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Pandemic Lending: Micro and Macro Effects of Model-Based Regulation

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Pandemic Lending: Micro and Macro Effects of Model-Based Regulation

Franco Fiordelisi, Giulia Fusi, Angela Maddaloni, David Marques-Ibanez [*]

Abstract

When the Covid-19 crisis struck, banks using internal-rating based (IRB) models quickly recognized the increase in risk and reduced lending more than banks using a standardized approach. This effect is not driven by borrowers' quality or by banks in countries with credit booms before the pandemic. The higher risk sensitivity of IRB models does not always result in lower credit provision when risk intensifies. Certain features of the IRB models – the use of a downturn Loss Given Default parameter – can increase banks' resilience and preserve their intermediation capacity also during downturns. Affected borrowers were not able to fully insulate and decreased corporate investments.

Keywords: Model-based regulation; Banks; Supervision; Lending; Covid-19

JEL Classification: G21, G28

"The ECB has responded forcefully to this historic crisis by adopting a wide-ranging set of carefully calibrated measures that collectively help mitigate the economic and financial fallout from the pandemic. Our measures contribute to easing financing conditions of firms and households and supporting banks in their effort to maintain viable liquidity conditions in the economy at large". Remarks by Isabel Schnabel, Member of the Executive Board of the ECB, at a 24-Hour Global Webinar co-organised by the SAFE Policy Center on "The COVID-19 Crisis and Its Aftermath: Corporate Governance Implications and Policy Challenges", Frankfurt am Main, 16 April 2020

"It is my belief that exogenous shocks to the economy and the banking sector require supervisors to exercise extreme caution and that, when facing events of this kind, in banking supervision or elsewhere, it is generally better to be safe than sorry". Keynote speech by Andrea Enria, Chair of the Supervisory Board of the European Central Bank, at the Austrian Financial Market Authority Supervisory Conference 2022, Vienna, 4 October 2022

1   Introduction

Banks are key providers of funds to the corporate sector and played a prominent role during the COVID-19 pandemic. To maintain their role as credit providers, the financial soundness and solvency of the banking sector are of vital importance. Preserving the financial stability of the banking system is a primary objective of banking supervision, which however needs to strike the appropriate balance between two different, albeit highly interrelated, dimensions of prudential policy. At the micro level, prudential supervision aims at safeguarding individual financial institutions from idiosyncratic risks by preventing them from building-up vulnerabilities resulting from excessive risk-taking. At the macro level, prudential supervision aims to detect threats to financial stability stemming from the interactions among individual financial institutions, while also accounting for the feedback loops between the financial sector and the real economy, to prevent or mitigate risks to the entire financial system arising from macroeconomic conditions (Osinski et al., 2013; Boissay and Cappiello, 2014).[1]

Although the micro- and macro approaches are complementary, their different focus

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[1]The Global Financial Crisis in 2007 showed that the stability of individual financial institutions alone is not enough to ensure the stability of the financial system as a whole. Thus, the Basel III accords have significantly changed prudential supervision, with a view to complementing micro-prudential supervision with a macro-prudential dimension.

can results in tensions - especially during downturns - and supervisor authorities are aware of this: "*During downturns […], diverging micro- and macro-prudential approaches could generate frictions. This, in turn, could lead to inefficient outcomes, especially as micro-prudential policies may inadvertently cause negative externalities on the financial system as a whole.*"(Boissay and Cappiello (2014), page 139). This is because during downturns, micro-prudential authorities are concerned with ensuring the stability of the individual financial institutions, whereas macro-prudential policies focus on stabilizing the system as a whole and ensuring that the crisis does not result in a credit crunch as a consequence of banks' deleveraging (Osinski et al., 2013).

The objectives of preserving the intermediation capacity of the banks - ensuring financing to the corporate sector – while safeguarding the solvency of banks may require policies that are not always aligned and that can conflict with each other causing negative externalities. For example, the current micro-regulatory framework requires banks to increase risk-weights of credit exposures to recognise lower borrowers' credit standing. This, in turn, raises capital requirements. Since equity is a limited resource and cannot be quickly raised by banks, especially during crisis periods, banks may be forced to reduce lending, especially towards riskier borrowers, to comply with capital regulation (e.g., by not extending expiring loans and/or selling corporate securities in their portfolios). In other words, micro-prudential policies aimed at increasing the resilience of individual banks may have systemic consequences, especially during downturns (Osinski et al., 2013; Boissay and Cappiello, 2014).

A key role in this framework is played by model-based regulation, which represents one of the most important changes in banking regulation occurred in the last decades. In contrast with the "one-size-fits-all" approach of Basel I, the Basel II and successive amendments allowed banks to use either the Standardised Approach (SA) or the Internal

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Ratings-Based (IRB) approach to calculate their minimum capital requirements.[2] The rationale behind model-based regulation was to increase the risk sensitivity of banks' capital by aligning more accurately capital requirements with the underlying risks to which a bank is exposed (Basel Committee on Banking Supervision, 2001). Thus, if IRB models work as intended, they would induce banks to incorporate growing borrowers' risk in a timely manner and respond more dynamically to changes in risk compared to banks using standardized approaches. Accordingly, this translates into higher capital absorbed by these exposures and could induce IRB banks to curtail their lending provision to maintain capital adequacy. In such a case, tensions between micro and macro prudential approaches increase since tighter requirements will translate into a reduced capacity for banks to extend credit to borrowers, potentially exacerbating the economic downturn. At the same time, IRB models have complex features and cannot be treated as a homogeneous group, as they typically vary across banks in both the risk parameters included in the model and their calibration.[3] In particular, the inclusion of parameters specifically designed to account for economic downturns should improve banks' resilience and ultimately support banks using IRB models to continue lending also during bad times. In such a case, tensions between micro and macro prudential approaches will be mitigated.

This discussion leads us to formulate the following two questions. Does model-based regulation unambiguously increase risk sensitiveness of capital requirements? Are there features of IRB models that can limit the negative impact on credit provision when a large shock occurs? The answer to the first question relates to the ability of IRB approaches to support the stability and soundness of banks and therefore achieving the objectives of

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[2]The SA approach entails a simpler methodology, whereby fixed risk-weights (i.e., pre-determined by the supervisory authorities) are assigned to different categories of borrowers (e.g., banks, corporate, retail, etc) so that risk-weights are the same for all banks. Instead, the IRB approach relies on banks' own (internal) models so that each bank calculates its own 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.

[3]The European Central Bank launched in 2016 a Targeted Review of Internal Models (TRIM) project aiming to harmonise supervisory practices relating to internal models within the Single Supervisory Mechanism area.

micro-prudential supervision. At the same time, we may want to assess whether some characteristics of the IRB models can mitigate the negative effects on credit supply during a downturn and therefore support the stability of the banking sector also from a macro-prudential point of view.

In this paper, we address these questions by exploiting the occurrence of the COVID-19 pandemic and relying on a Difference-in-Differences (DiD) identification strategy to study the reaction of a sample of euro area banks using IRB and SA approaches. The pandemic provides a *quasi-natural* experiment setting since i) COVID-19 is an exogenous shock and orthogonal to bank behaviour; and ii) it is reasonable to expect that the COVID-19 shock had a different impact (in terms of capital charges) on IRB and SA banks because of the different risk sensitivity of the two approaches. Although COVID-19 did not directly affect banks (neither IRB nor SA banks), it had an impact on banks' borrowers (especially non-financial corporations) and their risk profile. Following a change in borrowers' risk, we expect banks using internal models to react quicker than SA banks in making adjustments. The swifter reaction of IRB banks will be reflected in higher capital requirements, potentially inducing these banks to deleverage by reducing their credit exposures, especially towards riskier borrowers such as Non-Financial Corporations (NFCs). The effect for banks using a SA approach should be more muted since they use fixed risk-weights that are less sensitive to a sudden increase in risks.

In our first set of analyses, we compare the lending behaviour of IRB and large SA banks using a bank-level proprietary dataset on euro area banks. In the second step, we complement our analysis by using proprietary loan-level data on banks' "large exposures", including virtually all bank-firm relationships in the euro area either greater than €300 million or weighting more than 10% of banks' regulatory capital. For this analysis, we rely on a sample constituted by multiple lending relationships of a borrower to banks using different regulatory arrangements, therefore controlling for demand shocks. Our results

show that IRB banks reduced on-balance sheet credit exposures to NFCs, especially loans, relative to SA banks in the aftermath of March 2020, when the COVID-19 pandemic started. By exploiting the multiple lending relationships found in the large exposures data, we document that the decrease in loans was due to a reduction in credit supply - and not due to lower demand. Notably, exposures through off-balance sheet items, which are treated differently in the evaluation of risk-weighted assets, in particular loan commitments, did not follow the same pattern.

In the next steps of our analysis, we develop an alternative identification strategy focusing only on the sample of banks using IRB models, and we compare the lending behaviour of IRB banks with different levels of capital buffers above the minimum regulatory requirements. We show that capital-constrained IRB banks are forced to reduce lending in a pandemic scenario, whereas highly capitalised IRB banks have the option to use their capital buffers against the increase in the risk of their assets. Notably, when replicating this analysis on the sample of banks using the SA approach, we do not find consistent results, suggesting that this particular capital regulatory channel holds exclusively for IRB banks.

Finally, we provide evidence that the higher model-based risk sensitiveness of IRB models does not always result in lower credit provision when a large shock occurs. Specifically, our final analysis presents causal evidence that certain features of model-based regulation, like the downturn Loss Given Default (LGD) parameter, are important to ensure that capital is built-up appropriately ex-ante to increase resilience and moderate the negative effects on lending provision.

Our sample of large exposures provides us with several unique features that support the robustness of our results. First, the international dimension of banks and borrowers enables us to have findings that do not depend on a single country's experience. Furthermore, there is evidence that relationship lending - the number and duration of bank-firm

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relationships - affects bank credit provision to firms during a downturn (see for example, Sette and Gobbi, 2015). Moreover, "large exposures" were not supported during COVID-19 with Government Guarantees that could bias our analyses, as it would have been the case for loans to Small and Medium Enterprises (SMEs). Lastly, large exposures absorb a large amount of banks' equity. Thus, it is rational to expect that, after the COVID-19 eruption, banks would concentrate their efforts to reduce risk by decreasing the largest exposures.

Our paper contributes significantly to two distinct strands of literature analysing how regulatory requirements and financial crises affect bank lending. First, there is vast and growing literature analysing the relationship between bank regulation and bank credit supply. Most of this literature uses as an identification device the shock caused by tighter regulation, usually an increase in the minimum capital requirements, which would translate in lower lending. The setting of higher capital requirements by regulators is followed by a reduction in corporate and household lending (Bridges et al., 2014; Aiyar et al., 2014a; De Marco et al., 2021; Fraisse et al., 2020; De Jonghe et al., 2020a) and cross-border lending in the UK (Aiyar et al., 2014b). Banks participating in the European Banking Authority (EBA) capital exercise in 2011 reacted to higher capital requirements by reducing lending, rather than issuing new equity (Mésonnier and Monks, 2015; Gropp et al., 2019). Similarly, stress-tests exercises resulting in higher capital requirements are also affecting banks' willingness to supply credit (Acharya et al., 2018; Cortés et al., 2020). 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).

In the context of this literature, only a limited number of papers have directly investigated the role played by model-based regulation (Behn et al., 2016; Bruno et al., 2017; Behn et al., 2022) and are therefore closer in spirit to our analysis. Exploiting the episode

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of the failure of Lehman Brothers, Behn et al. (2016) show the pro-cyclical effect induced by model-based regulation on firm borrowing. Bruno et al. (2017) find that banks using IRB approaches more extensively respond to shocks by reshuffling their assets towards less capital intensive activities, thus the capital channel is stronger for IRB banks. Focusing on German banks, Behn et al. (2022) show that model-based risk estimates systematically under-predict actual default rates, and that both default and loss rates are higher for loans that were originated under the model-based approach. This paper suggests that IRB banks may be somewhat under capitalized and therefore when facing a large exogenous shock they would swiftly readjust to take into account the increased risk.

Our paper offers two main contributions to this literature. First and foremost, we identify the features of IRB models affecting lending and we provide readers with novel evidence that model-based sensitiveness to risk does not always result in lower credit provision when a shock occurs. We show that the effect of IRB regulation depends on the level of capitalisation when the shock hits as our findings indicate that poorly capitalised IRB banks decreased more their lending relative to more capitalized IRB banks. In particular, IRB banks close to the minimum regulatory requirements reduced their exposures more towards borrowers absorbing relatively more regulatory capital - borrowers for which credit risk mitigation was limited - and for borrowers belonging to the industrial sectors most affected by the pandemic. Additionally, when restricting the sample to IRB and SA banks with low capital buffers, we find evidence of a stronger economic significance of our results. Notably, we do not find a similar result when we restrict the analysis only to SA banks.

Next, we open the *black-box* of IRB models and we investigate the features driving this wedge in credit provision as a reaction to a large shock. By using confidential information concerning the revision of internal models carried out by the European supervisors over the last few years, we report that the use of advanced IRB approaches, and in particular

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the downturn LGD adjustment, permits banks to decrease their corporate exposures less (or increase their exposures more) compared to banks not using the downturn LGD parameter. This finding suggests that these complex IRB models are indeed better equipped to update the risk assessment in the event of a shock, in turn directly affecting credit exposures. IRB models that can be calibrated to evaluate the effects of high risk scenarios and the consequent losses render banks generally more resilient to shocks and able to continue lending even after a major negative event. Related to this aspect, and somewhat contrary to the evidence in Behn et al. (2016), we fail to provide support to the notion that IRB banks are underestimating credit risk. Indeed, exposures decrease more for those firms/sectors more affected by the pandemic, while we also exclude the possibility that credit was extended *zombie firms*.

The second important contribution to this literature stems from the multi-country dimension of our sample, which ensures that our results do not depend on a single country experience. Indeed, the banks in our sample are all directly supervised by the European Central Bank (ECB) following a harmonised approach, and thus our findings are not driven by specific features of national supervision in charge of the validation of IRB models.[4] Additionally, the recent analysis in Kosekova et al. (2022), based on loan-level data for the euro area, shows that bank-firm relationships differ significantly across countries, therefore insights based on single country analysis should be evaluated with care. Furthermore, macroeconomic conditions specific to a single country should play a much lower role in combination with the impact of model-based regulation in our analysis. After the Lehman Brothers bankruptcy, Behn et al. (2016) argue that IRB models induced a procyclical effect on corporate borrowing. Leveraging on the cross-country dimension of our dataset, we explore whether model-based regulation may have interacted and compounded with country-specific credit cycles. In this respect, we show that, although credit cycles in

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[4]IRB models were generally validated by national supervisory authorities before the Targeted Review of Internal Models (TRIM) carried out by the ECB.

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Euro area countries were different before the pandemic, the reduction in credit exposures induced by model-based regulation does not depend on these differences and it is not driven by banks experiencing a credit boom before 2020Q1.

Our paper also contributes to a large academic literature studying lending during financial crises. 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. Various studies show that when a large international shock occurs, banks tend to retrench and increase their relative exposure to domestic or geographically closer borrowers. For example, 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 borrowers geographically close (De Haas and Van Horen, 2013). 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 towards 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.[5] Somewhat differently from this literature, we do not find evidence of a retrenchment of foreign exposures vis-à-vis domestic exposures. Borrowers in our sample are large multinational companies of relatively good quality, and this may explain our results. At the same time, we show that even these large corporates are not able to fully insulate from the effect of IRB models on lending - for example using other forms of financing. We show that large corporates more dependent on the credit provided by IRB banks experience a larger drop in investments relative to other firms. The decrease is statistically significant for short-term financial investment (trade receivables), tangible fixed assets and intangible fixed-assets. Additionally, we document that investments in receivables and tangible fixed

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

assets were financed in 2020 by the usage of capital reserves instead of the issuance of new capital, therefore suggesting the presence of financing constraints.

A number of studies have recently analysed the impact on bank lending of the COVID-19 crisis. 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 the COVID-19. We contribute to this literature by emphasising an important additional channel of transmission of shocks through banks' regulation. We show that (low capitalized) IRB banks reduced their exposures more towards industries more affected by the pandemic and for which risk would have gone up the most. This suggests that model-based regulation has an impact on the allocation of funds to the corporate sector when a large shock occurs and that this effect works through the level of capital of the banks. We also provide complementary evidence to the analysis in Kapan and Minoiu (2021), who show that US banks with larger *ex-ante* credit line portfolios, thus higher risk of drawdowns, tightened more loan supply and the terms on new loans when the COVID-19 crisis occurred. In our sample, IRB banks decreased their on-balance sheet exposures, but not their loan commitments (off-balance sheet exposures). Different implications in terms of capital requirements of on- and off-balance sheet exposures seems particularly relevant for banks using internal model-based regulation.[6]

Our results have important policy implications. During this pandemic crisis, banks played a key role in smoothing the negative effects on the economy by providing funding to corporates and households, also thanks to the extensive support provided by the policy package approved in the wake of the COVID-19 pandemic. The EU banking package and the supervisory reliefs aimed at avoiding a credit retrenchment did not specifically address model-based regulation. Our analysis suggests that IRB models worked as in-

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[6]We do not find similar results for the sample of SA banks.

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tended, increasing the risk sensitivity of capital requirements and supporting the stability of banks at the occurrence of a large shock, thus achieving the micro-prudential objectives. At the same time, certain features of model-based regulation, like a downturn LGD, are critical to ensure that capital is built-up appropriately ex-ante to increase resilience and moderate the negative effects on lending provision, ultimately supporting macroeconomic stability.

The rest of the paper is organized as follows. Section 2 describes the bank- and loan-level variables employed in this paper as well as the identification strategy used to assess the lending behaviour of SA and IRB banks. Section 3 discusses the main results from our analyses, while Section 4 focuses on alternative identification strategies. In Section 5, the paper provides a set of robustness analyses while Section 6 focuses on assessing the economic impact on corporates. Section 7 concludes.

2 Data and Identification Strategy

2.1 Data Description

To investigate the lending behaviour of IRB and SA banks during the COVID-19 shock, this paper leverages two datasets with two distinct levels of aggregation: bank and loan-level data. Bank-level data are obtained from the confidential FINREP ("FINancial RE-Porting") and COREP ("COmmon REPorting") supervisory data from the European Central Bank. 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

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our analysis subsidiaries and foreign-owned banks.[7] Secondly, we keep the consolidated statements of banks, unless banks exclusively report at unconsolidated level.[8] Finally, we remove from our sample those banks that lack data on total assets, equity and net income or with total assets below €1 billion. This yields to a final bank-level sample of 250 banks (of which 70 banks using IRB models) classified either as ultimate parents or stand-alone banks across 17 countries. At the end of 2019, the banks in our sample had an overall asset size of 23.3 trillion (19.8 trillion for the 70 IRB banks), provided loans to the economy for 15.3 trillion (13 trillion from IRB banks) and loans to NFCs for 5.3 trillion (4.6 trillion from IRB banks). Table A1 in the Appendix 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.

For our analyses at loan-level, we exploit the unique dataset constituted by the micro-prudential supervisory framework on "large exposures". In 2014, the Basel Committee on Banking Supervision (BCBS) 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.[9,10,11] Credit institutions reporting FINREP supervisory data are also requested to

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

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

[9]The large exposure limit is set at 25% of a bank's eligible capital or 15% for exposures among Globally Systemic Banks (G-SIBs).

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

[11]The European Union implemented Basel III regulation via the Capital Requirements Regulation (CRR), and the 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

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report large exposures information with a value above or equal to EUR 300 million.[12]

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 the loan-level and building an identification strategy based on multiple-lending relationships, which enables us to establish if the observed variations in credit exposures are due to a decision of IRB banks (credit supply shock). Second, these loans refer to large, strategically important borrowers and it can be expected that banks change first their exposure towards these borrowers after the eruption of the COVID-19 pandemic in March 2020 in order to decrease their overall risk exposure. During stress periods, banks will either increase lending to support their important customers (large borrowers in a time of crisis) or decrease it to relieve the pressure on capital. Finally, large exposures 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 significant work in matching different samples and databases.[13] 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 by filtering out (i) public sector borrowers, such as general governments, central banks and municipalities, (ii) financial sector borrowers, including credit institutions and

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Exposures is provided by Art. 392.

[12]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.

[13]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 this 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 only relying on information in the "Large Exposure" dataset when the lenders are from different countries.

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 sector of the counterparty.[14] 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.

When analysing bank lending behaviour during the COVID-19 pandemic, an important issue to consider is the financial support provided by the governments to firms to alleviate the negative impact of the pandemic. To this end, we report in Table A2 in the Appendix the importance of public guarantees on credit exposures in the Euro area and in the four largest jurisdictions according to their nominal amount.[15] For each bucket and each country, we show the quota of loans that received governments' support (number of supported loans over total number of loans), and the quota of the volume of support granted (the amount guaranteed over the total amount of the loans). We show that public financial guarantees were widely used for loans in the smallest bucket (15.6% of credit exposures granted in the third quarter of 2020 received a public guarantee, so that the value of credit exposure publicly guaranteed was 27.5% of all loans), while they were relatively rare for the higher tranches of loans (0.6% of number of credit exposures, and 2.5% in terms of value). Given that our loan-level sample of large exposure includes only loans greater than €300 million (or loans greater than 10% of the Tier1 capital of the bank issuing the loan), we can conclude that the credit exposures analysed in our paper are not guaranteed and that governments' financial support did not influence our analyses.

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[14]We use the Nomenclature of Economic Activities (NACE) classification

[15]We select five buckets: up to €100 thousand; between €100 thousand and €10 million; between €10 million and €100 million; between €100 million and €300 million; and greater than €300 million.

2.2 Bank-level Analysis

The COVID-19 pandemic, a natural disaster hitting Europe since March 2020, provides us with an excellent setting to investigate whether model-based regulation provides banks with risk-sensitive risk weights and affects their lending provision. Specifically, we look at the lending behavior of banks to see whether banks using different approaches for capital regulation reacted differently to the COVID-19 shock.

Although COVID-19 did not directly hit banks (neither IRB banks nor SA banks), the economic channel linking the pandemic shock to banks is intuitive. The downturn caused by COVID-19 directly affected the solvency of NFCs, resulting in a heightened risk of firms failing to repay their debt obligations. From a bank perspective, the pandemic induced different effects on banks depending on the risk models used to determine capital charges. Therefore, the first step of our analysis entails comparing the reaction of IRB and SA banks. IRB banks using model-based risk-weights immediately registered, *ceteris paribus*, a deterioration of internal borrowers' rating, leading to an increase in their Risk-Weighted Assets (RWA), and thus in capital absorbed by the exposures. Conversely, SA banks using fixed risk-weights that are not - or much less - risk-sensitive, did not register any increase in their RWA and capital absorbed.

We begin our analysis using supervisory data at the bank-level. Our identification strategy relies on a Difference-In-Differences (DiD) approach, enabling us to identify whether, after the outbreak of the COVID-19 in March 2020, IRB banks dropped their lending more relative to SA banks. Our baseline identification strategy is based on the following model:

$$\Delta Log(Y)_{i,t} = \beta_1 IRB_i \times Post_t + \beta_2 X_{i,t-1} \times Post_t + \beta_3 X_{i,t-1} + \gamma_i + \gamma_{c \times t} + \epsilon_{i,t} \quad (1)$$

where our dependent variable ($\Delta Log(Y)_{i,t} = Log(Y_{i,t}) - Log(Y_{i,t-1})$) is the quarter-on-

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quarter growth rate of the credit exposures of bank i. We use various measures of on-and off-balance sheet credit exposures to gain a broad understanding of the impact of COVID-19. The analysis starts with a measure including all on- and off-balance sheet credit exposures (total credit origination).[16] In a second step, we disentangle this measure in total on-balance sheet and total off-balance sheet credit exposures. Finally, we focus on bank loans. For each of the variable employed in the model, we also distinguish the counterparties, thus differentiating between exposures towards NFCs and other than NFCs (Non-NFCs).[17]

Our treatment period variable ($Post$) takes the value of one for the quarters 2020Q2-2020Q3, and zero for 2019Q2-2020Q1.[18] The variable IRB_i takes the value of one for banks using internal models for the calculation of capital requirements for their *corporate* credit risk exposures (treatment group), and zero for banks using the Standardised Approach (control group). The coefficient of main interest is β_1 for the interaction variable $Post \times IRB_i$ that, *ceteris paribus*, captures the COVID-19 pandemic effect on IRB banks' lending.

Eq.(1) includes a vector of bank characteristics ($X_{i,t-1}$) that could affect bank lending behaviour. We control for bank' size using the natural logarithm of total asset ($Size$), while the distance between the reported Common Equity Tier 1 (CET1) ratio and banks' total SREP capital requirement (TSCR) is included to control for moral hazard incentives due to banks having less "skin-in-the-game" ($Distance$).[19] Bank profitability is controlled for with the inclusion of return on assets (ROA), while the ratio of deposits over liabil-

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[16]We thank Philip Strahan for this suggestion.

[17]Non-NFC includes exposures to governments, credit institutions, other financial institutions and retail customers.

[18]As a robustness check, we re-run the model in Eq. (1) omitting 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).

[19]SREP stands for Supervisory Review and Evaluation Process and it refers to the annual assessment conducted by the ECB to evaluate banks' risk profiles. TSCR includes the system-wide Pillar 1 requirements plus the bank-specific Pillar 2 requirements that is the outcome of the SREP assessment.

ities proxies for banks' funding preferences (*Deposit Ratio*). Finally, the RWA density (*Density*), calculated as the ratio between total RWA and total exposures, controls for banks' risk profile. The control variables are lagged by one quarter to reduce possible endogeneity concerns. We also include the interactions between each control variable and the treatment period. These interactions partial out the effect of observable covariates on banks' lending and ensure that the coefficient of main interest (β_1) is not driven by banks' heterogeneity.

To account for any remaining unobservable factors, we use different sets of fixed effects (FE). First, we include bank fixed-effects (γ_i) to control for unobserved firm fundamentals that are not captured via $X_{i,t-1}$. Furthermore, we progressively saturate our bank-level regressions with time FE and, in our richest specification, with *country × time* fixed effects (γ_{cxt}) to control for demand effects (Kok et al., 2021).[20] 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. ϵ is the error term. 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.

2.3 Loan-level Analysis

In the second step of our analysis, we replicate our baseline model using loan-level data on large exposures, and we estimate the following model:

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[20]The country refers to the country where the bank is headquartered.

$$\Delta Log(Y)_{i,t,j} = \beta_1 IRB_i \times Post_t + \beta_2 X_{i,t-1} \times Post_t + \beta_3 X_{i,t-1} + \beta_4 W_{i,j,t-1} \times Post_t +$$

$$\beta_5 W_{i,j,t-1} + \gamma_i + \gamma_{b \times t} + \epsilon_{i,t}$$

$$(2)$$

In this case, the dependent variable is measured by the quarter-on-quarter growth rate of credit exposures volume by the bank i to the borrower j ($\Delta Log(Y)_{i,j,t} = Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). To control for any demand factor and assess whether the changes in lending are due to a supply effect, we restrict our sample to firms with multiple-lending relationships, in line with the Khwaja and Mian (2008) approach. Specifically, our sample is constituted by companies that borrow at the same time from (at least) one IRB bank and (at least) one SA banks. By focusing on multiple-lending relationships and including *borrower* × *time* FE ($\gamma_{b \times t}$), we control for any time-varying unobserved borrowers' characteristics and potential changes in the credit demand at the level of the borrower. This empirical setting allows us to isolate credit supply changes from shifts in loan demand generated by a demand shock during the COVID-19 pandemic. The vector of bank characteristics ($X_{i,t-1}$) includes those specified for Eq.(1). We augment the model by adding an additional control ($W_{i,j,t-1}$) capturing the size of the large exposures of bank i toward borrower j relative to the size of the NFCs portfolio of bank i (*Exp_Size*). γ_i are bank fixed-effects, $\gamma_{b \times t}$ are *borrower* × *quarter* fixed-effects, and ϵ is the error term.

Finally, 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 analyses (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, when running Eq.(2), we restrict our analyses to bank-firm relationships that

can be observed for the entire period.

The definitions of the entire set of variables employed in our models are reported in Table A3 in the Appendix. The descriptive statistics of our dependent variables are reported in Table 1 for both bank-level (Panel A) and loan-level variables (Panel B). Overall, banks using SA model display an increase in total credit origination, on-balance sheet exposures and lending activities between 2019Q2 and 2020Q3, whereby IRB banks generally have lower mean growth rates compared to SA banks for each variable. In Panel C, we report the summary statistics of our control variables. IRB banks show (on average) a greater size than SA banks. However, SA banks have greater profitability, higher capital levels, a greater share of deposit funding and higher RWA density than IRB banks.

[Insert Table 1 here]

3 Model-Based vs Standard Approaches: Results

3.1 Testing for the parallel trend assumption

The difference-in-differences estimator relies on two main assumptions: i) the treatment must be orthogonal with respect to the outcome variables, and ii) 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, while we provide evidence to support the parallel trend assumption between the treatment and control groups. Specifically, we compare the growth of our main variable of interest - loans to NFCs - 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 were comparable. Table 2 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 NFCs credit exposure measures are largely statistically indistinguishable for the treatment group and for the control group prior to the COVID-19 pandemic development in Europe. Differences in means are instead significant for the post-treatment quarters.

[Insert Table 2 here]

Additionally, we plot the evolution over time of lending granted by the two groups of banks. As shown in Figure 1, the growth rate for credit exposure to NFCs (on-balance sheet exposures in Panel A and Loans in Panel B) is parallel between IRB and SA banks up to the first quarter 2020, after which it diverges. Overall, these results show that the parallel assumption condition holds, 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 Figure 1 here]

As a final test, we perform difference-in-means for various bank characteristics that may differ between IRB and SA banks. As shown in Table A4 in the Appendix, IRB and SA banks differ across several characteristics. This support our decision to include these variables in our models (Eqs. (1) and (2)) to restore the randomization condition.

3.2   Results: Bank-level analysis

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. Table 3 reports the results obtained estimating the model in Eq.(1) for different measures of credit to non-financial corporations. Specifically, we focus on i) credit origination NFCs, measuring all on- and off-balance sheet exposures (columns 1 and 2), ii) total on-balance sheet credit exposures (columns 3 and 4), and iii) total loans (columns 5 and 6).

The main coefficient of interest is the interaction $Post \times IRB_i$, showing the Average

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Treatment Effect (ATE) due to the COVID-19 pandemic for IRB banks. Overall, our results suggest that, following the eruption of the pandemic in March 2020, there are differences in the growth of credit exposures between banks adopting an IRB or a SA approach. In particular, banks using IRB models reduced their credit growth compared to banks using the SA approach. The growth rate of credit origination to NFCs declined between 1.35% and 1.86% more in IRB banks compared to SA. We obtain very similar results for the growth rate of on-balance sheet exposures (between 1.44% and 2.32%), and total loans and advances (between 1.62% and 2.45%) to NFCs. We notice that controlling for demand effects - by adding $country \times time$ fixed effects - reduces the magnitude of the coefficients, but not their significance.

[Insert Table 3 here]

All models include the interactions between the treatment period variable and each of the control variables ($Post \times Size$, $Post \times Distance$, $Post \times ROA$, $Post \times Dep\_Ratio$, and $Post \times Density$ respectively). The inclusion of these interactions enables us to control for the possibility that IRB banks might have realized the disruptive effects of COVID-19 on the economy before SA banks, resulting in IRB banks cutting their lending faster than other banks. The quicker reaction can be explained by the fact that IRB banks are usually larger and have a significantly more developed risk management departments. Interestingly, we find no evidence supporting the notion that banks' size, capitalization, profitability and RWA density played a significant role after the eruption of the pandemic. In the entire set of analyses at the bank-level (Table 3), these interactions are insignificant in explaining credit exposures growth. Conversely, we find evidence that credit exposures generally increased after the COVID-19 for banks with higher shares of deposit funding. Indeed, the term $Post \times Dep\_Ratio$ is always found positive and strongly significant, suggesting that banks with a more stable funding base were able to better withstand the liquidity shock caused by the COVID-19 eruption and therefore maintained the capacity

to continue to extend credit.

To gain a complete picture of the dynamics at play during the pandemic, we also explore banks' behaviour with respect to i) exposures other than to NFCs and, ii) off-balance sheet exposures. The results of these additional analyses are reported in Tables A5 and A6 in the Appendix, respectively. We do not find evidence that IRB banks have changed their lending behaviour toward counterparts that are not classified as NFCs. Likewise, IRB banks did not change their off-balance sheet credit exposures relative to SA banks.

All the specifications are saturated with bank fixed effects together with *time* or *country* × *time* fixed effects to control for changes in credit demand induced by the pandemic shock. As such, this set of analyses provides the first evidence that the reduction in credit growth was supply driven. IRB banks dropped more their overall, on-balance sheet and loan exposures after the outbreak of the COVID-19 pandemic compared to banks using the standardised approach. This behaviour involved only NFCs exposures, while other counterparties did not suffer the same reduction (see Table A5 in the Appendix).

3.3 Loan-level analysis: a supply-side effect?

In this section, we further investigate whether the gap in lending growth between IRB and 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 vs. SA banks), but we employ loan-level data 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 they absorb the largest amount of bank capital, and thus we could rationally expect that, after the COVID-19 shock, banks tried to adjust their asset position starting from these exposures.[21]

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[21] 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

Estimates for Eq.(2) are reported in Table 4. In Panel A, we focus first on on-balance sheet exposures (columns 1 to 3), and total loans and securities (columns 4 to 6) to NFCs. In Panel B, we focus on off-balance sheet exposures (columns 1 to 3), and loan commitments (columns 4 and 6) to NFCs. As for the previous models, the coefficient of main interest is for the interaction $Post \times IRB_i$, capturing the effect of higher capital requirements induced by model-based regulation due to COVID-19 pandemic for IRB banks on lending to large corporates.

The results reported in Panel A confirm the findings obtained using bank-level data. We show a substantial decline in on-balance sheet exposures (between 8.45% and 10.35%) and loans and securities exposures (between 11.00% and 13.29%), suggesting that IRB banks have a lower growth rate of exposures relative to SA banks. The decrease in exposures corresponds to an average lending drop per bank of about €7.2 billion.

The findings for off-balance sheet large exposures (Panel B of Table 4) show an opposite situation. IRB banks reacted to the shock by increasing more their off-balance sheet credit exposures (between 6.97% and 9.05%), and especially loan commitments (between 16.49% and 20.50%) to NFCs, relative to SA banks. These positions do not directly absorb regulatory capital and, thus, we show that IRB banks supported NFCs during the COVID-19 outbreak by increasing off-balance sheet exposures and gaining higher fees without an immediate impact on equity.

By using a sample of multiple-lending relationships that enables us to control for borrower demand, this second set of results provides further evidence that the contraction in on-balance sheet and loans extended by IRB banks compared to SA banks is the result of a bank decision. That is, the lower credit growth is due to a supply-side effect rather than a demand shock.

In Section 3, we have shown that, following the outbreak of the pandemic in March

mitigation or exemption clauses; (b) the 20 largest exposures even if they do not satisfy the definition of a large exposure.

2020, IRB banks reacted by recognising the increase in the riskiness of the borrowers and deleveraging via a reduction of their exposures to NFCs. This behaviour of IRB banks is observed both at the portfolio level (i.e., when using bank-level data) and at the level of individual exposures (i.e., when employing the "large exposures" data). These results support the presence of tensions between micro- and macro-prudential policies' objectives. Indeed, from a micro-prudential point of view, these results suggest that IRB models support the financial soundness of banks by increasing the risk sensitiveness of capital requirements. However, from a macro-prudential perspective, the deleveraging of banks might have exacerbated the crisis via the contraction in the credit supply to firms.

[Insert Table 4 here]

4   An alternative identification based on IRB banks

Our baseline identification strategy relies on the comparison between IRB and large SA banks' lending behaviour. The underpinning idea is that the macro-economic shock engendered by COVID-19 increased the capital absorbed by lending portfolios of IRB banks, but not those of SA banks. Risk-weights in SA models are in fact fixed and not risk-sensitive, at least in the short-term. So far, our results have provided support for this notion, as we have seen that IRB banks reduced their exposures to NFCs relative to SA banks during the COVID-19 emergency.

We argue that banks' lending reaction to the COVID-19 shock is also driven by the characteristics of the bank and the specific features of its IRB system. In this section, we shed further light on the underlying channels linking lending changes to COVID-19. First, we focus on the role of regulatory capital. Our hypothesis is that IRB banks operating well above minimum regulatory capital requirements were able to keep lending when COVID-19 worsened borrowers' credit standing, while capital constrained IRB banks did not

have the necessary capacity. Second, we assess the role played by the features of IRB systems and especially the inclusion of the downturn LGD parameter. We argue that the inclusion of this parameter might have mitigated the pandemic shock and supported credit expansion.

4.1 The role of capital in IRB banks reaction

To test whether our results are driven by banks' levels of capital, we restrict our sample to banks using IRB models that are similar vis-à-vis the supervisory authority's eyes, having their internal models been scrutinized and validated. In this setting, both the treatment and control groups of banks registered an increase in their RWA after the COVID-19 eruption. We argue that IRB banks operating with capital levels well above the minimum regulatory requirements have the option to decide whether to maintain their credit exposures (meeting increased capital requirements and covering losses with the capital surplus) or reduce lending. Conversely, IRB banks operating with capital levels close to the minimum regulatory requirements did not have the option to maintain the same credit exposures (being short of equity to satisfy the increased capital requirements) and were forced to reduce lending in a pandemic scenario. This alternative identification enables us to account for the fact that IRB banks and SA banks may have some fundamental differences that are affecting our results. For example, IRB banks may 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).

Our identification is straightforward. Our treatment (control) group includes banks reporting a distance between their CET1 ratio and their Total SREP Capital Requirement (TSCR) below (above) the first quartile of the distribution (*LowCap*) in the pre-pandemic period (as of 2019Q4). As such, we replicate the loan-level analysis by running the model in Eq.(2) using this alternative identification strategy. As per Section 3.3, our sample

relies on multiple-lending relationships, where we impose the condition that the borrower has to be associated with (at least) one bank with a low capital buffer and (at least) one bank with a high capital buffer.

As a first step, we test whether the parallel trend assumption between the treatment and control groups holds. We compare the quarterly growth of credit exposures (on-balance sheet and loans) to NFCs for IRB banks with a low- and high-distance from TSCR. Table 5 reports 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 5 here]

We estimate the impact of model-based regulation using this new identification strategy and report the results in Table 6. Low capitalised IRB banks have lower growth rates of on-balance sheet credit exposures (between 2.94% and 3.86%) and loans and securities (between 5.75% and -6.78%) relative to IRB banks with higher buffers (Panel A of Table 6). These findings confirm our hypothesis that IRB banks with capital well above their TSCR requirements 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.

[Insert Table 6 here]

As a first robustness check, we replicate this analysis on the pool of SA banks. Intuitively, if the reduction in lending is the outcome of the use of IRB models, we do not expect any difference between SA banks with different levels of capital buffers. This is because the SA approach is not-risk sensitive and thus the pandemic would produce the same effect on both groups of banks. As shown in Table A7 (in the Appendix), our results do not imply any statistically significant difference between highly and poorly capitalized SA banks in terms of credit provision during the COVID-19, supporting our argument

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that internal models are driving the impact on bank lending.

We further enrich our analysis by exploring the possibility that capital constrained IRB banks selected the borrowers to which reducing credit. Specifically, we investigate three sources of heterogeneity: i) the capital absorption of each specific 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 selectively reduced exposures with higher capital absorption. To this end, we augment the DiD specification of Eq.(2) 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 exposure by dividing the value of the exposure after the application of CRM factors 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.[22] 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 of Table 7 reports the DiD results when controlling for the influence of the CRM factor, where the main coefficient of interest is the triple interaction $Post_t \times LowCap_i \times CRM_j$. We observe a negative and statistical significant coefficient for loans and securities (column 1), implying that, after March 2020, low capitalized IRB banks cut more than highly capitalized IRB banks their exposures towards borrowers absorbing relatively more capital. This result is consistent with the notion that model-based capital regulation might induce procyclicality in bank lending. Banks' internal ratings

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[22]For example, if we observe in our data an original credit exposure of €100 million, which becomes €80 after the application of CRM, this implies a CRM factor of 0.8.

for borrowers (e.g., PDs) deteriorate swiftly following adverse macroeconomic scenarios, especially during crisis times. The deteriorated parameters feeding into their regulatory models cause higher capital absorption of that exposures and might incentivize banks to cut back on lending. At the same time, we show that this reaction also depends on the level of capital headroom when the shock hits.

In a similar fashion, we run a triple DiD to explore whether IRB banks close to their TSCR targeted the economic sectors to which reducing their exposures. Focusing on the triple interaction $Post_t \times LowCap_i \times Most\_Affected_j$, the variable $Most\_Affected$ is a dummy variable taking the value of one if the borrower belongs to one of the sectors identified by the European Banking Authority (2020) as being the most affected by 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.[23] Not surprisingly, the results in Panel B of Table 7 show that, after March 2020, capital-constrained IRB banks have decreased their loans and securities exposures more than highly capitalized banks (column 1) towards the most affected sectors of the economy.

Finally, the third dimension investigated is the country where the borrower is headquartered. Specifically, we explore whether, following a shock, banks differentiate between domestic and non-domestic borrowers. To this end, in Panel C of Table 7, we include a triple interaction ($Post_t imes LowCap_i \times Domestic_j$) 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 re-balancing towards banks' domestic market after the COVID-19 shock.

[Insert Table 7 here]

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[23]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.

To sum up, our triple DiD analyses show that the decline in lending of IRB banks operating close to their TSCR relative to IRB banks with higher capital did not affect all borrowers, rather it was concentrated 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. As such, IRB model worked as intended by micro-prudential supervisors by identifying correctly the most risky counterparties and reducing their exposures towards them. Nonetheless, the reaction of IRB banks might rise macro-prudential concerns if - by contracting lending to these borrowers - the crisis is exacerbated.

4.2   The role of IRB model features

In this section, we test whether the different features of IRB models influence banks' reactions to the pandemic shock. IRB models for credit risk are complex models based on several parameters, including the Probability of Default (PD), the Loss Given Default (LGD), the Exposure at Default (EAD), and the Maturity (M). These parameters give an assessment on the riskiness of the borrower and the potential loss the bank has to bear in case the borrower defaults. In detail, the Basel Committee proposes two types of IRB methodology. In the "Foundation" framework, regulators authorize banks to calculate risk-weights using their assessment of borrowers' PD, while the remaining parameters are derived through the application of standardised supervisory rules. By contrast, in the "Advanced" framework, the supervisory authorities permit banks to determine the risk-weights using internal models where all the parameters (i.e., PD, LGS, M, EAD) are internally calculated.

Among the different parameters envisaged by the IRB models, we focus on the Down-turn LGD, which is a specific LGD measure used as risk parameter in the Basel II/III

regulatory framework.[24] In simple words, the downturn LGD is the expected LGD during downturn periods (i.e., during crises). Banks estimating a downturn LGD use historical datasets of economic indicators of at least the most recent 20 years including downturn periods and thus have elevated levels of realised LGD. Intuitively, banks including a downturn LGD in their IRB models should be more resilient to the effects of the COVID-19 pandemic since their risk-weights are on average higher than those of banks not using a downturn LGD which, instead, would suffer a quicker increase in risk-weights from March 2020.

For this analysis, we obtain confidential information on the banks participating in the Targeted Review of Internal Models (TRIM).[25] Our treatment group includes banks that use a downturn LGD ($DLGD$) in their IRB model, while the control group comprises all IRB banks (both banks under the foundation and the advanced framework) not using the $DLGD$ parameter. As usual, we replicate the loan-level analysis (as illustrated in Section 2.3) by running the model in Eq.(2). As per Section 3.3, our estimation exploits multiple-lending relationships, where we impose the condition that the borrower has to be associated with (at least) one bank using downturn LGD and (at least) one bank that does not use it. Table 8 illustrates the test for the parallel trend assumption between these two groups of banks, confirming that there are no differences in their lending patterns before the COVID-19 shock.

[Insert Table 8 here]

The results reported in Table 9 show that IRB banks using a downturn LGD were able to increase credit exposures to borrowers more than banks in the control group (between 4.14% and 6.44%) and the difference is mainly due to loans and securities (between 5.45% and 6.45%). We do not find differences in off-balance sheet credit exposures. As a ro-

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[24]The European Banking Authority published in March 2019 its guidelines specifying how institutions should quantify the appropriate LGD estimation in an economic downturn.

[25]TRIM is a multi-year project carried out by the Single Supervisory Mechanism aimed at assessing the compliance to regulatory requirements of IRB models used by Significant Institutions.

bustness check, we restrict the control group to IRB banks under the advanced framework only. The results in Table A8 in the Appendix fully confirm our findings.

These results confirm our expectation that IRB banks including a downturn LGD in their IRB models are better equipped to deal with severe adverse events than those banks not incorporating this parameter. It follows that these banks could lend more (or drop lending less) relative to banks not using a downturn LGD when a shock occurs. Thus, the downturn LGD parameter could alleviate the tensions between micro- and macro-prudential objectives arising during economic downturns.

[Insert Table 9 here]

5   Robustness checks: Ruling-out alternative explanations

In this final set of estimations, we consider alternative channels that may explain the documented negative link between the use of model-based regulation and the drop in lending activities after the COVID-19 eruption. A first concern is that IRB banks are more sophisticated than SA banks, and, as such, they incorporated the COVID-19 negative effects earlier. Thus, one could argue that the observed lending drop is not due to the adoption of IRB models, but rather it is a consequence of better risk management skills. A second issue is related to the fact that IRB models generate a pro-cyclical effect and thus the lending drop after the COVID-19 is a rather mechanical consequence - more than a bank's decision to reduce its credit exposure - due to banks having experienced a credit boom before the start of the pandemic. A third concern is related to the possible worsening of the quality of the borrowers and the presence of *zombie lending*. After the start of the pandemic, banks may have decided to carry-on lending activities towards large borrowers even if these became too risky (zombie) and thus the drop observed is biased. We address these concerns in the following subsections.

5.1 Different risk management abilities

We start by testing whether the reaction of IRB banks is due to superior risk management skills that enabled IRB banks to react faster after the COVID-19 eruption. To this aim, 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 10. 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 COVID-19, rather it is a persistent effect over the entire 2020, and suggests that the effect is driven by the use of internal models contributing to the pro-cyclicality of lending.

[Insert Table 10 here]

5.2 Procyclicality

Several past papers (Danielsson et al., 2001; Kashyap and Stein, 2004; Repullo and Suarez, 2013) have shown that the introduction of internal-rating models increased the pro-cyclicality of bank lending. Thus, we have to consider whether our treatment variable group (IRB) is capturing a pro-cyclical effect and, thus, the negative effect on lending that we observe results from the compounding effect of the adoption of IRB models and pro-cyclicality. Notably, this issue in particular has not been addressed in previous studies looking at the impact of model-based regulation because these studies were analysing developments in a single country. The cross-country dimension of our database allows studying this particular aspect linking model-based regulation and pro-cyclicality. We

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split our sample in two groups, one constituted by Euro area countries that were experiencing a declining phase of credit growth (i.e., those with a ratio between credit growth and GDP growth below the Euro area mean), and one comprising Euro area countries in a phase with higher credit growth (i.e., those with a ratio between credit growth and GDP growth above the mean) before the outbreak of the pandemic. We estimate our model augmenting Eq.(2) with a triple interaction ($Post_t \times IRB_i \times Country\_Group_j$) and focusing on the large exposures sample restricted to borrowers with multiple relationships.[26] For this analysis, we adopt two identification strategies, that is, we compare IRB and SA (Panel A) banks as well as low and high capitalised IRB banks (Panel B).

The findings are shown in Table 11 and confirm that IRB banks generally decreased their on balance sheet exposure (loans and securities) after the start of the COVID-19 pandemic. However, we do not find statistical evidence that this effect differs for banks located in countries that were at different phases of the credit cycle before the pandemic. In other words, results are not driven by banks located in countries with credit booms and we do not find evidence that the decline in exposures may be due to possible *excessive lending* granted before the outbreak of the pandemic.

[Insert Table 11 here]

5.3 Zombie lending

The analyses reported so far might hide a zombie lending problem. That is, the observed decline in lending may be driven by the reduction in exposures to borrowers with relatively lower quality that may have been receiving credit more from IRB banks in the pre-pandemic period. In order to address this concern, we measure the quality of the borrowers using i) their PD (*ex-ante* measure of credit risk) and ii) the number of days for which the loan is past due (*ex-post* measure of credit risk). To retrieve this information,

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[26]In each sub-sample, we include bank-borrower relationship among banks in that same group of countries. Thus, we are not including the case of multiple-lending relationship if the first lending bank is from a high economic growth country and the second lending bank is from a low economic growth country.

we match our large exposure datasets with Anacredit.[27] We look at the distribution of these two measures for our sample of corporates and exclude from the sample borrowers with a PD or number of days of past due located in the highest 10th percentile of the distribution. In other words, we exclude from the estimation those borrowers with relative lower quality. We estimate our usual DiD model and report the results in Table 12. The decline in credit exposure and in particular in loans and securities granted remains more pronounced for IRB banks compared to SA banks even when restricting the sample to high quality borrowers. Therefore, we conclude that firms with lower quality - *zombie firms* - do not affect our results.

[Insert Table 12 here]

5.4 Capital constrained banks

In this subsection, we further investigate the role of capital buffers by restricting our analysis to banks - both IRB and SA - with a relatively low level of capital with respect to their TSCR. Specifically, we calculate the difference between the CET1 ratio and the Total SREP Capital requirements for all the banks and consider only those for which this difference belongs to the first quartile of the distribution. As expected, our main results are further confirmed in this setup (Table 13) with the economic significance of the coefficients being generally higher compared to the findings reported in Table 6. These results offer additional evidence that the reduction in lending is driven by the use of internal models.

[Insert Table 13 here]

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[27]AnaCredit is a dataset containing detailed information on individual bank loans in the euro area, harmonised across all Member States. "AnaCredit" stands for analytical credit datasets.

5.5 The indirect effect of government guarantees

Finally, we consider the indirect effect that government guarantees may have on large exposures. As shown in Table A2, "large exposures" were not supported during COVID-19 with governmental guarantees, thus limiting the bias in our analyses that would have arised if we were to focus on loans to SMEs. However, the benefit of government guarantees into other credit portfolios (e.g., SMEs) could be heterogeneous and this may have affected indirectly the lending provisions from IRB banks to large borrowers. Thus, we account for the fact that large exposures may have been indirectly influenced by government guarantees extended on other loan portfolios. To this aim, we replicate our main results and we re-run the models in Tables 6, 7, and 9 adding a control variable calculated as the ratio between total loans covered by a public guarantee over total loans. As expected, all main results are further confirmed in this setup (see Table A9).

6 Economic impact: a focus on borrowers

In previous sections, using an array of different identification strategies, we showed that banks using model based regulation decreased lending to large corporations relative to banks using the SA approach after the COVID-19 eruption. From the point of view of micro-prudential supervisors, these behaviours of banks are exactly what envisaged and intended by the regulatory framework. In this section, we conclude the paper by showing how the reduction in credit supply of IRB banks compared to SA banks generated a negative economic impact on the corporations involved and thus on the overall real economy. That is, we provide evidence of how micro-prudential approaches can have macro-prudential consequences. As such, this issue is particularly important to inform policy makers that, during the COVID-19 pandemic, had to devise policies to support funding to corporates and households to smooth the negative effects on the economy.

Concerning in particular the issue that we are studying, the lower credit granted from IRB banks may be compensated in case of a large shock by greater funding from SA banks, or by more funding from other sources, like bondholders and shareholders.[28]

To this aim, we collected accounting data from the Orbis database for the sample of NFCs borrowers analysed in the previous sections over the period 2015-2020, and we matched this information with the funding that NFCs obtained from IRB and SA banks reported in the ECB supervisory information on large exposures. Specifically, we first construct a borrower-level proxy to capture firm's dependency on IRB funding. This variable is calculated as the ratio of funds granted by IRB banks over total assets of the firm (*IRB Ratio*). We rank corporations according to this variable and divide the distribution in terciles. We define a dummy variable (*IRB Ratio dummy*) taking the value of one for borrowers that are more credit dependent on IRB banks (the third tercile of the *IRB Ratio* distribution) and zero for NFCs relying less on funding from IRB banks (the first tercile of the *IRB Ratio* distribution). Our identification strategy is based on a following model:

$$
\begin{aligned}
Log(Y)_{j,t} = {} & \beta_1 IRBratiodummy_{j,t} + \beta_2 IRBratiodummy_{j,t} \times Post_t \\
& + \beta_3 IssuedCapital_{j,t} + \beta_4 IssuedCapital_{j,t} \times Post_t \\
& + \beta_5 Reservecapital_{j,t} + \beta_6 Reservecapital_{j,t} \times Post_t \\
& + \beta_7 MostAffected_j + \beta_8 MostAffected_j \times Post_t + \\
& + \beta_9 X_{j,t-1} + \gamma_j + \gamma_t + \epsilon_{j,t}
\end{aligned} \tag{3}
$$

where our dependent variable ($Log(Y)_{j,t}$) is the log of various assets items for the borrower j at time t. We use various measures of assets - debtors receivables, other current assets, tangible fixed assets, and non-tangible fixed assets - to gain a broad understanding of the

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[28]As shown in the introduction, large exposures were not supported via governments guarantees during the COVID-19 pandemic.

impact that a shock to IRB funding during the COVID-19 generated on borrowers.[29]

For the purpose of this analysis, we focus on three main coefficients of interest in Eq.(3). The first (β_2) is the coefficient of the interaction between the IRB Ratio dummy and the post-COVID dummy and it captures whether borrowers, whose funding depended more on IRB banks, dropped their investment in 2020 compared to other borrowers (i.e., all NFCs before the COVID-19 or NFCs relying less on IRB banks' funding). The second coefficient of interest (β_4) is the interaction between issued capital (i.e., the log of common equity) and the post-COVID dummy. This coefficient shows whether borrowers' investments in 2020 were financed via equity issuance. The third coefficient of interest (β_6) is the interaction between reserve capital (i.e., the log of equity reserves), and the post-COVID dummy, capturing whether in 2020 the investments of these NFCs were funded by using equity reserves. The model is saturated with a vector of firm characteristics ($X_{j,t-1}$) affecting borrowers' assets, including the log of the operating turnover and the capital ratio (both measured with 1-year lag), the number of banks the corporation is borrowing from and a dummy with a value of one if the firm is listed. We also control for the firm being part of the industries most affected by the pandemic ($Most\_Affected \times Post$).

Our estimates (Table 14) show that IRB-dependent corporates dropped their investments more relative to other borrowers in 2020. The coefficients are statistically significant for short-term financial investment (trade receivables), tangible fixed assets and intangible fixed-assets. These results suggest that the previously documented decrease in credit granted by IRB banks induced more IRB dependent borrowers to reduce the selling of goods and services on credit (this enables NFCs to reduce funding needs and also increase cash inflow from selling). Similarly, these borrowers dropped investments in patents, copyrights, trademarks, franchise rights and other intangible assets that NFCs normally increase in good times, when funds are more easily available. Furthermore, the same

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[29]We also replicate the model using the number of employees and various performance measures.

borrowers did not acquire tangible assets in 2020.

Interestingly, we document that investments in receivables and tangible fixed assets were supported in 2020 by the usage of capital reserves (the interaction $Reserve\_Capital \times Post$ is negative), instead of resorting to other financing options. Conversely, the coefficient related to the issuance of new shares is not statistically significant, suggesting that borrowers faced difficulties in raising equity on a short notice in exceptional times. The results confirm that, in times of crises, large borrowers support their assets using their capital reserves. Overall, the results of Section 6 our provide important insights for policy makers. Model based regulation is able to achieve micro-prudential objectives by providing banks with risk sensitive estimates, but at the same time, it produced substantial negative effects on borrowers during the COVID-19, especially in tangible investments.

[Insert Table 14 here]

7 Conclusions

When the economy suffers a recession or is hit by catastrophic events, such as the Covid-19 pandemic, the banking system has the critical role to ensure the intermediation of funds toward firms that are still viable but may have temporary funding needs. Overall, we document how the current regulatory framework affects the intermediation function. We show that model-based regulation induces a reduction in credit exposures to corporates, in particular for IRB banks closer to minimum capital requirements. Therefore, IRB models increase the risk sensitiveness of capital requirements and support the financial soundness of banks. At the same time, we show that an appropriate calibration of IRB models and the use of a downturn LGD parameter can have a significant impact on preserving banks' resilience, so that banks are less constrained in the provision of credit also when a large shock occurs.

All in all, this study highlights the trade-off faced by policymakers between adopting

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regulatory policies that are able to quickly adjust for changes in the risk outlook - and therefore support the stability of the banking sector - and ensure that the reduction in credit supply will have limited impact on the economic recovery.

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Panel A: Total On-Balance Sheet Exposures to Non-Financial Corporations
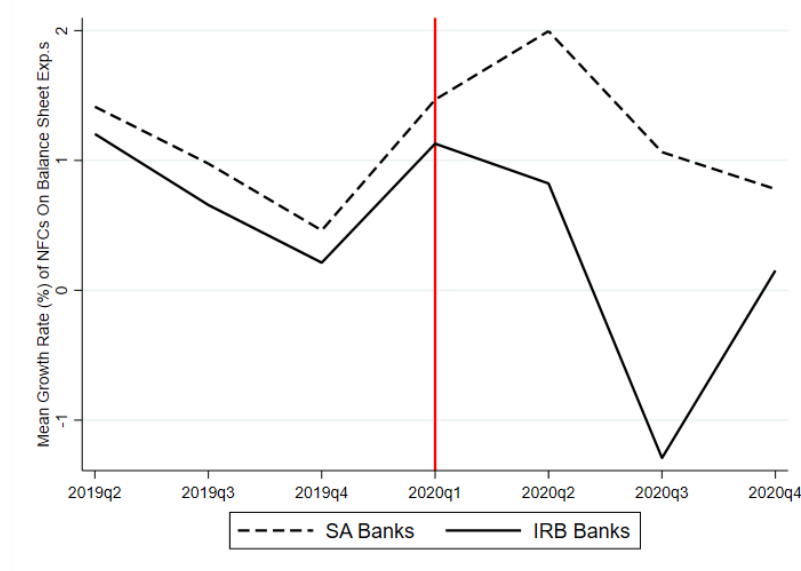
Panel B: Loans to Non-Financial Corporations
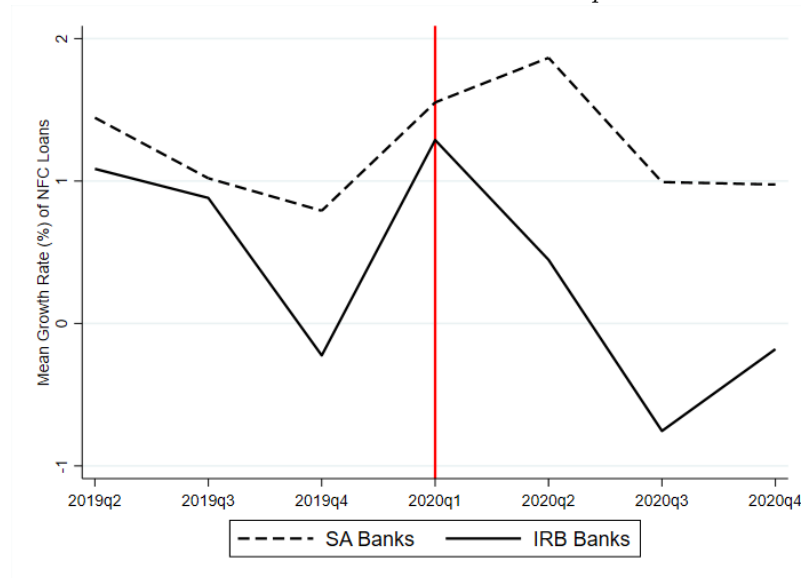
Figure 1: Credit exposures to Non Financial Corporations (NFC) at Bank Level.
The two figures plot the average growth rate of the two lending measures (On-balance sheet exposures to NFCs in Panel A, and Loans to NFCs in Panel B), computed quarter by quarter, according to the two groups of banks. Source of data: FINREP. SA banks include banks reporting all corporate credit risk exposure using a Standardized Approach, IRB banks are banks in which a fraction of credit risk exposure is evaluated using Internal Ratings Based approach (source: COREP).

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Table 1
Summary Statistics

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 or Internal-Rating Based Approach. 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 analyses. Panel B reports the summary statistics for the outcome variables used in the loan-level analyses. Panel C shows the summary statistics for the bank control variables. Variables are defined in Table A3.

	Standardised Approach				Internal-Rating Based Approach			
	N	Mean	Median	SD	N	Mean	Median	SD
Panel A. Outcome Variables at Bank-level (Growth Rates)								
Credit Origination (All Borr.s)	1080	0.0137	0.0090	0.0467	420	0.0060	0.0062	0.0395
Credit Origination (Non-NFC Borr.s)	1080	0.0140	0.0083	0.0721	420	0.0051	0.0070	0.0753
Credit Origination (NFC Borr.s)	1080	0.0196	0.0115	0.1407	420	0.0054	0.0051	0.0495
On-Balance Sheet (All Borr.s)	1080	0.0125	0.0090	0.0474	420	0.0060	0.0049	0.0409
On-Balance Sheet (Non-NFC Borr.s)	1080	0.0132	0.0079	0.0719	420	0.0069	0.0072	0.0578
On-Balance Sheet (NFC Borr.s)	1080	0.0180	0.0115	0.1466	420	0.0043	0.0047	0.0540
Total Loans (All Borr.s)	1080	0.0106	0.0102	0.0618	420	0.0041	0.0043	0.0372
Total Loans (Other Borr.s)	1080	0.0594	0.0388	0.2269	420	0.0521	0.0392	0.1596
Total Loans (Retail Borr.s)	1080	0.0095	0.0086	0.0631	420	0.0018	0.0079	0.1455
Total Loans (NFC Borr.s)	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
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
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
Distance (%)	1080	10.1597	9.7100	3.3191	420	9.7604	8.5985	3.8727
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
Large Exposure Size (%)	376	6.9971	3.5882	7.4972	1140	1.0133	0.3796	1.4435

Table 2
Difference in Means between SA and IRB banks (Dependent variables)

This table provides the pre- and post-treatment mean comparisons between banks using the Standardised Approach (SA) and banks using the Internal-Rating Based (IRB) Approach. 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. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels of the t-test for the difference in means. Variables are defined as is Table A3.

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***

Table 3

Covid-19 effects on Credit to NFCs: IRB vs SA banks (bank-level analysis)

This table reports the estimates of the difference-in-differences regressions as in (Eq.1). The outcome variables are: credit origination (on and off-balance sheet exposures) to non-financial corporations (columns 1 and 2), on-balance sheet exposures to non-financial corporations (columns 3 and 4), and loans to non-financial corporations (columns 5 and 6). 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 banks use the standardised approach. Bank-level controls include the natural logarithm of assets ($Size$), the distance from the TSCR requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), and RWA Density ($Density$). See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Credit Origination NFC		On-Balance Sheet NFC		Loans NFC	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times IRB_i$	-0.0186***	-0.0135**	-0.0232***	-0.0144**	-0.0245***	-0.0162***
	(0.0063)	(0.0066)	(0.0062)	(0.0062)	(0.0058)	(0.0058)
$Post_t \times Size_{i,t-1}$	0.0050***	0.0050***	0.0026	0.0026	0.0031*	0.0027
	(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0018)	(0.0019)
$Post_t \times Distance_{i,t-1}$	0.0002	0.0007	0.0001	0.0009*	-0.0006	0.0001
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$Post_t \times ROA_{i,t-1}$	0.0030	-0.0116	-0.0005	-0.0137	-0.0009	-0.0099
	(0.0118)	(0.0136)	(0.0105)	(0.0115)	(0.0096)	(0.0105)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0004***	0.0005***	0.0004***	0.0005***	0.0005***	0.0006***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$Post_t \times Density_{i,t-1}$	-0.0002	0.0001	-0.0003	0.0001	-0.0005**	-0.0002
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
N	1500	1500	1500	1500	1500	1500
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Country $\times$ Time FE	No	Yes	No	Yes	No	Yes

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Table 4
Large Exposures: The Covid-19 effects on On- and Off-Balance Sheet Exposures (loan-level analysis)

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.2). The sample is restricted to multiple-lending relationships, where the borrower is associated with at least one SA and one IRB bank. In Panel A, the outcome variables are total on-balance sheet exposures (columns 1 to 3), and loans & securities (columns 4 to 6). In Panel B, the outcome variables are total off-balance sheet exposures (columns 1 to 3), and loans commitments (columns 4 to 6). The outcome variables are expressed as quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). $Post_t$ 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 banks use the standardised approach. Bank-level controls include the natural logarithm of assets ($Size$), distance from the TSCR capital requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_size). See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total On-Balance Sheet			Loans & Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times IRB_i$	-0.0931***	-0.0845**	-0.1035***	-0.1227***	-0.1100**	-0.1329***
	(0.0285)	(0.0368)	(0.0378)	(0.0383)	(0.0437)	(0.0455)
$Post_t \times Size_{i,t-1}$	0.0198*	0.0217	0.0261**	0.0230**	0.0277**	0.0328**
	(0.0103)	(0.0135)	(0.0130)	(0.0111)	(0.0128)	(0.0128)
$Post_t \times Distance_{i,t-1}$	-0.0040	-0.0005	0.0000	-0.0031	0.0004	0.0015
	(0.0033)	(0.0041)	(0.0042)	(0.0036)	(0.0041)	(0.0042)
$Post_t \times ROA_{i,t-1}$	0.0909	0.1189*	0.1219	0.0908	0.1288	0.1214
	(0.0634)	(0.0666)	(0.0820)	(0.0683)	(0.0821)	(0.0928)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0008	0.0003	0.0006	0.0014	0.0010	0.0014
	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)
$Post_t \times Density_{i,t-1}$	0.0005	0.0012	0.0007	-0.0006	0.0008	-0.0000
	(0.0013)	(0.0015)	(0.0018)	(0.0015)	(0.0019)	(0.0021)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0006	0.0012	0.0001	0.0002	0.0014	0.0002
	(0.0027)	(0.0026)	(0.0028)	(0.0030)	(0.0032)	(0.0033)
N	1516	1516	1516	1516	1516	1516
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

	Total Off-Balance Sheet			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times IRB_i$	0.0736	0.0697*	0.0905**	0.1775***	0.1649**	0.2050***
	(0.0504)	(0.0411)	(0.0369)	(0.0631)	(0.0695)	(0.0582)
$Post_t \times Size_{i,t-1}$	0.0023	0.0018	-0.0041	-0.0002	0.0006	-0.0079
	(0.0094)	(0.0091)	(0.0093)	(0.0125)	(0.0131)	(0.0130)
$Post_t \times Distance_{i,t-1}$	-0.0016	-0.0057	-0.0057	0.0047	-0.0029	-0.0056
	(0.0112)	(0.0084)	(0.0091)	(0.0121)	(0.0103)	(0.0106)
$Post_t \times ROA_{i,t-1}$	-0.0730	-0.1166*	-0.0820	-0.0296	-0.1441	-0.1234
	(0.0840)	(0.0630)	(0.0649)	(0.1025)	(0.0960)	(0.1021)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0005	0.0006	0.0002	0.0000	0.0011	0.0007
	(0.0012)	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0015)
$Post_t \times Density_{i,t-1}$	0.0024	0.0019	0.0021	0.0060	0.0060	0.0072
	(0.0031)	(0.0034)	(0.0033)	(0.0038)	(0.0044)	(0.0043)
$Post_t \times Exp\_Size_{i,j,t-1}$	-0.0012	0.0001	-0.0004	-0.0024	-0.0018	-0.0026
	(0.0026)	(0.0021)	(0.0022)	(0.0033)	(0.0028)	(0.0029)
N	1224	1224	1224	1224	1224	1224
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

Table 5
Large Exposures: Difference in Means between High and Low Capitalized IRB Banks (loan-level analysis)

This table provides the pre-treatment mean comparisons between IRB banks with high and low distance from their TSCR capital requirements. The distance measure is constructed as the difference between banks' reported CET1 ratio and their TSCR requirement (Pillar 1 + Pillar 2 requirements). Banks are classified as "Low" if their distance is below the first quartile of the distribution as of 2019Q4 (i.e., banks with the lowest buffers) and as "High" otherwise. In Panel A, the means refer to the average quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$) of On-Balance Sheet exposures over the four quarters pre-shock (i.e., 2019Q2-2020Q1). In Panel B, the means refer to Loans & Securities over the same period. The last column reports the difference in means between High and Low capitalized banks. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels of the t-test for whether the difference in means between the groups is equal to zero.

Variable	Time	Obs High	Obs Low	Mean High	Mean Low	Diff
Panel A. Total On-Balance Sheet						
Total On-Balance Sheet	2019Q2	571	557	0.0020	-0.0020	0.0045
Total On-Balance Sheet	2019Q3	571	557	0.0095	0.0340	-0.0245
Total On-Balance Sheet	2019Q4	571	557	0.0140	-0.0525	0.0665
Total On-Balance Sheet	2020Q1	571	557	0.1300	0.1815	-0.0515
Panel B. Loans & Securities						
Loans to NFC	2019Q2	571	557	0.0070	0.0257	-0.0181
Loans to NFC	2019Q3	571	557	-0.0125	0.0149	-0.0265
Loans to NFC	2019Q4	571	557	0.0060	0.0085	-0.0025
Loans to NFC	2020Q1	571	557	0.0745	0.1128	-0.0371

Table 6
Alternative Identification for Large Exposures:
High vs Low Capitalized IRB Banks (loan-level analysis)

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures (Eq.2). The sample is restricted to multiple-lending relationships, where the borrower is associated with at least one IRB bank classified as "Low" and one IRB banks as "High" capitalized. In Panel A, the outcome variables are total on-balance sheet exposures (columns 1 to 3), and loans & securities (columns 4 to 6). In Panel B, the outcome variables are total off-balance sheet exposures (columns 1 to 3), and loans commitments (columns 4 to 6). The outcome variables are expressed in the quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). $Post_t$ takes one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. $LowCap_i$ takes the value of one for banks in the first quartile of the distance between CET1 Ratio and their TSCR requirement, and zero otherwise. Bank-level controls include the natural logarithm of assets ($Size$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_size). See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total On-Balance Sheet			Loans & Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times LowCap_i$	-0.0386**	-0.0294**	-0.0354*	-0.0664***	-0.0575***	-0.0678***
	(0.0168)	(0.0123)	(0.0182)	(0.0182)	(0.0206)	(0.0241)
$Post_t \times Size_{i,t-1}$	0.0345*	0.0251**	0.0296**	0.0395**	0.0368***	0.0397**
	(0.0194)	(0.0118)	(0.0138)	(0.0179)	(0.0120)	(0.0153)
$Post_t \times ROA_{i,t-1}$	-0.0439	0.1141	0.0741	-0.1849**	-0.1089	-0.1388
	(0.0810)	(0.0874)	(0.0894)	(0.0857)	(0.1146)	(0.1028)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0012	0.0011	0.0014	0.0021**	0.0024**	0.0028***
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0011)	(0.0010)
$Post_t \times Density_{i,t-1}$	0.0039	0.0000	0.0015	0.0056*	0.0037	0.0043
	(0.0023)	(0.0022)	(0.0025)	(0.0030)	(0.0038)	(0.0035)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0635***	0.0232**	0.0236**	0.0629***	0.0226	0.0254
	(0.0141)	(0.0110)	(0.0115)	(0.0159)	(0.0164)	(0.0170)
N	6660	6660	6660	6660	6660	6660
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

	Total Off-Balance Sheet			Loans Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times LowCap_i$	-0.0200	-0.0020	-0.0033	-0.0064	0.0133	0.0195
	(0.0159)	(0.0114)	(0.0154)	(0.0207)	(0.0148)	(0.0198)
$Post_t \times Size_{i,t-1}$	-0.0055	-0.0005	-0.0023	0.0106	0.0098	0.0051
	(0.0139)	(0.0108)	(0.0120)	(0.0173)	(0.0155)	(0.0170)
$Post_t \times ROA_{i,t-1}$	-0.1586**	-0.0541	-0.0475	-0.2225***	-0.0178	-0.0130
	(0.0657)	(0.0635)	(0.0683)	(0.0817)	(0.0852)	(0.1058)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0001	-0.0003	-0.0005	0.0007	-0.0005	-0.0007
	(0.0008)	(0.0006)	(0.0008)	(0.0010)	(0.0008)	(0.0011)
$Post_t \times Density_{i,t-1}$	0.0055**	0.0027	0.0027	0.0088**	0.0026	0.0033
	(0.0024)	(0.0025)	(0.0022)	(0.0033)	(0.0032)	(0.0028)
$Post_t \times Exp\_Size_{i,j,t-1}$	-0.0327**	-0.0190	-0.0217	-0.0308*	-0.0156	-0.0206
	(0.0129)	(0.0166)	(0.0165)	(0.0179)	(0.0232)	(0.0223)
N	5556	5556	5556	5556	5556	5556
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

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Table 7
Alternative Identification for Large Exposures: further evidence

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.2). The sample is restricted to multiple-lending relationships, where the borrower is associated with at least one IRB bank classified as "Low" and one IRB bank as "High" distance from capital requirements. The outcome variables are the quarterly growth rates of loans & securities (column 1), and loan commitments (column 2). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. $LowCap_i$ takes the value of one for banks in the first quartile of the distance between CET1 Ratio and their TSCR requirement, 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. Bank-level controls are the same of Table (3): estimates are available upon request to the authors. See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Loans & Securities	Loans Commitments
	(1)	(2)
Panel A: Credit Risk Mitigation		
$Post_t \times LowCap_i \times CRM_j$	-0.1043**	0.0198
	(0.0474)	(0.0583)
CRM_j	-0.0418	-0.0262
	(0.0404)	(0.0337)
$Post_t \times LowCap_i$	0.0235	-0.0344
	(0.0328)	(0.0505)
$Post_t \times Size_{i,t-1}$	0.0352**	0.0001
	(0.0145)	(0.0229)
$Post_t \times ROA_{i,t-1}$	-0.1070	-0.0119
	(0.1107)	(0.1324)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0025**	-0.0013
	(0.0010)	(0.0014)
$Post_t \times Density_{i,t-1}$	0.0038	0.0066*
	(0.0034)	(0.0036)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0245	-0.0173
	(0.0179)	(0.0286)
Panel B: Sectoral Exposure		
$Post_t \times LowCap_i \times Most\_Affected_j$	-0.0675***	0.0317
	(0.0196)	(0.0215)
$Most\_Affected_j$	0.0067	0.1349**
	(0.0163)	(0.0530)
$Post_t \times LowCap_i$	-0.0197	-0.0403
	(0.0293)	(0.0261)
$Post_t \times Size_{i,t-1}$	0.0391**	0.0063
	(0.0156)	(0.0223)
$Post_t \times ROA_{i,t-1}$	-0.1383	-0.0285
	(0.1037)	(0.1322)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0028***	-0.0011
	(0.0010)	(0.0014)
$Post_t \times Density_{i,t-1}$	0.0043	0.0072*
	(0.0034)	(0.0037)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0282	-0.0027
	(0.0173)	(0.0265)
Panel C: Domestic Borrower		
$Post_t \times LowCap_i \times Domestic_j$	0.0443	0.0243
	(0.0639)	(0.0291)
$Domestic_j$	0.0284	-0.0083
	(0.0194)	(0.0164)
$Post_t \times LowCap_i$	-0.0828**	-0.0246
	(0.0348)	(0.0228)
$Post_t \times Size_{i,t-1}$	0.0410**	0.0058
	(0.0155)	(0.0225)
$Post_t \times ROA_{i,t-1}$	-0.1400	-0.0209
	(0.1095)	(0.1339)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0028***	-0.0010
	(0.0010)	(0.0014)
$Post_t \times Density_{i,t-1}$	0.0044	0.0074*
	(0.0032)	(0.0038)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0329*	-0.0077
	(0.0181)	(0.0287)
N	6660	5933
Bank FE	Yes	Yes
Borrower $\times$ Time FE	Yes	Yes

Table 8

Large Exposures: Difference in Means between IRB banks using downturn LGD and IRB Banks not using it

This table provides the pre-treatment mean comparisons between IRB banks that do not use the downturn LGD parameter in their IRB model (No LGD), and the banks that use it (LGD). In Panel A, the means refer to the average quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$) of Total On-Balance Sheet exposures over the four quarters pre-shock (i.e., 2019Q2-2020Q1). In Panel B, the means refer to Loans & Securities over the same period. The last column reports the difference in means between banks lacking downturn LGD and banks that conversely use it. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels of the t-test for whether the difference in means between the groups is equal to zero.

Variable	Time	Obs No LGD	Obs LGD	Mean No LGD	Mean LGD	Diff
Panel A. Total On-Balance Sheet						
Total On-Balance Sheet	2019Q2	220	486	0.00455	-0.0020	0.0060
Total On-Balance Sheet	2019Q3	220	486	0.0220	0.0230	-0.0010
Total On-Balance Sheet	2019Q4	220	486	-0.0265	-0.0320	0.0050
Total On-Balance Sheet	2020Q1	220	486	0.1030	0.1425	-0.0395
Panel B. Loans & Securities						
Loans to NFC	2019Q2	220	486	0.04550	-0.0400	0.0855
Loans to NFC	2019Q3	220	486	0.0030	-0.0230	0.0260
Loans to NFC	2019Q4	220	486	-0.0555	0.0160	-0.0715
Loans to NFC	2020Q1	220	486	0.1360	0.1910	-0.0550

Table 9
Alternative Identification: the role of the downturn LGD (loan-level analysis)

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.2). The sample is restricted to multiple-lending relationships, where the borrower is associated with at least one bank that uses the downturn LGD parameter in its IRB model and one that does not. In Panel A, the outcome variables are total on-balance sheet exposures (columns 1 to 3), and loans & securities (columns 4 to 6). In Panel B, the outcome variables are total off-balance sheet exposures (columns 1 to 3), and loans commitments (columns 4 to 6). The outcome variables are expressed in the quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). $DLGD$ takes the value of one for banks that use the downturn LGD parameter in their IRB models, and zero for banks (both under the foundation and advanced IRB framework) that do not use it. Bank-level controls include the natural logarithm of assets ($Size$), distance from the CET1 capital requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_size). See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total On-Balance Sheet			Loans & Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times DLGD_i$	0.0644**	0.0491**	0.0414*	0.0645**	0.0611**	0.0545*
	(0.0257)	(0.0223)	(0.0245)	(0.0276)	(0.0265)	(0.0270)
$Post_t \times Size_{i,t-1}$	-0.0058	0.0066	0.0099	-0.0091	0.0130	0.0104
	(0.0167)	(0.0139)	(0.0117)	(0.0167)	(0.0171)	(0.0142)
$Post_t \times Distance_{i,t-1}$	0.0023	0.0061	0.0051	-0.0007	0.0087	0.0078
	(0.0052)	(0.0043)	(0.0043)	(0.0044)	(0.0055)	(0.0059)
$Post_t \times ROA_{i,t-1}$	-0.0022	0.0930	0.0580	-0.0941	-0.1008	-0.0904
	(0.1040)	(0.1162)	(0.1019)	(0.1169)	(0.1491)	(0.1170)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0009	0.0009	0.0010	0.0017	0.0020	0.0018
	(0.0011)	(0.0013)	(0.0013)	(0.0014)	(0.0017)	(0.0017)
$Post_t \times Density_{i,t-1}$	0.0032	0.0007	0.0011	0.0023	0.0028	0.0018
	(0.0041)	(0.0041)	(0.0035)	(0.0055)	(0.0066)	(0.0052)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0205***	0.0104**	0.0103	0.0217***	0.0146**	0.0139*
	(0.0035)	(0.0049)	(0.0064)	(0.0035)	(0.0063)	(0.0077)
N	4236	4236	4236	4236	4236	4236
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower $\times$ Time FE	No	Yes	Yes	No	Yes	Yes

	Total Off-Balance Sheet			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times DLGD_i$	-0.0261	-0.0334	-0.0329	-0.0180	-0.0341	-0.0228
	(0.0329)	(0.0293)	(0.0287)	(0.0374)	(0.0415)	(0.0386)
$Post_t \times Size_{i,t-1}$	0.0135	0.0065	0.0019	0.0370	0.0213	0.0141
	(0.0184)	(0.0164)	(0.0181)	(0.0263)	(0.0267)	(0.0261)
$Post_t \times Distance_{i,t-1}$	0.0209***	0.0147***	0.0151**	0.0138*	0.0141*	0.0067
	(0.0063)	(0.0050)	(0.0068)	(0.0070)	(0.0076)	(0.0080)
$Post_t \times ROA_{i,t-1}$	-0.0714	0.0408	0.1022	-0.1986	0.0132	0.0472
	(0.0948)	(0.0711)	(0.0791)	(0.1241)	(0.1188)	(0.1360)
$Post_t \times Dep\_Ratio_{i,t-1}$	-0.0022**	-0.0024***	-0.0030***	-0.0005	-0.0020*	-0.0016
	(0.0010)	(0.0008)	(0.0010)	(0.0014)	(0.0010)	(0.0014)
$Post_t \times Density_{i,t-1}$	0.0085***	0.0054	0.0046	0.0135***	0.0076	0.0076
	(0.0029)	(0.0034)	(0.0034)	(0.0042)	(0.0047)	(0.0046)
$Post_t \times Exp\_Size_{i,j,t-1}$	-0.0087***	-0.0088***	-0.0093***	-0.0090***	-0.0078***	-0.0094***
	(0.0014)	(0.0018)	(0.0021)	(0.0022)	(0.0023)	(0.0024)
N	3750	3750	3750	3750	3750	3750
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower $\times$ Time FE	No	Yes	Yes	No	Yes	Yes

Table 10
Robustness check:
Covid-19 effects on credit to NFCs omitting 2020Q1 (bank-level analysis)

This table reports the estimates of the difference-in-differences regressions as in (Eq.1). The outcome variables are: credit origination (on and off-balance sheet exposures) to non-financial corporations (columns 1 and 2), on-balance sheet exposures to non-financial corporations (columns 3 and 4), and loans to non-financial corporations (columns 5 and 6). 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. Bank-level controls include the natural logarithm of assets ($Size$), the distance from the TSCR requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), and RWA Density ($Density$). See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Credit Origination NFC		On-Balance Sheet NFC		Loans NFC	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times IRB_i$	-0.0194***	-0.0124**	-0.0246***	-0.0123**	-0.0255***	-0.0139**
	(0.0059)	(0.0062)	(0.0060)	(0.0060)	(0.0059)	(0.0060)
$Post_t \times Size_{i,t-1}$	0.0046***	0.0040**	0.0034**	0.0024	0.0043**	0.0031
	(0.0017)	(0.0018)	(0.0016)	(0.0017)	(0.0020)	(0.0021)
$Post_t \times Distance_{i,t-1}$	0.0002	0.0009	0.0001	0.0013**	-0.0005	0.0005
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$Post_t \times ROA_{i,t-1}$	0.0016	-0.0092	-0.0032	-0.0138	0.0007	-0.0061
	(0.0103)	(0.0110)	(0.0091)	(0.0095)	(0.0095)	(0.0103)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0004***	0.0006***	0.0004***	0.0006***	0.0005***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$Post_t \times Density_{i,t-1}$	-0.0002	-0.0000	-0.0003	-0.0000	-0.0004	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
N	1497	1497	1497	1497	1497	1497
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
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

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Table 11
Large Exposures:
Split between countries with different credit cycle in 2019Q4 (loan-level analysis)

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures (Eq.2). Panel A refers to the main identification strategy where the sample is restricted to multiple-lending relationships where the borrower is associated with at least one SA and one IRB bank. Panel B refers to the alternative identification strategy, where the sample includes borrowers associated with at least one IRB bank classified as "Low" and one IRB banks as "High" distance. The outcome variables are loans & securities (columns 1 to 3) and loans commitments (columns 4 to 6). The outcome variables are expressed in the quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). $Country\_Group_j$ takes the value of 1 if country j to which bank i belongs report a ratio between credit and GDP growth above the median in 2019Q4, and 0 otherwise. $Post_t$ 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. $LowCap_i$ takes the value of one for banks in the first quartile of the distance between CET1 Ratio and their TSCR requirement, and zero otherwise. Bank-level controls include the natural logarithm of assets ($Size$), distance from the CET1 capital requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_size). See Table A3 for the definition of the variables. The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Loans & Securities			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main identification (IRV vs. SA banks)						
$Post_t \times IRB_i \times Country\_Group_j$	-0.0330	0.0090	-0.0044	-0.1597	-0.3459	-0.1262
	(0.0552)	(0.0589)	(0.0623)	(0.2162)	(0.2125)	(0.1746)
$Post_t \times IRB_i$	-0.1085**	-0.1161*	-0.1309**	0.3847*	0.5343**	0.4136**
	(0.0544)	(0.0590)	(0.0584)	(0.2218)	(0.2074)	(0.1838)
$Post_t \times Country\_Group_j$	0.0025	-0.0194	-0.0032	0.1625	0.2953	0.0497
	(0.0471)	(0.0609)	(0.0611)	(0.2209)	(0.2127)	(0.1782)
$Post_t \times Size_{i,t-1}$	0.0241**	0.0288**	0.0331**	0.0246	0.0199	0.0266
	(0.0118)	(0.0131)	(0.0136)	(0.0232)	(0.0200)	(0.0221)
$Post_t \times Distance_{i,t-1}$	-0.0040	0.0004	0.0013	0.0022	-0.0102	-0.0114*
	(0.0041)	(0.0047)	(0.0050)	(0.0078)	(0.0064)	(0.0067)
$Post_t \times ROA_{i,t-1}$	0.0827	0.1233	0.1197	-0.0499	-0.1005	-0.2077
	(0.0674)	(0.0818)	(0.0933)	(0.1617)	(0.1418)	(0.1464)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0013	0.0010	0.0013	0.0018	0.0031**	0.0032**
	(0.0010)	(0.0010)	(0.0011)	(0.0014)	(0.0013)	(0.0013)
$Post_t \times Density_{i,t-1}$	-0.0007	0.0009	-0.0000	0.0049	0.0039	0.0100**
	(0.0015)	(0.0019)	(0.0021)	(0.0050)	(0.0049)	(0.0047)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0002	0.0016	0.0003	0.0106	0.0156	0.0140*
	(0.0030)	(0.0032)	(0.0034)	(0.0078)	(0.0104)	(0.0078)
N	1516	1516	1516	1276	1276	1276
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

	Loans & Securities			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Alternative identification ("Low" distance vs. "High" distance)						
$Post_t \times LowCap_i \times Country\_Group_j$	0.0302	0.0501	0.0330	-0.0399	-0.0463	-0.0221
	(0.0314)	(0.0393)	(0.0372)	(0.0485)	(0.0437)	(0.0458)
$Post_t \times LowCap_i$	-0.0892***	-0.0965***	-0.0950***	0.0283	0.0478	0.0441
	(0.0324)	(0.0341)	(0.0333)	(0.0339)	(0.0293)	(0.0306)
$Post_t \times Country\_Group_j$	-0.0219	-0.0121	-0.0098	0.0441	0.0371	0.0167
	(0.0254)	(0.0353)	(0.0363)	(0.0360)	(0.0292)	(0.0284)
$Post_t \times Size_{i,t-1}$	0.0404**	0.0388***	0.0418***	0.0056	-0.0001	-0.0003
	(0.0185)	(0.0120)	(0.0153)	(0.0155)	(0.0183)	(0.0191)
$Post_t \times ROA_{i,t-1}$	-0.2181**	-0.1541	-0.1699*	-0.1634	0.0232	-0.0306
	(0.0863)	(0.0995)	(0.0997)	(0.1142)	(0.1349)	(0.1485)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0021**	0.0027**	0.0030***	0.0008	-0.0005	-0.0005
	(0.0009)	(0.0011)	(0.0010)	(0.0008)	(0.0010)	(0.0012)
$Post_t \times Density_{i,t-1}$	0.0064**	0.0048	0.0051	0.0087**	0.0021	0.0045
	(0.0028)	(0.0035)	(0.0034)	(0.0039)	(0.0037)	(0.0036)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0597***	0.0196	0.0233	-0.0228	-0.0147	-0.0237
	(0.0172)	(0.0157)	(0.0167)	(0.0189)	(0.0242)	(0.0244)
N	6660	6660	6660	5280	5280	5280
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

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Table 12

Large Exposures: Covid-19 effects on On- and Off-Balance Sheet Exposures (loan-level analysis) omitting "zombie" borrowers

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.2). Panel A refers to the main identification strategy where the sample is restricted to multiple-lending relationships where the borrower is associated with at least one SA and one IRB bank. Panel B refers to the alternative identification strategy, where the sample includes borrowers associated with at least one IRB bank classified as "Low" and one IRB banks as "High" distance from capital requirements. Borrowers with probability of default or days of past due in the last 10th percentile of the empirical distribution were excluded. The outcome variables are loans & securities (columns 1 to 3) and loans commitments (columns 4 to 6). The outcome variables are expressed in the quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). $Post_t$ 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. $LowCap_i$ takes the value of one for banks in the first quartile of the distance between CET1 Ratio and their TSCR requirement, and zero otherwise. Bank-level controls include the natural logarithm of assets ($Size$), distance from the CET1 capital requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_size). See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Loans & Securities			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: SA vs IRB banks						
$Post_t \times IRB_i$	-0.1488***	-0.1742***	-0.1734***	0.1968*	0.2247**	0.2322**
	(0.0455)	(0.0471)	(0.0505)	(0.1036)	(0.0951)	(0.0892)
$Post_t \times Size_{i,t-1}$	0.0449***	0.0513***	0.0553***	-0.0227	-0.0340*	-0.0396**
	(0.0133)	(0.0150)	(0.0164)	(0.0162)	(0.0199)	(0.0195)
$Post_t \times Distance_{i,t-1}$	-0.0087	-0.0066	-0.0052	0.0005	0.0035	0.0012
	(0.0054)	(0.0064)	(0.0066)	(0.0265)	(0.0177)	(0.0203)
$Post_t \times ROA_{i,t-1}$	0.0227	0.0708	0.0263	-0.1240	-0.1517	-0.0839
	(0.0656)	(0.0710)	(0.0797)	(0.1916)	(0.1624)	(0.1902)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0009	0.0004	0.0008	0.0013	0.0017	0.0010
	(0.0008)	(0.0011)	(0.0012)	(0.0025)	(0.0022)	(0.0025)
$Post_t \times Density_{i,t-1}$	0.0008	0.0003	0.0005	0.0076	0.0100*	0.0090
	(0.0016)	(0.0019)	(0.0022)	(0.0051)	(0.0056)	(0.0059)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0015	0.0033*	0.0025	-0.0069**	-0.0127**	-0.0133***
	(0.0015)	(0.0016)	(0.0017)	(0.0032)	(0.0050)	(0.0049)
N	970	970	970	738	738	738
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

	Loans & Securities			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Alternative identification ("Low" distance vs. "High" distance)						
$Post_t \times LowCap_i$	-0.0519***	-0.0511**	-0.0585**	0.0210	0.0203	0.0534**
	(0.0180)	(0.0232)	(0.0286)	(0.0282)	(0.0173)	(0.0250)
$Post_t \times Size_{i,t-1}$	0.0435**	0.0524***	0.0562**	0.0040	-0.0143	-0.0217
	(0.0197)	(0.0166)	(0.0217)	(0.0218)	(0.0200)	(0.0219)
$Post_t \times ROA_{i,t-1}$	-0.1933*	-0.1337	-0.1815	-0.3154***	0.0252	0.0113
	(0.1002)	(0.1447)	(0.1494)	(0.1057)	(0.1277)	(0.1434)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0022**	0.0027**	0.0032**	0.0011	-0.0008	-0.0009
	(0.0009)	(0.0012)	(0.0012)	(0.0011)	(0.0010)	(0.0013)
$Post_t \times Density_{i,t-1}$	0.0049*	0.0026	0.0041	0.0135***	0.0028	0.0040
	(0.0029)	(0.0038)	(0.0042)	(0.0028)	(0.0041)	(0.0035)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0862***	0.0644**	0.0655**	-0.0224	-0.0504	-0.0575
	(0.0228)	(0.0289)	(0.0288)	(0.0325)	(0.0449)	(0.0449)
N	5328	5328	5328	4188	4188	4188
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

Table 13
Large Exposures:
Covid-19 effects on On- and Off-Balance Sheet Exposures (loan-level analysis) for "capital constrained" IRB and SA banks

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.2). The sample includes all borrowers (i.e., *not* only borrowers with multiple-lending relationships) but only banks with a difference between CET1 ratio and TSCR ratio in the first quartile of the distribution (i.e. "Low" distance banks). In Panel A, the outcome variables are total on-balance sheet exposures (columns 1 to 3), and loans & securities (columns 4 to 6). In Panel B, the outcome variables are total off-balance sheet exposures (columns 1 to 3), and loans commitments (columns 4 to 6). The outcome variables are expressed in the quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). $Post_t$ 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-level controls include the natural logarithm of assets ($Size$), distance from the CET1 capital requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_Size). See Table A3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. We include a set of fixed-effects where Country and NACE are at borrower level. Variables are winsorized at the 5% level. Clustered standard errors at bank-quarter-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total On-Balance Sheet			Loans & Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times IRB_i$	-0.2596***	-0.2235***	-0.2477***	-0.2020***	-0.1675**	-0.1416*
	(0.0701)	(0.0619)	(0.0728)	(0.0745)	(0.0710)	(0.0765)
$Post_t \times Size_{i,t-1}$	0.0679***	0.0579***	0.0634***	0.0456**	0.0523**	0.0389*
	(0.0240)	(0.0199)	(0.0226)	(0.0229)	(0.0203)	(0.0204)
$Post_t \times Distance_{i,t-1}$	-0.1292***	-0.0690**	-0.0896**	-0.1209***	-0.0415	-0.0395
	(0.0284)	(0.0335)	(0.0399)	(0.0317)	(0.0329)	(0.0376)
$Post_t \times ROA_{i,t-1}$	-0.2588**	0.1722	0.0443	-0.4657***	-0.1475	-0.1150
	(0.1282)	(0.1246)	(0.1912)	(0.1432)	(0.1385)	(0.1936)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0033**	0.0044***	0.0048***	0.0030	0.0041**	0.0044**
	(0.0017)	(0.0016)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
$Post_t \times Density_{i,t-1}$	0.0042	-0.0142***	-0.0093	0.0129**	-0.0003	-0.0006
	(0.0048)	(0.0039)	(0.0075)	(0.0050)	(0.0038)	(0.0076)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0086	0.0066	0.0001	0.0034	0.0020	-0.0060
	(0.0056)	(0.0051)	(0.0060)	(0.0059)	(0.0063)	(0.0064)
N	3964	3964	3964	3964	3964	3964
Bank FE	Yes	No	Yes	Yes	No	Yes
Country × NACE × Time FE	No	Yes	Yes	No	Yes	Yes

	Total Off-Balance Sheet			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times IRB_i$	0.1749***	0.1230***	0.1076***	0.3314***	0.2614***	0.2422***
	(0.0429)	(0.0465)	(0.0400)	(0.0693)	(0.0757)	(0.0572)
$Post_t \times Size_{i,t-1}$	-0.0339***	-0.0200	-0.0239	-0.0225	-0.0102	-0.0171
	(0.0130)	(0.0154)	(0.0146)	(0.0172)	(0.0180)	(0.0165)
$Post_t \times Distance_{i,t-1}$	0.0672***	0.0272*	0.0277*	0.0713***	0.0131	0.0026
	(0.0189)	(0.0149)	(0.0161)	(0.0270)	(0.0233)	(0.0256)
$Post_t \times ROA_{i,t-1}$	-0.0219	0.0418	0.1356	-0.0193	0.1801**	0.2207*
	(0.0794)	(0.0665)	(0.1154)	(0.1161)	(0.0864)	(0.1330)
$Post_t \times Dep\_Ratio_{i,t-1}$	-0.0016	-0.0008	-0.0015	-0.0002	-0.0002	-0.0013
	(0.0011)	(0.0011)	(0.0011)	(0.0015)	(0.0013)	(0.0012)
$Post_t \times Density_{i,t-1}$	0.0084**	0.0007	-0.0030	0.0149***	-0.0012	-0.0019
	(0.0035)	(0.0030)	(0.0049)	(0.0050)	(0.0031)	(0.0060)
$Post_t \times Exp\_Size_{i,j,t-1}$	-0.0126**	-0.0061	-0.0076	-0.0114*	0.0006	-0.0020
	(0.0050)	(0.0058)	(0.0065)	(0.0065)	(0.0084)	(0.0088)
N	3900	3900	3900	3783	3783	3783
Bank FE	Yes	No	Yes	Yes	No	Yes
Country × NACE × Time FE	No	Yes	Yes	No	Yes	Yes

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Table 14
Economic impact: Borrowers analysis

This table reports the estimates of the model as in Eq.(3) using a sample data of Non-Financial Corporation borrowers in the sample of large exposure used in previous analysis. The outcome variables are various asset items capturing NFCs investments, as trade receivables (denoted as "Debtors" in Orbis) and inventories ("Stock") & other current assets (columns 1 and 2), and tangible & intangible fixed assets (columns 3 and 4). All of the outcome variables are expressed in logs ($Log(Y_{j,t})$). $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. $IRB\ ratio_j$ takes the value of one for NFCs that relies more on funding from IRB banks, and zero if the NFC is less prone to get funded by IRB banks. Firm-level controls include the natural logarithm of lagged Turnover ($Log(Turnover)$), the Capital Ratio (Capital over Total Assets) ($Leverage$), the total number of banks NFC j relies upon ($Number\ of\ banks$) and a dummy taking value of one if the borrower is listed, and zero otherwise ($Listed\ borrower$). All variables are defined in Table A3. We include both time and borrower fixed-effects. Robust standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Current Assets		Fixed Assets	
	Trade Receivables	Inventories and other	Tangible fixed assets	Intangible fixed assets
	(1)	(2)	(3)	(4)
IRB ratio dummy$_j$	0.0015	-0.3234	0.2255	0.1545*
	(0.2306)	(0.2009)	(0.1699)	(0.0908)
IRB ratio dummy$_j \times Post_t$	-0.2703***	-0.0313	-0.1301*	-0.1671***
	(0.1035)	(0.0706)	(0.0753)	(0.0567)
Issued capital$_j$	0.0219***	0.0195***	0.0208***	0.0252***
	(0.0047)	(0.0055)	(0.0060)	(0.0047)
Issued capital$_j \times Post_t$	0.0004	-0.0036	0.0004	0.0020
	(0.0032)	(0.0025)	(0.0030)	(0.0022)
Reserve capital$_j$	0.0081***	0.0061***	0.0087***	0.0157***
	(0.0020)	(0.0020)	(0.0022)	(0.0022)
Reserve capital$_j \times Post_t$	-0.0017**	-0.0006	-0.0015**	-0.0010
	(0.0007)	(0.0007)	(0.0006)	(0.0007)
Most affected$_j$	0.1777*	-0.0015	-0.6229***	0.7513
	(0.1014)	(0.1069)	(0.0761)	(1.0343)
Most affected$_j \times Post_t$	-0.2346**	-0.1232	-0.1811**	-0.0803
	(0.0988)	(0.0774)	(0.0893)	(0.0651)
$Log(Turnover)_{j,t-1}$	0.3725**	0.2825**	0.3243**	0.0139
	(0.1509)	(0.1257)	(0.1465)	(0.0515)
$Leverage_{j,t-1}$	-0.8640**	-1.1803**	-1.9997*	-0.5148*
	(0.3631)	(0.5434)	(1.0800)	(0.2821)
Number of banks$_{j,t}$	-0.0018	0.0160**	0.0040	0.0060
	(0.0069)	(0.0065)	(0.0069)	(0.0052)
Listed borrower$_{j,t}$	0.1607	0.0693	0.1288*	0.0368
	(0.1572)	(0.0493)	(0.0688)	(0.0498)
N	1324	1324	1324	1324
Time FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes

Appendix

This table presents the number of banks used in our bank-level 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.

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

Table A2
Government guarantees

This table reports the quotas of credit exposures that received support by the governments in the aftermath of the Covid crisis. "Quota of loans" is the ratio between the number of guaranteed exposures and the total number of exposures. "Quota of volume" is the ratio between the overall value of exposures publicly guaranteed over the total value of all exposures. All figures are in percentage points. The sample is composed by 194 banks. Source: Anacredit.

	2020Q2		2020Q3	
	Quota of loans	Quota of volume	Quota of loans	Quota of volume
Panel A: Euro Area				
$< 100'000$	11.33	20.57	15.57	27.53
$100'000 - 10mil$	8.45	11.16	11.05	15.40
$10mil - 100mil$	3.94	5.75	4.11	7.12
$100mil - 300mil$	6.77	5.24	4.81	7.04
$> 300mil$	0.58	2.58	1.30	5.13
Panel B: France				
$< 100'000$	5.16	12.77	12.71	25.14
$100'000 - 10mil$	6.73	16.59	11.59	21.53
$10mil - 100mil$	6.78	8.31	6.50	11.48
$100mil - 300mil$	6.81	6.61	1.32	8.47
$> 300mil$	0.01	3.55	0.07	3.80
Panel C: Germany				
$< 100'000$	1.12	3.05	1.35	4.34
$100'000 - 10mil$	3.56	4.42	4.04	5.30
$10mil - 100mil$	5.87	5.75	5.63	6.33
$100mil - 300mil$	5.95	7.65	7.96	8.89
$> 300mil$	1.53	0.96	1.65	1.07
Panel D: Italy				
$< 100'000$	15.68	25.86	21.57	35.44
$100'000 - 10mil$	11.26	11.98	15.28	21.30
$10mil - 100mil$	0.56	2.44	1.48	6.29
$100mil - 300mil$	3.78	1.61	1.18	4.53
$> 300mil$	0.08	5.51	0.14	13.04
Panel E: Spain				
$< 100'000$	15.50	27.50	19.47	33.27
$100'000 - 10mil$	10.84	19.64	13.13	22.50
$10mil - 100mil$	0.99	6.42	1.12	7.28
$100mil - 300mil$	0.24	2.02	0.87	4.61
$> 300mil$	0.00	0.00	0.17	0.71

Table A3
Definitions of variables and data sources

This table provides the definitions and the data sources of the variables used in our empirical analyses.

Variable	Definition	Source	
Panel A. Outcome Variables			
Credit Origination	The sum of all on-balance sheet and off-balance sheet exposures of bank i	ECB Data	Supervisory
On-Balance Sheet	The sum of all on-balance sheet exposures of bank i, comprising, total loans, total securities, total equity instruments and total derivative assets	ECB Data	Supervisory
Total Loans	The sum of all loans and advances of bank i, comprising credit card debt, trade receivables, finance leases, reverse repurchase loans, other term loans, advances.	ECB Data	Supervisory
Off-Balance Sheet	The sum of all off-balance sheet exposures of bank i, comprising loan commitments, financial guarantees and other commitments	ECB Data	Supervisory
Loan Commitments	The sum of all commitments of bank i to provide credit under pre-specified terms and conditions (e.g., acceptances, forward deposits, undrawn credit facilities).	ECB Data	Supervisory
Panel B. Identification Variables			
IRB	It takes the value of one for banks reporting corporate credit risk using internal models and zero if the banks use the standardised approach	ECB Data	Supervisory
LowCap	It takes the value of one for banks in the first quartile of the distance between CET1 Ratio and their TSCR requirement, and zero otherwise	ECB Data	Supervisory
CRM	It is a continuous variable calculated as the value of the exposure of borrower j to bank i after the application of Credit Risk Mitigation (CRM) relative to its total original in the pre-shock period (2019Q2)	ECB Data	Supervisory
Most Affected	It takes the value of one for the borrower j belonging to the NACE sectors: C (Manufacturing), D (Electricity, gas, steam and air conditioning supply), F (Construction), G (Wholesale and retail trade), H (Transporting and storage), I (Accommodation and food service activities), N (Administrative and support service activities), R (arts, entertainment and recreation). The classification of sectors into most affected follows the EBA (2020)	-	
Domestic	It takes the value of one if borrower j and bank i are headquartered in the same country.	-	
DLGD	It takes the value of one for banks that use the downturn LGD parameter in their IRB models, and zero otherwise	Confidential Data on TRIM Exercise	
Country Group	It takes the value of one if country j, in which bank i is headquartered, reports a ratio between credit and GDP growth above the median in 2019Q4, and 0 otherwise	ECB Statistical Data Warehouse	
Panel C. Bank-level Variables			
Total Assets (Log)	Natural logarithm of total assets of the bank i.	ECB Data	Supervisory
Distance (%)	Distance between bank i's reported CET1 ratio and its Total SREP Capital Requirement (TSCR)	ECB Data	Supervisory
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	ECB Data	Supervisory
RWA Density (%)	Total risk-weighted assets of bank i as a percentage of total original exposures	ECB Data	Supervisory
Large Exposure Size (%)	Size of the large exposures toward borrower j relative to the size of the non-financial corporation portfolio of bank i	ECB Data	Supervisory
Public Guarantees	A continuous variable calculated as the share of loans covered by a public guarantee over the total amount of loans	Anacredit	
Panel D. Firm-level Variables			
Trade Receivables	Amount owed to the borrower (from clients and customers only)	Orbis	
Inventories	Total inventories (included raw materials, in progress and finished goods)	Orbis	
Other current assets	All other current assets such as receivables from other sources (taxes, group companies, etc), short term investment of money and cash at bank and in hand	Orbis	
Tangible fixed assets	All tangible assets such as buildings and machinery	Orbis	
Intangible fixed assets	All intangible assets such as formation expenses, research expenses, goodwill, development expenses and all other expenses with a long term effect	Orbis	
IRB Ratio	Sum of all the IRB loans taken by borrower j divided by total assets. Converted into a dummy that takes the value of one for the upper tertile and zero for the lower tertile	ECB Data Orbis	Supervisory
Issued capital	Issued Share capital (Authorized capital)	Orbis	
Reserve capital	All shareholders funds not linked with the Issued capital including Undistributed profit and Minority interests, if any	Orbis	
Turnover (Log)	Natural logarithm of the operating revenues for borrower j. Total operating revenues include net sales, other operating revenues and stock variations	Orbis	
Leverage	Total capital divided by total assets	Orbis	
Number of banks	Number of banks from which the borrower i receives loans	Orbis	
Listed borrower	It takes value of one if borrower i is listed, and zero otherwise	Orbis	

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Table A4
Difference in Means between SA and IRB banks

This table provides the pre- and post-treatment mean comparisons for the control variables between banks using the Standardised Approach (SA) and banks using the Internal-Rating Based (IRB) Approach. Column (5) reports the difference in means between SA and IRB banks. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels of the t-test for the difference in means. Variables are defined as is Table 3.

Variable	Time	Obs SA	Obs IRB	Mean SA	Mean IRB	Diff (SA -IRB)
		(1)	(2)	(3)	(4)	(5)
Panel A. Size: Pre-treatment Mean Comparison						
Size	2019Q2	180	70	22.9845	25.2765	-2.2920***
Size	2019Q3	180	70	22.9965	25.2935	-2.2975***
Size	2019Q4	180	70	23.0015	25.2740	-2.2730***
Size	2020Q1	180	70	23.0210	25.3110	-2.2900***
Panel B. Distance: Pre-treatment Mean Comparison						
Distance	2019Q2	180	70	10.4000	9.7655	0.6345
Distance	2019Q3	180	70	10.3985	9.5850	0.8135
Distance	2019Q4	180	70	10.7970	10.2350	0.5620
Distance	2020Q1	180	70	10.3835	10.4805	-0.0970
Panel C. ROA: Pre-treatment Mean Comparison						
ROA	2019Q2	180	70	0.6155	0.5465	0.0690
ROA	2019Q3	180	70	0.5790	0.4880	0.0910**
ROA	2019Q4	180	70	0.6150	0.5430	0.0720
ROA	2020Q1	180	70	0.5150	0.5110	0.0040
Panel D. Deposit Ratio: Pre-treatment Mean Comparison						
Deposit Ratio	2019Q2	180	70	85.1265	71.1030	14.0230***
Deposit Ratio	2019Q3	180	70	85.1270	70.5600	14.5670***
Deposit Ratio	2019Q4	180	70	85.9125	71.6430	14.2695***
Deposit Ratio	2020Q1	180	70	85.7745	71.3035	14.4710***
Panel E. RWA Density: Pre-treatment Mean Comparison						
Density	2019Q2	180	70	39.5190	27.1955	12.3235***
Density	2019Q3	180	70	39.6050	27.1960	12.4090***
Density	2019Q4	180	70	39.5610	27.0425	12.5180***
Density	2020Q1	180	70	39.2645	26.9450	12.3200***

Table A5
Covid-19 effects on Credit to non-NFCs: IRB vs SA banks (bank-level analysis)

This table reports the estimates for our difference-in-differences regressions as in (Eq.1). The outcome variables are: total credit origination (on and off-balance sheet exposures) to other than non-financial corporations, on-balance sheet exposures to other than non-financial corporations, total loans to other than non-financial corporations and retail customers, and total loans to retail customers. 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 banks use the standardised approach. Bank-level controls include the natural logarithm of assets ($Size$), the distance from the TSCR requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), and RWA Density ($Density$). See Table 3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Credit Orig. to non-NFC		On Balance Sheet non-NFC		Other Loans		Retail Loans	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Post_t \times IRB_i$	0.0065	0.0101	0.0008	0.0045	-0.0127	-0.0186	-0.0037	-0.0008
	(0.0069)	(0.0078)	(0.0064)	(0.0070)	(0.0263)	(0.0300)	(0.0028)	(0.0031)
$Post_t \times Size_{i,t-1}$	-0.0015	-0.0007	-0.0017	-0.0014	0.0150*	0.0171*	0.0018**	0.0018*
	(0.0022)	(0.0024)	(0.0020)	(0.0021)	(0.0082)	(0.0093)	(0.0008)	(0.0009)
$Post_t \times Distance_{i,t-1}$	0.0016**	0.0021***	0.0016**	0.0021***	-0.0021	-0.0022	0.0001	0.0004
	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0028)	(0.0029)	(0.0003)	(0.0003)
$Post_t \times ROA_{i,t-1}$	0.0041	-0.0147	0.0035	-0.0170	0.0460	0.0057	0.0077*	0.0062
	(0.0108)	(0.0116)	(0.0113)	(0.0117)	(0.0427)	(0.0435)	(0.0042)	(0.0057)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0006***	0.0007***	0.0005***	0.0007***	0.0003	0.0005	0.0002***	0.0003***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0006)	(0.0007)	(0.0001)	(0.0001)
$Post_t \times Density_{i,t-1}$	0.0006*	0.0007**	0.0005	0.0006*	0.0001	0.0007	-0.0001	-0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0011)	(0.0011)	(0.0001)	(0.0001)
N	1500	1500	1500	1500	1500	1500	1500	1500
Bank-levels controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

Covid-19 effects on Off-balance Sheet Exposures (bank-level analysis)

This table reports the estimates of the difference-in-differences regressions as in (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. 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 banks use the standardised approach. Bank-level controls include the natural logarithm of assets ($Size$), the distance from the TSCR requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), and RWA Density ($Density$). See Table 3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total Off-Balance Sheet		Off-Balance Sheet non-NFC		Off-Balance Sheet NFC	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times IRB_i$	0.0211*	0.0199	0.0361*	0.0419*	0.0194	0.0183
	(0.0115)	(0.0134)	(0.0190)	(0.0219)	(0.0157)	(0.0189)
$Post_t \times Size_{i,t-1}$	0.0012	0.0011	-0.0030	-0.0044	0.0062	0.0053
	(0.0035)	(0.0041)	(0.0061)	(0.0073)	(0.0043)	(0.0054)
$Post_t \times Distance_{i,t-1}$	-0.0005	-0.0003	-0.0007	-0.0002	0.0004	0.0004
	(0.0010)	(0.0012)	(0.0015)	(0.0019)	(0.0014)	(0.0016)
$Post_t \times ROA_{i,t-1}$	0.0271	0.0302	0.0120	0.0347	0.0239	0.0148
	(0.0194)	(0.0244)	(0.0296)	(0.0380)	(0.0269)	(0.0306)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0001	0.0001	0.0002	0.0001	0.0001	0.0002
	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)
$Post_t \times Density_{i,t-1}$	0.0009*	0.0008	0.0008	0.0009	0.0012*	0.0012*
	(0.0004)	(0.0005)	(0.0008)	(0.0009)	(0.0006)	(0.0007)
N	1452	1452	1452	1452	1452	1452
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Country $\times$ Time FE	No	Yes	No	Yes	No	Yes

	Total Loan Commitments		Loan Committments non-NFC		Loan Commitments NFC	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times IRB_i$	0.0155	0.0080	0.0287	0.0281	0.0150	0.0151
	(0.0118)	(0.0133)	(0.0180)	(0.0205)	(0.0183)	(0.0220)
$Post_t \times Size_{i,t-1}$	0.0050	0.0055	-0.0000	-0.0019	0.0088*	0.0067
	(0.0038)	(0.0043)	(0.0058)	(0.0068)	(0.0052)	(0.0064)
$Post_t \times Distance_{i,t-1}$	-0.0012	-0.0017	-0.0018	-0.0023	0.0005	0.0005
	(0.0011)	(0.0013)	(0.0015)	(0.0017)	(0.0018)	(0.0021)
$Post_t \times ROA_{i,t-1}$	0.0339*	0.0281	-0.0000	0.0236	0.0399	0.0189
	(0.0199)	(0.0259)	(0.0296)	(0.0405)	(0.0322)	(0.0360)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0001	0.0003	0.0001	0.0002	0.0001	0.0003
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0006)
$Post_t \times Density_{i,t-1}$	0.0009*	0.0008	0.0007	0.0004	0.0015*	0.0014
	(0.0005)	(0.0006)	(0.0008)	(0.0009)	(0.0008)	(0.0009)
N	1452	1452	1452	1452	1452	1452
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Country $\times$ Time FE	No	Yes	No	Yes	No	Yes

Table A7

Alternative Identification for Large Exposures:

High vs Low Capitalized SA Banks (loan-level analysis)

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.1). The sample is restricted to multiple-lending relationships, where the borrower is associated with at least one SA bank classified as "Low" and one SA bank as "High" distance from capital requirements. In Panel A, the outcome variables are total on-balance sheet exposures (columns 1 to 3), and loans & securities (columns 4 to 6). In Panel B, the outcome variables are total off-balance sheet exposures (columns 1 to 3), and loans commitments (columns 4 to 6). The outcome variables are expressed in quarterly growth rates $(Log(Y_{i,j,t}) - Log(Y_{i,j,t-1}))$. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. $LowCap_i$ takes the value of one for banks in the first quartile of the distance between CET1 Ratio and their TSCR requirement, and zero otherwise. Bank-level controls include the natural logarithm of assets ($Size$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_size). See Table 3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total On-Balance Sheet			Loans & Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times LowCap_i$	-0.0058	-0.0008	-0.0024	-0.0072	-0.0021	-0.0035
	(0.0119)	(0.0109)	(0.0128)	(0.0130)	(0.0122)	(0.0141)
$Post_t \times Size_{i,t-1}$	-0.0026	-0.0044	-0.0039	-0.0029	-0.0046	-0.0042
	(0.0041)	(0.0041)	(0.0045)	(0.0045)	(0.0045)	(0.0049)
$Post_t \times ROA_{i,t-1}$	0.0103	0.0069	0.0026	0.0020	-0.0016	-0.0061
	(0.0249)	(0.0270)	(0.0282)	(0.0264)	(0.0281)	(0.0298)
$Post_t \times Dep\_Ratio_{i,t-1}$	-0.0000	0.0001	-0.0000	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
$Post_t \times Density_{i,t-1}$	-0.0001	-0.0001	0.0000	-0.0003	-0.0003	-0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0002	0.0001	0.0001	0.0003	0.0001	0.0001
	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
N	2100	2100	2100	2100	2100	2100
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

	Total Off-Balance Sheet			Loans Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times LowCap_i$	0.0739**	0.0652*	0.0687*	0.0068	-0.0098	0.0004
	(0.0345)	(0.0370)	(0.0361)	(0.0542)	(0.0605)	(0.0564)
$Post_t \times Size_{i,t-1}$	-0.0184	-0.0195	-0.0199	-0.0248	-0.0259	-0.0268
	(0.0121)	(0.0134)	(0.0131)	(0.0209)	(0.0236)	(0.0235)
$Post_t \times ROA_{i,t-1}$	-0.1228	-0.1332	-0.1380	-0.0606	-0.0646	-0.0808
	(0.0889)	(0.0890)	(0.0914)	(0.1319)	(0.1334)	(0.1338)
$Post_t \times Dep\_Ratio_{i,t-1}$	-0.0012	-0.0006	-0.0004	-0.0016	-0.0010	-0.0005
	(0.0015)	(0.0015)	(0.0015)	(0.0020)	(0.0020)	(0.0019)
$Post_t \times Density_{i,t-1}$	-0.0011	-0.0020	-0.0023	-0.0009	-0.0022	-0.0026
	(0.0031)	(0.0030)	(0.0031)	(0.0041)	(0.0041)	(0.0041)
$Post_t \times Exp\_Size_{i,j,t-1}$	-0.0036	-0.0054*	-0.0061**	-0.0044	-0.0066*	-0.0077*
	(0.0022)	(0.0027)	(0.0029)	(0.0030)	(0.0038)	(0.0039)
N	1216	1216	1216	1216	1216	1216
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower ×Time FE	No	Yes	Yes	No	Yes	Yes

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Table A8
Alternative Identification: the role of the downturn LGD – robustness check (loan-level analysis)

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.1). The sample is restricted to multiple-lending relationships, where the borrower is associated with at least one bank that uses the downturn LGD parameter in its IRB model and one bank that does not use it. In Panel A, the outcome variables are total on-balance sheet exposures (columns 1 to 3), and loans & securities (columns 4 to 6). In Panel B, the outcome variables are total off-balance sheet exposures (columns 1 to 3), and loans commitments (columns 4 to 6). The outcome variables are expressed in quarterly growth rates ($Log(Y_{i,j,t}) - Log(Y_{i,j,t-1})$). $DLGD$ takes the value of one for banks that use the downturn LGD parameter in their IRB models, and zero for banks under the advanced IRB framework that do not. Bank-level controls include the natural logarithm of assets ($Size$), distance from the CET1 capital requirements ($Distance$), Return on Assets (ROA), Deposit Ratio (Dep_Ratio), RWA Density ($Density$), and the relative size of the large exposure (Exp_size). See Table 3 for the definition of the variables. We only show estimates for the interaction terms ($Post_t \times X_{i,t-1}$). The estimates for control variables ($X_{i,t-1}$) are available upon request to the authors. Variables are winsorized at the 5% level. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total On-Balance Sheet			Loans & Securities		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$Post_t \times DLGD_i$	0.0572	0.0675**	0.0665*	0.0823*	0.0884**	0.0854*
	(0.0360)	(0.0251)	(0.0345)	(0.0429)	(0.0321)	(0.0445)
$Post_t \times Size_{i,t-1}$	0.0087	-0.0086	-0.0066	-0.0061	-0.0087	-0.0120
	(0.0221)	(0.0114)	(0.0203)	(0.0261)	(0.0143)	(0.0246)
$Post_t \times Distance_{i,t-1}$	-0.0060	0.0114*	0.0111	-0.0028	0.0156*	0.0192*
	(0.0097)	(0.0065)	(0.0085)	(0.0100)	(0.0080)	(0.0095)
$Post_t \times ROA_{i,t-1}$	0.1258	0.1641	0.1743	0.0113	-0.1148	-0.0185
	(0.2102)	(0.1104)	(0.1282)	(0.2094)	(0.1566)	(0.1564)
$Post_t \times Dep\_Ratio_{i,t-1}$	0.0013	0.0005	0.0004	0.0014	0.0018	0.0007
	(0.0019)	(0.0014)	(0.0018)	(0.0022)	(0.0017)	(0.0020)
$Post_t \times Density_{i,t-1}$	0.0008	0.0025	0.0018	0.0016	0.0080	0.0041
	(0.0066)	(0.0043)	(0.0041)	(0.0076)	(0.0071)	(0.0060)
$Post_t \times Exp\_Size_{i,j,t-1}$	0.0087***	0.0058**	0.0059*	0.0112***	0.0092**	0.0101**
	(0.0015)	(0.0022)	(0.0032)	(0.0016)	(0.0034)	(0.0041)
N	2862	2862	2862	2862	2862	2862
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

	Total Off-Balance Sheet			Loan Commitments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
$Post_t \times DLGD_i$	-0.0169	-0.0320	-0.0396	-0.0039	-0.0265	-0.0291
	(0.0375)	(0.0327)	(0.0322)	(0.0402)	(0.0491)	(0.0403)
$Post_t \times Size_{i,t-1}$	0.0031	0.0070	0.0095	0.0181	0.0179	0.0225
	(0.0238)	(0.0181)	(0.0178)	(0.0320)	(0.0348)	(0.0274)
$Post_t \times Distance_{i,t-1}$	0.0221**	0.0162***	0.0165*	0.0097	0.0180*	0.0027
	(0.0091)	(0.0054)	(0.0079)	(0.0122)	(0.0089)	(0.0102)
$Post_t \times ROA_{i,t-1}$	-0.2364*	0.0335	0.0926	-0.4819***	-0.0103	-0.0600
	(0.1216)	(0.0923)	(0.0869)	(0.1446)	(0.1440)	(0.1665)
$Post_t \times Dep\_Ratio_{i,t-1}$	-0.0014	-0.0027**	-0.0033***	0.0015	-0.0026*	-0.0013
	(0.0012)	(0.0009)	(0.0009)	(0.0016)	(0.0014)	(0.0017)
$Post_t \times Density_{i,t-1}$	0.0156***	0.0068	0.0056	0.0246***	0.0089	0.0109*
	(0.0036)	(0.0043)	(0.0041)	(0.0045)	(0.0058)	(0.0061)
$Post_t \times Exp\_Size_{i,j,t-1}$	-0.0090***	-0.0093***	-0.0103***	-0.0103***	-0.0087***	-0.0112***
	(0.0011)	(0.0017)	(0.0018)	(0.0015)	(0.0025)	(0.0024)
N	2832	2832	2832	2832	2832	2832
Bank FE	Yes	No	Yes	Yes	No	Yes
Borrower × Time FE	No	Yes	Yes	No	Yes	Yes

Table A9
Large Exposures: Coefficient comparison with and without Public Guarantees included among controls (loan-level analysis)

This table reports the estimates of the difference-in-differences regressions for the loan-level sample of large exposures as in (Eq.2). The first column reports the coefficients as in Tables 6, 7, and 8 (Panels A, B, and C, respectively) i.e. those associated with the specification with no Public Guarantees among the controls. The second column reports instead the coefficients of the same regression including also Public Guarantees as a control. For each bank i Public Guarantees is a continuous variable calculated as the share of loans covered by a public guarantee over the total amount of loans. The outcome variable is the quarterly growth rates of loans & securities. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q2-2020Q1. $LowCap_i$ takes the value of one for banks in the first quartile of the distance between CET1 Ratio and their TSCR requirement, and zero otherwise. For the sake of brevity we show the coefficients on the interactions of main interest. 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. $Most\_Affected_j$ takes the value of one for those borrowers belonging to the NACE sectors: C,D,F,G,H,I,N,R. $Domestic_j$ takes the value of one if the borrower and the bank are headquartered in the same country. $DLGD$ takes the value of one for banks that use the downturn LGD parameter in their IRB models, and zero for banks (both under the foundation and advanced IRB framework) that do not use it. Bank-level controls include include the natural logarithm of assets, distance from the CET1 capital requirements, Return on Assets, Deposit Ratio, RWA Density and the relative size of the large exposure. The estimates for the control variables are available upon request to the authors. Clustered standard errors at bank-level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Loans & Securities	Loans & Securities
	(1)	(2)
Panel A: Table 6 re-estimation (High vs Low capitalised)		
$Post_t \times LowCap_i$	-0.0678***	-0.0605**
	(0.0241)	(0.0253)
Panel B: Table 7 re-estimation (Triple interactions)		
$Post_t \times LowCap_i \times CRM_j$	-0.1043**	-0.1076**
	(0.0474)	(0.0523)
$Post_t \times LowCap_i \times Most\_Affected_j$	-0.0675***	-0.0916***
	(0.0196)	(0.0215)
$Post_t \times LowCap_i \times Domestic_j$	0.0443	0.0254
	(0.0639)	(0.0483)
Panel C: Table 9 re-estimation (DLGD)		
$Post_t \times DLGD_i$	0.0545*	0.0341*
	(0.0270)	(0.0197)
Public Guarantees control	No	Yes
Bank FE	Yes	Yes
Borrower × Time FE	Yes	Yes

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