Pandemic Lending:

The Unintended Effects of Model-based Regulation

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Abstract

Does model-based bank regulation constrain lending when it matters the most? Using an extensive loan-level supervisory dataset on credit exposures, we select firms with multiple lending relationships. We document that during the Covid-19 pandemic, banks using their own (i.e., internal-rating based or IRB) models to measure credit risk, decreased their lending more than banks using standard (i.e. fixed risk-weights) models to the same borrower. At the same time, IRB banks increased their off-balance sheet exposures that do not absorb bank capital. The decline in on-balance sheet credit exposures did not affect all borrowers, rather it focused on borrowers in the economic sectors most affected by the pandemic and for which credit risk mitigation techniques had a a limited impact.

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

1 Introduction

Bank behaviour is inherently pro-cyclical (Gorton and He, 2008). During upswings of the business cycle, banks tend to overestimate the creditworthiness of their borrowers, resulting in possibly an *excessive* credit expansion, while they swiftly contract their credit supply during downturns.

Various factors contribute to amplify the cyclicality of banks' lending: accounting rules, financial innovation (as the asset securitization), and model-based capital regulation. For example, accounting standards and, especially provisioning requirements, exacerbate the credit cycle by failing to adopt a forward-looking approach for the recognition of impaired loans (Laeven and Majnoni, 2003; Saurina, 2009). In general, banks can provision for loans losses and write-off loans only *after* the credit exposures become impaired.[1] Inevitably, over the business cycle, this accounting framework yields to a situation where banks provision "too little" during booms while they are forced to quickly increase them during recessions, constraining new lending and magnifying the credit cycle.[2] Securitization activities also amplify the cyclicality of banks' lending: securitization enables banks to sell illiquid assets and generate cash-flows that, in times of economic growth, can be used to boost new loans resulting in an increase in the credit supply (Loutskina and Strahan, 2009; Brunnermeier and Sannikov, 2014). Model-based regulation for the calculation of capital requirements is another key factor inducing pro-cyclicality in bank lending (Danielsson et al., 2001; Kashyap and Stein, 2004; Repullo and Suarez, 2013).[3] This is the focus of this paper.

[1] With the notable exception of Spain, where banks have adopted a dynamic provisioning approach since 2000, the rest of countries follow an *ex-post* approach.

[2] The introduction of the new accounting standard for financial instruments (IFRS 9) was designed to address these limitation and ensure more adequate and timely recognition of provisions. The standard became effective on 1 January 2018, however, banks were given the choice to opt for five year transitional arrangements in order to phase in the impact of IFRS 9 on regulatory capital. In the context of Covid-19 pandemic, the European Central Bank (2020) has recommended Significant Institutions that have not already done so to adopt transitional arrangements in order to filter out from their prudential capital requirements part of the volatility generated by the use of IFRS 9 models.

[3] "Model-based regulation" refers to the option granted to banks to use their own (internal) model, which have been *ex-ante* scrutinized and authorized by the supervisory authority, to estimate credit risk parameters (such as probability of default and loss given default) that banks use to calculate risk weights and thus the minimum level of regulatory capital.

In contrast with the "one-size-fits-all" approach of Basel I agreement, the Basel II and successive amendments offered banks the option to chose whether using either the Standardised Approach (SA) or the Internal Ratings-Based (IRB) approaches to calculate the minimum capital requirements. The SA approach entails a simpler methodology, whereby risk-weights (i.e., pre-determined by the supervisory authorities) are assigned to different categories of borrowers (e.g., banks, corporate, etc). The IRB is a more sophisticate approach relying on banks' own (internal) models to calculate loan-specific risk-weights. The rationale is that model-based regulation increases the risk sensitivity of capital requirements. At the same time, it may exacerbate business cycle fluctuations if banks using internal models respond more dynamically to changes in capital charges by adjusting their lending. During upswings of the business cycle, the favourable economic conditions result in low probability of default of borrowers and in low risk weights, while the credit risk parameters inevitably deteriorate during recessions, forcing banks to hold higher capital against their loan portfolio, ultimately worsening the initial downturn. In other words, IRB model may increase the risk of a credit crunch during bad times (see, among others, Goodhart et al. (2004); Gordy and Howells (2006) for a discussion of the pro-cyclical features of Basel).

This leads to the following question: Does model-based regulation generate a credit crunch at a time of crisis? Our paper addresses this question by exploiting the Covid-19 pandemic that provides us a *quasi natural* experiment setting since (i) Covid-19 is an exogenous shock and orthogonal with bank behavior; (b) it is reasonable to expect that Covid-19 has a different impact (in terms of capital charges) on IRB and SA banks. Using a Difference-in-Differences (DiD) setting, we compare lending behaviour of IRB and SA banks. We document an overall reduction in loans and securities investments of IRB banks (especially to Non-Financial Corporations, NFC) relative to SA banks in the aftermath of March 2020. Conversely we show that IRB banks increase their overall off-balance sheet exposures, driven, in particular, by higher loan commitments (such as undrawn credit lines). These off-balance sheet positions do not generally absorb bank capital. These findings support the notion that model-based regulation induces more cyclicality compared to standardised approaches. Next, we further validate our results by accounting for the fact that the lending reduction can be the outcome of either a demand- or supply-shock. We exploit a proprietary loan-level dataset on bank's large exposures, including virtually all bank-firm relationships weighting more than 10%

of banks' eligible capital. This allows us to control for any demand shock by exploiting multiple bank-firm relationships (i.e., same firms borrowing at the same time from banks using different regulatory approaches). We also investigate to which borrowers lending was reduced. We show that IRB banks decreased their exposure towards the sectors most affected by the Covid-19 crisis more than SA banks. We also show that the decline in lending of IRB banks relative to SA banks did not affect all borrowers, rather it focused on credit exposures with a limited impact of credit risk mitigation techniques, and credit exposures toward borrowers in the economic sectors most affected by the pandemic.

Our analysis is based on a large sample of 293 Euro area Banks (of which 65 banks using IRB models). As of end of 2019, banks in our sample have an overall asset size of 22.8 trillion (of which, 19.6 trillion for the 65 IRB banks), provide loans to the economy for 14.9 trillion (12.9 trillion from IRB banks) and loans to NFC for 5.2 trillion (4.6 trillion are from IRB banks). We use granular supervisory data covering credit institutions operating in the Euro Area using different approaches for the calculation of the risk-based capital requirements.

Our paper contributes to two strands of the literature analysing the relationship between regulation and bank lending. The first branch includes papers dealing with the relationship between capital regulation and lending (Bridges et al., 2014; Aiyar, Calomiris and Wieladek, 2014; Aiyar, Calomiris, Hooley, Korniyenko and Wieladek, 2014; De Marco and Wieladek, 2015; Mésonnier and Monks, 2015; Jiménez et al., 2017; Acharya et al., 2018; Gropp et al., 2019; Cortés et al., 2020; Fraisse et al., 2020; De Jonghe, Dewachter and Ongena, 2020). The second group of papers focuses on lending during financial crises (Ivashina and Scharfstein, 2010; Puri et al., 2011; De Haas and Van Horen, 2013; Popov and Van Horen, 2015; **?**), and Covid-19 (Hasan et al., 2021; Dursun-de Neef and Schandlbauer, 2020); a few papers also account for the role played by model-based regulation (Behn et al., 2016; Bruno et al., 2017). The literature dealing with the impact of bank capital requirements on credit supply has been the subject of long-standing academic and policy discussion. All these papers use as an identification device the shock caused by a regulatory increase in the minimum capital requirements. Capital requirements increments have been found to be followed by a reduction in corporate and household lending (Bridges et al., 2014; Aiyar, Calomiris and Wieladek, 2014; De Marco and Wieladek, 2015) and cross-border lending (Aiyar, Calomiris, Hooley, Korniyenko and Wieladek, 2014) in the UK. By contrast, the introduction of counter-cyclical capital buffers in Spain smoothed the credit supply cycles, sustaining lending to firms and employment in crisis periods (Jiménez et al., 2017). Banks participating in the European Banking Authority capital exercise of 2011 reacted to higher capital requirements by reducing lending, rather than issuing new equity (Mésonnier and Monks, 2015; Gropp et al., 2019). In the same spirit, there is evidence of a decrease in corporate lending of French and Belgian banks as a result of higher capital requirements set by regulators (Fraisse et al., 2020; De Jonghe, Dewachter and Ongena, 2020). Higher capital requirements induced by stress-tests are also reported affecting banks' willingness to supply credit (Acharya et al., 2018; Cortés et al., 2020).

The second group includes a handful of papers focusing on lending during crises. Following the the Lehman Brothers collapse, US banks almost halved their lending to large corporates (Ivashina and Scharfstein, 2010), while they decreased less the lending to markets that were geographically close, where they were more experienced and where they operated a subsidiary (De Haas and Van Horen, 2013). Puri et al. (2011) reports that German savings banks affected by the US subprime mortgage crisis substantially rejected loan applications more than the non-affected banks after August 2007. Ongena et al. (2015) find that internationally borrowing banks contract their credit more towards small and medium-sized firms in Eastern Europe and Turkey than locally funded domestic banks during the financial crisis. Likewise, Popov and Van Horen (2015) show that the sovereign stress exported by GIIPS countries between 2009 and 2011 had a sizeable negative impact on bank lending of non-GIIPS countries.[4] Behn et al. (2016), and Bruno et al. (2017) also take into account the lending reaction to financial shocks, but they distinguish between IRB and SA banks showing a decline in lending of IRB banks relative to SA banks following the collapse of Lehman Brothers in 2008 (Behn et al., 2016) and during the European Sovereign crisis (Bruno et al., 2017).

In this paper, we analyse the impact of model-based regulation during the Covid-19 crisis, an exogenous shock that it is not directly related to the financial health of banks. Differently from Behn et al. (2016), we analyse the lending behavior of a large sample of Euro area banks (not only German) vis-a-vis large borrowers (including also non-domestic euro area borrowers). Moreover, and differently from Bruno et al. (2017), by using supervisory data we can control

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

for on-balance sheets changes as well as off-balance sheets changes in exposures and document a reshuffle towards less capital intensive activities. Very recently, a few papers have analyzed the impact of Covid-19 on lending. Hasan et al. (2021) show a rise in the pricing of syndicated loans as a result of an increase in borrowers and lenders' exposures to the pandemic while Dursun-de Neef and Schandlbauer (2020) document a higher loan supply by banks highly exposed to Covid-19.

Our paper contributes to past studies in various ways. First and foremost, we focus on the Covid-19 that has a different nature from the financial shocks analyzed in past papers. Covid-19 is essentially a natural disaster directly impacting on households and business. In this pandemic crisis, banks have not been the main affected firms as in preceding financial crises, rather banks are one of the key players in facing the Covid-19 negative effects by funding the economic agents hit by the pandemic. The need for maximising the capacity of banks to lend money and support businesses to recover from the Covid-19 crisis was largely recognized by politicians, and resulted in the the banking package adopted on June, 19$^{\text{th}}$ 2020 by the European Parliament providing temporary, targeted, and exceptional legislative changes to the European capital requirements regulation.[5] As far as we are aware, our paper is the first in providing causal evidence that the rigidity imposed by model-based regulation (not changed by the EU banking package) constrained IRB banks in providing on-balance sheet loans to corporations. Second, all financial shocks analyzed by past papers called for a stricter regulation and, thus, the decline in lending could be considered a somehow intended consequence of having a model-based regulation. In the case of the Covid-19 shock, we document a decline in lending due to model-based regulation and, this is certainly an unintended consequence of the rigidity imposed by a model-based regulation. Also, the magnitude of the Covid-19 shock is greater than any shocks previously analyzed and it calls for urgent analyses of any factor that may impede the extension of funds to corporations. To this aim, our paper provides important policy implications.

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

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

2 Data and Variables

Our study uses two main types of data with two distinct levels of aggregation: bank and loan-level data. Bank-level data are obtained from the confidential FINREP (”FINancial REPorting”) and COREP (”COmmon REPorting”) supervisory data from the European Central Bank (ECB). The FINREP framework is intended for financial accounting reporting while COREP is the framework for the capital adequacy regime envisaged by Basel III regulation. As such, these data contain detailed information on the consolidated and unconsolidated financial statements and capital adequacy of virtually all Euro area credit institutions on a quarterly basis. We compile the final bank-level dataset in the following way. First, we exclude from our analyses subsidiaries and foreign-owned banks. Secondly, we keep the consolidated statements of banks, unless banks exclusively report at unconsolidated level.[6] Finally, we remove from our sample those banks that lack data on total assets, equity and net income. This yields to a final sample of 293 banks classified either as ultimate parent or stand-alone banks across 19 countries (see Table 1).

[Insert Table 1 here]

Table 1 shows the sample composition by reporting the number of banks used for our bank-level analyses by country and by the approach used to determine minimum capital requirements for credit and market risks. Furthermore, in the Appendix, Table A1 presents the full list of IRB banks included in our empirical analyses. It is worth noting that, with the exclusion of two Greek banks (i.e., Alpha Bank and National Bank of Greece), all banks using internal models for market risk also calculate capital charges for the corporate credit exposures using internal models.

For our analyses at loan-level, we exploit the unique dataset constituted by the microprudential supervisory framework on ”Large Exposures”. In 2014, the Basel Committee on Banking Supervision (BCBS, henceforth) set out the large exposures framework to complement risk-based capital requirements as the latter do not protect banks from large losses resulting from the sudden

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

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.[7,8,9] Credit institutions reporting FINREP supervisory data are also requested to report large exposures information with a value above or equal to EUR 300 million.[10]

The use of loan-level data on large exposures provides three important advantages. First, while bank-level data enable us to estimate differential changes between IRB and SA banks, they do not allow us to disentangle changes due to credit supply effects from changes due to credit demand effects. We address this shortcoming using data at loan level and building an identification strategy based on multiple-lending relationships, which enables us to establish whether variations in on-balance sheet credit exposures are due to an intentional decision of IRB banks. Second, these loans refer to large borrowers that are strategically important for banks and are those that one can expect to see modified first after the eruption of the Covid-19 pandemic in March 2020. Banks will either increase lending to support their important customers (large borrowers in a time of crisis) or decrease it to relief equity capital pressures. Third, these data allow us to work with a global sample of borrowers, which is a major advantage compared to the use of national credit registries.

The use of "large exposure" data is not easy. [11] 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 identify non-financial corporations (NFCs) by filtering out (i) public sector borrowers, such as general governments, central banks and municipalities, (ii) financial sector borrowers, including credit institutions and financial corporation (e.g., mutual funds and insurances) and (iii) households. Furthermore, a successful match with Orbis enriches the data with information on the country and NACE sector

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

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

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

[10] 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

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

of the counterparty. In the second step, we manually map the remaining counterparties lacking the LEI code across banks and across countries using the counterparty name as reported by the credit institutions and we fill the missing information using several sources such as gleif.org and SNL. Finally, we drop from our sample those borrowers for which we completely lack information on the sector, thus limiting the risk of including exposures other than NFCs. To the best of our knowledge, we are the first to exploit these data to explore the lending dynamics of Euro area banks.[12]

3 Identification strategy

The Covid-19 pandemic is a natural disaster that has been hitting Europe since March 2020 and it provides a very interesting setting to investigate whether banks using different capital regulation calculation methods varied their lending activities in a different way.[13] As shown by past papers (Danielsson et al., 2001; Kashyap and Stein, 2004; Repullo and Suarez, 2013), the introduction of internal-rating models increased the pro-cyclicality of bank lending and thus IRB banks may be unable to lend to non-financial corporations, just at the time when firms would need it the most, due to regulation. Specifically, our identification strategy relies on a difference-in-differences (DiD) approach enabling to test whether, after the outbreak of Covid-19 in March 2020, there are differences in the growth rates of on- and off-balance sheet credit exposures between banks using IRB or SA. We run our analysis using data both at the bank- and loan-levels. The first analysis enables us to identify whether IRB banks dropped their lending relative to SA banks, while the second analysis using loan-level data (focusing on *large exposures*, those that are the most likely to react to Covid-19 pandemic) allows us to assess whether the lending decline is due to a supply effect.

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

[13] Banks' capital requirements are a function of banks' total risk-weighted exposures, which, in a simplistic way, can be divided into credit (CR), market (MK) and operational (OP) risk exposures. For the calculation of capital charges due to OP risk, banks are obliged to use the standardised approach, whereas for CR and MK risk, banks can chose to rely on their own internal models.

3.1 Bank-level Analysis

At the bank-level, our identification strategy is based on the following DiD model:

$$\Delta Log(Y)_{i,t} = \alpha_i + \alpha_t + \beta_1 Post_t + \beta_2 IRB_i + \beta_3 Post_t \times IRB_i + \beta_4 X_{i,t} + \epsilon_{i,t} \tag{1}$$

where $\Delta Log(Y)_{i,t}$ is the quarter-on-quarter growth rate of the exposures volume of bank i in quarter t $(Log(Y_{i,t}) - Log(Y_{i,t-1}))$.[14] We use various measures of on- and off-balance sheet credit exposure to gain a broad understanding of the impact of Covid-19: total loans (distinguishing between total loans to non-financial firms, and total loans to other than non-financial firms), total securities (distinguishing between total securities issued by non-financial firms, and issued by other than non-financial firms), total off-balance sheet exposures (distinguishing between off-balance sheet exposures towards non-financial firms, and off-balance sheet exposures towards other than non-financial firms), and total loan commitments (distinguishing between loan commitments towards non-financial firms, and those towards other than non-financial firms). $Post_t$ takes the value of 1 for the quarters 2020Q2-2020Q3 and zero for 2019Q4-2020Q1. We adopt two different definitions of treated group (IRB_i) since banks can validate internal models for both credit and market risks. Specifically, the variable IRB_CR_i takes the value of one if the bank uses internal models for the calculation of capital requirements for their *corporate* credit risk exposures. As of end of 2019, there are 78 European banks using internal models in least one credit portfolios.[15] For the purpose of this study, we take a restrictive approach by considering as IRB only those banks using internal model for corporate portfolios: this yields to a final sample of 65 banks classified as IRB.[16] Similarly, the variable IRB_MR_i takes the value of one if the bank uses internal models for the calculation of capital requirements for their *market* risk exposures. This definition of IRB banks is more appropriate when assessing the impact of the pandemic on banks' securities investments. As

[14] We note that all of our results are robust to expressing the outcome variables as a year-on-year growth rate (results not presented for brevity).

[15] To clarify on this, under the IRB approach, credit risk (CR henceforth) exposures are allocated into the following portfolios: central governments and central banks, institutions, corporate and retail

[16] Within the IRB approach for credit risk, banks can further chose between the Foundation Internal Ratings-Based (F-IRB) approach and the Advanced Internal Ratings-Based (A-IRB) approach for the calculation of risk-weights. Both the F-IRB and the A-IRB require banks to provide regulators with their own estimates of the probability of default (PD) of the borrower, whereas banks using the A-IRB are also expected to calculate the loss given default (LGD), the exposure at default (EAD) and the maturity (M). These four risk parameters are then utilized in a specific formula proposed by the Basel Committee on Banking Supervision (BCBS). As in Behn et al. (2016), we do not distinguish between the A-IRB and F-IRB approaches because the risk weights depend on the loan's PD in both cases.

at the end of 2019, there are 32 European banks using internal models for calculating the minimum capital level to cover market risks. $X_{i,t}$ represents a vector of bank characteristics, including the natural logarithm of total assets, the percentage of equity over assets and return on assets. α_i and α_t are bank and time fixed effects, respectively; $\epsilon_{i,t}$ is the error term. The definitions of the variables are presented in Table 2.

[Insert Tables 2 Here]

As a robustness check, we run again the model in Eq. (1) by omitting the 2020Q1 (when the Covid-19 pandemic started in Europe), and we compare lending during 2019 with the second and third quarter of 2020.[17]

3.2 Loan-level Analysis

Using loan-level data, our identification strategy enable us to establish whether changes in lending dynamics (investigated using the model in the Eq.(1),) are driven by supply (bank) effects. To this end, we investigate whether lending changes are due to a decision of IRB banks by running the following DiD model using loan-level data on banks' large exposures:

$$\Delta Log(Y)_{i,t,j} = \alpha_i + \alpha_j + \beta_1 Post_t + \beta_2 IRB_i + \beta_3 Post_t \times IRB_i + \beta_4 X_{i,t} + \epsilon_{i,t} \tag{2}$$

where the variables $Post_t$, and IRB_i are the same of the model in the Eq.(1), the dependent variable $\Delta Log(Y)_{i,t,j}$ is the quarter-on-quarter growth rate of the exposures of bank i, to firm j at time t. We use two main measures of credit growth: total on-balance sheet growth and loans and securities growth. We control for observed and unobserved bank heterogeneity by including a set of control variables ($X_{i,t}$), the natural logarithm of total assets, equity over assets, return on assets and bank-fixed effects (α_i), respectively. In our less restrictive setup, entailing the full set of bank-firm pairs, borrowers unobserved heterogeneity (α_j) is captured via the inclusion of sector*country*quarter fixed effects (Morais et al., 2019; De Jonghe, Dewachter, Mulier, Ongena and Schepens, 2020). In our more restrictive setup, we focus on those firms with multiple lending relationships in the spirit of Khwaja and Mian (2008), and we control for unobserved firm fundamentals via firm fixed

[17] 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 reference date, when several municipalities in Northern Italy entered lockdown (Albuquerque et al., 2020; Ramelli and Wagner, 2020).

effects. In Section 4.3, we discuss in greater details the different setups used for our analyses at loan-level.

4 Results

In this section, we present our results. First, we discuss whether the Covid-19 shock generated a different impact on lending for IRB and SA banks. Second, we show whether lending changes in IRB banks in the aftermath of March 2020 are due to a decision of IRB banks (supply-side effect). Third, we run a follow-up analysis to investigate whether the changes in lending of IRB banks regarded all borrowers or focused on some specific borrowers. To do so, we take into account the role of credit risk mitigation techniques and the borrowers' industry.

4.1 Preliminary Analyses

We first report the summary statistics for all variables used in our empirical analyses (Table 3) by distinguishing between IRB and SA banks. Focusing on both bank-level variables (Panel A) and loan-level variables (Panel B), SA banks have generally increased their on-balance and off-balance sheet activities between 2019Q4 and 2020Q3, while IRB banks generally show lower mean growth rates in each variable than SA banks. Looking at the Panel C, IRB banks display (on average) a greater size, lower capital levels and lower profitability than SA banks.

[Insert Table 3 here]

The difference-in-differences estimator relies on two main assumptions: the treatment must be orthogonal with respect to the outcome variables, and treated and untreated banks must satisfy the parallel trend assumption. While it seems to be obvious that the Covid-19 pandemic was exogenous and not caused by the outcome of interest, we provide evidence to support the parallel trends assumption between the treatment and control groups. Specifically, we compare the growth of various credit exposure for banks using an IRB-approach (treatment group) and for those using the SA approach (control group). Our objective is to assess whether, in quarters prior to the outburst of the pandemic, IRB and SA banks are comparable. Table 4 reports the mean growth rates between banks in the control and treatment groups (columns (1) and (2), respectively). Column (3) shows that the difference-in-means for credit exposure measures for the treatment groups are largely statistically indistinguishable from the control group prior the Covid-19 pandemic development in Europe. These results provide evidence that the parallel assumption condition is met, and this is particularly important for safely run our DiD models, especially since our selection criteria is somehow endogenous (the decision of using IRB approach is granted by the supervisory authority on banks' request).

[Insert Table 4 here]

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

In Table 5, we report the results obtained running the model in Eq.(1). Using bank-level supervisory data, we compare whether, after the Covid-19 pandemic eruption in March 2020, there are differences in the growth of on- and off-balance sheet credit exposures between banks adopting an IRB or a SA approach. Since IRB models can be used for determining both capital requirements on credit and market risk, we selected two different treatment groups (IRB_CR_i, and IRB_MR_i respectively) when we estimate the Covid effect on lending and securities investments. Specifically, in Panel B of Table 5, we define treated banks as those using IRB models for credit risk measurement in columns (1), (2), and (3), and for market risk measurement in columns (4), (5), and (6).

We find evidence that, after March 2020, banks using IRB models experienced a lower growth rate on their on-balance sheet credit exposures compared to banks using a SA approach (Column 1 of Panel A), driven by both lower lending and lower securities investments. Specifically, the coefficient of main interest is the interaction variable ($Post \times IRB$) showing the Average Treatment Effect (ATE) due to the Covid-19 pandemic for IRB banks. Focusing on the Panel A (Columns 2 and 3), we observe a strong decline in lending (-0.8%), especially to non-financial corporations (-2.2%). Likewise, we report a decline in securities exposures (Panel B) for both banks using IRB models on credit and market risks, especially towards NFC (-6.5% for banks with IRB-credit models and -10.0% for banks with IRB-market models, columns 2 and 5, respectively). These results are consistent with the fact that IRB models increase lending pro-cyclicality more than SA models (Repullo and Suarez, 2013). After Covid-19 erupted, macro- and micro-economic conditions worsened, in turn yielding to a worsening in IRB banks' models estimates of borrowers creditworthiness, higher capital requirements, and thus a decline in their lending capability. Furthermore, our results show that IRB banks reacted to the shock by increasing more their off-balance sheet credit exposures (Table 6), especially loan commitments, relative to SA banks. These positions do not directly absorb regulatory capital and, thus, banks are able to support borrowers (especially, NFC) by increasing off-balance sheet exposures and gaining higher fees without an immediate absorption of their equity.

[Insert Tables 5 here]

[Insert Tables 6 here]

An alternative explanation to our results may be that IRB banks (being usually larger banks with more developed risk management departments) realized the disruptive effects of Covid-19 on the economy before SA banks, resulting in IRB banks cutting their lending faster than other institutions. To rule out this alternative explanation, we replicate our analysis by omitting from the sample the first quarter of 2020 (when the Covid-19 was at its early stages and thus SA 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) are reported in Table 7. As shown in Panel A of Table 7, during the second and third quarter of 2020, IRB banks have substantially decreased their overall lending activities (-1.2%), especially towards NFC (-1.8%), compared to SA banks. The decline is even more pronounced in securities investments for IRB banks relative to SA banks (-4.3% for banks with IRB-credit models and -4.8% for banks with IRB-market models). Our results broadly 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 more quick reaction of IRB banks to the Covid-19, rather it is a persistent effect over the entire 2020 and it is driven by the use of internal models contributing to the pro-cyclicality of lending.

[Insert Table 7 here]

To sum up, we show IRB banks dropped their on-balance sheet exposures (especially, toward NFC) and increased their off-balance sheet exposures relative to banks using SA models, after the outburst of the Covid-19 pandemic in Europe.

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

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

We run model in the Eq.(2) in a three-stage setting. First, we use the full sample by considering all lending positions, that is all single- and multi-bank firm relationships. Indeed, while in the other two steps we focus on a multiple relationships setting, the inclusion of the full set of bank-firm pairs enable us to exploit the largest available sample. In details, in this setting, we follow the existing literature and we control for demand shocks by saturating the model with sector*country*quarter fixed effects, where the sector is defined by the NACE code and the country refers to the country where the firm is headquartered (Degryse et al., 2019; Morais et al., 2019; De Jonghe, Dewachter, Mulier, Ongena and Schepens, 2020; Jakovljević et al., 2020).[19] In the second stage of our analysis, we rely on Khwaja and Mian (2008) to identify and control for credit demand shocks. This approach entails selecting a sample of firms borrowing at the same time from more than one bank (i.e., multiple-relationship lending) between 2019Q4 and 2020Q3. Various papers have used multiple bank-firm relationships to identify credit supply shocks (Khwaja and Mian, 2008; Jiménez et al., 2012; Gropp et al., 2019). As such, we study the differences in lending conditions to the same borrower before and after the Covid-19 shock between IRB and SA banks and, with the inclusion

[18]As defined by BIS (2018), large exposures are the sum of all exposures of a bank to a single counter-party that are equal to or above 10% of its Tier 1 capital. Banks also have to report to national supervisors: (a) all other exposures that would have been a large exposure without considering the effect of credit risk mitigation or exemption clauses; (b) the 20 largest exposures even if they do not satisfy the definition of a large exposure.

[19]In untabulated results, we find consistent results when proxying demand shock with sector*country*quarter fixed effects where country is the two-digits NUTS regional codes and sector is the two-digit NACE code. However, this strategy limits our sample to European borrowers.

of firm fixed effects, we control for demand-side shock such as changes in borrowers' demand and riskiness. In the third stage, we further restrict our sample to multiple-lending relationships where there is (at least) one IRB bank and (at least) one SA banks.[20] Adopting such a strategy is important in our setting since we could not rule out the possibility that the Covid-19 pandemic generated a demand shock. By focusing on multiple relationship lending form IRB and SA banks, any change in the amount that banks lend can be attributed to a supply effect.

Table 8 reports the estimates for the model in the Eq.(2). We focus on two main outcome variables. First, we use ad dependent variable a broad measure of bank credit exposures as the total on-balance sheet exposures, comprising loans and securities held, equity instruments and derivatives assets (columns 1 to 3), and then we restrict our focus on loans and securities held (columns 4 to 6) to mitigate concerns that our findings are driven by equity and derivatives adjustments.[21] To control for demand shocks, we use different sets of fixed effects: when using the full sample (Panel A), we include only bank fixed effects (Columns 1 and 4), then we use only sector*country*time fixed effects (columns 2 and 5), and finally we saturate the model with both bank and sector*country*time fixed effects (in columns 3 and 6). When focusing on multiple-lending relationships (Panel B and Panel C), we include only firm fixed effects (Columns 1 and 4), then we use firm and bank fixed effects (columns 2 and 5), and finally we saturate the model with firm, bank and time fixed effects (in columns 3 and 6). Furthermore, all specifications include control variables at bank-level (the natural logarithm of total assets, equity to asset ratio and return on assets). The variable of main interest is the double interaction term ($Post_t \times IRB\_CR_i$) capturing the ATE due to the Covid-19 pandemic for IRB banks after March 2020.

[Insert Table 8 here]

Focusing on the full sample of firms (Panel A of Table 8), we find that the double interaction term estimates are negative and statistically significant across the different levels of fixed effects, indicating that, compared to banks using SA models institutions, IRB banks decreased their overall on-balance sheet exposures and credit supply following the Covid-19 shock in March 2020. Looking at the most saturated models (Columns 3 and 6 of Panel A), IRB banks declined by 4.3% their on-

[20]To clarify the difference between the second and the third sample, we do not impose any conditions on the type of banks associated with the firms in the second sample. This means that, while all firms in the sample borrow money from at least two different banks, all these banks can use the SA approach or the IRB approach.

[21]The nature of the data prevents us to further separate loans from securities held in the portfolio.

balance sheet credit exposure and by 3.6% their loans and securities investments in comparison to SA banks after March 2020. In Panel B of Table 8, we restrict our sample to firms borrowing from multiple banks (not necessarily from an IRB bank and a SA bank). The coefficient estimates for $Post \times IRB$ retains its negative sign, confirming the findings obtained when using the entire sample of bank-firms pairs. IRB banks responded to the Covid-19 shock by reducing their exposures relative to SA banks after March 2020. The decline is observed both at the aggregated level (Columns 1 to 3) and for investments in loans and securities (Columns 4 to 6). As before, focusing on the most saturated models (including firm, bank and time fixed effects), on-balance sheet exposures and loans and securities investments decline by 8.8% and 8.9% for IRB than for SA banks (Columns 3 and 6 of Panel B) relative to SA banks. In the third setup, we further restrict the sample by including only borrowers with multi-lending relationships under the condition that, among the banks associated with the same firms, at least one is an IRB and one a SA bank. Not surprisingly, the sample size drop substantially. Our findings (Panel C in Table 8) confirm the evidence provided so far on the negative relationship between the use of IRB models and credit growth following an exogenous credit shock. The second and third quarters of 2020 have seen a greater reduction in the overall on-balance sheet exposures of IRB compared to SA banks (Columns 1 and 3), driven, in particular, by lower loans and securities investments (Columns 3 to 6).

Consistently the section 4.2, we investigate whether the drop in lending of IRB banks (larger banks with more developed risk management departments) was due to their greater ability in realizing the Covid-19 disruptive effect. As such, we replicate our analysis by omitting the first quarter of 2020 (when the Covid-19 was at the early stages). The results from re-running the model in Eq.(2) are reported in Table 9. These findings confirm the decline in credit supply by IRB banks compared to SA banks after March 2020, indicating that the observed difference is not driven by a faster reaction of IRB banks to the Covid-19, but it is a enduring effect over the entire 2020.

[Insert Table 9 here]

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

4.4 Was the lending drop targeted?

In this section, we run a follow-up analyses to investigate whether IRB banks selected which borrowers to reduce lending. First, we investigate whether IRB banks tried to drop loans with higher capital absorption. To this end, we augment the DiD specification of Eq.(2) with an interaction term capturing the riskiness of the loan (CRM_j). 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 the CRM factor for each loan exposures by dividing the value of the exposures after the application of CRM by its total original value. To exemplify this, a CRM value of 1 implies that the exposure does not benefit from any credit risk mitigation, and the entire original value of the exposure needs to be considered for the calculation of capital requirements.[22] We use the CRM factor calculated as of 2019Q3 as a proxy for the riskiness of the credit exposures pre-shock, where the higher the CRM, the riskier is the exposure. The results of our triple DiD are presented in Table 10. In all our three settings (Panel A, B and C), the coefficient of main interest is the triple interaction ($Post_t \times IRB\_CR_i \times CRM_j$). We observe a negative and strongly significant coefficient for both on-balance sheet exposures (Columns 1 to 3) and loans and securities (Columns 4 to 6). This suggests that after March 2020, IRB banks have cut more their exposures towards riskier borrowers (i.e., borrowers absorbing more capital) than banks using the standardised approach. This is consistent with the notion that model-based capital regulation induces cyclicality in bank lending, especially during crisis times, as IRB banks react quickly to adverse macroeconomic scenarios.

[Insert Table 10 here]

In the second step, we explore whether IRB banks dropped their lending relative to SA banks in the economic sectors most affected by the pandemic. As previously done, we augment the DiD specification of Eq.(2) with an interaction term ($Most\_Affected_j$) capturing whether the borrowers is in an economic sector most affected by the pandemic. Specifically, the variable $Most\_Affected_j$

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

is a dummy variable taking the value of one if the borrower belongs to one of the sectors identified as having the highest risk of fall in economic output due to Covid-19, and zero otherwise. For this classification, we rely on the International Labour Organization (2020) (ILO, hereafter), which identifies the following sectors as suffering from the most pronounced fall in output: Manufacturing; Wholesale and Retail Trade; Accommodation and Food Services; Real Estate Activities; Business and Administrative Activities.[23]. First, Figure 1 displays the portfolio composition of SA and IRB in terms of sectoral exposures to the least and most affected sectors by the Covid-19 pandemic in the pre- and post- shock (2019Q3 and 2020Q3, respectively). The graphs show that both the groups of banks are exposed very similarly to the most affected sectors. Not surprisingly, the results in Table 11 show that, after March 2020, IRB banks have decreased their exposures towards the most affected sectors of the economy more than SA banks. The results are strongly consistent across the samples used (full sample, multiple lending relationships and multiple lending relationship with matched SA and IRB bank) and across the several levels of fixed effects employed.

[Insert Figure 1 here]

[Insert Table 11 here]

To sum up, we show that the decline in lending of IRB banks relative to SA banks did not affect all borrowers, rather it focuses 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.

5 Conclusions

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

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

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

it is critical that the banking system works effectively to ensure the intermediation of funds toward firms that are still viable but may have temporary funding needs. Overall, we document a reduction in lending and securities investments of banks using internal models compared to banks using fixed risk-weights after March 2020. By drawing on a unique loan-level dataset on large exposures (greater than 10% of a bank's Tier 1 equity capital) of Euro area banks, we confirm these findings and, especially, we show that this decline is driven by supply-side effect. Specifically, we focus on a sample of firms with multiple-lending relationships where borrowers received funds from at least one IRB bank and one SA banks and we document that IRB banks declined on-balance sheet credit exposure in comparison to SA banks. We also show that the decline in lending of IRB banks relative to SA banks did not affect all borrowers, rather it focued on credit exposures with a limited impact of credit risk mitigation techniques, and credit exposures toward borrowers in the economic sectors most affected by the pandemic. These findings are consistent with the view that IRB models increase pro-cyclicality in banking and place emphasis on the need to further calibrate and validate IRB models to prevent excessive fluctuation around the business cycle, especially when the economy is severely hit by a catastrophe, as the Covid-19 pandemic.

Our results have important policy implications since we empirically document the negative (unintended) consequences of setting mechanical rules in banking regulation. Importantly, the economic detriment induced by model-based capital regulation during catastrophic events regards the largest banks in the industry. As of end of 2019, European banks using IRB models have an overall asset size of 19.6 trillion, provide loans to the economy for 12.9 trillion and loans to NFC for 4.6 trillion.

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Tables

Table 1: Number of banks by country according to the approach used for credit and market risk

		(1)	(2)	(3)	(4)
		Credit Risk		Market Risk	
Country	Total	SA	IRB	SA	IRB
Austria	21	18	3	19	2
Belgium	9	4	5	7	2
Cyprus	5	5	-	5	-
Germany	95	78	17	88	7
Estonia	6	6	-	6	-
Finland	11	7	4	10	1
France	15	8	7	10	5
Greece	9	8	1	6	3
Ireland	5	2	3	5	-
Italy	32	23	9	29	3
Latvia	9	9	-	9	-
Lithuania	3	3	-	3	-
Luxembourg	9	6	3	9	-
Malta	9	9	-	9	-
Netherlands	12	6	6	8	4
Portugal	12	11	1	11	1
Slovenia	4	4	-	4	-
Slovakia	3	3	-	3	-
Spain	24	18	6	20	4
Total	293	228	65	261	32

This table presents the number of banks used in our empirical analyses by country and according to whether they use the Standardised Approach (SA) or the Internal-Rating Based Approach (IRB) for the calculation of credit and market risk for the purpose of capital requirements. Specifically, in column (2), we define banks as IRB if they report corporate credit risk under the IRB approach while in column (4), IRB denotes those reporting market risk using internal models.

Table 2: Definitions of Variables

Variable	Definition
Panel A. Outcome Variables	
On-Balance Sheet	Aggregated on-balance sheet exposures of bank i, comprising, total loans, total securities, total equity instruments and total derivative assets.
Total Loans	Total loans of bank i, comprising credit card debt, trade receivables, finance leases, reverse repurchase loans, other term loans, advances.
Loans to NFC	Total loans of bank i where the counterparty is a non-financial corporation.
Loans to non-NFC	Total loans of bank i where the counterparty is other than a non-financial corporation (i.e., government, credit institutions, other-financial corporations, households).
Total Securities	Total debt instruments held by bank i.
Securities of NFC	Total debt instruments issued by non-financial corporations held by bank i
Securities of non-NFC	Total debt instruments issued by counterparties other than non-financial corporations (i.e., government, credit institutions, other-financial corporations, households) held by bank i
Off-Balance Sheet	Aggregated off-balance sheet exposures of bank i, comprising Loan Commitments, Financial Guarantees and Other Commitments. Loan commitments are firm commitments to provide credit under pre-specified terms and conditions (e.g., acceptances, forward deposits, undrawn credit facilities). Financial Guarantees are contracts that require the issuer to make specified payments to reimburse the holder for a loss it incurs because a specified debtor fails to make payment when due in accordance with the original or modified terms of a debt instrument (e.g., credit derivatives, irrevocable standby letters of credit). Other Commitments are other Off-balance sheet not included in Loan Commitments and Financial Guarantees.
Off-Balance Sheet NCF	Aggregated off-balance sheet exposures of bank i where the counterparty is a non-financial corporation.
Off-Balance Sheet non-NCF	Sum of total off-balance sheet exposures of bank i where the counterparty is other than a non-financial corporation (i.e., government, credit institutions, other-financial corporations, households).
Loan Commitments	Total commitments of bank i to provide credit under pre-specified terms and conditions (e.g., acceptances, forward deposits, undrawn credit facilities).
Loan Commitments NFC	Total commitments of bank i where the counterparty is a non-financial corporation.
Loan Commitments to non-NFC	Total commitments of bank i where the counterparty is other than a non-financial corporation (i.e., government, credit institutions, other-financial corporations, households).
Panel B. Control Variables	
Total Assets	Natural logarithm of total assets of bank i.
Equity Ratio	The ratio of total equity to total assets of bank i expressed as a percentage (%).
ROA	Return on assets of bank i, calculated as net income divided by total assets (%).

Table 3: Summary Statistics of SA and IRB banks

	SA				IRB			
Variable	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.
Panel A. Outcome Variables at Bank-level (Growth Rates)								
On-Balance Sheet	909	0.0115	0.0093	0.0394	260	-0.0022	-0.0016	0.0346
Total Loans	909	0.0089	0.0099	0.0355	260	-0.0025	0.0011	0.0332
Loans to NFC	909	0.0128	0.0102	0.0422	260	0.0045	0.0058	0.0396
Loans to non-NFC	909	0.0249	0.0226	0.0694	260	0.0265	0.0252	0.0634
Total Securities	551	0.0179	0.0049	0.1023	232	0.0049	-0.0018	0.0678
Securities of NFC	551	0.0084	0.000	0.164	232	0.0064	0.001	0.1461
Securities of non-NFC	551	0.0197	0.0049	0.1049	232	0.0044	-0.0023	0.0696
Off-Balance Sheet	827	0.0153	0.0121	0.0845	252	0.0143	0.014	0.0694
Off-Balance Sheet to NFC	827	0.017	0.0129	0.1186	252	0.0051	0.0103	0.0792
Off-Balance Sheet to non-NFC	827	0.0149	0.0063	0.1298	252	0.009	0.0098	0.1009
Loan Commitments	827	0.0198	0.0143	0.0954	252	0.0151	0.0167	0.0725
Loan Commitments NFC	827	0.028	0.0144	0.1429	252	0.0109	0.0056	0.0954
Loan Commitments to non-NFC	827	0.011	0.0059	0.1368	252	0.0067	0.0138	0.0965
Panel B. Outcome Variables at Loan-level (Growth Rates)								
On-Balance Sheet	1528	0.0053	0.000	0.0929	9010	0.011	-0.0006	0.3037
Loans and Securities	1528	-0.0013	0.000	0.7642	9010	0.0248	-0.0005	0.9065
Panel C. Control Variables								
Total Assets (Log)	909	22.5063	22.7258	1.3615	260	25.5624	25.3967	1.3693
Equity/Assets (%)	909	9.6134	8.9232	3.9376	260	7.1628	6.428	2.538
ROA (%)	909	0.4639	0.3945	0.4333	260	0.4342	0.356	0.3595

This table provides the summary statistics (number of observations (N), mean , median and standard deviation (Std. Dev.)) for the variables used in the paper according to whether banks use the Internal-Rating Based (IRB) or the Standardised Approach (SA) approach for the calculation of capital requirements. For the purpose of this table, IRB denotes those banks reporting *corporate credit risk* under the IRB approach. All the variables in Panel A and Panel B are expressed as quarterly growth rates ($\Delta Log(Y_{i,t}) - \Delta Log(Y_{i,t-1})$). Panel A provides the summary statistics for the outcome variables used in the bank-level analysis. Panel B reports the summary statistics for the outcome variables used in the loan-level analysis for the full sample. Panel C shows the summary statistics for the control variables. Variables are defined as is Table 2.

Table 4: Difference in Means between SA and IRB banks

Variables (Growth Rates)	(1) **Mean SA**	(2) **Mean IRB**	(3) **Diff. in Means**
Panel A. Pre-treatment Mean Comparisons			
On-Balance Sheet	0.0100	0.0079	0.0021
Total Loans	0.0106	0.0086	0.0020
Loans to NFC	0.0145	0.0125	0.0020
Loans to non-NFC	0.0139	0.0120	0.0019
Total Securities	0.0043	0.0019	0.0024
Securities NFC	0.0001	0.0192	-0.0191
Securities non-NFC	0.0088	0.0051	0.0037
Off-Balance Sheet	0.0076	0.0055	0.0021
Off-Balance Sheet to NFC	0.0066	0.0022	0.0044
Off-Balance Sheet to non-NFC	0.0050	0.0068	-0.0018
Total Loan Commitments	0.0085	0.0085	0.000
Loan Commitments to NFC	0.0046	0.0049	-0.0003
Loan Commitments to non-NFC	0.0069	0.0131	-0.0062
Panel B. Post-treatment Mean Comparisons			
On-Balance Sheet	0.0166	-0.0032	0.0198***
Total Loans	0.0113	-0.0041	0.0115***
Loans to NFC	0.0113	-0.0057	0.0191***
Loans to non-NFC	0.0314	0.0394	-0.0079***
Total Securities	0.0328	0.0098	0.0230**
Securities NFC	0.0376	-0.0102	0.0478**
Securities non-NFC	0.0423	-0.0183	0.0239
Off-Balance Sheet	0.0264	0.0284	-0.0019
Off-Balance Sheet to NFC	0.0289	0.0284	0.0005
Off-Balance Sheet to non-NFC	0.0199	0.0260	-0.0060
Loan Commitments	0.0329	0.0393	-0.0064
Loan Commitments to NFC	0.0429	0.0420	0.0009
Loan Commitments to non-NFC	0.0203	0.0323	-0.0119

This table provides pre-treatment mean comparisons between banks using the Standardised Approach (SA) and banks using the Internal-Rating Based (IRB) approach for the calculation of capital requirements. For the purpose of this table, IRB denotes those banks reporting *corporate credit risk* under the IRB approach. In Panel A, the means reported in columns (1) and (2) refer to the average quarterly growth rates over the eight quarters pre-shock (i.e., 2018Q2-2020Q1). In Panel B, the means refers to the two quarters post-shock (2020Q2-2020Q3). Column (3) reports the difference in means between SA and IRB banks. Variables are defined as is Table 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Difference-in-Differences Regression: On-balance Sheet Exposures

	(1)	(2)	(3)	(4)
Panel A. On-balance Sheet and Loans				
	On-Balance Sheet	Total Loans	Loans to NFC	Loans to non-NFC
$Post_t \times IRB\_CR_i$	-0.0135***	-0.0084*	-0.0218***	0.0119
	(0.0044)	(0.0045)	(0.0051)	(0.0081)
$Log(Assets)_{i,t}$	0.2215***	0.2037***	0.1298***	0.5327***
	(0.0496)	(0.0451)	(0.0472)	(0.0907)
$Equity\_Ratio_{i,t}$	0.0039	0.0093*	0.0079*	-0.0035
	(0.0048)	(0.0048)	(0.0046)	(0.0078)
$ROA_{i,t}$	-0.0028	-0.0061	-0.0116	0.0183
	(0.0080)	(0.0077)	(0.0076)	(0.0155)
Observations	1,169	1,169	1,169	1,169
R-squared	0.3698	0.3295	0.3975	0.3401
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B. Securities						
	Total Securities	Securities of NFC	Securities of non-NFC	Total Securities	Securities of NFC	Securities of non-NFC
$Post_t \times IRB\_CR_i$	-0.0255**	-0.0648***	-0.0200*			
	(0.0116)	(0.0230)	(0.0121)			
$Post_t \times IRB\_MR_i$				-0.0355***	-0.1004***	-0.0250*
				(0.0121)	(0.0326)	(0.0132)
$Log(Assets)_{i,t}$	0.0187	-0.0799	0.0167	0.0741	-0.1212	0.0931
	(0.1207)	(0.2127)	(0.1226)	(0.1161)	(0.2089)	(0.1202)
$Equity\_Ratio_{i,t}$	-0.0168	-0.0266	-0.0160	-0.0101	-0.0305	-0.0083
	(0.0131)	(0.0206)	(0.0136)	(0.0129)	(0.0198)	(0.0134)
$ROA_{i,t}$	0.0110	0.0422	0.0024	0.0123	0.0485	0.0058
	(0.0245)	(0.0387)	(0.0255)	(0.0237)	(0.0389)	(0.0251)
Observations	783	783	783	783	783	783
R-squared	0.3936	0.3131	0.3708	0.3872	0.3145	0.3639
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the estimates for our difference-in-differences regressions (Eq.(1)). In Panel A, the outcome variables are: on-balance sheet exposures, total loans, loans to non-financial corporations (NFC), and loans to other than non-financial corporations. In Panel B, the outcome variables are: total securities, securities of non-financial corporations and securities of other than 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 2019Q4-2020Q1. In columns (1)-(4) of Panel A and in column (1)-(3) of Panel B, IRB_CR_i takes the value of one for bank reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. In columns (4)-(6) of Panel B, IRB_MR_i takes the value of one for those banks reporting *market risk* using internal models and zero otherwise. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Variables are winsorized at the 5% level.

Table 6: Difference-in-Differences Regression: Off-Balance Sheet Exposures

	(1) Off-Balance Sheet	(2) Off-Balance Sheet to NFC	(3) Off-Balance Sheet to non-NFC	(4) Loan Commitments	(5) Loan Commitments to NFC	(6) Loan Commitments to non-NFC
$Post_t \times IRB\_CR_i$	0.0146	0.0250**	0.0311**	0.0262**	0.0326**	0.0372**
	(0.0102)	(0.0123)	(0.0154)	(0.0107)	(0.0147)	(0.0151)
$Log(Assets)_{i,t}$	0.1046	0.1304	0.3419**	0.1211	0.0652	0.3752**
	(0.1146)	(0.1463)	(0.1688)	(0.1226)	(0.1653)	(0.1787)
$Equity\_Ratio_{i,t}$	0.0061	0.0133	0.0269	0.0025	0.0079	0.0314*
	(0.0105)	(0.0137)	(0.0169)	(0.0117)	(0.0177)	(0.0186)
$ROA_{i,t}$	0.0045	0.0078	-0.0122	0.0162	-0.0085	-0.0025
	(0.0197)	(0.0263)	(0.0304)	(0.0228)	(0.0320)	(0.0358)
Observations	1,079	1,079	1,079	1,079	1,079	1,079
R-squared	0.2432	0.2450	0.2251	0.2412	0.2380	0.1978
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the estimates for our difference-in-differences regressions (Eq.(1)). The outcome variables are: off-balance sheet exposures, off-balance sheet exposures to non-financial corporations (NFC), off-balance sheet exposures to other than non-financial corporations, total loan commitments, loan commitments towards non-financial corporations, loan commitments towards other than 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 2019Q4-2020Q1. IRB_CR_i takes the value of one for bank reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Variables are winsorized at the 5% level.

Table 7: Difference-in-Differences Regression. On-Balance Sheet Exposures - Robustness Test

	(1)	(2)	(3)	(4)		
Panel A. On-balance Sheet and Loans						
	Total On-Balance Sheet	Total Loans	Loans to NFC	Loans to non-NFC		
$Post_t \times IRB\_CR_i$	-0.0170***	-0.0122***	-0.0176***	0.0135**		
	(0.0034)	(0.0035)	(0.0041)	(0.0068)		
$Log(Assets)_{i,t}$	0.0938***	0.0711***	0.0159	0.2607***		
	(0.0203)	(0.0186)	(0.0243)	(0.0409)		
$Equity\_Ratio_{i,t}$	0.0003	0.0051**	0.0033	-0.0061		
	(0.0023)	(0.0022)	(0.0028)	(0.0047)		
$ROA_{i,t}$	-0.0093	-0.0083	-0.0025	0.0079		
	(0.0062)	(0.0064)	(0.0074)	(0.0125)		
Observations	1,731	1,731	1,731	1,731		
R-squared	0.3225	0.3035	0.3122	0.2268		
Bank FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B. Securities						
	Total Securities	Securities of NFC	Securities of non-NFC	Total Securities	Securities of NFC	Securities of non-NFC
$Post_t \times IRB\_CR_i$	-0.0183*	-0.0427**	-0.0157			
	(0.0094)	(0.0180)	(0.0099)			
$Post_t \times IRB\_MR_i$				-0.0214**	-0.0478*	-0.0154
				(0.0094)	(0.0247)	(0.0102)
$Log(Assets)_{i,t}$	0.1385**	0.1050	0.1122**	0.1462***	0.1366	0.1187**
	(0.0578)	(0.0933)	(0.0552)	(0.0552)	(0.0903)	(0.0538)
$Equity\_Ratio_{i,t}$	-0.0100	-0.0169	-0.0117*	-0.0084	-0.0124	-0.0096
	(0.0070)	(0.0104)	(0.0070)	(0.0065)	(0.0096)	(0.0066)
$ROA_{i,t}$	0.0013	0.0243	-0.0107	0.0022	0.0290	-0.0102
	(0.0181)	(0.0300)	(0.0180)	(0.0180)	(0.0296)	(0.0180)
Observations	1,121	1,121	1,121	1,121	1,121	1,121
R-squared	0.3172	0.2347	0.3083	0.3148	0.2380	0.3020
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the estimates for our robustness test on our difference-in-differences regressions (Eq.(1)). In Panel A, the outcome variables are: on-balance sheet exposures, total loans, loans to non-financial corporations (NFC), and loans to other than non-financial corporations. In Panel B, the outcome variables are: total securities, securities of non-financial corporations and securities of other than 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 2019Q1-2019Q4. The regression excludes 2020Q1. In columns (1)-(4) of Panel A and in column (1)-(3) of Panel B, IRB_CR_i takes the value of one for bank reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. In columns (4)-(6) of Panel B, IRB_MR_i takes the value of one for those banks reporting *market risk* using internal models and zero otherwise. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Variables are winsorized at the 5% level.

Table 8: Large Exposures Lending: Intensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)
	Total On Balance Sheet			**Loans and Securities**		
Panel A. Full Sample						
$Post_t \times IRB\_CR_i$	-0.0682***	-0.0381***	-0.0430***	-0.0683***	-0.0342**	-0.0361***
	(0.0084)	(0.0128)	(0.0130)	(0.0091)	(0.0136)	(0.0139)
$Post_t$	-0.0226***			-0.0198***		
	(0.0067)			(0.0073)		
IRB_CR_i		0.0309**			0.0273*	
		(0.0138)			(0.0149)	
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,538	10,538	10,538	10,538	10,538	10,538
R-squared	0.0350	0.1538	0.1639	0.0267	0.1504	0.1581
Sector*Country*Time	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Panel B. Multi-bank Firms						
$Post_t \times IRB\_CR_i$	-0.0775***	-0.0735***	-0.0882***	-0.0832***	-0.0794***	-0.0892***
	(0.0130)	(0.0131)	(0.0134)	(0.0153)	(0.0154)	(0.0158)
$Post_t$	0.0038	-0.0334***		0.0035	-0.0241*	
	(0.0098)	(0.0117)		(0.0119)	(0.0140)	
IRB_CR_i	0.0502**			0.0440*		
	(0.0210)			(0.0237)		
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,627	6,627	6,627	6,627	6,627	6,627
R-squared	0.0721	0.0902	0.0943	0.0667	0.0775	0.0791
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes
Panel C. Multi-bank Firms SA and IRB Matching						
$Post_t \times IRB\_CR_i$	-0.0429*	-0.0425*	-0.0493**	-0.0599**	-0.0616**	-0.0685**
	(0.0243)	(0.0244)	(0.0243)	(0.0271)	(0.0271)	(0.0269)
$Post_t$	0.0257	0.0090		0.0314	0.0090	
	(0.0189)	(0.0213)		(0.0214)	(0.0236)	
IRB_CR_i	0.0183			0.0220		
	(0.0284)			(0.0304)		
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,406	1,406	1,406	1,406	1,406	1,406
R-squared	0.0312	0.0746	0.0899	0.0356	0.0834	0.0937
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.(2)). The outcome variables are: total on-balance sheet exposures, loans and securities and they are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). Panel A presents the results for the full sample of firms (i.e., including single-bank firms). Panel B reports the results for the sub-sample of firms with multiple-lending relationships. Panel C show the findings from our smallest sample of firms with multiple-lending relationship where the associated banks need to be at least one SA and one IRB bank. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q4-2020Q1 IRB_CR_i takes the value of one for bank reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. Bank Controls include: the natural logarithm of assets, equity to assets ratio and return on assets of bank i at time t. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Variables are winsorized at the 5% level.

Table 9: Large Exposures Lending: Intensive Margin - Robustness Test

	(1)	(2)	(3)	(4)	(5)	(6)
	Total On Balance Sheet			**Loans and Securities**		
Panel A. Full Sample						
$Post_t \times IRB\_CR_i$	-0.0342***	-0.0096	-0.0156	-0.0317***	-0.0073	-0.0048
	(0.0079)	(0.0115)	(0.0118)	(0.0087)	(0.0126)	(0.0132)
$Post_t$	-0.0090			-0.0136*		
	(0.0074)			(0.0082)		
IRB_CR_i		0.0018			0.0080	
		(0.0113)			(0.0124)	
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,272	13,272	13,272	13,272	13,272	13,272
R-squared	0.0189	0.1324	0.1417	0.0121	0.1301	0.1368
Sector*Country*Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Panel B. Multi-bank Firms						
$Post_t \times IRB\_CR_i$	-0.0625***	-0.0522***	-0.0567***	-0.0664***	-0.0563***	-0.0534***
	(0.0131)	(0.0128)	(0.0129)	(0.0160)	(0.0161)	(0.0162)
$Post_t$	0.0213*	0.0014		0.0242*	0.0058	
	(0.0112)	(0.0140)		(0.0140)	(0.0175)	
IRB_CR_i	0.0349**			0.0295		
	(0.0173)			(0.0199)		
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,778	8,778	8,778	8,778	8,778	8,778
R-squared	0.0422	0.0520	0.0541	0.0402	0.0472	0.0481
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes
Panel C. Multi-bank Firms SA and IRB Matching						
$Post_t \times IRB\_CR_i$	-0.0344**	-0.0336*	-0.0339*	-0.0371*	-0.0390*	-0.0386*
	(0.0173)	(0.0184)	(0.0184)	(0.0216)	(0.0226)	(0.0226)
$Post_t$	0.0124	0.0030		0.0231	0.0179	
	(0.0116)	(0.0164)		(0.0165)	(0.0209)	
IRB_CR_i	-0.0119			-0.0230		
	(0.0195)			(0.0219)		
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,731	1,731	1,731	1,731	1,731	1,731
R-squared	0.0149	0.0526	0.0607	0.0189	0.0546	0.0591
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

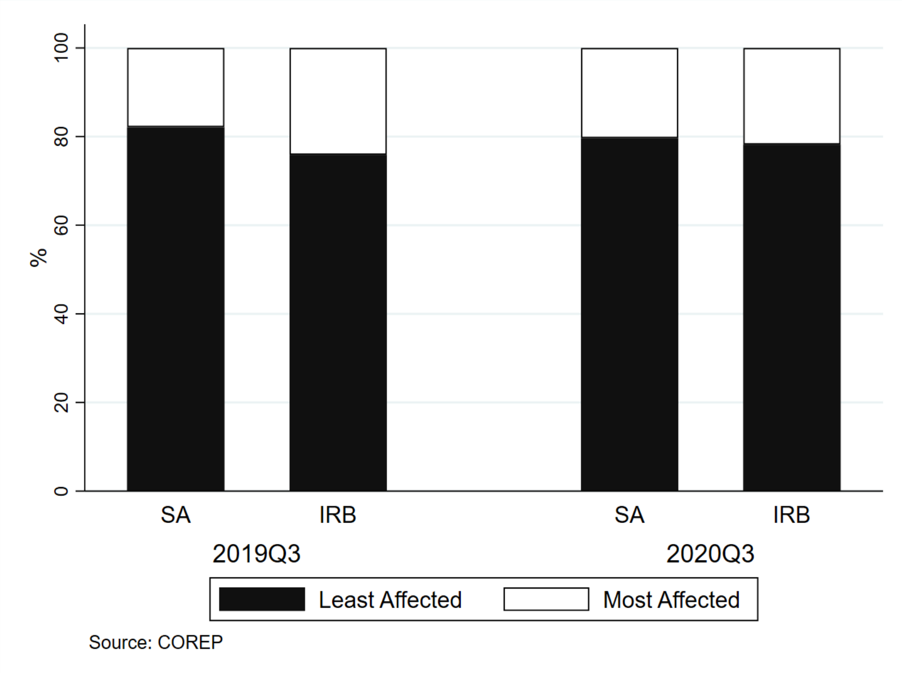
This table presents the robustness estimates of our difference-in-differences regressions for large exposures lending (Eq.(2)). The outcome variables are: total on-balance sheet exposures, loans and securities and they are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). Panel A presents the results for the full sample of firms (i.e., including single-bank firms). Panel B reports the results for the sub-sample of firms with multiple-lending relationships. Panel C show the findings from our smallest sample of firms with multiple-lending relationship where the associated banks need to be at least one SA and one IRB bank. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q1-2019Q4. The regression excludes 2020Q1. IRB_CR_i takes the value of one for bank reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. Bank Controls include: the natural logarithm of assets, equity to assets ratio and return on assets of bank i at time t. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Variables are winsorized at the 5% level.

Table 10: Large Exposures Lending: Intensive Margin - Credit Risk Mitigation Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Total On Balance Sheet			**Loans and Securities**		
Panel A. Full Sample						
$Post_t \times IRB\_CR_i \times CRM_j$	-0.2086***	-0.1153***	-0.1420***	-0.1918***	-0.1006***	-0.1196***
	(0.0256)	(0.0331)	(0.0324)	(0.0280)	(0.0361)	(0.0358)
$Post_t \times IRB\_CR_i$	0.0927***	0.0371	0.0486**	0.0767***	0.0267	0.0351
	(0.0200)	(0.0252)	(0.0246)	(0.0216)	(0.0272)	(0.0267)
$Post_t \times CRM_j$	0.0635***	0.0244	0.0448	0.0478***	0.0332	0.0458
	(0.0160)	(0.0295)	(0.0285)	(0.0171)	(0.0321)	(0.0313)
$IRB\_CR_i \times CRM_j$	0.0497*	0.0334	0.0476	0.0460	0.0369	0.0425
	(0.0299)	(0.0239)	(0.0374)	(0.0325)	(0.0263)	(0.0410)
IRB_CR_i		0.0047			0.0006	
		(0.0220)			(0.0241)	
$Post_t$	-0.0713***			-0.0555***		
	(0.0137)			(0.0147)		
CRM_j	-0.0075	-0.0096	-0.0139	-0.0016	-0.0194	-0.0196
	(0.0232)	(0.0212)	(0.0326)	(0.0247)	(0.0233)	(0.0353)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,765	8,765	8,765	8,765	8,765	8,765
R-squared	0.0386	0.1596	0.1684	0.0303	0.1543	0.1610
Sector*Country*Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Panel B. Multi-bank Firms						
$Post_t \times IRB\_CR_i \times CRM_j$	-0.1890***	-0.2542***	-0.2557***	-0.2173***	-0.2609***	-0.2622***
	(0.0459)	(0.0449)	(0.0444)	(0.0540)	(0.0534)	(0.0534)
$Post_t \times IRB\_CR_i$	0.0567*	0.0990***	0.0907***	0.0669*	0.0953***	0.0895***
	(0.0308)	(0.0299)	(0.0297)	(0.0353)	(0.0338)	(0.0343)
$Post_t \times CRM_j$	0.0742**	0.1369***	0.1261***	0.0886**	0.1302***	0.1225***
	(0.0356)	(0.0338)	(0.0330)	(0.0433)	(0.0417)	(0.0417)
$IRB\_CR_i \times CRM_j$	0.0958**	0.1673	0.1696	0.1266***	0.1855	0.1871
	(0.0403)	(0.1404)	(0.1365)	(0.0464)	(0.1745)	(0.1722)
$Post_t$	-0.0350*	-0.1110***		-0.0413*	-0.0935***	
	(0.0190)	(0.0201)		(0.0228)	(0.0237)	
IRB_CR_i	-0.0202			-0.0444		
	(0.0320)			(0.0360)		
CRM_j	-0.0854**	-0.1435	-0.1398	-0.1080**	-0.1745	-0.1718
	(0.0409)	(0.1377)	(0.1338)	(0.0470)	(0.1716)	(0.1691)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,033	6,033	6,033	6,033	6,033	6,033
R-squared	0.0731	0.0901	0.0945	0.0694	0.0792	0.0810
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes
Panel C. Multi-bank Firms SA and IRB Matching						
$Post_t \times IRB\_CR_i \times CRM_j$	-0.1209**	-0.1480**	-0.1583**	-0.1460**	-0.1911***	-0.1998***
	(0.0593)	(0.0620)	(0.0623)	(0.0666)	(0.0692)	(0.0694)
$Post_t \times IRB\_CR_i$	0.0141	0.0259	0.0272	0.0141	0.0331	0.0332
	(0.0384)	(0.0383)	(0.0392)	(0.0408)	(0.0403)	(0.0412)
$Post_t \times CRM_j$	0.0980**	0.1198**	0.1227**	0.0987*	0.1350**	0.1367**
	(0.0469)	(0.0485)	(0.0486)	(0.0540)	(0.0559)	(0.0561)
$IRB\_CR_i \times CRM_j$	0.0938*	0.2007	0.1989	0.1252**	0.2309	0.2299
	(0.0481)	(0.1866)	(0.1798)	(0.0530)	(0.2094)	(0.2038)
$Post_t$	-0.0164	-0.0388		-0.0095	-0.0451	
	(0.0272)	(0.0300)		(0.0294)	(0.0319)	
IRB_CR_i	-0.0294			-0.0469		
	(0.0391)			(0.0416)		
CRM_j	-0.0903*	-0.1529	-0.1473	-0.1014*	-0.1559	-0.1514
	(0.0511)	(0.1821)	(0.1754)	(0.0562)	(0.2044)	(0.1988)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,299	1,299	1,299	1,299	1,299	1,299
R-squared	0.0336	0.0739	0.0874	0.0399	0.0856	0.0944
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.(2)). The outcome variables are: total on-balance sheet exposures, loans and securities and they are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). Panel A presents the results for the full sample of firms (i.e., including single-bank firms). Panel B reports the results for the sub-sample of firms with multiple-lending relationships. Panel C show the findings from our smallest sample of firms with multiple-lending relationship where the associated banks need to be at least one SA and one IRB bank. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q4-2020Q1 IRB_CR_i takes the value of one for bank reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. CRM_j is a continuous variable ranging from 0 to 1, where the higher the value, the riskier is the exposures. CRM_j is calculated as the value of the exposure after the application of CMR divided by the value of the original exposure. Bank Controls include: the natural logarithm of assets, equity to assets ratio and return on assets of bank i at time t. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Variables are winsorized at the 5% level.

Figure 1: Large Exposures to Least and Most Affected Sectors (as a percentage of NFC Large Exposures %)



The graphs shows the ratio of large exposures of SA and IRB banks in 2019Q3 and 2020Q3 towards least and most affected sectors over the total portfolio of large exposures towards NFC. Most Affected Sectors include: Manufacturing; Wholesale and Retail Trade; Accommodation and Food Services; Real Estate Activities; Business and Administrative Activities (International Labour Organization, 2020)

Table 11: Large Exposures Lending: Intensive Margin - Sectoral Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Total On Balance Sheet			**Loans and Securities**		
Panel A. Full Sample						
$Post_t \times IRB\_CR_i \times Most\_Affected_j$	-0.0635***	-0.0569***	-0.0608***	-0.0576***	-0.0508***	-0.0528***
	(0.0156)	(0.0176)	(0.0174)	(0.0170)	(0.0192)	(0.0191)
$Post_t \times IRB\_CR_i$	-0.0383***	-0.0363***	-0.0388***	-0.0422***	-0.0377***	-0.0382***
	(0.0106)	(0.0129)	(0.0130)	(0.0115)	(0.0141)	(0.0142)
$Post_t \times Most\_Affected_j$	0.0313***	0.0472***	0.0508***	0.0246***	0.0404***	0.0423***
	(0.0088)	(0.0119)	(0.0115)	(0.0093)	(0.0126)	(0.0123)
$IRB\_CR_i \times Most\_Affected_j$	0.0184	0.0101	0.0157	0.0227*	0.0134	0.0191
	(0.0126)	(0.0132)	(0.0138)	(0.0137)	(0.0144)	(0.0151)
$Post_t$	-0.0373***			-0.0305***		
	(0.0076)			(0.0083)		
IRB_CR_i		0.0304**			0.0303**	
		(0.0126)			(0.0136)	
$Most\_Affected_j$	-0.0121	-0.0175*	-0.0213**	-0.0117	-0.0160*	-0.0197*
	(0.0080)	(0.0090)	(0.0095)	(0.0084)	(0.0096)	(0.0101)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,769	10,769	10,769	10,769	10,769	10,769
R-squared	0.0354	0.0815	0.0919	0.0270	0.0722	0.0802
Country*Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Panel B. Multi-bank Firms						
$Post_t \times IRB\_CR_i \times Most\_Affected_j$	-0.0669***	-0.0821***	-0.0864***	-0.0660**	-0.0765***	-0.0794***
	(0.0259)	(0.0248)	(0.0244)	(0.0303)	(0.0292)	(0.0291)
$Post_t \times IRB\_CR_i$	-0.0462**	-0.0356**	-0.0484***	-0.0524**	-0.0441**	-0.0527**
	(0.0180)	(0.0176)	(0.0174)	(0.0215)	(0.0208)	(0.0208)
$Post_t \times Most\_Affected_j$	0.0445**	0.0609***	0.0632***	0.0441*	0.0557**	0.0572***
	(0.0194)	(0.0179)	(0.0175)	(0.0233)	(0.0216)	(0.0215)
$IRB\_CR_i \times Most\_Affected_j$	0.0149	0.0062	0.0083	0.0158	-0.0054	-0.0039
	(0.0321)	(0.0519)	(0.0512)	(0.0372)	(0.0606)	(0.0601)
$Post_t$	-0.0165	-0.0611***		-0.0167	-0.0494***	
	(0.0141)	(0.0152)		(0.0175)	(0.0185)	
IRB_CR_i	0.0401*			0.0333		
	(0.0227)			(0.0263)		
$Most\_Affected_j$	-0.0162	0.0470	0.0435	-0.0552	0.0593	0.0567
	(0.0720)	(0.1026)	(0.1002)	(0.0864)	(0.1111)	(0.1091)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,627	6,627	6,627	6,627	6,627	6,627
R-squared	0.0725	0.0907	0.0948	0.0670	0.0779	0.0795
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes
Panel C. Multi-bank Firms SA and IRB Matching						
$Post_t \times IRB\_CR_i \times Most\_Affected_j$	-0.1517***	-0.1550***	-0.1462***	-0.1126*	-0.1171**	-0.1087*
	(0.0552)	(0.0526)	(0.0526)	(0.0602)	(0.0577)	(0.0577)
$Post_t \times IRB\_CR_i$	0.0058	0.0071	-0.0020	-0.0243	-0.0250	-0.0341
	(0.0288)	(0.0289)	(0.0288)	(0.0326)	(0.0327)	(0.0325)
$Post_t \times Most\_Affected_j$	0.0982**	0.1018**	0.0921**	0.0791	0.0844*	0.0752
	(0.0462)	(0.0431)	(0.0433)	(0.0504)	(0.0472)	(0.0474)
$IRB\_CR_i \times Most\_Affected_j$	0.0609	0.0101	0.0070	0.0391	-0.0139	-0.0170
	(0.0438)	(0.0589)	(0.0580)	(0.0478)	(0.0651)	(0.0645)
$Post_t$	-0.0027	-0.0208		0.0084	-0.0156	
	(0.0203)	(0.0227)		(0.0239)	(0.0261)	
IRB_CR_i	-0.0043			0.0047		
	(0.0307)			(0.0335)		
$Most\_Affected_j$	-0.1534**			-0.2800**		
	(0.0731)			(0.1158)		
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,406	1,406	1,406	1,406	1,406	1,406
R-squared	0.0360	0.0798	0.0947	0.0389	0.0861	0.0962
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

This table presents the estimates for our difference-in-differences regressions for large exposures lending (Eq.(2)). The outcome variables are: total on-balance sheet exposures, loans and securities and they are expressed as quarterly growth rates ($Log(Y_{i,t}) - Log(Y_{i,t-1})$). Panel A presents the results for the full sample of firms (i.e., including single-bank firms). Panel B reports the results for the sub-sample of firms with multiple-lending relationships. Panel C show the findings from our smallest sample of firms with multiple-lending relationship where the associated banks need to be at least one SA and one IRB bank. $Post_t$ takes the value of one for the period 2020Q2-2020Q3 and zero for 2019Q4-2020Q1 IRB_CR_i takes the value of one for bank reporting *corporate credit risk* using internal models and zero if the bank uses the standardised approach. $Most\_Affected_j$ takes the value of one for those borrowers belonging to the NACE sectors: C,G,I,L,N. Bank Controls include: the natural logarithm of assets, equity to assets ratio and return on assets of bank i at time t. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Variables are winsorized at the 5% level.

Appendix

Table A1: List of banks using Internal Models for Credit and Market Risk

Bank	Country	Credit Risk	Market Risk
ABN Amro Group	Netherlands	✓	✓
Aareal Bank Ag	Germany	✓	-
Aktia Bank Abp	Finland	✓	-
Alpha Bank	Greece	-	✓
Allied Irish Banks	Ireland	✓	-
Banca Monte Dei Paschi Di Siena	Italy	✓	-
Banca Popolare Di Sondrio	Italy	✓	-
Banco BPM	Italy	✓	✓
Banco Comercial Português	Portugal	✓	✓
Bawag Holding Gmbh	Austria	✓	-
BFA Tenedora De Acciones	Spain	✓	✓
BNP Paribas	France	✓	✓
BPER Banca	Italy	✓	-
Banco Bilbao Vizcaya Argentaria	Spain	✓	✓
Banco Santander	Spain	✓	✓
Banco De Sabadell	Spain	✓	-
Bankinter	Spain	✓	-
Banque Internationale à Luxembourg	Luxembourg	✓	-
Banque et Caisse d'Epargne de l'Etat	Luxembourg	✓	-
Bayerische Landesbank	Germany	✓	-
Belfius Banque	Belgium	✓	✓
Commerzbank	Germany	✓	✓
Crédit Agricole	France	✓	✓
CaixaBank	Spain	✓	✓
Crédit Mutuel	Framce	✓	-
Cooperative Rabobank	Netherlands	✓	✓
Credito Emiliano Holding	Italy	✓	-
Deutsche Apotheker	Germany	✓	-
Deutsche Bank	Germany	✓	✓
DZ Bank Ag	Germany	✓	✓
DekaBank	Germany	✓	✓
Deutsche Pfandbriefbank A	Germany	✓	-
Erste Group Bank	Austria	✓	✓

Erwerbsgesellschaft der S-Finanzgruppe	Germany	✓	-
Eurobank Ergasias	Greece	✓	✓
Groupe BPCE	France	✓	✓
HSBC France	France	✓	✓
HSH Nordbank	Germany	✓	-
ING Groep	Netherlands	✓	✓
Intesa Sanpaolo	Italy	✓	✓
Investeringsmaatschappij Argenta	Belgium	✓	-
KBC Group	Belgium	✓	✓
LSF Nani Investments	Portugal	✓	-
Landesbank Baden-Württemberg	Germany	✓	✓
Landesbank Hessen - Thüringen Girozentrale	Germany	✓	✓
Mediobanca	Italy	✓	-
Münchener Hypothekenbank	Germany	✓	-
National Bank of Greece	Greece	-	✓
Norddeutsche Landesbank	Germany	✓	✓
Nordea Bank Abp	Finland	✓	✓
OP Osuuskunta	Finland	✓	-
Rci Banque	France	✓	-
Raiffeisen Bank International	Austria	✓	✓
Société Générale	France	✓	✓
The Bank of Ireland	Ireland	✓	-
UniCredit	Italy	✓	✓
Ulster Bank Ireland	Ireland	✓	-

The sample of IRB banks also includes: one Finnish bank, one Italian, two Belgian, three German and three Dutch banks reporting Corporate Credit Risk, whose name cannot be disclosed.

Source: European Banking Authority