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BANKS' INTERNAL MODELS AND RWA VARIABILITY: STRATEGIC MODELLING PORTFOLIO REALLOCATION?

by Maria Alessia Aiello*, Salvatore Cardillo* and Caterina Ciancaglioni*

Abstract

We analyse the effects of internal ratings-based (IRB) models on risk-weighted asset (RWA) variability, investment strategies and capital management among significant banks in the euro area, using a unique supervisory dataset. Our findings indicate a decline in RWA density (i.e. the ratio of risk-weighted assets to total exposure at default) following the adoption of internal models. The magnitude of this reduction varies across banks and is influenced by balance sheet characteristics. We find no evidence that, in the post-2015 SSM setting, weakly capitalized or fragile banks reduced RWA density more than other banks after the adoption of IRB models along the margins examined in the paper. This is consistent with the view that harmonized supervision may have limited the scope for opportunistic post-adoption reductions in RWAs. Finally, we provide evidence that IRB models encourage banks to reallocate credit towards more profitable assets – particularly those to large non-financial corporations – while reducing sovereign and central bank exposures.

JEL Classification: G21, G28.

Keywords: risk-weighted assets, internal ratings-based models, bank regulation.

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1 Introduction[1]

Risk-weighted assets (RWA) are a cornerstone of the system of minimum capital ratios, originally designed by the Basel Committee on Banking Supervision (BCBS), and are one of the key tools banks use to assess and quantify the risks associated with their assets. Over the last few decades, the Basel framework has radically changed since the possibility of adopting banks' internal rating-based (IRB) models for credit risk to compute RWA was introduced with the so-called Basel II package.[2] By tying capital charges to predicted asset risk, model-based regulation avoids penalizing banks for holding safe assets on their balance sheets, so that the distortion in the allocation of credit that accompanied the simple flat capital charge of Basel I is eliminated (Behn et al., 2022). To determine asset-specific risk, this revised regulatory setting relies on credit risk estimates produced by a complex array of risk models designed and calibrated by banks themselves and subsequently approved by the supervisors. Consequently, many banks have more than 100 different risk models with thousands of parameters, all of which require constant validation and recalibration by the bank's risk management team, as well as surveillance by the supervisors. Given that equity is expensive, banks may have an incentive to use this discretion to select modelling assumptions that lower regulatory capital requirements, despite the supervisory validation of the models. Since its establishment in November 2014, the Single Supervisory Mechanism (SSM) strengthened supervisory oversight and harmonized the validation process for internal models of euro area banks, following concerns about the complexity and the degree of discretion in the assumptions of such models, and on the resulting opaqueness of the modelling approaches (ECB, 2021).

We start our research by observing that RWA density — commonly measured as the ratio of RWA to exposure at default (EAD)[3] — has shown significant variation across banks and a gradual downward convergence over time, as highlighted by Böhnke et al. (2023).[4] The adoption

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[2]The Basel framework defines two main IRB approaches: Foundation IRB (F-IRB) and Advanced IRB (A-IRB). In this paper, we focus on IRB models without distinguishing between the two approaches.

[3]Literature defines it as the ratio between RWA over either total assets (Mariathasan and Merrouche, 2014) or Exposure-at-Default (EAD). This paper relies on this latter definition. Compared to RWA over total assets, the advantage of relying on the RWA density defined as RWA over EAD better assesses the off-balance sheet exposures and accounts for the effects of risk mitigation techniques (Credit Risk Mitigation, CRM) and conversion factors (Credit Conversion Factors, CCF). It captures the mechanical reduction of RWA density when a bank shifts portfolio shares to IRB.

[4]See Figure 2.

of IRB models can, in principle, affect both banks' heterogeneity in RWA measurement practices (Avramova and Le Leslé, 2012) and the decline in reported riskiness, reflecting banks' efforts to minimize capital charges for a given level of credit risk. Our work investigates the relationship among the RWA density at the bank level, banks' characteristics (e.g. financial structure, riskiness, and capital headroom over regulatory and supervisory requirements), and different capital allocation strategies adopted by banks after the IRB adoption. We aim to address two research questions: 1) What explains the RWA density heterogeneity across IRB banks? 2) Is IRB adoption followed by differential changes in RWA density, lending, NPL ratios, or portfolio composition among fragile or less-capitalized banks? In the spirit of Mariathasan and Merrouche (2014), we test two different ex-ante hypotheses, both based on the general idea that IRB models can influence banks' risk assessment and, consequently, capital management:

- *Strategic Modelling* relies on the assumption that a riskier and/or under-capitalized bank may strategically use IRB models, which typically allow for optimization of risk weights, to reduce RWA and achieve capital relief opportunistically, *ceteris paribus*. IRB banks could therefore underestimate asset risks to reduce capital requirements;

- *Portfolio Reallocation* is based on the idea that an IRB bank can change the composition of its exposures. IRB adoption is associated with lower average risk weights. Thus, banks may shift resources from assets with low capital charges (typically, domestic central governments and central banks, which have a zero risk-weight treatment) to assets requiring more equity funding (non-financial corporations) that, under the IRB, benefit from a more favourable prudential treatment. This portfolio reallocation may ultimately increase lending activity.

Our findings indicate a decline in RWA density following the adoption of internal models. The magnitude of this reduction varies across banks and is influenced by balance-sheet characteristics. In particular, intermediaries with a better capital adequacy have, on average, higher densities, consistent with the main findings in Avramova and Le Leslé (2012). When testing the strategic-modelling hypothesis, our analytical framework does not deliver evidence that less-capitalized or riskier banks reduced RWA density more than other banks after IRB adoption. This result contrasts with earlier evidence and is consistent with the view that the post-2015 SSM supervisory framework may have limited the scope for strategic post-adoption reductions in RWAs. Finally, when analysing the portfolio reallocation hypothesis, we find that, after adopting IRB models, banks increase their exposures toward non-financial corporations, especially the larger ones.[5] A plausible interpretation for this finding is that the IRB adoption mainly impacted banks' risk weights for exposures toward large firms that — conversely to those towards Small and Medium enterprises (SMEs) — did not benefit from the regulation called "SME supporting factor" that entry into force since the very beginning of SSM.[6]

Literature review. Our work contributes to the empirical literature on financial regulation. While the academic literature on prudential capital and regulatory requirements is quite vast, papers on RWA heterogeneity across European banks and the factors affecting it are more limited and fragmented. The first strand of literature analyzes the evolution of RWA and the potential role of regulatory arbitrage. Differences in risk weights across banks may arise from variations in supervisory practices, regulatory environments, and the adoption of internal models. For example, Böhnke et al. (2023) observe that European listed banks' RWA densities converge downwards over time, something that cannot be entirely explained by differences in banks' balance sheet characteristics, country risk, and/or time of IRB implementation. Hence, they find that banks in high-risk countries, with lax regulation, tend to reduce their RWA densities. On the contrary, banks in countries with strict supervision reduce their RWA densities to a lesser extent after switching to the IRB approach, and banks' densities subsequently remain largely stable, even increasing in response to the tightening of regulations. Behn et al. (2022) highlight the undesired effects of model-based regulation, showing that German banks systematically underreported risk, with underreporting more pronounced for large institutions with higher gains from it. Similarly, Bruno et al. (2015) find that risk weights are affected by the bank's size, business model, and asset mix and by IRB adoption. They also find that lower risk weights are positively linked to the banks' capital cushion and that IRB adoption is more widespread in countries where supervisory capture is potentially stronger, due to a banking industry that is both larger (compared to GDP) and more concentrated. Lastly, their results point out that regulatory risk weights are not disconnected from market-based measures of bank risk. Mariathasan and Merrouche (2014) examine the relationship between banks' approval for the IRB approaches of Basel II and the ratio of RWA to total

[5] In this paper, we consider corporate exposure at default (EAD) as a proxy of bank loans to firms.

[6] A capital reduction factor for loans to SMEs — the SME supporting factor — was introduced by the CRR to allow credit institutions to counterbalance the rise in capital requirements resulting from the Capital Conservation Buffer (CCB), and to provide an adequate flow of credit to this particular group of companies. While the CCB has been gradually phased-in from 2016 to 2019, at least in some countries, the SME SF was implemented as early as 2014, thus currently reducing the capital requirements for exposures to SMEs in comparison with the pre-CRR/CRD IV framework.

assets and finds that risk-weight density becomes lower once regulatory approval is granted. The decline in risk weights is particularly pronounced among weakly capitalized banks, where the legal framework for supervision is weak, and in countries where supervisors are overseeing many IRB banks. Finally, Avramova and Le Leslé (2012) provide an overview of the concerns surrounding the variations in the calculation of risk-weighted assets (RWA) across banks and jurisdictions and how this might undermine the Basel III capital adequacy framework. They also discuss the key drivers behind the differences in these calculations. Ferri and Pesic (2017) propose a new metric to identify RWA density, as the ratio between RWA and Exposure-At-Default (EAD), to better gauge the effects of the lawful capital-saving roll-out effects of the IRB approach in terms of regulatory arbitrage. The authors find IRB banks – especially Advanced-IRB ones – have more latitude for risk weights manipulation. Another strand of research focuses on the behavior of undercapitalized banks in strategically using IRB models to reduce RWA opportunistically and achieve capital relief. Specifically, banks with lower capital buffers might exploit internal models' increased complexity and opacity to "game the system" by underestimating risks to optimize their capital ratios beyond prudent levels (Avramova and Le Leslé, 2012). "Strategic" IRB modelling has two main implications. First, it implies relatively lax supervisory standards, which contradicts the potential for heightened supervisory scrutiny over undercapitalized banks. Second, it suggests systematic underreporting and underestimation of risk, likely resulting in ex-post systematically higher fractions of non-performing loans (Mariathasan and Merrouche, 2014). Systematic underreporting of risk may not only result from intentional manipulation but also from incorrect implementation of internal models. Thus, laxer credit risk assumptions and weights may stem from flawed modelling rather than deliberate behaviour (Mariathasan and Merrouche, 2014). Other contributions examine the broader effects of capital regulation on banks' balance sheet profitability. Beltratti and Paladino (2016) find that banks that are more aggressive in reducing their RWA densities subsequently have a lower return on equity and are more likely to raise new capital during a credit crisis. To meet regulatory and supervisory capital requirements, banks can reduce lending or raise new capital. Further, banks with low profitability are more likely to reduce lending. A recent work by Fiordelisi et al. (2025) finds that model-based regulation reduces credit exposures to corporations, particularly for IRB banks that are closer to minimum capital requirements, when the COVID-19 pandemic hit the European economy. Ferri and Pesic (2017), assess the impact of model-based capital regulation on bank profitability, finding that regulatory arbitrage via IRB model calibration significantly affects reported profits of European banks. To the best of our knowledge, this is the first paper investigating the impact of risk density on SSM banks, drilling down into banks' RWA at the portfolio level. Our contribution is twofold. First, we use a unique confidential supervisory reporting dataset to assess banks' evolution of RWA density, starting from the setup of the SSM, to identify the main drivers of risk density variability, among which are banks' capital headroom over regulatory and supervisory requirements. Second, we exploit the implications of strategic modelling and portfolio reallocation to analyse the effects of the IRB approach in terms of banks' risk-taking. Compared to previous findings obtained in the literature (Avramova and Le Leslé, 2012; Ferri and Pesic, 2017; Mariathasan and Merrouche, 2014) — that find that part of the decline in reported riskiness is more pronounced among weakly capitalized banks and especially in jurisdictions with weaker supervisory scrutiny — the analytical framework considered in our paper does not provide evidence of the reduction in RWA density by weakly capitalized or fragile banks after IRB adoption along the margins considered in this paper. Our empirical setting is consistent with the view that harmonized supervision may have limited the scope for opportunistic post-adoption reductions in RWAs.

The remainder of the paper is organized as follows: Section 2 outlines the institutional framework for the empirical analysis; Section 3 describes the data and the empirical models; Section 4 reports several robustness checks, while Section 5 concludes.

2 Institutional framework

Risk-based capital requirements are defined by the Basel Framework, the full set of standards of the Basel Committee on Banking Supervision (BCBS), which is the primary global standard setter for the prudential regulation of banks (BCBS, 2005). The Basel framework has then been implemented in the European Union mainly through the Capital Requirements Regulation (CRR) and Capital Requirements Directive (CRD). While the original Basel framework dates back to 1988, the entry into force of the Basel II framework in 2007 has significantly modified the credit risk assessment of financial institutions. The regime of Basel I classifies each bank asset in a list of predetermined buckets and assigns a fixed risk weight to each category (a flat tax). In contrast, the Basel II framework allows for establishing a stronger link between capital charges and the actual risk of assets (Behn et al., 2016). This framework allows banks to choose between the standardized approach (SA) and the internal ratings-based approach (IRB) for calculating capital requirements.

Under the IRB approach, the risk weight of each asset depends on banks' internal risk models. The determinants of asset risk estimates are four parameters: the probability of default (PD), the loss given default (LGD), the exposure at default (EAD), and the effective maturity of the loan. Banks estimate all four parameters under the advanced IRB (A-IRB) approach, while they estimate only the PD in the foundation IRB (F-IRB) approach and fixed standard values are assumed for the other parameters (LGD, EAD).[7] In both methods, capital requirements are determined in terms of RWA, which are estimated by multiplying each risk weight by the value of the corresponding asset. The principle is quite straightforward: the higher the risk on a specific asset position, the higher the capital charge. The latest iteration, known as the "Basel III", was developed in response to the Global Financial Crisis (GFC) in 2007/2008 and finally concluded in 2017 (BCBS, 2017), taking into account the weaknesses identified in the financial sector during the GFC. Basel III included, among others, several features to limit banks' heterogeneity and variability of RWA, especially when computing them with IRB models. In particular, some changes to the IRB approach were introduced (notably the adoption of input floors on the parameters), allowing banks to estimate the parameters used in the calculation of RWA. Also, the option to use the IRB approach has been limited to certain types of exposures.[8] Finally, a new measure, i.e. the output floor, sets a lower limit (floor) on the RWA (output) calculated by banks using their internal models.[9] These final reforms, in addition to the measures already implemented, should further increase the resilience of banks and the banking system.[10] The reforms still need to be implemented in major jurisdictions around the globe and face significant pushback from bank lobby groups (Behn et al., 2022). The revised Basel framework also introduced a non-risk-based measurement to supplement the risk-based capital requirements. The new minimum requirement (the leverage ratio, defined as the

[7]Under the IRB approach, banks must categorise banking-book exposures into broad classes of assets with different underlying risk characteristics. The classes of assets are (a) corporate, (b) sovereign (including central banks, public sector entities (PSEs) identified as sovereigns, multilateral development banks (MDBs)), (c) banks, (d) retail, and (e) equity. Within the corporate asset class, five sub-classes of specialised lending are separately identified. Within the retail asset class, three sub-classes are separately identified. Within the corporate and retail asset classes, other sub-classes may also apply, provided certain conditions are met.

[8]One of the main changes introduced in 2017 to the IRB approach for credit risk is the removal of the option to use the A-IRB approach for exposures to financial institutions and large corporates; moreover, no IRB approach would be used for equity exposures; lastly, where the IRB approach is retained, minimum levels are applied on the probability of default and for other inputs.

[9]Output floor is a measure that sets a lower limit (floor) on the RWA (output) calculated by banks using their internal models. It has been agreed that, if the output floor is fully implemented, RWA computed using internal models cannot fall below 72.5 percent of the RWA computed using the standardized approach.

[10]See https://www.ecb.europa.eu/press/financial-stability-publications/macroprudential-bulletin/focus/2023/html/ecb.mpbu202312_focus01.en.html

ratio of Tier 1 Capital over the Exposure Measure[11]) had two objectives: first, it is intended to restrict the build-up of leverage in the banking sector to avoid destabilizing deleveraging processes that could damage the broader financial system and the economy; second, it has been conceived to reinforce the risk-based requirements with a simple, non-risk-based "backstop" measure.

In addition to this revised regulatory framework, supervisors have started to carry out on-site reviews to ensure that approved internal models comply with currently applicable regulatory standards. In Europe, the Supervisory Authority (SSM) launched a multi-year project (Targeted Review of Internal Models, TRIM) to improve the consistency of internal models across the euro area. This initiative started at the beginning of 2016, in close cooperation with the National Competent Authorities (NCAs) that are part of European banking supervision, and was finalized in April 2021. Indeed, one concern of supervisors was the unwarranted (i.e. non-risk-based) variability of the outputs to calculate regulatory capital requirements (ECB, 2021). This coincided with concerns from banking supervisors and external stakeholders about the complexity of such models and the resulting opaqueness of the modelling approaches. This opacity also made it increasingly difficult for supervisors to assess whether risks have been captured correctly and consistently through these internal models.

3 Data and empirical model

3.1 Data and stylized facts

We construct a unique panel dataset by exploiting quarterly bank-level data sourced from confidential supervisory statistics for the period spanning from March 2015 to December 2023. These data are harmonized across the SSM jurisdictions and they are representative of the most important bank balance sheets and income statement items collected from SSM Supervisory statistics (the full list of variables is available in Appendix A.2.).[12] The European banks included in the dataset are the Significant Institutions (SIs)[13] under ECB direct supervision. Our dataset includes a total of 124 banks across the SSM, under a changing composition approach,[14] sampled in an unbalanced

[11]The Exposure Measure represents the total exposures of the bank and includes non-risk weighted on-balance sheet assets, derivative exposures, securities financing transactions (SFTs) and off-balance sheet items converted into credit exposure equivalents.

[12]The data are considered at the highest level of consolidation.

[13]The list of the significant banks under ECB direct supervision is available at the SSM website: https://www.bankingsupervision.europa.eu/banking/list/html/index.en.html.

[14]The Significant Institutions were 109 at the end of 2023. We also include banks that has been ruled out of and/or have been included in the SI list during the reference period. We excluded banks for which we have data points for

panel. The sample accounts for around 83.9% of the SSM banking system in terms of total assets calculated at the highest level of consolidation as of December 2023. Table 1 shows the descriptive statistics for the variables used in the baseline regressions. The risk density distribution is not skewed, and the mean and median display similar values. As shown in Table 2, the IRB dummy at the bank level is not significantly correlated with any of our control variables except for size. This result is expected, as IRB models tend to be more easily adopted by larger and more structured institutions. Figure 1 illustrates the evolution of the stock of loans to Euro Area households and non-financial corporations reported by monetary financial institutions according to the ECB Monetary Financial Institutions Dataset. Whereas at the aggregate level we observe an increasing trend in the dynamics of lending, heterogeneity emerges at the country level. Such heterogeneity is also observed when looking at the dynamics of the RWA density (Figure 2), which, however, tends to downward converge over time (as in Böhnke et al. (2023)). This trend may reflect an improvement in banks' asset quality as well as changes in regulatory requirements. Since internal models could play a key role in explaining these paths, we investigate their effects on banks' RWA density within a harmonized supervisory framework.

Figure 3 shows that the evolution of RWA from credit risk (predominant in European banks'balance sheets) is quite stable across countries.

Figures 4 and 5 show, respectively, the evolution of capital headroom (above the minimum supervisory requirements, see also infra) across countries and the evolution of capital demand by the supervisory authority, between 2015 and 2023. Given that capital demand has stabilized over time, capital headroom shows increasing convergence (for most countries), highlighting the process of capital strengthening carried on by European banks. Finally, Figure 6 summarizes the cross-country trend of the incidence of IRB RWA over total RWA from credit risk.

3.2 The main determinants of RWA variability

Our empirical design starts by investigating the RWA variability across banks, by studying the relation between the risk density at the bank level, defined as the ratio of RWA over EAD, and several banks' characteristics. Compared to RWA over total assets, the advantage of relying on the RWA density defined above is twofold. On the one hand, EAD better assesses the off-balance sheet exposures and accounts for the effects of risk mitigation techniques (Credit Risk Mitigation,

fewer than 8 quarters. We also kept out of our sample the banks with a negative capital surplus, as they are deemed in breach of prudential regulation.

CRM) and conversion factors (Credit Conversion Factors, CCF). On the other hand, RWA/EAD embeds migration effects from Standardized to IRB approaches (Ferri and Pesic, 2017) and clean the risk-weighted density from the so called ”roll-out effect” of IRB models (that is, the gradual implementation of the IRB models across the different portfolios), capturing the mechanic reduction of RWA density when a bank shifts portfolio shares to IRB. Furthermore, compared to the ratio of RWA to total assets, the ratio over EAD represents an appropriate metric to compare banks' riskiness under a risk-sensitive framework (Cannata et al., 2012).[15] Given the predominance of credit risk in European banks' balance sheets — which account for around 85 percent of total RWA in the period 2015-2023 — our analysis exclusively focuses on credit RWA (see also Berg and Koziol (2017)). Following the approach adopted by Ferri and Pesic (2017), we define a baseline model in which the dependent variable is regressed on a set of explanatory variables, including banks' capitalization, a measure for the adoption of internal ratings-based (IRB) models, and a set of time-varying bank-level controls. These controls — all standardized to banks' total assets — include gross loans, the held-for-trading (HFT) portfolio, and customer deposits, to account for balance-sheet composition, gross non-performing loans (NPL) as a proxy of banks' risk profile, along with the natural logarithm of total assets as a measure of bank size. We consider as a capitalization measure $cet1s$, which captures banks' capital headroom above the minimum supervisory and regulatory requirements. It is measured as the difference between the actual bank-level CET1 ratio and the overall capital demand, including Pillar 1, Pillar 2, and the capital buffers that progressively entered into force from 2015 onwards.[16] Such data is utilized in a unique, confidential supervisory reporting dataset, which enables us to retrieve capital demand and capital headroom on a bank-by-bank basis for the entire considered period. Compared to other capitalization measures, the capital surplus overcomes potential endogeneity issues. The staggered validation by supervisors of the internal models approach among IRB banks implied that, at a given point in time, the loan pool of a given bank included both IRB and Standard loans. We model IRB adoption in two alternative ways. First, by defining a dummy variable representing the first date of using IRB models (or first-time adoption), equal to one from the first quarter of IRB use onward

[15] To assess the RWA variability, several approaches have been developed in the literature. For instance, Bastos e Santos et al. (2020) developed a novel approach to measuring RWA variability – the variability ratio – by comparing a market-implied measure of RWA with banks' reported regulatory RWA. They assess the determinants of this variability and find an association between this measure of RWA variability and (i) the share of opaque assets held by banks (e.g. derivatives); (ii) the degree to which a bank is capital-constrained; and (iii) jurisdiction-specific factors. Their results also point to the importance of jurisdiction-specific factors in explaining RWA variability and the importance of RWA variability on profitability through higher funding costs.

[16] See Appendix A.1. for the complete definition of capital headroom, according to reference year.

and zero otherwise.[17] Second, by defining a continuous variable as the share of RWA from credit risk calculated via IRB models over total RWA from credit risk (IRB share) at consolidated level, which captures the effects of the progressive IRB model adoption as it covers an increasing share of the portfolio along time.[18] To account for potential correlation among density from the same bank, the baseline models are estimated with bank-quarter fixed-effect panel models with standard errors clustered at the bank level in all regressions.

$$dens_{i,t} = \alpha_1 irb\_fta_{i,t} + \alpha_2 cet1s_{i,t} + \alpha_3 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{1}$$

$$dens_{i,t} = \alpha_1 irb\_sh_{i,t} + \alpha_2 cet1s_{i,t} + \alpha_3 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{2}$$

where i, c and t are the bank, the country and the quarter, respectively. The inclusion of bank (ω_i) and time-fixed effects (δ_t) is needed to control for idiosyncratic banks' characteristics and quarterly shocks common to all banks, respectively. We also augmented the baseline equation with country-time fixed effects ($\gamma_{c,t}$) to control for unobserved changes in the business cycle and/or country-specific regulations that vary over time, potentially affecting banks' density. Equations (1) and (2) differ in terms of the IRB dummy chosen, i.e. either the IRB first-time adoption (irb_fta) or the IRB share (irb_sh).[19] $\mathbf{X}_{i,t-1}$ is a vector including the above-mentioned bank-level control variables, which capture differences in the observed banks' balance-sheet structure and characteristics. The set of bank-level controls also aims to provide insight into differences in banks' lending and investment strategies.

Table 2 summarizes the results of our baseline regressions. As expected, risk density is positively correlated with the CET1 ratio, but negatively correlated with IRB adoption. This result highlights that banks with relatively higher capitalization have, on average, higher density. The results are broadly consistent across the different specifications, both in terms of the magnitude and significance of the key estimated coefficients. These findings are consistent with Avramova and Le Leslé (2012), which suggests that the IRB approach provides a capital incentive for banks with good risk management, requiring less capital for less-risky assets than the standardized approach.

[17] The IRB model validation typically encompasses a lag between the approval by the supervisors and the effective implementation.

[18] According to our data, IRB banks make quite extensive use of internal models, as the observed share of RWA calculated via such models is at least equal to 20 percent of total RWA from credit risk.

[19] In the remainder of the paper all the described regressions are run with irb_fta and irb_sh alternatively. We will show results in the respective tables but, for the sake of clarity, the equations will be represented with the generic notation IRB indicating both.

A key aspect that emerges is that these results are robust also when country-time fixed effects are not included, meaning that this evidence holds both considering within and across country variation (columns 1 and 3 of Table 2).

3.2.1 A staggered difference-in-difference approach

To further strengthen our identification strategy and address the staggered nature of IRB adoption across banks, we complement the baseline fixed-effects regressions with a difference-in-differences (DiD) estimator following Callaway and Sant'Anna (2021). Since banks receive supervisory approval for IRB models in different quarters, conventional two-way fixed-effects models may deliver biased estimates when treatment effects are heterogeneous over time or across cohorts. The Callaway–Sant'Anna estimator[20] overcomes these issues by comparing each cohort of newly treated banks exclusively to banks that have not yet adopted IRB in that same quarter, thus ensuring valid counterfactuals. We define treatment as the quarter of first-time IRB approval and estimate group–time average treatment effects (ATTs) as well as dynamic (event-study) effects around the adoption date. This approach enables us to track the evolution of risk density before and after IRB implementation while verifying the parallel-trends assumption via pre-treatment coefficients. Let $G_i = g$ denote the quarter in which bank i first adopts the IRB approach (cohort). The group–time ATT is:

$$ATT(g,t) = \mathbb{E}[\,\mathbb{E}(dens_{i,t} \mid G_i = g,\, X_{i,t-1}) - \mathbb{E}(dens_{i,t} \mid C_{i,t} = 0,\, X_{i,t-1}) \mid G_i = g]\,, \qquad t \geq g, \quad (3)$$

where $C_{i,t} = 0$ denotes banks that are untreated at time t, and $X_{i,t-1}$ includes your full set of lagged bank-level controls consistent with our baseline model. The results confirm a robust decline in risk density after IRB adoption, fully consistent with our baseline estimates. The group–time ATTs show that banks experience a decline in density beginning in the first quarters after receiving supervisory approval, and the effect strengthens over time as internal models are rolled out to a larger share of the portfolio. Importantly, the event-study coefficients reveal no evidence of differential pre-trends, supporting the validity of the parallel-trends assumption (Figure 7). Taken together, the results indicate that the lower density observed among IRB banks is not solely attributable to differences in capitalization or balance-sheet structure but reflects a causal impact of the transition to the IRB framework.

[20] We estimate it with the corresponding STATA package Rios-Avila et al. (2021).

3.3 Strategic modelling

This paragraph investigates whether riskier and/or under-capitalized banks strategically use IRB models to reduce RWA.

One of the primary objectives of the Basel framework that emerged around the regulatory debate was to stimulate more sophisticated and relevant banks to invest in more advanced risk evaluation methodologies (BCBS, 2005). This should ultimately lead to more robust risk management and reduced capital absorption. As suggested by Avramova and Le Leslé (2012), Mariathasan and Merrouche (2014), and Ferri and Pesic (2017), a potential drawback of this regulatory framework is that banks may aggressively pursue strategies to minimize capital absorption. This is particularly true for larger banks, which often rely more heavily on non-common equity funding and may exploit regulatory provisions to enhance their capitalization. In this context, internal models leverage sophisticated methodologies that embody wide discretionary choices by the bank.

3.3.1 Strategic modelling for low capital banks

In this paragraph, we investigate whether, conditional on IRB adoption, less-capitalized banks experience larger reductions in RWA density than other banks, which would be consistent with the specific weak-bank strategic-modelling channel emphasized in the earlier literature. Specifically, banks with lower capital buffers might exploit the increased complexity and opacity of internal models to ”game the system”, underestimating risks to optimize their capital ratios beyond prudent levels (Avramova and Le Leslé, 2012).

We test the “strategic modelling” hypothesis in equations (4), and (5) using two capitalization measures: one is the $cet1s$, as defined above, and the other is a dummy variable — defined as *capcluster* — indicating the level of capitalization in relative terms concerning the universe of SSM banks. Following Mariathasan and Merrouche (2014), we classify banks into three clusters based on their CET1 ratio: *lowcap* (cluster 1), *medcap* (cluster 2), and *highcap* (cluster 3), with thresholds defined as the sample average distribution of the CET1 ratio plus/minus half a standard deviation across banks[21]. To control for differences in magnitude and facilitate comparison the

[21] Mariathasan and Merrouche (2014) use plus/minus one standard deviation as thresholds, but in our case, the lower bound would be a value under the minimum pillar one requirement in terms of total capital ratio (i.e. 8 percent), which would imply that such banks would technically breach regulatory requirements. For the sake of clarity and due to its scarce relevance, we do not show cluster 2 in the results.

regulatory variable $cet1s$ is standardized via z-score transformation.[22]

$$dens_{i,t} = \alpha_1 irb_{i,t} * cet1s_{i,t} + \alpha_2 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{4}$$

$$dens_{i,t} = \alpha_1 irb_{i,t} * capcluster_{i,t} + \alpha_2 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{5}$$

Table 3 summarizes the results of the two regressions, with odd and even columns referring to the irb_fta and irb_sh, respectively. Results appear univocal: in almost none of the specifications of our model, the estimated coefficient represented by the interaction between the capital measures and the IRB is statistically significant, thereby not supporting the hypothesis of strategic IRB. Instead, we only find a weak significance of the interaction with *highcap*, which supports the idea that more capitalized banks tend to pursue a more effective capital allocation via the adoption of IRB models. These findings are interesting since they spot some differences with previous literature. Indeed, Mariathasan and Merrouche (2014) and Ferri and Pesic (2017) find that part of the decline in reported riskiness is particularly pronounced among weakly capitalized banks, especially in jurisdictions with weaker supervisory scrutiny. Their analyses differ from ours in two significant ways. First, while our sample includes only significant institutions under the SSM, their samples encompass banks from 21 OECD countries (Mariathasan and Merrouche, 2014) and 29 European countries (Ferri and Pesic, 2017), including those outside the SSM. This suggests that the supervisory pressure exerted in banks may differ across jurisdictions. Second, their data cover the period from 2007 to the early 2010s, whereas ours range from 2015 to 2023. Indeed, during the period considered in the aforementioned works, the implementation of IRB models was not fully exploited by the largest banks, and the years considered were those immediately in the aftermath of the GFC, which may be a potential confounder in the analysis. Therefore, the geographical differences could imply heterogeneity in supervisory approaches' roles and adequacy, and the different periods may reflect varying stages on the IRB "learning curve" for both authorities and banks. The complexity of adopting and supervising IRB models shortly after their introduction could have been greater than it is after more than a decade of use.

[22]The standardization is performed by rescaling the variable to have a mean of zero and a standard deviation of one. All the interacting variables are also estimated linearly.

3.3.2 Strategic modelling for fragile banks: dynamic responses

To assess the strategic modelling assumption for fragile banks in a dynamic way, we employ local projection (LP) methods to estimate impulse response functions (Jordà, 2005). We define fragile banks as those banks having both a higher NPL ratio (i.e. higher than the Q3 of the gross NPL ratio distribution) and low capitalization. Thus, these intermediaries tend to be relatively riskier. The LP framework is asymptotically equivalent to vector autoregression (VAR) models (Plagborg-Møller and Wolf, 2021), while offering greater flexibility in accommodating panel structures in a straightforward and computationally tractable manner. Specifically, we want to answer this question: do fragile banks modify their densities/lending/NPL ratios after IRB validation? To this aim, we estimate the following panel model:

$$Y_{i,t+h} = \sum_{k=1}^{4} \beta_k \, \mathrm{Y}_{i,t-k} + \theta \, (fragility_{i,t} \times irb_{i,t}) + \mathbf{X}_{i,t-1} \, \boldsymbol{\phi} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t+h} \tag{6}$$

where the outcome variable $Y_{i,t+h}$ is either the RWA density, or lending (proxied by the corporate EAD) or the NPL ratio of a bank i between quarter t and quarter $t+h$; $irb_{i,t}$ is the dummy variable representing the IRB approval date (or first-time adoption) and $fragility_{i,t}$ is a dummy variable identifying a bank with both a high NPL ratio (i.e. higher than the Q3 of the gross NPL ratio distribution) and low capital.

Figure 8 illustrates the cumulative responses on the target variables of a fragile bank after the IRB validation at quarter t from impact up to quarter $t+12$. The bands show the 95% confidence intervals of the estimated coefficient θ for each horizon h. Standard errors are clustered at the bank level.[23] The upper chart shows that the IRB validation of a fragile bank has a negligible impact on RWA density over time. This result is similarly obtained when considering the impact on lending and NPL ratios (middle and bottom charts of Figure 8), thus suggesting that fragile banks after the IRB validation do not modify these metrics. Hence, we find no evidence that fragile banks display differential, post-IRB-adoption changes in RWA density, lending or NPL ratios along the margins examined in this paper.[24]

[23] All results are robust when considering $\Delta dens_{i,t+h}$.

[24] It should be noticed that the absence of the differential goes against the specific mechanism emphasized by Mariathasan and Merrouche (2014), where weakly capitalized banks have stronger incentives to manipulate risk weights. However, the absence of this differential effect does not rule out strategic modelling more generally. Other forms of strategic modelling could still operate through margins not tested in this paper, such as portfolio-level model choices, PD/LGD calibration, model roll-out, or anticipatory adjustments before approval, that we leave for future work.

3.3.3 Strategic modelling for IRB banks directly impacted by the TRIM

As described previously, Targeted Review of Internal Models (TRIM) represented an important step by supervisors toward ensuring that approved internal models were consistent across the euro area. In this paragraph, we employ an identification strategy that relies on a Difference-In-Differences (DiD) approach, enabling us to identify whether, after the first wave of the TRIM at the beginning of 2016, IRB banks modify density more relative to SA banks. The TRIM exercise sought to reduce unwarranted cross-bank variability in risk-weighted assets, enforce consistent model governance standards, and enhance the reliability and comparability of IRB-based capital metrics across the SSM. It constitutes, then, a plausibly regulatory shock that affected only a subset of institutions (the ones adopting internal models); this asymmetry in treatment intensity and the clearly defined temporal implementation allow TRIM to be exploited within a Difference-in-Differences framework. In particular, we want to test whether IRB banks made a strategic use of internal models that emerged after the TRIM inspections. Thus, we would expect IRB banks to increase their density, as a consequence of the findings raised by the supervisor that required adjustments of modelling parameters (i.e. PD, LGD). If this is the case, we would find a positive and significant coefficient of the interaction term. We consider the following model:

$$dens_{i,t} = \alpha_1 treated\_fta_i * post\_trim_t + \alpha_2 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t}$$

$$dens_{i,t} = \alpha_1 treated\_fta\_pure_i * post\_trim_t + \alpha_2 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{7}$$

Our treatment period variable ($post\_trim_t$) takes the value of one after 2016Q1. The variable $treated\_fta_i$ takes the value of one for banks (treatment group) using internal models and zero for banks using the Standardised Approach (control group) before the beginning of the TRIM. The coefficient of main interest is the interaction $post\_trim_t \times treated\_fta_i$ showing the Average Treatment Effect (ATE), due to the TRIM effect on IRB banks' density. Furthermore, we progressively saturate the bank-level regressions with the same vector of bank characteristics $\mathbf{X}_{i,t-1}$ that could affect bank lending behaviour, as well as the fixed effects used for testing the strategic modelling assumption. In both specifications (Table 4), the estimated coefficients of interest are not statistically significant. Therefore, our assessment of the TRIM exercise does not provide evidence of a differential post-TRIM change in RWA density among IRB banks relative to SA banks. While this result does not separately identify a causal effect of TRIM or of harmonized supervision, it is consistent with the view that supervision in the post-2015 SSM setting may have limited the scope for opportunistic reductions in RWAs Results are robust even when considering a pure control group ($treated\_fta\_pure_i$), as those banks remained SA even after the first wave of TRIM (Table 4, column 2).

3.4 Portfolio reallocation

We finally assess banks' portfolio reallocation towards higher risk-weighted assets after the IRB adoption, particularly toward non-financial corporations.

In the spirit of Bruno et al. (2017), we regress the growth rates of two variables, one capturing the share of EAD referred to exposures towards central governments and central banks ($sov\_cb\_ead_{i,t}$) and one capturing the exposure toward non-financial corporates ($corp\_ead_{i,t}$), respectively, compared to one quarter before ($\Delta sov\_cb\_ead_{i,t}$ and $\Delta corp\_ead_{i,t}$) over the IRB adoption, the capital headroom and our baseline set of explanatory control variables (equations 8 and 9). These new specifications are needed to assess whether the banks' lending policy in our sample was somehow affected by the IRB models and the level of banks' capitalization.

$$\Delta sov\_cb\_ead_{i,t} = \alpha_1 irb_{i,t} + \alpha_2 cet1s_{i,t} + \alpha_3 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{8}$$

$$\Delta corp\_ead_{i,t} = \alpha_1 irb_{i,t} + \alpha_2 cet1s_{i,t} + \alpha_3 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{9}$$

Table 5 Panel A shows the results of equations 8 and 9. In particular, it highlights that IRB adoption has a positive and significant impact on the growth rate of corporate exposures, suggesting the importance of a more efficient and calibrated risk weighting policy for supporting credit lending to the real economy. Capital headroom over the regulatory minimum is also a driver in increasing the exposure to non-financial corporations, since the coefficient *zcet1s* has a positive sign. Results are confirmed in Table 5 Panel B, when controlling for the capital dummy. The increase in corporate exposure is mainly explained by the increase in the exposures towards large corporations (Table 6 Panel A and B). This suggests the impact on large exposures derived by the IRB adoption, while exposures towards Small and Medium enterprises (SMEs) may have benefited from the so called "SME supporting factor" since the very beginning of SSM.[25]

[25] A capital reduction factor for loans to SMEs — the SME supporting factor — was introduced by the CRR to allow credit institutions to counterbalance the rise in capital requirements resulting from the Capital Conservation Buffer (CCB), and to provide an adequate flow of credit to this particular group of companies. While the CCB has been gradually phased-in from 2016 to 2019, at least in some countries, the SME SF was implemented as early as

4 Robustness checks

The previous sections investigated whether the assumptions of business-model heterogeneity, strategic modelling, and portfolio reallocation could explain the variation of RWA density across SSM banks. This section presents several robustness checks to further validate our findings. All sets of checks are performed on both the baseline model and the two extended versions, which incorporate the strategic hypothesis and the portfolio reallocation hypothesis. The results are available upon request. Overall, robustness checks generally confirm our qualitative findings, despite some differences in the magnitude of coefficients emerging due to differences in the sample of banks considered and/or the reference time.

4.1 Heterogeneity across different business models

We define an alternative baseline model that includes a dummy variable describing the notion of banks' business model, following the data-driven approach and employing a hierarchical clustering algorithm to categorize banks (as in Bonaccorsi di Patti and Palazzo (2020)). The approach is based on building a hierarchy of clusters; the algorithm starts with all data points assigned to a cluster, and at each subsequent step, the algorithm merges into the same cluster the two nearest ones until there is only a single cluster left. The decision to merge two clusters is taken based on a metric measuring the 'closeness' of two clusters.[26] Banks are grouped into three different clusters according to two main banks' balance-sheet items, i.e. loans and deposits, accounting for their business models (see Figure 9 showing the dendrogram from the cluster analysis). This specification is needed to assess differences in RWA variability due to heterogeneous business models across banks, if any.

Each class is represented by a dummy variable – defined as $bm_{i,t}$ — included in the benchmark equation alternatively. To assess the impact of different business models, we augmented equations (1) and (2) with the business model dummy variable and the interaction between the IRB variables and the business model dummy variable.

$$dens_{i,t} = \alpha_1 irb_{i,t} * bm_{i,t} + \alpha_2 cet1r_{i,t} + \alpha_3 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{10}$$

2014, thus currently reducing the capital requirements for exposures to SMEs in comparison with the pre-CRR/CRD IV framework.

[26] We follow the method proposed by Ward (1963), according to which the criterion for choosing the pair of clusters to be merged at each step is based on the optimal value of an objective function.

The coefficient α_1 represents our coefficient of interest, identifying the impact of IRB adoption for different banks' business models on the density. Results show no significant differences among business model classes emerge, on average. We also adopt an alternative business model classification based on the official SSM supervisory data.[27] More in detail, the SSM classification comprises seventeen business model types (plus one residual category), which we aggregate into four macro-categories: class 1 for banks specialized in lending; class 2 for investment banks and asset management/custodian banks (i.e., banks more engaged in market-based activities rather than traditional banking); class 3 for G-SIBs and universal banks; and class 0 for residual/undefined categories. Also in this case, the results do not show significant differences across business models.

4.2 Simultaneity and different materiality thresholds

In this section, we perform further controls to circumvent potential simultaneity biases involving the variables of our model. First, to address potential endogeneity arising from the simultaneous use of RWA density and CET1 ratio, we included 1-period lagged values of the CET1 ratio in our model. Second, we replace our key independent variable on IRB (both the dummy and the shared one) with 1-year lagged (i.e. t-4) values. We find that the negative correlation between the CET1 ratio and the 4-period shifted risk density appears weak, if not insignificant. Third, we verify that the pairwise correlation between density and RWA is significantly low. To take into consideration a "materiality threshold" in the IRB models adoption, we examine whether there are notable differences in behavior between banks that extensively rely on IRB models and those intermediaries adopting IRB approach only to a limited part of their portfolios.[28] To do this, we define a new IRB dummy equal to 1 in case the banks' IRB RWA is at least 50 percent of the total RWA, 0 otherwise. This threshold allows us to isolate a subset of banks that evaluate the majority of their portfolios with IRB. The results of the test for materiality threshold deliver results consistent with the benchmark analysis.

4.3 Disintangling the price and the quantity effects of RWA density

Given that variations in risk density could result from changes in both RWA and exposure at default, we separate these two components to assess whether the "price" effect (i.e., change in

[27]Banks' business models follow the classification adopted by the SSM Statistics: https://www.bankingsupervision.europa.eu/banking/statistics/html/index.en.html.

[28]According to our data, all banks in the sample using IRB model apply on at least 20 percent of total RWA.

RWA) or the "quantity" effect (i.e., change in EAD) prevails. To this aim, we adopt two alternative dependent variables: RWA to total assets ratio and EAD to total assets ratio, and test the effects on those two components of the CET1 ratio and IRB models.

Investigating the "price" and "quantity" effect separately leads to more nuanced evidence. On the one hand, while the CET1 ratio has a statistically significant effect on RWA density, the relationship with the EAD to total asset ratio is not significant. In theory, a higher CET1 ratio can result from both higher capital demand from supervisors and greater capital headroom. Literature (BCBS, 2017) associates increased capital requirements with a rise in banks' funding costs due to the higher cost of equity relative to debt; if higher funding costs are passed on to customers (pass-through), this can lead to a contraction in lending and, consequently, a slowdown in economic activity. On the other hand, we observe a positive and significant correlation between IRB adoption and EAD, suggesting that the reduction in risk weights (and, consequently, in capital absorption) associated with IRB adoption may lead to an increase in banks' lending activity. As expected, IRB adoption is negatively correlated with RWA, a piece of evidence consistent with one of the primary objectives of Basel II reform, which is to encourage banks to invest in more advanced and less capital-consuming risk evaluation methodologies (BCBS, 2005). Since the overall effect of IRB adoption on risk density is negative, we can assume that the "price effect" on RWA prevails over the "quantity effect" on EAD.

4.4 Testing before the Covid-19 pandemic outbreak

Since the period considered encompasses the COVID-19 crisis, we estimated the regressions until its outbreak to avoid it representing an important confounder in the analysis. Our main findings are qualitatively confirmed even when considering only the pre-pandemic period. However, this test yields some interesting insights that, while going beyond the scope of this research, are worth mentioning. Specifically, the control variable *loans*, which is not significant in our baseline model, appears to be strongly positively correlated with density. This result is somewhat expected, as — *ceteris paribus* — an increase in the share of loans to customers mechanically leads to a higher RWA density.[29] These findings could support the hypothesis of some crowding-out effect on banks' risk-accounting practices triggered by the implementation of loan-support measures during the pandemic. Further supporting this interpretation, additional control regressions conducted for

[29] Such evidence is consistent with the literature. See, among others, Avramova and Le Leslé (2012); Bruno et al. (2017); Ferri and Pesic (2017); Mariathasan and Merrouche (2014).

the post-COVID period only indicate no significant correlation between loans and density. These findings could serve as a starting point for future research on the impact of COVID-related policies on credit dynamics.

4.5 Portfolio reallocation in COVID-19 times

We further test the portfolio reallocation hypothesis after the COVID-19 pandemic outbreak, i.e. from the first quarter of 2020[30] onward, to investigate whether banks reallocated more intensively their exposures in reaction to the severe shock triggered by the pandemic. Indeed, several European countries adopted public support measures to provide liquidity and sustain credit, including government guarantee programs.[31] To this aim, we apply the approach followed by Bruno et al. (2017), who assessed the impact of RWA-based capital regulation on the way banks allocated funds during the turbulent period covering the GFC and the sovereign debt crisis, to investigate whether and to what extent the COVID-19 pandemic crisis triggered a portfolio reallocation from corporate to sovereign exposures for European banks. Following such an approach, we regress the growth rates of these two portfolios over our baseline set of explanatory variables, interacted with a dummy variable named $post_t$ equal to one for each quarter after 1 January 2020 and 0 otherwise, and test whether such a phenomenon has affected the size and composition of banks' exposures (equations 11 and 12). Again, we control for both the CET1 ratio and the capital headroom. While Altavilla et al. (2021) investigate whether COVID-19 government loan guarantees determined bank lending reallocation and impacted credit risk, this is the first paper — to the best of our knowledge — to analyze the potential existence of reallocation effects across banks' exposures triggered by the COVID-19 shock by focusing on the IRB adoption of European banks.

$$\Delta sov\_cb\_ead_{i,t} = \alpha_1 irb_{i,t} * post_t + \alpha_2 cet1s_{i,t} + \alpha_3 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{11}$$

$$\Delta corp\_ead_{i,t} = \alpha_1 irb_{i,t} * post_t + \alpha_2 cet1s_{i,t} + \alpha_3 \mathbf{X}_{i,t-1} + \omega_i + \delta_t + \gamma_{c,t} + u_{i,t} \tag{12}$$

[30] The news about a new, unknown virus spreading in China was disseminated worldwide on 31st December 2019. The Covid-19 pandemic was found to reach Europe when, on Friday 21st February 2020, a 39-year-old man living in the north of Italy was diagnosed with the Covid-19 virus without having had any previous links with China. It has been, therefore, conventionally indicated as the "case zero" (European Centre for Disease Prevention and Control — ECDC).

[31] Most Euro Area governments launched large programs of public loan guarantees to preserve access to bank loans for businesses during the COVID-19 pandemic. The features of the loan guarantee schemes varied across countries, but they all had to comply with the guidelines adopted by the European Commission. Guarantee schemes aimed at supporting firms and self-employed persons that have been affected by the COVID-19 crisis but had not been in financial difficulties at the end of 2019. The schemes are generally applied to new lending and typically to medium and long-term loans with an average maturity of five years (Falagiarda et al., 2020).

Compared to running the regression over the entire period (2015-2023, see Table 6), some interesting results are obtained (Table 7); in particular, we do not find a similar increase in banks' exposures to firms. This effect could be related to the 'prudential reclassification' of loans to the non-financial private sector (Aiello et al., 2023) that, as a result of the COVID-19 pandemic, benefited from government guarantees and were reclassified within the sovereign and central bank category. Therefore, we notice that, after the pandemic outbreak, the dynamics observed over the entire period were altered.

5 Conclusions

This paper investigates the variability of RWA density and the implications of internal rating-based (IRB) model adoption on a sample of significant institutions in the euro area over a ten-year period, which extends beyond the immediate aftermath of the Global Financial Crisis. The results highlight the presence of heterogeneity across SSM banks in terms of RWA density, and that part of that variability is linked to banks' characteristics. In particular, IRB banks with a better capital adequacy have, on average, a higher density than the IRB intermediaries with lower capitalization. Furthermore, the analytical framework considered in our paper does not provide evidence that, in the post-2015 SSM setting, weakly capitalized or fragile banks reduced RWA density more than other banks after IRB adoption along the margins examined in the paper. This is consistent with the view that harmonized supervision may have limited the scope for opportunistic post-adoption reductions in RWAs. Finally, we provide evidence that IRB models encourage banks to reallocate credit toward more profitable assets — particularly large non-financial corporations — while reducing exposures to sovereigns and central banks.

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Figures

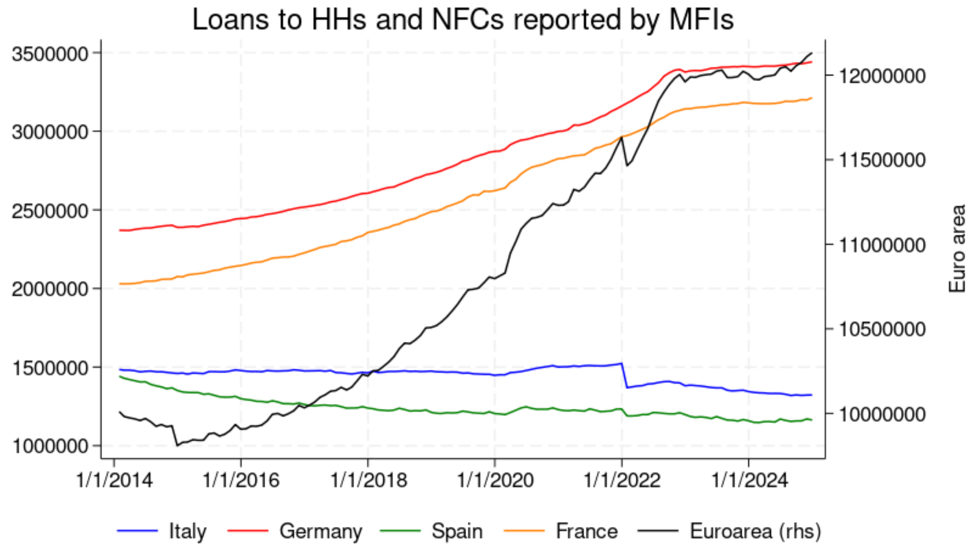

Figure 1: Evolution of the stock of loans to euro area Households and Non-financial corporations reported by MFIs. Data are expressed in millions of euros. The Figure shows data for a subset of the largest SSM countries. The drop observed in Italy as of 1 January 2022 is motivated by a change in the reporting methodology implemented by the Bank of Italy. Source: ECB.

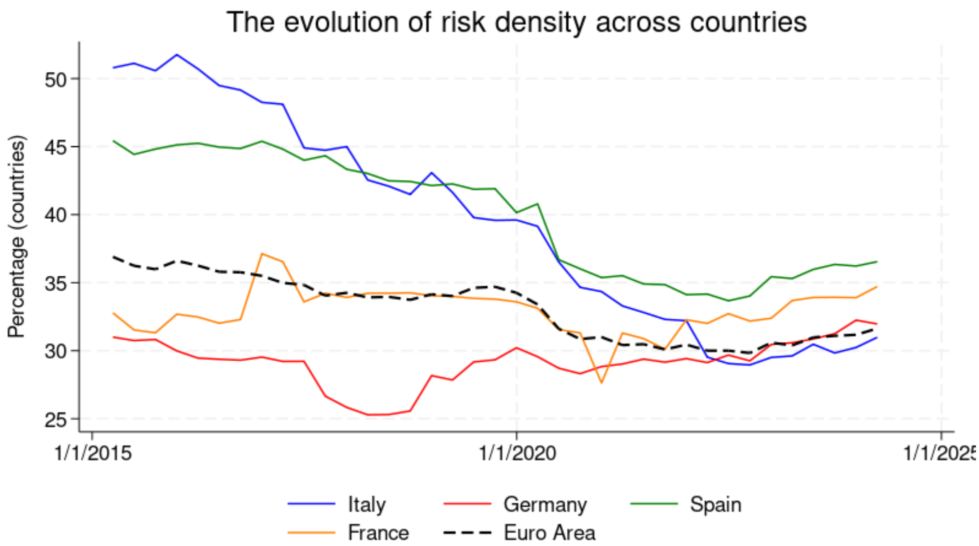

Figure 2: Banks' risk density follows the definition reported in Annex A.2. The Figure shows data for a subset of the largest SSM countries and weighted averages for the whole of SSM banks. Source: ECB harmonized Supervisory Statistics.

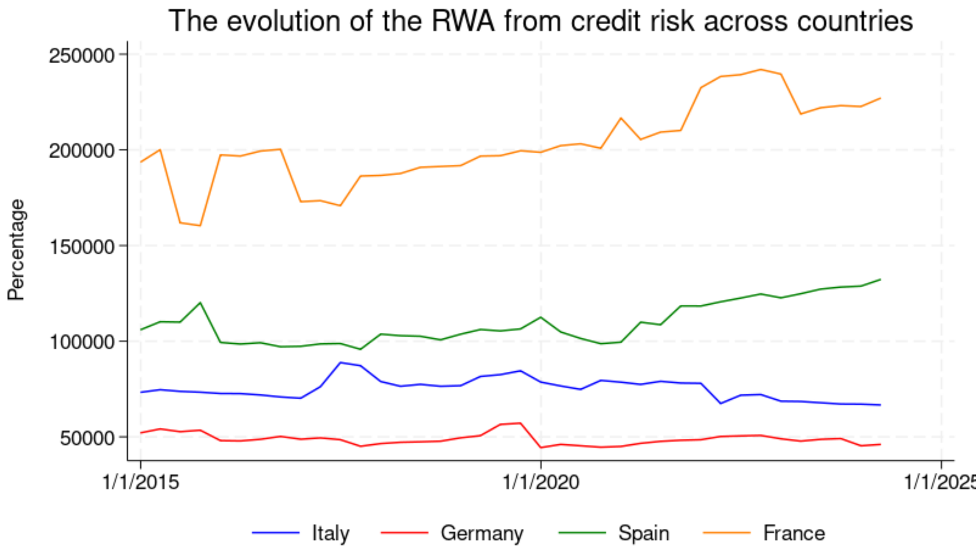

Figure 3: Data are expressed in millions of euros. The Figure shows data for a subset of the largest SSM countries. Source: ECB harmonized Supervisory Statistics.

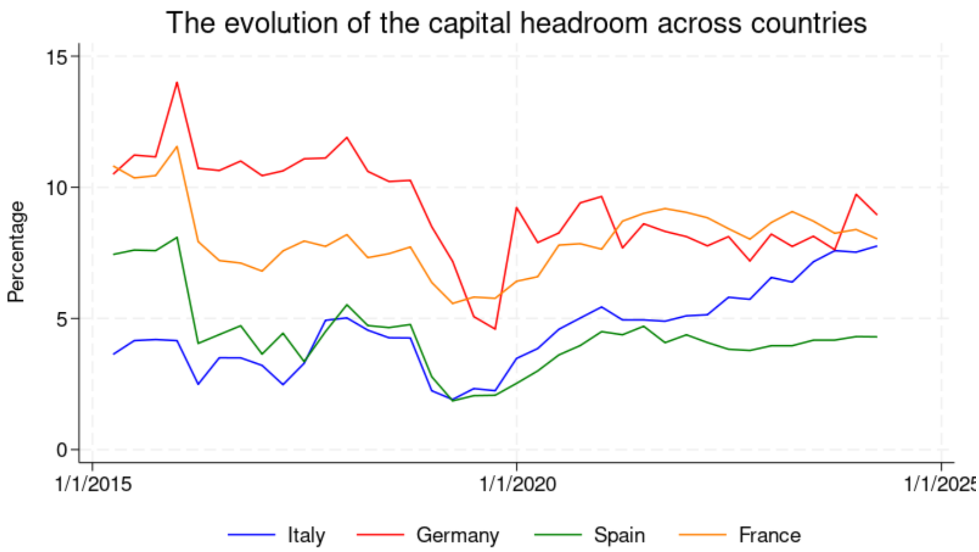

Figure 4: Banks' capital headroom is computed as reported in Annex A.1. The Figure shows data for a subset of the largest SSM countries and weighted averages for the whole of SSM banks. Source: ECB harmonized Supervisory Statistics

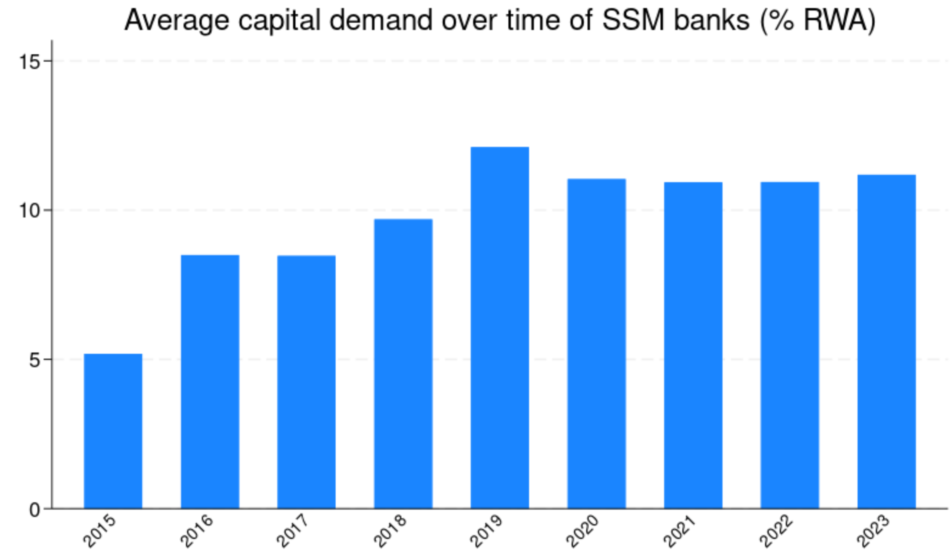

Figure 5: Evolution of banks' capital demand over time across SSM banks. The capital demand is defined as reported in Appendix A.1. Source: ECB Supervisory data.

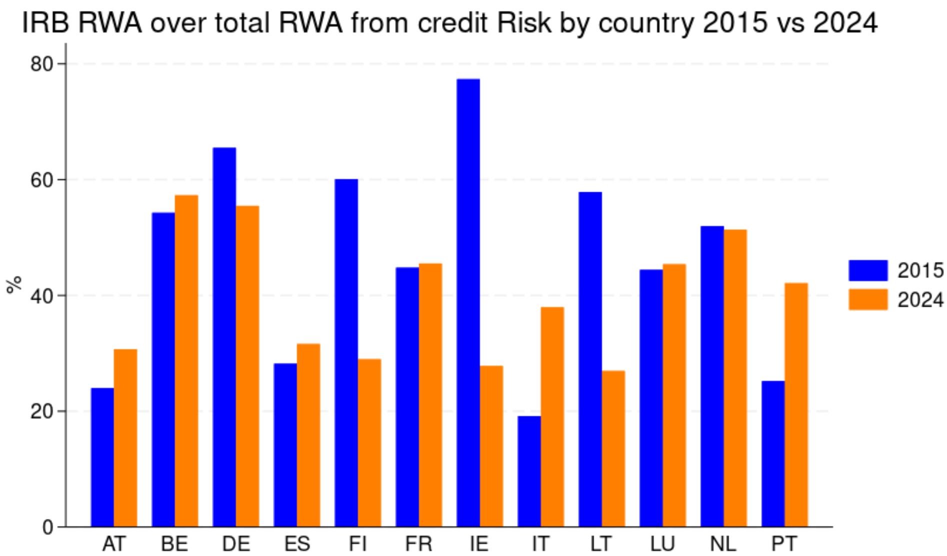

Figure 6: Comparison of IRB RWA over total RWA from credit risk by country between 2015 and 2024. Source: ECB Supervisory data.

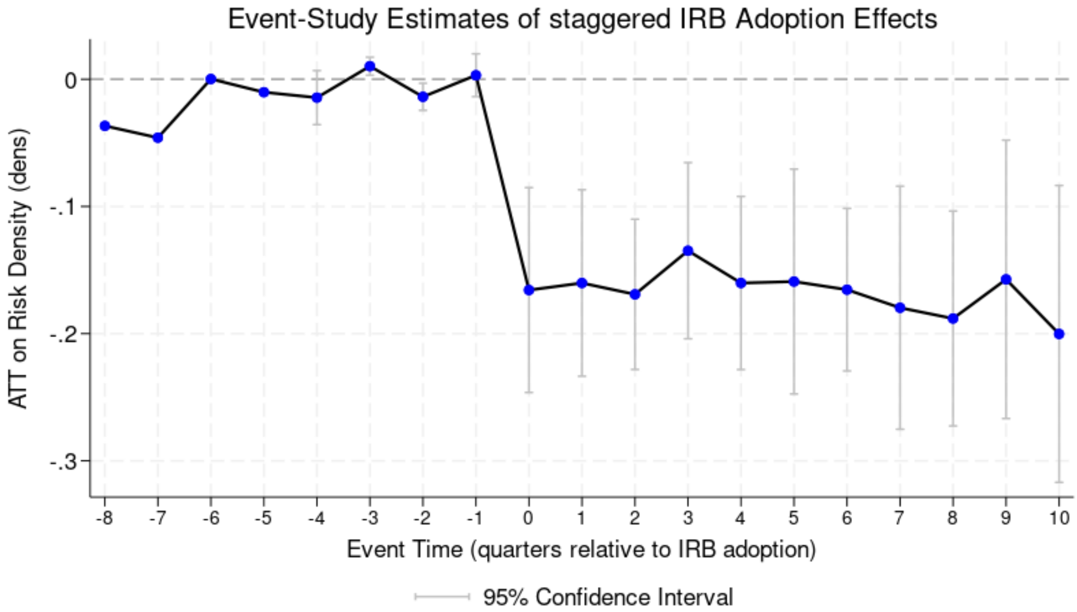

Figure 7: Dynamic Treatment Effects of IRB Adoption on Risk-Weighted Asset Density. This Figure reports event–study estimates of the effect of IRB adoption on banks' credit risk density, measured as RWA over EAD. Estimates are obtained using the staggered difference-in-differences estimator of Callaway and Sant'Anna (2021), implemented via the `csdid` procedure. The specification includes bank fixed effects, quarter fixed effects, and country–time fixed effects, and controls for capitalization (CET1 surplus), bank size, gross loans, held-for-trading assets, customer deposits, and the NPL ratio. Solid dots represent point estimates of the group–time average treatment effect (ATT), and vertical bars represent 95 percent confidence intervals.

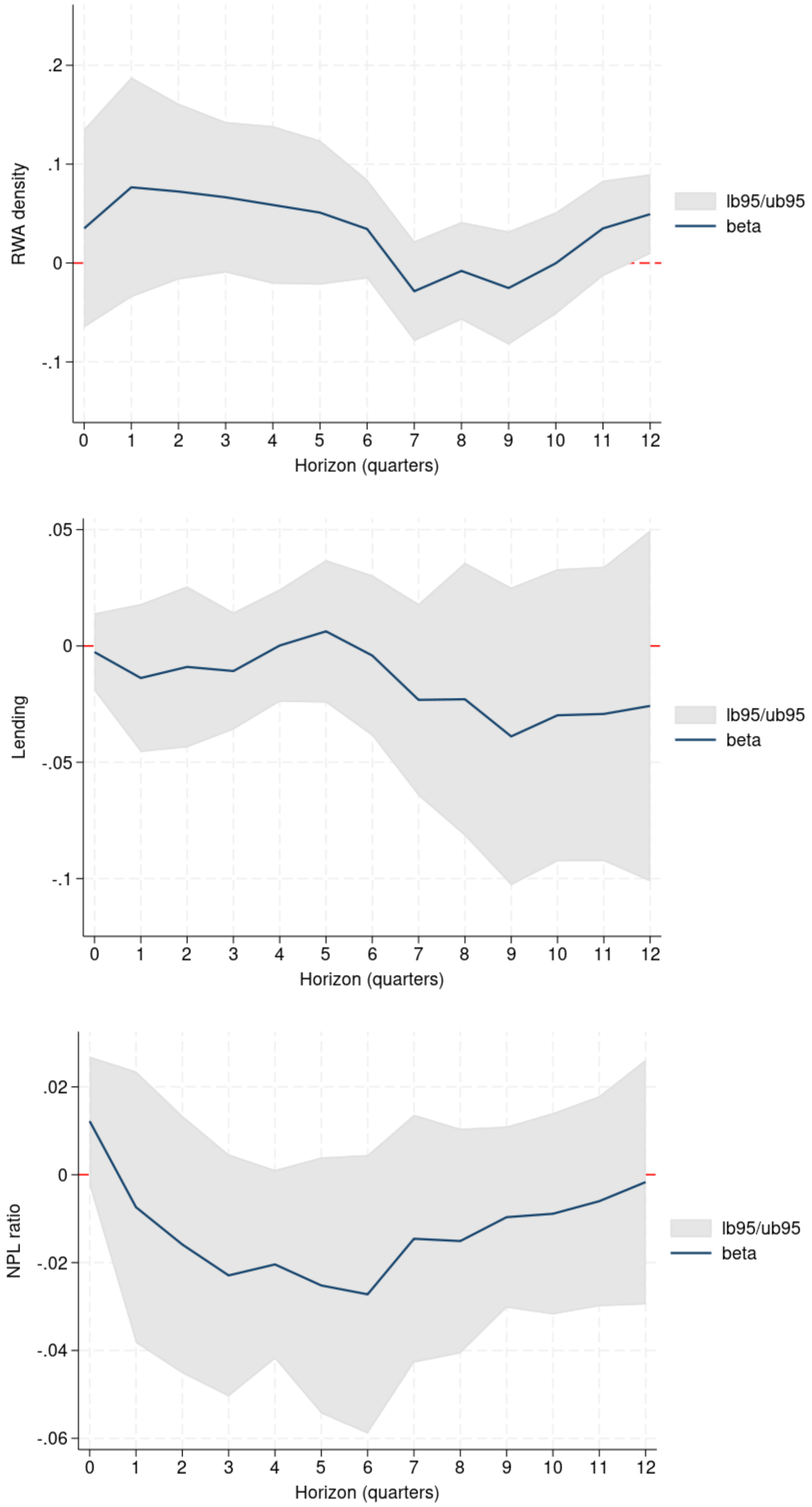

Figure 8: Local projection estimates of the response of RWA density, lending and NPL ratio to IRB validation of fragile banks.

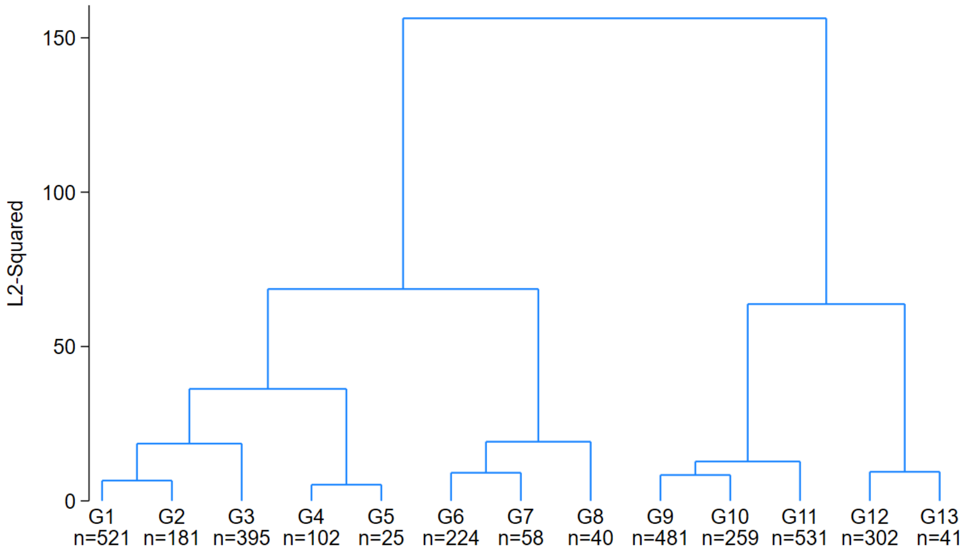

Figure 9: Dendrogram from cluster analysis based on Ward linkage method.

Tables

Table 1: Descriptive statistics

	N	Mean	Std. Dev.	p25	Median	p75	Min.	Max.
Endogenous variables								
$dens_{i,t}$	3,160	0.40	0.22	0.27	0.36	0.51	0.01	1.46
$sov\_cb\_ead_{i,t}$	3,160	0.23	0.12	0.15	0.21	0.30	0.00	0.70
$corp\_ead_{i,t}$	3,160	0.25	0.15	0.13	0.25	0.34	0.00	0.84
Variable of interest								
$irb\_fta_{i,t}$	3,160	0.62	0.48	0.00	1.00	1.00	0.00	1.00
$irb\_sh_{i,t}$	3,160	0.43	0.37	0.00	0.48	0.80	0.00	1.00
Bank control variables								
$cet1r_{i,t}$	3,160	0.07	0.04	0.05	0.06	0.08	0.01	0.40
$cet1s_{i,t}$	3,160	3.75	2.08	2.44	3.38	4.70	0.08	17.60
$loans_{i,t}$	3,160	0.81	0.22	0.69	0.80	0.92	0.00	1.68
$hft_{i,t}$	3,160	0.06	0.11	0.00	0.01	0.07	0.00	0.82
$deposits_{i,t}$	3,160	0.19	0.15	0.09	0.17	0.25	0.00	0.92
$nplratio_{i,t}$	3,160	0.04	0.08	0.01	0.02	0.04	0.00	0.55
$size_{i,t}$	3,160	11.27	1.55	10.46	11.12	12.25	7.18	14.83

This table reports the summary statistics for the variables used in the equations for the period comprising quarterly data from Q1-2015 to Q4-2023. The variable $dens_{i,t}$ is the ratio of risk-weighted assets (RWA) to exposure at default (EAD), $irb\_fta_{i,t}$ is a dummy variable representing the first date of using IRB models (or first-time adoption), equal to one from the first quarter of IRB use onward and zero otherwise, while $irb\_sh_{i,t}$ is a continuous variable as from credit risk calculated via IRB models. For the definitions of the variables, we refer to Appendix A.2.

Table 2: Effects of IRB models on banks' risk density

VARIABLES	(1) dens	(2) dens	(3) dens	(4) dens
irb_fta	-0.112***	-0.0883**		
	(0.0382)	(0.0395)		
irb_sh			-0.237***	-0.184***
			(0.0651)	(0.0552)
cet1s	0.0178***	0.0168***	0.0167***	0.0151***
	(0.00397)	(0.00498)	(0.00382)	(0.00500)
size	-0.0158	-0.00607	-0.0137	-0.00378
	(0.0236)	(0.0228)	(0.0233)	(0.0230)
loans	0.0481**	0.0353*	0.0495**	0.0334*
	(0.0239)	(0.0203)	(0.0235)	(0.0183)
hft	0.109	0.137	0.128	0.145
	(0.105)	(0.106)	(0.0997)	(0.101)
deposits	-0.00605	-0.0106	-0.00716	-0.00794
	(0.0781)	(0.0762)	(0.0741)	(0.0723)
nplratio	0.0309	0.115	0.0651	0.171
	(0.116)	(0.192)	(0.114)	(0.216)
gdp	-0.000507		-0.000424	
	(0.000748)		(0.000730)	
govdebt	0.000834*		0.000888*	
	(0.000488)		(0.000473)	
Bank Fixed Effects	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,821	2,781	2,821	2,781
R-squared	0.975	0.976	0.975	0.976
Number of Banks	124	124	124	124
Number of Countries	19	19	19	19

Robust standard errors standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Results of strategic modelling

VARIABLES	(1) dens	(2) dens	(3) dens	(4) dens	(5) dens	(6) dens	(7) dens	(8) dens
irb_fta	-0.0899**		-0.0899**		-0.0903**		-0.0783*	
	(0.0403)		(0.0407)		(0.0439)		(0.0437)	
irb_sh		-0.189***		-0.181***		-0.208***		-0.190***
		(0.0583)		(0.0550)		(0.0608)		(0.0606)
zcet1s			0.0329***	0.0288***				
			(0.0113)	(0.0110)				
lowcap					-0.0320	-0.0296		
					(0.0229)	(0.0199)		
highcap							0.0333*	0.0270
							(0.0182)	(0.0191)
irb_fta × zcet1s			0.0102					
			(0.0106)					
irb_sh × zcet1s				0.0170				
				(0.0158)				
irb_fta × lowcap					0.0253			
					(0.0227)			
irb_sh × lowcap						0.0335		
						(0.0250)		
irb_fta × highcap							-0.0356*	
							(0.0212)	
irb_sh × highcap								-0.0438
								(0.0337)
size	0.00608	0.00683	-0.00444	-0.00288	-0.0198	-0.0135	-0.0202	-0.0149
	(0.0264)	(0.0253)	(0.0229)	(0.0231)	(0.0235)	(0.0249)	(0.0223)	(0.0221)
loans	0.0412**	0.0384**	0.0350*	0.0315*	0.0395*	0.0389**	0.0411**	0.0411**
	(0.0201)	(0.0184)	(0.0204)	(0.0183)	(0.0205)	(0.0185)	(0.0206)	(0.0189)
hft	0.130	0.136	0.138	0.146	0.130	0.138	0.137	0.143
	(0.107)	(0.101)	(0.105)	(0.0993)	(0.109)	(0.105)	(0.110)	(0.103)
deposits	-0.0219	-0.0189	-0.00827	-0.00474	-0.0557	-0.0460	-0.0630	-0.0581
	(0.0780)	(0.0735)	(0.0760)	(0.0714)	(0.0783)	(0.0751)	(0.0757)	(0.0729)
nplratio	0.157	0.232	0.133	0.198	0.290*	0.334**	0.259	0.303*
	(0.196)	(0.215)	(0.202)	(0.223)	(0.151)	(0.166)	(0.156)	(0.169)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,781	2,781	2,781	2,781	2,781	2,781	2,781	2,781
R-squared	0.976	0.977	0.977	0.978	0.975	0.976	0.975	0.976
Number of Banks	124	124	124	124	124	124	124	124
Number of Countries	19	19	19	19	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Results for IRB banks directly impacted by the TRIM

VARIABLES	(1) dens	(2) dens
treated_fta × post_trim	0.0145	
	(0.0216)	
treated_fta_pure ×post_trim		-0.0158
		(0.0178)
size	-0.0332	-0.0391*
	(0.0207)	(0.0218)
loans	0.0299	0.0263
	(0.0211)	(0.0221)
hft	0.137	0.0999
	(0.108)	(0.110)
deposits	-0.0554	-0.0451
	(0.0686)	(0.0671)
nplratio	0.270	0.316*
	(0.169)	(0.164)
Bank Fixed Effects	Yes	Yes
Country-Time Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	2,781	2,455
R-squared	0.974	0.977
Number of Banks	124	124
Number of Countries	19	19

Table 5: Effects of IRB models on the growth rates of the sovereign and corporate exposures

Panel A

VARIABLES	(1) Δsov_cb_ead	(2) Δsov_cb_ead	(3) Δcorp_ead	(4) Δcorp_ead
irb_fta	-0.0104*		0.0142**	
	(0.00611)		(0.00678)	
irb_sh		-0.00831		0.0412***
		(0.00917)		(0.0143)
zcet1s	-0.00328	-0.00349*	0.00367**	0.00442**
	(0.00201)	(0.00198)	(0.00178)	(0.00175)
size	0.0176***	0.0168***	-0.00282	-0.00423
	(0.00605)	(0.00577)	(0.00426)	(0.00403)
loans	-0.000267	-0.00103	0.00373	0.00356
	(0.00817)	(0.00807)	(0.00601)	(0.00475)
hft	-0.0294	-0.0285	-0.00130	-0.00483
	(0.0304)	(0.0308)	(0.0265)	(0.0267)
deposits	0.00776	0.00893	-0.0198**	-0.0200**
	(0.0183)	(0.0182)	(0.00948)	(0.00979)
nplratio	-0.00141	-0.000654	0.0559**	0.0396*
	(0.0304)	(0.0262)	(0.0260)	(0.0207)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,658	2,658	2,658	2,658
R-squared	0.350	0.350	0.303	0.309
Number of Banks	124	124	124	124
Number of Countries	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B

VARIABLES	(1) Δsov_cb_ead	(2) Δsov_cb_ead	(3) Δcorp_ead	(4) Δcorp_ead
irb_fta	-0.0109*		0.0147**	
	(0.00638)		(0.00687)	
irb_sh		-0.00712		0.0397***
		(0.00935)		(0.0143)
lowcap	0.00180	0.00168	-0.00182	-0.00197
	(0.00289)	(0.00292)	(0.00177)	(0.00174)
size	0.0186***	0.0177***	-0.00394	-0.00543
	(0.00562)	(0.00543)	(0.00392)	(0.00383)
loans	-0.000866	-0.00174	0.00438	0.00445
	(0.00824)	(0.00814)	(0.00588)	(0.00469)
hft	-0.0273	-0.0265	-0.00354	-0.00731
	(0.0296)	(0.0300)	(0.0280)	(0.0284)
deposits	0.0124	0.0141	-0.0252***	-0.0266***
	(0.0169)	(0.0168)	(0.00819)	(0.00827)
nplratio	-0.0214	-0.0224	0.0781***	0.0670***
	(0.0238)	(0.0207)	(0.0174)	(0.0138)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,658	2,658	2,658	2,658
R-squared	0.350	0.349	0.301	0.306
Number of Banks	124	124	124	124
Number of Countries	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects of IRB models on the growth rates of the corporate exposures: large vs SME exposures

Panel A

VARIABLES	(1) Δlarge_ead	(2) Δlarge_ead	(3) Δsme_ead	(4) Δsme_ead
irb_fta	0.00983*		0.00435	
	(0.00557)		(0.00330)	
irb_sh		0.0355**		0.00572
		(0.0136)		(0.00965)
zcet1s	0.00429**	0.00492***	-0.000621	-0.000499
	(0.00187)	(0.00177)	(0.000978)	(0.000939)
size	-0.00174	-0.00331	-0.00108	-0.000920
	(0.00494)	(0.00448)	(0.00243)	(0.00271)
loans	0.00596	0.00556	-0.00222	-0.00200
	(0.00595)	(0.00558)	(0.00348)	(0.00337)
hft	0.0117	0.00877	-0.0130	-0.0136
	(0.0295)	(0.0295)	(0.0138)	(0.0137)
deposits	-0.0337**	-0.0334**	0.0138	0.0135
	(0.0160)	(0.0144)	(0.0143)	(0.0144)
nplratio	0.0435	0.0287	0.0123	0.0109
	(0.0370)	(0.0305)	(0.0229)	(0.0231)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,658	2,658	2,658	2,658
R-squared	0.299	0.304	0.263	0.263
Number of Banks	124	124	124	124
Number of Countries	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B

VARIABLES	(1) Δlarge_ead	(2) Δlarge_ead	(3) Δsme_ead	(4) Δlarge_ead
irb_fta	0.0104*		0.00435	
	(0.00583)		(0.00333)	
irb_sh		0.0336**		0.00603
		(0.0135)		(0.00991)
lowcap	-0.00146	-0.00163	-0.000358	-0.000342
	(0.00221)	(0.00218)	(0.00157)	(0.00158)
size	-0.00332	-0.00487	-0.000628	-0.000560
	(0.00482)	(0.00443)	(0.00232)	(0.00256)
loans	0.00666	0.00649	-0.00228	-0.00204
	(0.00575)	(0.00541)	(0.00346)	(0.00334)
hft	0.00945	0.00630	-0.0130	-0.0136
	(0.0305)	(0.0308)	(0.0136)	(0.0134)
deposits	-0.0402**	-0.0411***	0.0151	0.0145
	(0.0155)	(0.0139)	(0.0140)	(0.0141)
nplratio	0.0689**	0.0588**	0.00915	0.00824
	(0.0290)	(0.0241)	(0.0208)	(0.0212)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,658	2,658	2,658	2,658
R-squared	0.296	0.301	0.263	0.263
Number of Banks	124	124	124	124
Number of Countries	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Effects of IRB models on the growth rates of the sovereign and corporate exposures before and post the Covid-19 era

Panel A

VARIABLES	(1) Δsov_cb_ead	(2) Δsov_cb_ead	(3) Δcorp_ead	(4) Δcorp_ead
irb_fta×post	0.00393		-0.00232	
	(0.00392)		(0.00184)	
irb_sh × post		0.00434		-0.00292
		(0.00555)		(0.00242)
irb_fta	-0.0120*		0.0147**	
	(0.00641)		(0.00672)	
irb_sh		-0.0104		0.0422***
		(0.00932)		(0.0142)
zcet1s	-0.00362*	-0.00377*	0.00317*	0.00390**
	(0.00202)	(0.00199)	(0.00187)	(0.00186)
loans	-0.00262	-0.00306	0.00514	0.00493
	(0.00866)	(0.00866)	(0.00604)	(0.00490)
nplratio	-0.00356	-0.000725	0.0534*	0.0360
	(0.0306)	(0.0269)	(0.0276)	(0.0226)
size	0.0179***	0.0169***	-0.00256	-0.00388
	(0.00611)	(0.00586)	(0.00425)	(0.00402)
hft	-0.0281	-0.0271	-0.00325	-0.00694
	(0.0300)	(0.0307)	(0.0269)	(0.0271)
deposits	0.00656	0.00812	-0.0192*	-0.0194*
	(0.0181)	(0.0182)	(0.00978)	(0.0101)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,658	2,658	2,658	2,658
R-squared	0.351	0.350	0.304	0.310
Number of Banks	124	124	124	124
Number of Countries	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B

VARIABLES	(1) Δsov_cb_ead	(2) Δsov_cb_ead	(3) Δcorp_ead	(4) Δcorp_ead
irb_fta×post	0.00400		-0.00274	
	(0.00407)		(0.00171)	
irb_sh × post		0.00424		-0.00287
		(0.00566)		(0.00239)
irb_fta	-0.0127*		0.0158**	
	(0.00668)		(0.00692)	
irb_sh		-0.00926		0.0410***
		(0.00950)		(0.0141)
post×lowcap	-0.00248	-0.00179	0.000891	0.000526
	(0.00316)	(0.00318)	(0.00168)	(0.00166)
lowcap	0.00282	0.00248	-0.00213	-0.00220
	(0.00334)	(0.00334)	(0.00195)	(0.00182)
loans	-0.00327	-0.00376	0.00602	0.00580
	(0.00875)	(0.00874)	(0.00588)	(0.00479)
nplratio	-0.0194	-0.0202	0.0773***	0.0660***
	(0.0232)	(0.0203)	(0.0168)	(0.0137)
size	0.0188***	0.0177***	-0.00406	-0.00544
	(0.00555)	(0.00539)	(0.00388)	(0.00381)
hft	-0.0263	-0.0253	-0.00450	-0.00833
	(0.0295)	(0.0302)	(0.0286)	(0.0291)
deposits	0.0111	0.0134	-0.0243***	-0.0261***
	(0.0168)	(0.0167)	(0.00844)	(0.00842)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,658	2,658	2,658	2,658
R-squared	0.350	0.349	0.301	0.306
Number of Banks	124	124	124	124
Number of Countries	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix

A.1. Computation of the CET1 ratio capital headroom

Due to the several changes in the regulatory framework, we define capital demand in different ways according to the year of reference. Since the SSM was launched in November 2014, 2015 represents the first period for computing the capital demand (for the following year) according to a common methodology for the 120 largest banking groups in the Euro Area.[32]

In general, the CET1 capital headroom is defined as the difference between the capital demand and the actual CET1 ratio at the bank level. More precisely, the capital demand is computed differently according to the phasing-in and difference in the supervisory SREP methodologies for the period considered:

- in the year 2015, the capital demand is equal to the Basel minimum CET1 Pillar 1 requirements (4.5 percent) and the phased-in Capital conservation buffer.[33]
- From January 2016 to December 2018, the capital demand was expressed as the summation of Basel minimum CET1 Pillar 1 requirements (4.5 percent), the phased-in Capital conservation buffer, the Other systemically important intuitions (O-SIIs) / Global systemically important institutions (G-SIIs) buffers (when applicable), the Systemic Risk Buffer (when applicable), and the Pillar 2 requirement set by the supervisory set at the bank-level.
- From January 2019 onward, the capital demand was expressed as the Overall Capital Requirement (OCR) in terms of CET1 ratio including the 4.5 percent Basel minimum CET1 Pillar 1 requirements, the bank-specific Pillar 2 requirement, and the Combined Buffer Requirement (CBR) – which comprises the Capital Conservation Buffer, the Countercyclical Capital Buffer (when applicable), the Systemic Risk Buffer (when applicable), and buffers for systemic institutions (G-SII and O-SII buffers, where applicable).[34]

[32] The outcomes of the Supervisory Review and Evaluation Process (SREP) assessment cycle of a given year generally translate into the SREP decisions applicable for the following year period, i.e. the outcomes of the 2015 SREP assessment cycle are reflected in SREP decisions applicable for 2016-year period.

[33] For further details, see: https://www.esrb.europa.eu/national_policy/html/index.en.html.

[34] For the computation of the CET1 ratio capital headroom, we also take into account Additional Tier 1 and Tier 2 capital shortfall to be fulfilled with CET1 capital.

A.2. Description of key variables

Variable	Label	Description	Source
Endogenous variables			
Risk Density	$dens_{i,t}$	The ratio of risk-weighted assets (RWA) to exposure at default (EAD)	ECB Supervisory Statistics
Variation of EAD toward central government and central banks	$\Delta sov\_cb\_ead_{i,t}$	The variation rates of the EAD of the exposures towards central governments and central banks portfolios	ECB Supervisory Statistics
Variation of EAD toward NFCs	$\Delta corp\_ead_{i,t}$	The variation rates of the EAD of the exposures towards non-financial corporations	ECB Supervisory Statistics
Variable of interest			
Internal rating based First-time adoption dummy	$irb\_fta_{i,t}$	A dummy variable representing the IRB approval date which is equal to one from the quarter of IRB approval onward and zero otherwise	ECB Supervisory Statistics
Internal rating based share	$irb\_sh_{i,t}$	A continuous variable as the share of RWA from credit risk calculated via IRB models	ECB Supervisory Statistics
Bank control variables			
CET1 ratio	$cet1r_{i,t}$	Bank's CET1 over total assets	ECB Supervisory Statistics
CET1 capital headroom	$cet1s_{i,t}$	Bank's capital headroom	ECB Supervisory Statistics
Capital cluster dummy	$capcluster_{i,t}$	Clusters based on banks' CET1 ratio distribution	ECB Supervisory Statistics
Business model dummy	$bm_{i,t}$	Dummy identifying different business models	ECB Supervisory Statistics
Post dummy	$post_t$	A dummy variable equal to one from 2020 onward, zero otherwise	
Loans	$loans_{i,t}$	Bank's customer loans	ECB Supervisory Statistics
Held-for-trading portfolio	$hft_{i,t}$	Bank's held-for-trading portfolio	ECB Supervisory Statistics
Customer deposits	$deposits_{i,t}$	Bank's customer deposits	ECB Supervisory Statistics
Npl ratio	$nplratio_{i,t}$	Bank's gross npl ratio	ECB Supervisory Statistics
Bank size	$size_{i,t}$	log of bank's total assets	ECB Supervisory Statistics
Macro-economic variables			
GDP growth rate	$gdp_{c,t}$	Real GDP growth rate at country level	World Bank
Government Debt	$gov\_debt_{c,t}$	Government debt at country level	World Bank