced by model-based regulation on aggregate firm borrowing. Furthermore, Bruno et al. (2017) find that banks respond to shocks with a reshuffle towards less capital intensive activities, and this is more pronounced for banks using internal models. In line with this, we expect that IRB banks reacted to the Covid-19 pandemic shock quicker than SA banks. IRB banks, especially those with smaller capital ratios, have been constrained in lending during the Covid-19 pandemic in comparison to SA banks by the procyclical effect generated by the model-based regulation. Based on these past papers, our study is the first to document the credit crunch induced by the model-based capital regulation to the largest banks in the presence of a large exogenous shock (not a financial crisis which directly affects the stability of the banks). To this aim, we focus on the Euro area banks vis-à-vis large borrowers (including also non-domestic euro area borrowers).

We also contribute to the academic literature that focuses on lending during financial crises (Ivashina and Scharfstein, 2010; Puri et al., 2011; De Haas and Van Horen, 2013; Popov and Van Horen, 2015; Ongena et al., 2015), and the Covid-19 pandemic (Hasan et al., 2021; Dursun-de Neef and Schandlbauer, 2020). Following the Lehman Brothers collapse, US banks almost halved their lending to large corporates (Ivashina and Scharfstein, 2010), while they decreased less the lending to markets that were geographically close, where they were more experienced and where they operated a subsidiary (De Haas and Van Horen, 2013). Puri et al. (2011) reports that German savings banks affected by the US subprime mortgage crisis substantially rejected loan applications more than the non-affected banks after August 2007. Ongena et al. (2015) find that banks borrowing internationally decreased credit supply more towards small and medium-sized firms in Eastern Europe and Turkey than locally funded domestic banks during the financial crisis. Likewise, Popov and Van Horen (2015) show that the sovereign stress exported by GIIPS countries between 2009 and 2011 had a sizeable negative impact on bank lending of non-GIIPS countries.[1] Behn, Haselmann and Wachtel (2016), and Bruno et al. (2017) also take into account the lending reaction to financial shocks, but they distinguish between IRB and SA banks showing a decline in lending of IRB banks relative to SA banks following the collapse of Lehman Brothers in 2008 (Behn, Haselmann and Wachtel, 2016) and during the European Sovereign crisis (Bruno et al., 2017).

In this paper, we analyse the impact of model-based regulation during the Covid-19 crisis, an exogenous shock that it is not directly related to the financial health of banks. Hasan et al. (2021) show a rise in the pricing of syndicated loans as a result of an increase in borrowers and lenders' exposures to the pandemic while Dursun-de Neef and Schandlbauer (2020) document a higher loan supply by banks highly exposed to Covid-19.

In this pandemic crisis, banks have not been the main affected firms as in preceding financial crises, but rather they have been one of the key players in facing the Covid-19 negative effects by funding the economic agents hit by the pandemic. The need for maximizing the capacity of banks to lend money and support businesses to recover from the Covid-19 crisis was largely recognized by politicians, and resulted in the banking package adopted on June, 19$^{\text{th}}$ 2020 by the European Parliament providing temporary, targeted, and exceptional legislative changes to the European

[1] GIIPS countries refer to Greece, Ireland, Italy, Portugal and Spain.

capital requirements regulation.[2] As far as we are aware, our paper is the first in providing causal evidence that the rigidity imposed by model-based regulation (which has not been directly addressed by the EU banking package) constrained IRB banks in providing on-balance sheet loans to corporations. Second, all financial shocks analyzed by past papers called for a stricter regulation and, thus, the decline in lending could be considered a somehow intended consequence of having a model-based regulation. In the case of the Covid-19 shock, we document a decline in lending due to model-based regulation and, this is certainly an un-intended consequence of the rigidity imposed by a model-based regulation. Also, the magnitude of the Covid-19 shock is greater than any shocks previously analyzed and it calls for urgent analyses of any factor that may impede the extension of funds to corporations. To this aim, our paper provides important policy implications.

The rest of the paper is organized as follows. Section 2 describes the data and variables used. Our identification strategy is explained in Section 3. Section 4 discusses the results and outlines the policy discussion while finally, Section 5 presents additional identification strategies while Section 6 concludes.

2 Data and Variables

Our study uses two main types of data with two distinct levels of aggregation: bank and loan-level data. Bank-level data are obtained from the confidential FINREP ("FINancial REPorting") and COREP ("COmmon REPorting") supervisory data from the European Central Bank (ECB). The FINREP framework is intended for financial accounting reporting while COREP is the framework for the capital and funding adequacy regime envisaged by Basel III regulation. As such, these data contain detailed information on the consolidated and unconsolidated financial statements and capital adequacy of virtually all Euro area credit institutions on a quarterly basis. We compile the final bank-level dataset in the following way. First, we exclude from our analyses subsidiaries

[2]The targeted amendments concern: (i) changes to the minimum amount of capital that banks are required to hold for non-performing loans (NPL) under the "prudential backstop"; (ii) the extension by two years of transitional arrangements related to the implementation of the international accounting standard IFRS 9; (iii) the temporary reintroduction of a prudential filter for sovereign bond exposures; (iv) the exclusion of "overshootings" in banks' internal models for market risks to mitigate negative effects of the extreme market volatility observed during the Covid-19 pandemic; (v) targeted changes to the calculation of the leverage ratio and a delay in the introduction of the leverage ratio buffer by one year to January 2023; (vi) transitional arrangements for exposures to national governments and central banks denominated in a currency of another member state, in order to support funding options in non-euro member states mitigating the consequences of the Covid-19 pandemic; (vi) the earlier introduction of some capital relief measure for banks under Capital Requirements Regulation 2, most notably with respect to preferential treatment of certain loans backed by pensions or salaries and their SMEs and infrastructure loans, thus encouraging the credit flow to pensioners, employees, businesses and infrastructure investments.

and foreign-owned banks.[3] Secondly, we keep the consolidated statements of banks, unless banks exclusively report at unconsolidated level.[4] Finally, we remove from our sample those banks that lack data on total assets, equity and net income or with total asset below €1 billion. This yields to a final sample of 250 banks classified either as ultimate parent or stand-alone banks across 17 countries (see Table 1). Table 1 shows the sample composition by reporting the number of banks used for our bank-level analyses by country and by the approach used to determine the minimum capital requirements. It is worth clarifying that, throughout the rest of the paper, banks are classified as IRB is they use their own internal models to calculate capital charges for their *corporate* credit exposures.

[Insert Table 1 here]

For our analyses at loan-level, we exploit the unique dataset constituted by the microprudential supervisory framework on "Large Exposures". In 2014, the Basel Committee on Banking Supervision (BCBS, henceforth) set out the large exposures framework to complement risk-based capital requirements as the latter do not protect banks from large losses resulting from the sudden default of a single counterparty or group of connected counterparties. According to this supervisory framework, an institution's exposure is defined as "large" when, before applying credit risk mitigations and exemptions, it is equal or higher than 10% of an institution's eligible capital *vis-à-vis* a single client or a group of connected clients.[5,6,7] Credit institutions reporting FINREP supervisory data are also requested to report large exposures information with a value above or equal to EUR 300 million.[8]

The use of loan-level data on large exposures provides three important advantages. First, while bank-level data enable us to estimate differential changes between IRB and SA banks, they do not allow us to disentangle changes due to credit supply effects from changes due to credit demand effects. We address this shortcoming using data at loan level and building an identification strategy based on multiple-lending relationships, which enables us to establish whether variations in credit

[3]We keep in our sample six subsidiaries of foreign-owned banks as these banks are classified as Significant Supervised Entities by the ECB.

[4]This is often the case of smaller credit institutions that are not part of any banking group.

[5]The large exposure limit is set at 25% of a bank's eligible capital or 15% for exposures among GSIBs.

[6]Eligible capital is defined as the sum of Tier 1 capital plus one-third or less of Tier 2 capital (CRR , Art.4(71)).

[7]The European Union implemented Basel III regulation via the Capital Requirements Regulation (CRR) and Capital Requirements Directive IV (CRD IV) of 26 June 2013. The Framework for Large Exposures can be found in Articles 387 to 403 of the CRR. In particular, the definition of Large Exposures is provided by Art. 392.

[8]The data on "Large Exposures (LE)" are part of the COREP supervisory reporting framework and are included in the templates C.27 to C.31. For this study, we use the template LE1 (C.27): identification of the counterparty, and LE2 (C.28): exposures to individual client and group of connected clients.

exposures are due to a decision of IRB banks (credit supply shock). Second, these loans refer to large borrowers that are strategically important for banks and are those that one can expect to see modified first after the eruption of the Covid-19 pandemic in March 2020. Banks will either increase lending to support their important customers (large borrowers in a time of crisis) or decrease it to relief equity capital pressures. Finally, these data allow us to work with a global sample of borrowers, which is a major advantage compared to the use of national credit registries.

The construction of our database involved a significant work in matching different samples and databases.[9] We proceed in three steps. First, we exploit the (limited) available data on the counterparties and we merge the data using the LEI code of the borrower with Bureau van Dijk's Orbis data. This first steps allows us to identify non-financial corporations (NFCs) by filtering out (i) public sector borrowers, such as general governments, central banks and municipalities, (ii) financial sector borrowers, including credit institutions and financial corporation (e.g., mutual funds and insurances) and (iii) households. Furthermore, a successful match with Orbis enriches the data with information on the country and NACE sector of the counterparty. In the second step, we manually map the remaining counterparties lacking the LEI code across banks and across countries using the counterparty name as reported by the credit institutions and we fill the missing information using several sources such as gleif.org and SNL. Finally, we drop from our sample those borrowers for which we completely lack information on the sector, thus limiting the risk of including exposures other than NFCs. To the best of our knowledge, we are the first to exploit these data to explore the lending dynamics of Euro area banks.[10]

3 Identification strategy

The Covid-19 pandemic is a natural disaster that has been hitting Europe since March 2020 and it provides a very interesting setting to investigate whether banks using different capital regulation calculation methods changed their lending portfolio in a different way.[11] As shown by past papers

[9]The COREP supervisory framework "Large Exposures" requires banks to provide the following information on the counterparty: the unique borrower identifier, name, Legal Entity Identifier (LEI code), country, sector, and NACE classification of the borrower. However, the majority of exposures lack of these qualitative information, with the unique identifier and name of the borrower being often the only information identifying the counterparty. Furthermore, as per regulation, the unique borrower identifier depends on the national reporting system. In practical terms, this implies that a borrower cannot be uniquely identified when the lenders are from different countries.

[10]Covi et al. (2021) use the "Large Exposure" data to document the degree of interconnectedness and systemic risk of the euro area banking system, thus focusing on interbank exposures rather thank bank-firm relationships.

[11]Banks' capital requirements are a function of banks' total risk-weighted exposures, which, in a simplistic way, can be divided into credit (CR), market (MK) and operational (OP) risk exposures. For the calculation of capital

(Danielsson et al., 2001; Kashyap and Stein, 2004; Repullo and Suarez, 2013), the introduction of internal-rating models increased the pro-cyclicality of bank lending. Therefore, IRB banks may be unable to lend to non-financial corporations, just at the time when firms would need it the most, due to features of the regulation. Our identification strategy relies on a difference-in-differences (DiD) approach enabling to test whether, after the outbreak of Covid-19 in March 2020, there are differences in the growth rates of on- and off-balance sheet credit exposures between banks using IRB or SA models.

Specifically, our identification strategy is based on the following DiD model:

$$\begin{aligned}\Delta Log(Y)_t = \beta_1 IRB_i \times Post_t + \beta_2 Size_{i,t-1} + \beta_3 Size_{i,t-1} \times Post_t + \\ \beta_4 Capital_{i,t-1} + \beta_5 Capital_{i,t-1} \times Post_t + \beta_6 X_{i,t} + \gamma_i + \gamma_{c\times t} + \epsilon_{i,t}\end{aligned} \tag{1}$$

where our dependent variable ($\Delta Log(Y)_t$) is the quarter-on-quarter growth rate of credit exposures volume. We use various measures of on- and off-balance sheet credit exposure to gain a broad understanding of the impact of Covid-19. We begin our analysis using a broad measure including all on- and off balance sheet credit exposures (*Total Credit Origination*).[12] In a second step, we disentangle this measure in *Total On-Balance Sheet*, and *Total Off-Balance Sheet* credit exposures. For each of these variables, we also distinguish between credit exposures towards Non-Financial Corporations (NFCs) and other than Non-Financial Corporations (Non-NFCs).[13]

Importantly, we run our DiD model in two steps: first, we use data at the bank-level, then we replicate our model using loan-level data. The first sample enables us to identify whether IRB banks dropped their lending more relative to SA banks: the dependent variable is thus measured by the quarter-on-quarter growth rate of credit exposures volume by of bank i ($\Delta Log(Y)_{i,t} = Log(Y_{i,t}) - Log(Y_{i,t-1})$). In the second step of our analysis, we use loan-level data (focusing on *large exposures*, those that are the most likely to react to Covid-19 pandemic): the dependent variable is measured by the quarter-on-quarter growth rate of credit exposures volume by the bank i to the borrower j ($\Delta Log(Y)_{i,j,t} = Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). We restrict our sample to firms with multiple-lending relationships (a company that borrows at the same time from various banks

charges due to OP risk, banks are obliged to use the standardised approach, whereas for CR and MK risk, banks can choose to rely on their own internal models.

[12]We thank Philip Strahan for this suggestion

[13]Non-NFC includes exposures to governments, credit institutions, other financial institutions and households.

using different regulatory approaches) to control for any demand shock and assess whether the lending changes (observed in the first step of our analysis) are due to a supply (bank) effect.

The time period considered includes four quarters before and two quarters after March 2020. Thus, our treatment period variable (*Post*) takes the value of 1 for the quarters 2020Q2-2020Q3, and zero for 2019Q2-2020Q1[14]. The treatment group is composed by banks using internal models: the variable *IRB* takes the value of one if the bank uses internal models for the calculation of capital requirements for their *corporate* credit risk exposures, and zero otherwise. We also include a vector of bank characteristics (X) that could affect bank lending behaviour. We control for bank' size using the natural logarithm of total asset (*Size*) while the percentage of equity over assets is included to control for moral hazard incentives due to banks having less "skin-in-the-game" (*Capital*). We also include the interactions $Size \times Post$ and $Capital \times Post$ to control for the fact that the reaction to Covid may be driven by the size or capitalization of banks.[15] Bank profitability is controlled for with the inclusion of return on assets (*ROA*), while the ratio of deposits over liabilities proxies for the funding preferences of banks (*Deposit Ratio*). Finally, the RWA density (*RWA Density*), calculated as the ratio between total RWA and total exposures, controls for banks' risk profile. These control variables are lagged by one quarter to reduce possible endogeneity concerns. ϵ is the error term. All variables used in the paper are summarized in Table 2.

[Insert Tables 2 Here]

To account for unobservable factors, we use a set of fixed effects (FE). First, we include bank fixed-effects (γ_i) to control for unobserved firm fundamentals. Furthermore, in our richest specification, we saturate the regressions with *country* $\times$ *time* fixed effects (γ_{cxt}) to control for demand effects.[16] Demand fixed-effects are necessary to account for demand-driven differences across European banks. This is especially important in light of the great heterogeneity in terms of government responses across Europe during the Covid-19 pandemic, which may have resulted in different demand conditions.

[14] As a robustness check, we run again the model in Eq. (1) by omitting the 2020Q1 (when the Covid-19 pandemic started in Europe), and we compare lending during 2019 with the second and third quarter of 2020. While it is difficult to pinpoint an exact day for the start of the pandemic crisis in Europe, several papers use the 21st of February 2020 as a reference date, when several municipalities in Northern Italy entered lockdown (Albuquerque et al., 2020; Ramelli and Wagner, 2020).

[15] We thank Philip Strahan for this suggestion.

[16] The country refers to the country where the bank is headquartered

Bertrand et al. (2004) show that the persistence of the treatment variable in a DiD setup induces serial correlation in the regression error within treated units. To adjust for this serial correlation, we cluster standard errors at the bank level.

4 Results

In this section, we present our results. First, we discuss preliminary analyses to show the features of our sample and test differences between IRB and SA banks prior the Covid-19 shock. Second, we discuss whether the Covid-19 shock generated a different impact on lending for IRB and SA banks using bank-level supervisory data. Third, we exploit the loan-level data on large exposures and we investigate whether lending changes in IRB banks in the aftermath of March 2020 are due to a decision of IRB banks (supply-side effect).

4.1 Preliminary Analyses

In this section, we report the summary statistics for all variables used in our empirical analyses and we text differences between IRB and SA banks prior the Covid-19 shock.

The descriptive statistics are reported in Table 3 for both bank-level (Panel A) and loan-level variables (Panel B). Banks using SA model display an increase in total credit origination, on-balance sheet exposures and lending activities between 2019Q2 and 2020Q3, while IRB banks generally show lower mean growth rates in each variable than SA banks. In Panel C, we report the summary statistics of our control variables. IRB banks show (on average) a greater size that SA banks. However, SA banks have greater profitability and capital levels and higher ratios of deposit funding and RWA density than IRB banks.

[Insert Table 3 here]

The difference-in-differences estimator relies on two main assumptions: the treatment must be orthogonal with respect to the outcome variables, and treated and untreated banks must satisfy the parallel trend assumption. Given the nature of the Covid-19 shock, we assume that the pandemic was exogenous and not caused by the outcome of interest, and we provide evidence to support the parallel trends assumption between the treatment and control groups. Specifically, we compare the growth of our main variable of interest - loans to NFC - for banks using an IRB-approach (treatment group) and for those using the SA approach (control group) over the four quarters pre-treatment. Our objective is to assess whether, in the quarters prior to the outbreak of the pandemic, IRB and SA banks are comparable. Table 4 reports the mean growth rates between banks in the control and treatment groups (columns (3) and (4), respectively). Column (5) shows that the difference-in-means for NFC credit exposure measures for the treatment groups are largely statistically indistinguishable from the control group prior to the Covid-19 pandemic development in Europe. Differences in means are instead significant for the post quarters. These results provide evidence that the parallel assumption condition is met, and this is particularly important for safely run our DiD models, especially since our selection criteria is somehow endogenous (the decision of using IRB approach is granted by the supervisory authority on banks' request).

[Insert Table 4 here]

4.2 Did banks using internal models decrease their lending more relative to other banks?

Did banks using internal models decrease their lending more relative to other banks? In this section, we answer this question using bank-level supervisory data. Specifically, we compare whether, after the Covid-19 pandemic eruption in March 2020, there are differences in the growth of credit exposures between banks adopting an IRB or a SA approach. Table 5, Table 6 and Table 7 report the results obtained running the model in Eq.(1).

First, we run our analysis focusing on *Total Credit Origination*, that is an overall measure of credit provided by banks to a corporation (all on- and off-balance sheet credit exposures). In Table 5, we report the findings concerning all borrowers (columns (1)-(2)), and then we disentangle the total credit origination between Non-NFC borrowers (columns (3)-(4)) and NFC borrowers (columns (5)-(6)) . The coefficient of main interest is the interaction variable $Post \times IRB_i$, showing the Average Treatment Effect (ATE) due to the Covid-19 pandemic for IRB banks. We do not find evidence that, after March 2020, banks using IRB models experienced a different growth rate on *Total Credit Origination* compared to banks using the SA approach (Column 1 and 2 in Table 5). The situation is different when we disentangle the borrowers' industry. In columns 5 and 6 of Table 5), we observe a clear decline in total credit origination to NFC (approximately -1.7%), suggesting the IRB banks reduced more their overall exposures to NFCs compared to SA banks. We do not find any statistically significant difference in *Total Credit Origination* to non-NFCs. Our results suggest that Covid-19 did not produce an effect in inter-bank lending and lending to Government and other borrowers, but the IRB drop is to NFC companies, as manufacturing, food and beverage, and transportation companies.

[Insert Table 5 here]

We continue our analysis by investigating the changes in overall on-balance sheet exposures of IRB and SA banks following March 2020.[17] By progressively disentangling *Total Credit Origination*, we aim to check whether the observed decline in IRB overall exposures towards NFC concretely reflected in a lower growth in lending.

The results, reported in Table 6, show a decline (-1.8%) in the growth of total On-Balance Sheet exposures toward NFC for banks using IRB models compared to SA banks (columns 5 and 6). In line with the findings of Table 5, we do not find a similar drop for on-balance sheet exposure to all borrowers and Non-NFC (columns 1 to 4 in Table 6). We also explore banks' behaviour with respect to off-balance sheet exposures. In this regard, we do not find evidence that IRB banks have changed off-balance sheet credit exposures (both to NFC and non-NFC) relative to SA banks (the results are reported in Table A1 in Appendix).

[Insert Table 6 here]

In our last analysis using bank-level data, we investigate changes in bank willingness to extend bank loans. In Table 7, we document an overall decrease in the growth rate of bank lending of IRB banks compared to SA banks (column 1 and 2). Not surprisingly, when we disentangle the loans according to the type of borrowers, we find that the observed overall decline is driven by lower credit granted to NFC (approximately -1.9%, column 7 and 8), whereas we do not report a similar drop for loan to Non-NFC or retail borrowers (columns3 and 4).

[Insert Table 7 here]

The inclusion of the interactions between the treatment period variable and banks' size and capitalization ($Post \times Size$ and $Post \times Capital$, respectively) enables us to control for the fact that IRB banks - being usually larger and more capitalized banks with more developed risk management departments - realized the disruptive effects of Covid-19 on the economy before SA banks, resulting

[17] On-Balance Sheet credit exposures include loans and securities held, equity instruments and derivatives assets.

in IRB banks cutting their lending faster than other institutions. Interestingly, we find no evidence supporting the notion that banks' size and capitalization played a significant role after the eruption of the Covid pandemic. In the entire set of analyses at bank-level (Tables 5, 6, and 7), these interactions are insignificant in explaining credit exposures growth. To further check this important issue, we replicate our analyses by omitting from the sample the first quarter of 2020 (when the Covid-19 was at its early stages and SA banks may have not understood its impact on the economy) and comparing the lending behaviour of IRB banks and SA during 2019 (pre-treatment period) and the second and third quarter of 2020 (treatment period), when the impact of Covid-19 was widely realized by all banks. The results from re-running the model in Eq.(1) with the new pre-treatment period are reported in Table 8. Interestingly, we show that, during the second and third quarter of 2020, IRB banks have substantially decreased their total credit origination to NFC (-1.5%), on-balance sheet exposures to NFC (-1.6%), and loans to NFC (-1.7%) compared to SA banks. Our results strongly confirm the observed decline in credit supply by IRB banks compared to SA banks after March 2020 suggesting that the difference is not due to a quicker reaction of IRB banks to the Covid-19, rather it is a persistent effect over the entire 2020, and it is driven by the use of internal models contributing to the pro-cyclicality of lending.

[Insert Table 8 here]

To sum up, we show IRB banks dropped their on-balance sheet exposures to NFC, especially loans, after the outbreak of the Covid-19 pandemic in Europe.

4.3 Is the lending decline due to a decision of IRB banks?

In this section, we investigate whether the overall reduction in loans and securities investments of IRB banks relative to SA banks in the aftermath of March 2020 is due to a decision of IRB banks (supply-side effect). Our identification strategy is based on the usual selection criteria (IRB and SA banks, respectively), while the main difference is related to the use of loan-level data (the ECB confidential supervisory dataset on "Large Exposures") to capture the net effect of banks' actions on the supply of loans, while holding borrowers' characteristics constant. We focus on large exposures as these credit exposures are those absorbing the largest amount of bank equity capital, and thus we could rationally expect that, after the Covid-19 shock, banks try to adjust their lending starting from these exposures.[18]

We run the model in the Eq.(1) using a sample of data at loan-level (bank-borrower relationship). Specifically, building on the methodology of Khwaja and Mian (2008), we restrict our sample to firms with multiple-lending relationships, thus focusing on those companies that borrow at the same from (at least) one IRB bank and (at least) one SA banks. Adopting such a strategy is important in our setting to isolate credit supply changes from shifts in loan demand generated by a demand shock during the Covid-19 pandemic. In other words, by focusing on multiple-lending relationships and including for $Borrower \times Time$ fixed effects, we control for any time-varying unobserved firm characteristics and any observed change in the amount that banks lend can be attributed to credit supply effects.

Given that an exposure is classified as "large" if it is above a specific threshold (i.e., %10 Tier 1 ratio or above EUR 300 million), it may be the case that the bank-firm relationship is not observed throughout the six quarters considered for our regressions (i.e., the relationship is not observed if the value of the exposure falls below the threshold(s)). To avoid potential issues related to observations falling out of the sample due to the threshold, we restrict our analyses to bank-firm relationships that can be observed for the entire period.[19]

As in section 4.2, we initially focus on *Total Credit Origination*. The coefficient of main interest is the interaction variable $Post \times IRB_i$, showing the Average Treatment Effect (ATE) due to the Covid-19 pandemic for IRB banks. We do not find evidence that, after March 2020, Covid-19 produced a differential effects in the growth of *Total Credit Originated* by IRB banks relative to SA banks (see Table 9).

[Insert Table 9 here]

Next, we distinguish between On- and Off-Balance Sheet credit exposures and we report the findings in Panel A and Panel B of Table 10, respectively. The results for large on-balance sheet exposures are strongly consistent with the results obtained using bank-level data (Tables 6, 7, and 8). In fact, we show a substantial decline in total On-Balance Sheet large exposures (-8.8%) and

[18] As defined by BIS (2018), large exposures are the sum of all exposures of a bank to a single counterparty that are equal to or above 10% of its Tier 1 capital. Banks also have to report to national supervisors: (a) all other exposures that would have been a large exposure without considering the effect of credit risk mitigation or exemption clauses; (b) the 20 largest exposures even if they do not satisfy the definition of a large exposure. Credit institutions reporting FINREP supervisory data are also requested to report large exposures information with a value above or equal to EUR 300 million

[19] We thank Steven Ongena for raising this point.

large loans and securities exposures (-10.5%), thus suggesting that IRB banks have a lower growth rate relative to SA banks (Panel A of Table 10). Importantly, the results reported in Table 10 are obtained using a sample of multiple-lending relationships that allow to control for borrowers demand, thus drop in credit exposures can be attributed to a supply effect. Results for Off-Balance Sheet large exposures (Panel B of Table 10) show an opposite situation: IRB banks reacted to the shock by increasing more their off-balance sheet credit exposures (7.6%, as shown in column 3), especially loan commitments (13.8%, as shown in column 6), relative to SA banks. These positions do not directly absorb regulatory capital and, thus, banks are able to support borrowers (especially NFC) by increasing off-balance sheet exposures and gaining higher fees without an immediate impact on equity.

[Insert Table 10 here]

To sum up, we provide robust evidence that the observed lower on-balance sheet growth rate of IRB banks in comparison to SA banks is driven by a bank decision. Thus, we can rule out that our results are driven by the Covid-19 generating an immediate demand shock and we conclude that the reduction in lending can be attributed to a supply effect.

5 Alternative identification strategies

The identification strategy in previous sections is based on comparing the lending behaviour of IRB and large SA banks. In this section, we change our identification strategy and we focus exclusively on the sample of banks using IRB models. This empirical strategy allows us to compare banks that are similar vis-a-vis the supervisory authority's eyes, having their internal models been scrutinized and validated. Additionally, this alternative identification enables us to account for the fact that IRB banks can have greater access to an internal capital market and better survive in times of crisis (as shown by Santioni et al. (2020) for the global financial crisis).

Specifically, we compare the lending behaviour of IRB banks with a lower and greater amount of capital. For this exercise, we include in our treatment (control) group those banks reporting a below (above) the median CET1 Ratio as of 2019Q2. The rationale behind this identification strategy is that the level of equity capital is likely to have played a key role in banks' reaction to the Covid-19 pandemic. Banks operating with capital levels close to the minimum regulatory requirements are forced to reduce lending in a pandemic scenario. By contrast, a higher amount of capital ensures that banks can cover losses with the capital surplus and they can support lending.

As such, we replicate the loan-level analysis (as illustrated in Section 3) by running the model in the Equation (1). First, we test whether the parallel trend assumption between the treatment and control groups is supported by comparing the growth of large exposures lending to NFC quarter-by-quarter for banks with a low- and high- CET1 Ratio. Table 11 presents the results using difference-in-means estimations prior to the Covid-19 shock. Banks in the control and treatment groups are largely statistically indistinguishable in the run up to the Covid-19 eruption.

[Insert Table 11 here]

As per Section 4.3, our sample is based on multiple-lending relationships, where we impose the condition that the firm has to be associated with (at least) one bank with high CET1 Ratio and (at least) one with low CET1 Ratio. Firstly, we report our results focusing on a broad measure of bank credit exposures (*Total Credit Origination*) including all large On- and Off-Balance Sheet exposures. Consistently with the results obtained for our main identification (Table 9), we do not find evidence that, after March 2020, low capitalised IRB banks experienced a different growth rate on *Total Credit Origination* compared to banks with a higher amount of own funds. (Table 12).

[Insert Table 12 here]

Interestingly, we find different results when disentangling *Total Credit Origination* into On- and Off-Balance sheet credit exposures. Low capitalised IRB banks show a lower growth rate of large on-balance sheet credit exposures (-3.5%) and large loans (-5.3%) relatively to IRB banks with more equity capital (see Panel A of Table 13). These findings confirm our hypothesis that IRB banks with more capital were able to support their lending to firms during a pandemic, while capital constrained IRB banks were forced to reduce their exposures to avoid violating minimum capital requirements. These results are strongly consistent with those reported in the Table 10. The smaller magnitude of the coefficient estimates is not surprising, and it is due to the greater similarity between treated and control groups in this alternative identification strategy. Panel B of Table 13 show that there is not difference in the growth rate of Off-Balance Sheet credit exposure between IRB banks with more and less capital.

[Insert Tables 13 here]

Finally, we explore how IRB banks with a lower CET1 selected the borrowers to which reduce their exposure. Specifically, we investigate three sources of heterogeneity: i) the capital absorption of each exposure, ii) borrowers' industry (Covid-19 affected vs non-affected sectors), and iii) borrowers' country (domestic vs. non-domestic). First, we study whether IRB banks reduce exposures with higher capital absorption. To this end, we augment the DiD specification of Eq.(1) with a triple' interaction term capturing the riskiness of the loan ($Post \times LowCap \times CRM$). Credit Risk Mitigation (CRM) techniques refer to institutions' guarantees, credit derivatives, on-balance sheet netting and financial collateral agreements used to reduce the credit risk associated with an exposure. Using Large Exposures data, we are able to calculate a CRM factor for each loan exposures by dividing the value of the exposures after the application of CRM by its total original value. To exemplify this, a CRM value of 1 implies that the exposure does not benefit from any credit risk mitigation, and the entire original value of the exposure needs to be considered for the calculation of capital requirements.[20] We use the CRM factor calculated as of 2019Q2 as a proxy for the riskiness of the credit exposures pre-shock, where the higher the CRM, the riskier is the exposure. Panel A Table 14 reports our triple DiD results. The coefficient of main interest is the triple interaction ($Post_t \times IRB\_CR_i \times CRM_j$). We observe a negative and strongly statistical significant coefficient for loans and securities (Columns 4 to 6). This suggests that, after March 2020, low capitalized IRB banks cut more their exposures towards borrowers absorbing more capital than high capitalized banks. This is consistent with the notion that model-based capital regulation induces cyclicality in bank lending, especially during crisis times, as IRB banks react quickly to adverse macroeconomic scenarios feeding into their regulatory models.

[Insert Table 14 here]

In a similar fashion, we run a triple DiD to explore whether low capitalized IRB banks dropped their lending relative to banks with higher capital in the economic sectors most affected by the pandemic. As usual, we augment the DiD specification of Eq.(1) with an interaction term ($Most\_Affected$) capturing whether the borrowers is in an economic sector most affected by the pandemic. Specifically, the variable $Most\_Affected$ is a dummy variable taking the value of one if

[20] For example, we observe in our data an original credit exposure of €100 million, which becomes €80 after the application of CRM, yielding to a CRM of 0.8.

the borrower belongs to one of the sectors identified by the European Banking Authority (2020) as being the most affected from the pandemic, including: Manufacturing; Energy Supplier, Construction, Wholesale and Retail Trade; Accommodation and Food Services; Transport and Storage; Business and Administrative Activities; Arts, entertainment and recreation.[21] Not surprisingly, the results in Panel B of Table 14 show that, after March 2020, IRB banks with low capital levels have decreased their loans and securities exposures (Column 4 to 6) towards the most affected sectors of the economy more than highly capitalized banks. The results are strongly consistent across the different fixed effects specifications employed.

The third dimension investigated is the borrowers' country. Specifically, we explore whether, following a shock, banks differentiate between domestic and non-domestic borrowers. To this end, in Panel C of Table 14, we include a triple interaction where $Domestic_j$ takes the value of one if the headquarter of the firm coincides with the country where the bank is headquartered, and zero otherwise. Interestingly, we do not find any evidence of retrenchment. Unlike other studies (Giannetti and Laeven, 2012), there is no evidence of a *flight home* or portfolio rebalancing towards banks' domestic market after a shock.

To sum up, our triple DiD analysis enables us to show that the decline in lending of IRB banks with low capital relative to IRB banks with higher capital did not affect all borrowers, rather it focused on credit exposures with a limited impact of credit risk mitigation techniques, and credit exposures toward borrowers in the economic sectors most affected by the pandemic.

6 Conclusions

Does model-based capital regulation constrain lending when it matters the most? Our paper answer this question. By using the Covid-19 pandemic as an exogenous shock, we examine whether model-based capital regulation affects the supply of loans.

Bank behaviour is inherently pro-cyclical (Gorton and He, 2008) and the choice granted to banks to use their internal models for the calculation of minimum capital requirement for credit risk further increases lending pro-cyclicality. This feature can become very critical when the economy is suffering a recession or is hit by catastrophic events, as the Covid-19 pandemic. In such instances,

[21] Given this classification, the borrowers with the following NACE codes as classified as "high risk" and thus take the value of one: C,D,F,G,H,I,N,R.

it is critical that the banking system works effectively to ensure the intermediation of funds toward firms that are still viable but may have temporary funding needs. Overall, we document a reduction in On-Balance Sheet credit exposures, especially loans, to NFCs of banks using internal models compared to banks using fixed risk-weights after March 2020. By drawing on a unique loan-level dataset on large exposures (greater than €300 million or 10% of a bank's Tier 1 equity capital) of Euro area banks, we confirm these findings and, especially, we show that this decline is driven by supply-side effects. Specifically, we focus on a sample of firms with multiple-lending relationships where borrowers received funds from at least one IRB bank and one SA bank and we document that IRB banks declined On-Balance Sheet credit exposures to NFCs in comparison to SA banks. In a following analysis, we focus on a sample of IRB banks and we distinguish between banks with high and low capital levels. Our results indicate that, after March 2020, banks closer to minimum capital requirements had a more pronounced decrease in lending compared to banks with higher capital. We also show that the contraction in the credit supply of low capitalized IRB banks did not affect all borrowers, rather it focused on credit exposures with a limited impact of credit risk mitigation techniques, and credit exposures toward borrowers in the economic sectors most affected by the pandemic. These findings are consistent with the view that IRB models increase pro-cyclicality in banking and place emphasis on the need to further calibrate and validate IRB models to prevent excessive fluctuation around the business cycle, especially when the economy is severely hit by a catastrophe, as the Covid-19 pandemic.

Our results have important policy implications since we empirically document the negative (unintended) consequences of banking regulation which inherently creates incentives for quick adjustments of the credit supply in the face of important exogeneous shocks. Importantly, the economic detriment induced by model-based capital regulation during catastrophic events regards the largest banks in the industry and may have significant consequences for the financing of the corporate sector.

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Tables

Table 1: Number of banks by country and capital requirement approach

Country	Total	Standardised Approach	Internal-Rating Based Approach
Austria	20	17	3
Belgium	7	3	4
Cyprus	3	3	-
Germany	95	78	17
Estonia	3	1	2
Finland	10	6	4
France	14	7	7
Greece	6	5	1
Ireland	4	1	3
Italy	32	23	9
Latvia	4	2	2
Lithuania	3	1	2
Luxembourg	8	5	3
Malta	2	2	-
Netherlands	11	5	6
Portugal	6	5	1
Spain	22	16	6
Total	250	180	70

This table presents the number of banks used in our empirical analyses by country and according to whether they use the Standardised Approach (SA) or the Internal-Rating Based Approach (IRB) for the calculation of corporate credit risk.

Table 2: Definitions of Variables

Variable	**Definition**
Panel A. Outcome Variables	
Total Credit Origination	The sum of all On-Balance Sheet and Off-Balance Sheet Exposures of bank i.
On-Balance Sheet Exposures	The sum of all on-balance sheet exposures of the bank i, comprising, total loans, total securities, total equity instruments and total derivative assets.
Total Loans	The sum of all loans of bank i, comprising credit card debt, trade receivables, finance leases, reverse repurchase loans, other term loans, advances.
Off-Balance Sheet Exposures	The sum of all off-balance sheet exposures of bank i, comprising loan commitments, financial guarantees and other commitments.
Loan Commitments	The sum of all commitments of the bank i to provide credit under prespecified terms and conditions (e.g., acceptances, forward deposits, undrawn credit facilities).
Panel B. Control Variables	
Total Assets (Log)	Natural logarithm of total assets of the bank i.
Capital (%)	The ratio of total equity to total assets of bank i expressed as a percentage.
ROA (%)	Return on assets of bank i, calculated as net income divided by total assets.
Deposit Ratio (%)	Current, overnight and redeemable at notice deposits of bank i as a percentage of total liabilities.
RWA Density (%)	Total risk-weighted assets of bank i as a percentage of total original exposures.

This table provides the definitions of the variables used in our empirical analysis. All the definitions are taken from FINREP and COREP supervisory reporting frameworks.

Table 3: Summary Statistics of SA and IRB banks

	Standardised Approach				**Internal-Rating Based Approach**			
	N	Mean	Median	SD	N	Mean	Median	SD
Panel A. Outcome Variables at Bank-level (Growth Rates)								
Total Credit Origination (All Borrowers)	1080	0.0137	0.0090	0.0467	420	0.0060	0.0062	0.0395
Total Credit Origination (Non-NFC Borrowers)	1080	0.0140	0.0083	0.0721	420	0.0051	0.0070	0.0753
Total Credit Origination (NFC Borrowers)	1080	0.0196	0.0115	0.1407	420	0.0054	0.0051	0.0495
Total On-Balance Sheet (All Borrowers)	1080	0.0125	0.0090	0.0474	420	0.0060	0.0049	0.0409
Total On-Balance Sheet (Non-NFC Borrowers)	1080	0.0132	0.0079	0.0719	420	0.0069	0.0072	0.0578
Total On-Balance Sheet (NFC Borrowers)	1080	0.0180	0.0115	0.1466	420	0.0043	0.0047	0.0540
Total Loans (All Borrowers)	1080	0.0106	0.0102	0.0618	420	0.0041	0.0043	0.0372
Total Loans (Other Borrowers)	1080	0.0594	0.0388	0.2269	420	0.0521	0.0392	0.1596
Total Loans (Retail Borrowers)	1080	0.0095	0.0086	0.0631	420	0.0018	0.0079	0.1455
Total Loans (NFC Borrowers)	1080	0.0162	0.0101	0.1328	420	0.0056	0.0066	0.0534
Panel B. Outcome Variables at Loan-level (Growth Rates)								
Total Credit Origination	448	0.0009	0.0000	0.0575	1470	0.0025	0.0062	0.1153
Total On-Balance Sheet	376	-0.0039	-0.0027	0.1038	1140	0.0067	0.0019	0.2328
Total Loans & Securities	376	0.0008	-0.0036	0.1493	1140	0.0146	-0.0017	0.2509
Total Off-Balance Sheet	246	0.0123	0.0000	0.3057	978	0.0147	0.0000	0.1436
Total Loan Commitments	246	0.0046	0.0000	0.5202	978	0.0101	0.0000	0.2258
Panel C. Control Variables								
Total Asset (Log)	1080	22.9946	22.8490	0.8059	420	25.2947	25.1391	1.5677
Equity Ratio (%)	1080	8.9210	8.7510	2.8396	420	7.5925	6.7914	2.8842
ROA (%)	1080	0.5668	0.5577	0.2224	420	0.5172	0.5075	0.1937
Deposit Ratio (%)	1080	86.5448	93.2632	15.3167	420	71.9651	71.0663	16.3200
RWA Density (%)	1080	39.0801	40.4030	9.9258	420	26.7971	25.4464	6.9811

This table provides the summary statistics (number of observations (N), mean, median and standard deviation (SD)) for the variables used in the paper according to whether banks use the Standardised Approach (SA) or Internal-Rating Based (IRB) Approach for the calculation of capital requirements. All the variables in Panels A and B are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). Panel A provides the summary statistics for the outcome variables used in the bank-level analysis. Panel B reports the summary statistics for the outcome variables used in the loan-level analysis. Panel C shows the summary statistics for the control variables. Variables are defined as is Table 2.

Table 4: Difference in Means between SA and IRB banks

Variable	Time	Obs SA	Obs IRB	Mean SA	Mean IRB	Diff (SA -IRB)
		(1)	(2)	(3)	(4)	(5)
Panel A. Pre-treatment Mean Comparison						
Loans to NFC	2019Q2	180	70	0.0105	0.0145	-0.0040
Loans to NFC	2019Q3	180	70	0.0160	0.0065	0.0035
Loans to NFC	2019Q4	180	70	0.0075	0.0055	0.0020
Loans to NFC	2020Q1	180	70	0.0125	0.0175	-0.0045
Panel B. Post-treatment Mean Comparison						
Loans to NFC	2020Q2	180	70	0.0115	0.0000	0.0115**
Loans to NFC	2020Q3	180	70	0.0100	-0.0145	0.0240***

This table provides mean comparisons between banks using the Standardised Approach (SA) and banks using the Internal-Rating Based (IRB) approach for the calculation of capital requirements. In Panel A, the means reported refer to the average quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$) of Loans to NFC over the four quarters pre-shock (i.e., 2019Q2-2020Q1). In Panel B, the means refers to the two quarters post-shock (2020Q2-2020Q3). Column (5) reports the difference in means between SA and IRB banks. Variables are defined as is Table 2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Covid-19 effects on Total Credit Origination: IRB vs SA banks (bank-level analysis)

	All borrowers		Non-NFC borrowers		NFC borrowers	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times IRB_i$	-0.0036	-0.0048	0.0024	0.0006	-0.0164***	-0.0167***
	(0.0048)	(0.0057)	(0.0061)	(0.0076)	(0.0058)	(0.0059)
$Size_{t-1}$	-0.1664***	-0.1615***	-0.1982***	-0.2007***	-0.0869***	-0.0793**
	(0.0291)	(0.0291)	(0.0383)	(0.0390)	(0.0303)	(0.0347)
$Post_t \times Size_{t-1}$	-0.0029*	-0.0012	-0.0047**	-0.0027	0.0025	0.0032*
	(0.0016)	(0.0019)	(0.0022)	(0.0025)	(0.0016)	(0.0016)
$Capital_{t-1}$	-0.0008	0.0006	0.0014	0.0018	-0.0042	-0.0025
	(0.0026)	(0.0027)	(0.0034)	(0.0034)	(0.0029)	(0.0029)
$Post_t \times Capital_{t-1}$	0.0005	0.0007	0.0020**	0.0022**	-0.0008	-0.0004
	(0.0007)	(0.0007)	(0.0009)	(0.0010)	(0.0008)	(0.0008)
ROA_{t-1}	-0.0006	-0.0072	-0.0036	-0.0117	0.0026	0.0008
	(0.0080)	(0.0080)	(0.0110)	(0.0111)	(0.0097)	(0.0098)
$Deposit\_Ratio_{t-1}$	0.0017**	0.0013*	0.0021**	0.0016*	0.0011**	0.0006
	(0.0007)	(0.0007)	(0.0008)	(0.0009)	(0.0005)	(0.0005)
$RWA\_Density_{t-1}$	-0.0009	-0.0007	-0.0003	-0.0002	-0.0012	-0.0007
	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0008)	(0.0009)
N	1500	1500	1500	1500	1500	1500
Adj. R^2	0.177	0.213	0.151	0.169	0.120	0.184
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Country*Time FE	No	Yes	No	Yes	No	Yes

This table reports the estimates for our difference-in-differences regressions (Eq.1). The the outcome variables are: total credit origination (on + off balance sheet exposures), total credit origination to other than non-financial corporations, and total credit origination to non-financial corporations. See Table 2 for the definition of the variables. The outcome variables are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. IRB_i takes the value of one for banks reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. Clustered standard errors at bank-level in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Covid-19 effects on On-Balance Sheet exposures: IRB vs SA banks (bank-level analysis)

	All borrowers		Non-NFC borrowers		NFC borrowers	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times IRB_i$	-0.0084*	-0.0086	-0.0028	-0.0038	-0.0207***	-0.0179***
	(0.0047)	(0.0054)	(0.0058)	(0.0069)	(0.0058)	(0.0056)
$Size_{t-1}$	-0.1683***	-0.1639***	-0.1824***	-0.1812***	-0.1210***	-0.1173***
	(0.0296)	(0.0300)	(0.0366)	(0.0382)	(0.0290)	(0.0319)
$Post_t \times Size_{t-1}$	-0.0033**	-0.0019	-0.0045**	-0.0032	0.0001	0.0009
	(0.0016)	(0.0018)	(0.0021)	(0.0023)	(0.0017)	(0.0018)
$Capital_{t-1}$	0.0010	0.0020	0.0030	0.0029	-0.0039	-0.0017
	(0.0025)	(0.0026)	(0.0033)	(0.0034)	(0.0028)	(0.0028)
$Post_t \times Capital_{t-1}$	0.0006	0.0008	0.0018**	0.0017*	-0.0012*	-0.0003
	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0007)	(0.0008)
ROA_{t-1}	-0.0034	-0.0080	-0.0027	-0.0090	0.0001	-0.0008
	(0.0082)	(0.0082)	(0.0107)	(0.0106)	(0.0092)	(0.0095)
$Deposit\_Ratio_{t-1}$	0.0016**	0.0013*	0.0022***	0.0018*	0.0005	0.0000
	(0.0006)	(0.0007)	(0.0008)	(0.0009)	(0.0004)	(0.0005)
$RWA\_Density_{t-1}$	-0.0011	-0.0010	-0.0005	-0.0003	-0.0014*	-0.0016*
	(0.0007)	(0.0008)	(0.0009)	(0.0010)	(0.0008)	(0.0009)
N	1500	1500	1500	1500	1500	1500
Adj R^2	0.182	0.220	0.153	0.181	0.147	0.207
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Country*Time FE	No	Yes	No	Yes	No	Yes

This table reports the estimates for our difference-in-differences regressions (Eq.1). The outcome variables are: total on-balance sheet exposures, total on-balance sheet exposures to other than non-financial corporations, and total on-balance sheet exposures to non-financial corporations. See Table 2 for the definition of the variables. The outcome variables are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. IRB_i takes the value of one for banks reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. Clustered standard errors at bank-level in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Covid-19 effects on Loans: IRB vs SA banks (bank-level analysis)

	All borrowers		Other borrowers		Retail borrowers		NFC borrowers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Post_t \times IRB_i$	-0.0111***	-0.0072*	-0.0162	-0.0267	-0.0033	-0.0027	-0.0229***	-0.0189***
	(0.0034)	(0.0039)	(0.0256)	(0.0292)	(0.0025)	(0.0031)	(0.0056)	(0.0055)
$Size_{t-1}$	-0.1094***	-0.1095***	-0.4717***	-0.4967***	-0.0553***	-0.0569***	-0.0997***	-0.0902***
	(0.0214)	(0.0231)	(0.1527)	(0.1710)	(0.0167)	(0.0162)	(0.0287)	(0.0283)
$Post_t \times Size_{t-1}$	-0.0003	-0.0005	0.0140*	0.0160*	0.0008	0.0012	0.0006	0.0010
	(0.0012)	(0.0014)	(0.0075)	(0.0093)	(0.0008)	(0.0010)	(0.0018)	(0.0020)
$Capital_{t-1}$	0.0010	0.0014	0.0144	0.0079	-0.0012	-0.0005	-0.0011	0.0007
	(0.0018)	(0.0021)	(0.0127)	(0.0145)	(0.0018)	(0.0020)	(0.0031)	(0.0031)
$Post_t \times Capital_{t-1}$	-0.0001	0.0003	-0.0004	0.0000	0.0002	0.0005	-0.0017**	-0.0010
	(0.0005)	(0.0005)	(0.0031)	(0.0031)	(0.0003)	(0.0004)	(0.0007)	(0.0007)
ROA_{t-1}	-0.0094	-0.0107	0.0378	0.0448	-0.0027	-0.0036	-0.0029	-0.0037
	(0.0066)	(0.0067)	(0.0446)	(0.0434)	(0.0043)	(0.0049)	(0.0073)	(0.0077)
$Deposit\_Ratio_{t-1}$	0.0011**	0.0008*	0.0058*	0.0057*	0.0002	0.0001	0.0004	-0.0000
	(0.0005)	(0.0005)	(0.0033)	(0.0029)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
$RWA\_Density_{t-1}$	-0.0002	-0.0007	0.0173***	0.0240***	0.0006	0.0003	-0.0014**	-0.0015**
	(0.0006)	(0.0006)	(0.0046)	(0.0051)	(0.0004)	(0.0005)	(0.0007)	(0.0008)
N	1500	1500	1500	1500	1500	1500	1500	1500
Adj. R^2	0.161	0.208	0.042	0.063	0.390	0.431	0.189	0.250
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No	Yes	No
Country*Time FE	No	Yes	No	Yes	No	Yes	No	Yes

This table reports the estimates for our difference-in-differences regressions (Eq.1). The outcome variables are: total loans, total loans to other than non-financial corporations and retail, total loans to retail, and total loans to non-financial corporations. See Table 2 for the definition of the variables. The outcome variables are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. IRB_i takes the value of one for banks reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. Clustered standard errors at bank-level in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Robustness check: Covid-19 effects on credit to NFC omitting 2020Q1 (bank-level analysis)

	Credit Origination		On-Balance Sheet		Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times IRB_i$	-0.0173***	-0.0151**	-0.0230***	-0.0159***	-0.0245***	-0.0169***
	(0.0056)	(0.0061)	(0.0056)	(0.0057)	(0.0055)	(0.0058)
$Size_{t-1}$	-0.0706***	-0.0691***	-0.0645***	-0.0598***	-0.0465**	-0.0415**
	(0.0172)	(0.0166)	(0.0199)	(0.0197)	(0.0209)	(0.0197)
$Post_t \times Size_{t-1}$	0.0018	0.0021	0.0009	0.0007	0.0021	0.0016
	(0.0016)	(0.0019)	(0.0016)	(0.0018)	(0.0018)	(0.0022)
$Capital_{t-1}$	-0.0046	-0.0039	-0.0023	-0.0015	0.0003	0.0010
	(0.0030)	(0.0028)	(0.0029)	(0.0028)	(0.0034)	(0.0033)
$Post_t \times Capital_{t-1}$	-0.0008	-0.0004	-0.0010	-0.0002	-0.0013*	-0.0005
	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
ROA_{t-1}	-0.0027	-0.0048	-0.0056	-0.0072	-0.0067	-0.0100
	(0.0089)	(0.0095)	(0.0083)	(0.0091)	(0.0071)	(0.0076)
$Deposit\_Ratio_{t-1}$	0.0012*	0.0006	0.0006	0.0001	0.0004	-0.0001
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
$RWA\_Density_{t-1}$	-0.0011	-0.0008	-0.0011	-0.0011	-0.0014*	-0.0013*
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)
N	1488	1488	1488	1488	1488	1488
Adj. R^2	0.100	0.171	0.151	0.210	0.192	0.260
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Country*Time FE	No	Yes	No	Yes	No	Yes

This table reports the estimates for our difference-in-differences regressions (Eq.1). The outcome variables are: total credit origination to non-financial corporations, on-balance sheet exposures to non-financial corporations, and loans to non-financial corporations. See Table 2 for the definition of the variables. The outcome variables are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q1-2019Q4. The regression excludes 2020Q1. IRB_i takes the value of one for banks reporting *corporate credit risk* using internal models, and zero if the bank uses the standardised approach. Clustered standard errors at bank-level in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Large Credit Exposures: Covid-19 effects on *Total Credit Origination* (loan-level analysis)

	Total Credit Origination		
	(1)	(2)	(3)
$Post_t \times IRB_i$	-0.0003	-0.0230	-0.0222
	(0.0204)	(0.0192)	(0.0189)
$Size_{t-1}$	-0.0161	-0.0005	0.0876
	(0.0999)	(0.0031)	(0.1006)
$Post_t \times Size_{t-1}$	0.0059	0.0082	0.0071
	(0.0047)	(0.0056)	(0.0051)
$Capital_{t-1}$	0.0050	-0.0002	0.0011
	(0.0067)	(0.0008)	(0.0075)
$Post_t \times Capital_{t-1}$	0.0006	-0.0015	-0.0015
	(0.0018)	(0.0016)	(0.0019)
ROA_{t-1}	-0.0473*	-0.0336***	-0.0593*
	(0.0253)	(0.0111)	(0.0314)
$Deposit\_Ratio_{t-1}$	-0.0023	0.0003	0.0043***
	(0.0017)	(0.0002)	(0.0015)
$RWA\_Density_{t-1}$	0.0068**	0.0005	0.0036
	(0.0027)	(0.0004)	(0.0024)
N	1918	1918	1918
Bank FE	Yes	No	Yes
Firm*Time FE	No	Yes	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.1) on a sample restricted to multiple-lending relationships (where the associated banks need to be at least one SA and one IRB bank). The outcome variable is the quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$) of *Total Credit Origination*. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. IRB_i takes the value of one for banks reporting *corporate credit risk* using internal models, and zero if the bank uses the standardised approach. Bank controls include the natural logarithm of assets ($Size$), equity to assets ratio ($Capital$), Return on Assets (ROA), Deposit Ratio, and RWA Density of bank i at time t. See Table 2 for the definition of the variables. Clustered standard errors at bank-level are reported in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Large Credit Exposures: Covid-19 effects on *On- and Off- Balance Sheet Exposures* (loan-level analysis)

	Total On-Balance Sheet			Loans and Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times IRB_i$	-0.0741**	-0.0816**	-0.0877**	-0.0879**	-0.1013**	-0.1053**
	(0.0324)	(0.0388)	(0.0405)	(0.0399)	(0.0424)	(0.0453)
$Size_{t-1}$	-0.2818	-0.0009	-0.0567	-0.3236	-0.0009	-0.1449
	(0.1889)	(0.0050)	(0.2428)	(0.2246)	(0.0060)	(0.2855)
$Post_t \times Size_{t-1}$	0.0119	0.0196	0.0217*	0.0101	0.0217*	0.0225*
	(0.0075)	(0.0125)	(0.0122)	(0.0084)	(0.0125)	(0.0123)
$Capital_{t-1}$	-0.0053	-0.0012	-0.0021	-0.0050	-0.0016	-0.0054
	(0.0156)	(0.0018)	(0.0200)	(0.0180)	(0.0020)	(0.0225)
$Post_t \times Capital_{t-1}$	0.0019	0.0042	0.0043	0.0001	0.0037	0.0038
	(0.0040)	(0.0040)	(0.0038)	(0.0048)	(0.0047)	(0.0046)
ROA_{t-1}	0.0664***	0.0219	0.0744***	0.0510*	0.0189	0.0638**
	(0.0241)	(0.0376)	(0.0217)	(0.0293)	(0.0400)	(0.0271)
$Deposit\_Ratio_{t-1}$	-0.0042	-0.0003	-0.0039	-0.0034	-0.0003	-0.0050
	(0.0030)	(0.0005)	(0.0042)	(0.0039)	(0.0006)	(0.0056)
$RWA\_Density_{t-1}$	0.0025	-0.0012	-0.0003	-0.0044	-0.0011	-0.0049
	(0.0043)	(0.0009)	(0.0053)	(0.0045)	(0.0010)	(0.0069)
N	1516	1516	1516	1516	1516	1516
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Firm*Time FE	No	Yes	Yes	No	Yes	Yes
	Total Off-Balance Sheet			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times IRB_i$	0.0686	0.0558	0.0761**	0.1367**	0.1169**	0.1374**
	(0.0445)	(0.0345)	(0.0338)	(0.0581)	(0.0514)	(0.0529)
$Size_{t-1}$	0.2525*	0.0016	0.0934	0.3621	0.0029	0.2334
	(0.1468)	(0.0051)	(0.1010)	(0.2409)	(0.0064)	(0.2271)
$Post_t \times Size_{t-1}$	-0.0014	-0.0012	-0.0036	0.0018	-0.0012	-0.0030
	(0.0088)	(0.0089)	(0.0075)	(0.0119)	(0.0125)	(0.0111)
$Capital_{t-1}$	0.0122	-0.0033	0.0135	0.0156	-0.0062	0.0066
	(0.0203)	(0.0040)	(0.0166)	(0.0358)	(0.0055)	(0.0326)
$Post_t \times Capital_{t-1}$	0.0016	-0.0065	-0.0060	0.0101	-0.0007	-0.0000
	(0.0093)	(0.0077)	(0.0084)	(0.0118)	(0.0114)	(0.0124)
ROA_{t-1}	-0.0886	0.0027	-0.1309*	-0.1862	-0.0085	-0.1657
	(0.0954)	(0.0309)	(0.0726)	(0.1426)	(0.0441)	(0.1112)
$Deposit\_Ratio_{t-1}$	-0.0012	0.0009**	0.0030	-0.0050	0.0009	0.0028
	(0.0037)	(0.0004)	(0.0036)	(0.0057)	(0.0006)	(0.0062)
$RWA\_Density_{t-1}$	0.0171**	0.0023*	0.0134**	0.0323**	0.0037**	0.0244**
	(0.0080)	(0.0011)	(0.0064)	(0.0137)	(0.0016)	(0.0122)
N	1224	1224	1224	1224	1224	1224
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Firm*Time FE	No	Yes	Yes	No	Yes	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.1) on a sample restricted to multiple-lending relationships (where the associated banks need to be at least one SA and one IRB bank). In Panel A, the outcome variable is *On-Balance Sheet* exposures (columns 1, 2, and 3), and *Loans and Securities* (columns 4, 5, and 6). In Panel B, the outcome variable is *Off-Balance Sheet* exposures (columns 1, 2, and 3), and *Loans Commitments* (columns 4, 5, and 6). The outcome variables are expressed in the quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. IRB_i takes the value of one for banks reporting *corporate credit risk* using internal models, and zero if the bank uses the standardised approach. Bank controls include the natural logarithm of assets ($Size$), equity to assets ratio ($Capital$), Return on Assets (ROA), Deposit Ratio, and RWA Density of bank i at time t. See Table 2 for the definition of the variables. Clustered standard errors at bank-level are reported in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Large Credit Exposures: Difference in Means between High vs Low Capitalized IRB Banks (loan-level)

Variable	Time	High	Low	Mean High	Mean Low	Diff
Panel A. Pre-treatment Mean Comparison						
Loans to NFC	2019Q2	396	646	-0.0080	-0.0040	-0.0040
Loans to NFC	2019Q3	396	646	-0.0155	0.0040	-0.0190
Loans to NFC	2019Q4	396	646	0.0135	0.0120	0.0015
Loans to NFC	2020Q1	396	646	0.1405	0.2220	-0.0815
Panel B. Post-treatment Mean Comparison						
Loans to NFC	2020Q2	396	646	-0.0615	-0.0545	-0.0065
Loans to NFC	2020Q3	396	646	-0.0225	-0.1285	0.1060

This table provides pre-treatment mean comparisons between banks with high and low capital levels. Banks are classified as "Low" if they are below the median of the distribution of Common Equity Tier 1 ratio as of 2019Q2 (i.e., banks with the lowest CET1 ratios) and as "High" otherwise. In Panel A, the means reported refer to the average quarterly growth rates $(Log(Y_{i,t}) - Log(Y_{i,t-1}))$ of large exposures Loans to NFC over the four quarters pre-shock (i.e., 2019Q2-2020Q1). In Panel B, the means refers to the two quarters post-shock (2020Q2-2020Q3). Column (5) reports the difference in means between HIgh and Low capitalized banks. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Alternative Identification for Large Credit Exposures: Covid-19 effects on *Total Credit Origination* (loan-level analysis)

	Total Credit Origination		
	(1)	(2)	(3)
$Post_t \times LowCap_i$	0.0001	0.0038	0.0028
	(0.0123)	(0.0134)	(0.0130)
$Size_{t-1}$	-0.1848*	0.0032	-0.0489
	(0.1029)	(0.0036)	(0.0974)
$Post_t \times Size_{t-1}$	0.0013	0.0037	0.0033
	(0.0051)	(0.0069)	(0.0063)
ROA_{t-1}	-0.0370	-0.0329	-0.0236
	(0.0721)	(0.0221)	(0.0649)
$Deposit\_Ratio_{t-1}$	-0.0015	0.0006***	0.0014
	(0.0015)	(0.0002)	(0.0019)
$RWA\_Density_{t-1}$	0.0027	0.0006	-0.0039
	(0.0063)	(0.0009)	(0.0062)
N	6242	6242	6242
Bank FE	Yes	No	Yes
Firm*Time FE	No	Yes	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.1). The outcome variables is total credit origination and it is expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). The table shows the findings from our sample of firms with multiple-lending relationships, where the associated banks need to be at least one High Capitalized and one Low Capitalized IRB bank. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. $LowCap_i$ takes the value of one for banks reporting below the median CET1 Ratios as of 2019Q2 and zero otherwise. Bank controls include the natural logarithm of assets ($Size$), Return on Assets (ROA), Deposit Ratio, and RWA Density of bank i at time t. See Table 2 for the definition of the variables. Clustered standard errors at bank-level in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Alternative Identification for Large Credit Exposures: Covid-19 effects on *Total On-Balance Sheet* and *Loans and Securities* exposures (loan-level analysis)

	Total On-Balance Sheet			Loans and Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times LowCap_i$	-0.0240	-0.0305*	-0.0353**	-0.0383**	-0.0458**	-0.0529***
	(0.0169)	(0.0152)	(0.0154)	(0.0174)	(0.0196)	(0.0185)
$Size_{t-1}$	-0.3368	-0.0011	-0.1046	-0.1403	0.0028	0.0644
	(0.2224)	(0.0050)	(0.2359)	(0.1993)	(0.0049)	(0.2195)
$Post_t \times Size_{t-1}$	-0.0005	0.0127	0.0145	-0.0071	0.0101	0.0072
	(0.0108)	(0.0110)	(0.0120)	(0.0095)	(0.0107)	(0.0143)
ROA_{t-1}	0.0958	-0.0373	-0.0236	-0.0392	-0.1068**	-0.1238
	(0.0994)	(0.0390)	(0.1454)	(0.1519)	(0.0516)	(0.2142)
$Deposit\_Ratio_{t-1}$	0.0049	0.0008***	-0.0011	0.0062	0.0010**	-0.0013
	(0.0041)	(0.0003)	(0.0050)	(0.0038)	(0.0004)	(0.0054)
$RWA\_Density_{t-1}$	0.0015	0.0029**	0.0012	-0.0047	0.0033**	-0.0062
	(0.0090)	(0.0011)	(0.0119)	(0.0094)	(0.0014)	(0.0144)
N	6242	6242	6242	6242	6242	6242
Bank FE	Yes	No	Yes	Yes	No	Yes
Firm*Time FE	No	Yes	Yes	No	Yes	Yes

	Total Off-Balance Sheet			Loans Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times LowCap_i$	-0.0054	0.0064	0.0094	0.0206	0.0130	0.0276
	(0.0227)	(0.0235)	(0.0221)	(0.0209)	(0.0260)	(0.0229)
$Size_{t-1}$	0.0331	0.0073	0.0041	0.1567	-0.0021	0.1576
	(0.1363)	(0.0059)	(0.0937)	(0.2110)	(0.0077)	(0.1664)
$Post_t \times Size_{t-1}$	0.0021	0.0007	-0.0030	0.0190	0.0170	0.0106
	(0.0100)	(0.0091)	(0.0122)	(0.0118)	(0.0117)	(0.0133)
ROA_{t-1}	-0.1340	0.0032	-0.0310	-0.1943	0.0872*	-0.0878
	(0.1262)	(0.0358)	(0.0830)	(0.1771)	(0.0467)	(0.1212)
$Deposit\_Ratio_{t-1}$	-0.0064**	0.0005	0.0047	-0.0057	0.0004	0.0073
	(0.0029)	(0.0004)	(0.0037)	(0.0052)	(0.0005)	(0.0052)
$RWA\_Density_{t-1}$	0.0097	-0.0011	-0.0100	0.0310*	-0.0032	0.0005
	(0.0127)	(0.0019)	(0.0127)	(0.0176)	(0.0024)	(0.0173)
N	5288	5288	5288	5288	5288	5288
Bank FE	Yes	No	Yes	Yes	No	Yes
Firm*Time FE	No	Yes	Yes	No	Yes	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.1) on a sample restricted to multiple-lending relationships (where the associated banks need to be at least one High Capitalized and one Low Capitalized IRB bank). In Panel A, the outcome variable is *On-Balance Sheet* exposures (columns 1, 2, and 3), and *Loans and Securities* (columns 4, 5, and 6). In Panel B, the outcome variable is *Off-Balance Sheet* exposures (columns 1, 2, and 3), and *Loans Commitments* (columns 4, 5, and 6). The outcome variables are expressed in the quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. $LowCap_i$ takes the value of one for banks reporting below the median CET1 Ratios as of 2019Q2 and zero otherwise. Bank controls include the natural logarithm of assets ($Size$), Return on Assets (ROA), Deposit Ratio, and RWA Density of bank i at time t. See Table 2 for the definition of the variables. Clustered standard errors at bank-level are reported in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 14: Alternative Identification for Large Credit Exposures: further evidence

	Total Credit Origination			Loans & Securities			Loans Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Credit Risk Mitigation									
$Post_t \times LowCap_i \times CRM_j$	-0.0293	-0.0160	-0.0069	-0.1528**	-0.1362**	-0.1330***	0.1547	0.1289	0.1225
	(0.0454)	(0.0357)	(0.0384)	(0.0581)	(0.0522)	(0.0476)	(0.1015)	(0.1016)	(0.1102)
$Post_t$	-0.0433			0.0642			-0.3841		
	(0.1216)			(0.2412)			(0.3004)		
$LowCap_i$		-0.0046			-0.0238			0.1136**	
		(0.0187)			(0.0295)			(0.0542)	
CRM_j	-0.0036	0.0189	-0.0105	-0.0149	-0.0326	-0.0514	0.0120	0.1044*	0.0555
	(0.0200)	(0.0267)	(0.0236)	(0.0322)	(0.0368)	(0.0362)	(0.0434)	(0.0520)	(0.0628)
Panel B: Sectoral Exposures									
$Post_t \times LowCap_i \times Most\_Affected_j$	-0.0044	0.0007	0.0015	-0.0732***	-0.0537*	-0.0533**	0.0698*	0.0153	0.0166
	(0.0126)	(0.0150)	(0.0099)	(0.0187)	(0.0319)	(0.0221)	(0.0370)	(0.0558)	(0.0251)
$Post_t$	-0.0254			0.1309			-0.4415		
	(0.1249)			(0.2386)			(0.2974)		
$LowCap_i$		0.0037			0.0029			0.0280	
		(0.0077)			(0.0125)			(0.0359)	
$Most_Affected_j$	0.0135***	0.0355**	-0.0002	-0.0003	0.0265	-0.0290	0.0259	0.2041	0.1596*
	(0.0032)	(0.0155)	(0.0059)	(0.0087)	(0.0213)	(0.0226)	(0.0187)	(0.1883)	(0.0906)
Panel C: Domestic Borrowers									
$Post_t \times LowCap_i \times Domestic_j$	0.0010	-0.0009	-0.0022	0.0199	0.0002	0.0005	0.0610	0.0426	0.0393
	(0.0165)	(0.0155)	(0.0175)	(0.0474)	(0.0498)	(0.0511)	(0.0448)	(0.0534)	(0.0544)
$Post_t$	-0.0779			0.0183			0.1419		
	(0.1247)			(0.2798)			(0.2524)		
$LowCap_i$		-0.0074			0.0103			0.0266	
		(0.0071)			(0.0153)			(0.0192)	
$Domestic_j$	-0.0001	-0.0125*	0.0005	0.0055	-0.0136	0.0020	0.0183	0.0051	0.0171
	(0.0044)	(0.0063)	(0.0054)	(0.0185)	(0.0164)	(0.0186)	(0.0221)	(0.0184)	(0.0242)
Bank Controls Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6200	6200	6200	6200	6200	6200	5464	5464	5464
Bank FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Firm*Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.1). The outcome variables are: total credit origination, loans and securities, loan commitments, and they are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). In Panel A to Panel C, $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1 and $LowCap_i$ takes the value of one for banks below the median of the distribution of Common Equity Tier 1 as of 2019Q2 (i.e., banks with the lowest CET1 ratios) and zero otherwise. In Panel A, CRM_j is a continuous variable calculated as the value of the exposure after the application of CMR of bank i to borrower j in 2019Q2 divided by the value of the original exposure. In Panel B, $Most\_Affected_j$ takes the value of one for those borrowers belonging to the NACE sectors: C,D,F,G,H,I,N,R. In Panel C, $Domestic_j$ takes the value of one if the borrower and the bank are headquartered in the same country. The samples include only firms with multiple-lending relationships. In all panels, bank controls are included in the estimation and include the natural logarithm of assets ($Size$), $Post \times Size$, Return on Assets (ROA), Deposit Ratio, and RWA Density of bank i at time t. See Table 2 for the definition of the variables. In all panels, fixed effects are included as displayed in Panel C. Clustered standard errors at bank-level in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Table A1: Difference-in-Differences Regression: Off-balance Sheet Exposures (Bank-Level)

Panel A: Off-Balance Exposures						
	Total Off-Balance Sheet		Off-Balance Sheet non-NFC		Off-Balance Sheet NFC	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times IRB_i$	0.0150	0.0149	0.0286	0.0358*	0.0149	0.0129
	(0.0105)	(0.0129)	(0.0175)	(0.0206)	(0.0145)	(0.0183)
$Size_{t-1}$	-0.0377	-0.0340	-0.0282	-0.0172	0.0296	0.0261
	(0.0610)	(0.0671)	(0.0843)	(0.0947)	(0.0772)	(0.0878)
$Post_t \times Size_{t-1}$	0.0003	0.0001	-0.0028	-0.0044	0.0050	0.0040
	(0.0031)	(0.0038)	(0.0056)	(0.0069)	(0.0040)	(0.0051)
$Capital_{t-1}$	-0.0004	-0.0007	0.0059	0.0042	0.0062	0.0040
	(0.0066)	(0.0069)	(0.0091)	(0.0098)	(0.0065)	(0.0073)
$Post_t \times Capital_{t-1}$	0.0022	0.0021	0.0029	0.0039	0.0032*	0.0030
	(0.0014)	(0.0016)	(0.0025)	(0.0029)	(0.0019)	(0.0020)
ROA_{t-1}	0.0117	0.0009	-0.0038	-0.0126	0.0026	-0.0050
	(0.0205)	(0.0193)	(0.0282)	(0.0307)	(0.0235)	(0.0251)
$Deposit\_Ratio_{t-1}$	0.0015	0.0010	-0.0014	-0.0014	0.0027**	0.0023*
	(0.0011)	(0.0012)	(0.0022)	(0.0022)	(0.0012)	(0.0012)
$RWA\_Density_{t-1}$	-0.0020	-0.0004	-0.0026	-0.0011	-0.0027	-0.0020
	(0.0016)	(0.0018)	(0.0026)	(0.0028)	(0.0018)	(0.0022)
Panel B: Loan Committments						
	Total Loan Committments		Loan Committments non-NFC		Loan Committments NFC	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times IRB_i$	0.0077	0.0033	0.0188	0.0258	0.0098	0.0091
	(0.0113)	(0.0131)	(0.0169)	(0.0193)	(0.0168)	(0.0212)
$Size_{t-1}$	-0.0169	-0.0080	-0.0315	-0.0048	0.0273	0.0362
	(0.0648)	(0.0730)	(0.0789)	(0.0893)	(0.0899)	(0.1012)
$Post_t \times Size_{t-1}$	0.0049	0.0046	0.0022	-0.0008	0.0079*	0.0054
	(0.0033)	(0.0038)	(0.0052)	(0.0064)	(0.0047)	(0.0061)
$Capital_{t-1}$	0.0006	0.0003	0.0093	0.0095	0.0058	0.0026
	(0.0065)	(0.0071)	(0.0084)	(0.0095)	(0.0072)	(0.0082)
$Post_t \times Capital_{t-1}$	0.0028*	0.0023	0.0029	0.0030	0.0051**	0.0044*
	(0.0016)	(0.0018)	(0.0024)	(0.0027)	(0.0024)	(0.0026)
ROA_{t-1}	0.0127	0.0028	0.0028	0.0009	0.0101	0.0024
	(0.0158)	(0.0165)	(0.0247)	(0.0286)	(0.0250)	(0.0267)
$Deposit\_Ratio_{t-1}$	0.0017	0.0016	-0.0023	-0.0019	0.0036***	0.0032**
	(0.0012)	(0.0012)	(0.0019)	(0.0019)	(0.0014)	(0.0014)
$RWA\_Density_{t-1}$	-0.0015	-0.0009	-0.0024	-0.0021	-0.0025	-0.0021
	(0.0016)	(0.0017)	(0.0023)	(0.0025)	(0.0021)	(0.0023)
N	1452	1452	1452	1452	1452	1452
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Country*Time FE	No	Yes	No	Yes	No	Yes

This table reports the estimates for our difference-in-differences regressions (Eq.1). In Panel A, the outcome variables are: total off-balance sheet exposures, total off-balance sheet exposures to other than non-financial corporations, and total off-balance sheet exposures to non-financial corporations. In Panel B, the outcome variables are: total loan commitments, total loan commitments to other than non-financial corporations, and total loan commitments to non-financial corporations. See Table 2 for the definition of the variables. The outcome variables are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. IRB_i takes the value of one for banks reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. Clustered standard errors at bank-level in parentheses. Variables are winsorized at the 5% level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.