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Brunella Bruno , Immacolata Marino , Giacomo Nocera

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Internal Ratings and Bank Opacity: Evidence from Analysts' Forecasts

Brunella Bruno*
Baffi Carefin - Bocconi University, Department of Finance
Via Roentgen 1
20136 Milano (Italy)
E-mail: brunella.bruno@unibocconi.it

Immacolata Marino
University of Naples Federico II, Department of Economics and Statistics
via Cinthia - Monte S. Angelo
80126 Napoli (Italy)
E-mail: immacolata.marino@unina.it

Giacomo Nocera
Audencia Business School, Department of Finance
8 route de la Jonelière
44312 Nantes Cedex 3 (France)
Email: gnocera@audencia.com

Abstract

We document that reliance on internal ratings-based (IRB) models to compute credit risk and capital requirements reduces bank opacity. Greater reliance on IRB models is associated with lower absolute forecast error and reduced disagreement among analysts regarding expected bank earnings per share. These results are stronger for banks that apply internal ratings to the most opaque loans and adopt the advanced version of IRB models, which entail a more granular risk assessment and greater disclosure of risk parameters. The results stem from the higher earnings informativeness and the more comprehensive disclosure of credit risk in banks adopting internal ratings. We employ an instrumental variables approach to validate our findings.

JEL classification: G20, G21, G28.

Keywords: Transparency, Disclosure, Credit risk, Bank regulation.

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* Corresponding author.

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ABSTRACT

We document that reliance on internal ratings-based (IRB) models to compute credit risk and capital requirements reduces bank opacity. Greater reliance on IRB models is associated with lower absolute forecast error and reduced disagreement among analysts regarding expected bank earnings per share. These results are stronger for banks that apply internal ratings to the most opaque loans and adopt the advanced version of IRB models, which entail a more granular risk assessment and greater disclosure of risk parameters. The results stem from the higher earnings informativeness and the more comprehensive disclosure of credit risk in banks adopting internal ratings. We employ an instrumental variables approach to validate our findings.

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1. Introduction

Bank opacity is a central issue in the banking literature. Previous studies posit that banks are inherently opaque institutions due to their specific asset and liability composition (Morgan, 2002; Flannery et al., 2004; Hirtle, 2006; and Dang et al., 2016). The combination of opaque assets, high leverage, along with a large proportion of insured liabilities, raises agency conflicts and moral hazard concerns. This, in turn, increases the external funding premium, potentially hindering the bank's ability to raise funds and supply credit, and threatens their stability. For this reason, bank balance sheet transparency is at the center of debates on bank fragility and regulation (Morgan, 2002; Jones et al., 2012; Bushman, 2016).

In this study, we present the first empirical analysis of the impact of banks' internal ratings, i.e., their internal assessment of risk exposures to compute capital requirements, on bank opacity. We measure bank opacity by using the absolute forecast error and the disagreement among equity analysts about expected earnings per share (EPS). Previous works have shown that analysts' earnings forecasts can be used to derive an independent (external) assessment of firm opacity (Flannery et al., 2004). *Ceteris paribus*, larger analyst absolute forecast errors or greater disagreement among forecasters implies that the firm is more difficult to evaluate.

There are two contrasting views of the potential effect of internal ratings on bank opacity.

On the positive side, internal ratings may prove useful in reducing uncertainty about bank balance sheets because of more effective risk management (the *risk management mechanism*) and enhanced information disclosure requirements (the *information disclosure mechanism*). The former mechanism entails more precise risk models and better management practices, so internal ratings could lead to more reliable and less volatile earnings. As for the latter mechanism, since banks adopting IRB models (IRB banks) are required to disclose details on their risk parameters in the Pillar III report, investors and analysts could benefit from a richer information set that result in more accurate earnings forecasts. On the negative side, however, empirical studies document opportunistic under-reporting of risk and miscalculation of capital requirements in IRB banks (Mariathasan and Merrouche, 2014; Behn et al., 2016). Risk under-reporting is more likely in low capital banks, consistent with a capital arbitrage motive (Begley et al., 2017; Plosser and Santos, 2018). Whether and how internal ratings affect bank opacity is, therefore, an empirical question.

To address this issue, we investigate the degree of IRB implementation by European banks from 2008 to 2015. The focus on Europe and on this specific time window provides an insightful setting because IRB models have been adopted in Europe by a wider array of banks than in the US, where they are only used by top tier institutions.[1] Also, starting in 2008, their adoption has been gradual and uneven among banks. To account for this aspect of IRB adoption, we manually collect data for bank asset portfolios (corporate, retail, and government) and for both types of IRB approach – the foundation (FIRB) and the advanced (AIRB) approach. We then construct various measures of bank's reliance on the IRB approach, to capture both the extensive and intensive margin of their usage.

We find that it is not just the adoption, but rather the intensity of internal ratings usage that affects and reduces bank opacity. Banks are more transparent when they apply the IRB models to at least two of their credit portfolios as opposed to a single one, and especially when they use them to assess the corporate portfolio. These results are stronger for banks that implement the AIRB approach which entails more granular risk assessment and greater disclosure of risk parameters than the FIRB version.

[1] For instance, in 2016 only 15 core banks in the US with total assets above USD 250 billion had their internal ratings validated for regulatory purposes.

To alleviate the concern that the IRB variable is not fully exogenous to bank opacity, we instrument the IRB variable with the average IRB adoption of other banks in the country. The instrumental variables results confirm that IRB usage significantly reduces bank opacity.

In further analyses, we examine the effect of IRB adoption by poorly capitalized banks. We find that the beneficial effect of IRB usage on bank opacity diminishes for weak banks, which are plausibly more exposed to regulatory arbitrage incentives, consistent with Plosser and Santos (2018). We also investigate whether and to what extent internal ratings mitigate the intrinsic opacity of non-performing loans (NPLs), since loans that are past due or unlikely to be repaid are not only risky but also very difficult to assess (Flannery, 2014). Our results show that advanced IRB models mitigate NPLs' detrimental effect on bank opacity.

Lastly, we explore the two mechanisms (risk management and information disclosure) through which the usage of the IRB approach translates into higher transparency. Our findings suggest that both mechanisms are at play: IRB models enhance bank transparency by delivering both higher earnings quality (measured in terms of earnings response coefficient) and better informational disclosure through Pillar III reporting.

The paper contributes to various strands of literature. Our work is closely related to the literature on bank opacity (e.g., Flannery et al., 2004, 2013, and Dang et al., 2017). While existing literature has explored the balance sheet items contributing most to a bank's opacity, we document that it is not only the items but the way they are measured and reported through risk measurement models that affects bank opacity.

We also extend research on the effects of IRB implementation. While investigations in this field focus on the impact of the IRB approach on loan pricing (Repullo and Suarez, 2004), bank lending (Bruno et al., 2017; Gallo, 2021), and risk-management practices (e.g., Cucinelli et al., 2018), we are the first to investigate the relationship between internal ratings and bank opacity. We uncover a novel beneficial effect of IRB implementation mainly driven by the intensity of usage of internal ratings, rather than their mere adoption.

Our results complement studies on the failure of model-based regulations for banks (Begley, 2017; Plosser and Santos, 2018; Behn et al., 2022). The key insight from these articles is that internal ratings provide incentives to under-report risk and pursue capital arbitrage. Our findings support the view that capital mitigates uncertainty (Morgan, 2002). We add that also the way to assess capital is important: the positive effect of internal ratings on bank opacity is lower in the least capitalized banks, in which an opportunistic use of IRB approach is more likely, as found by Plosser and Santos (2018).

At a broader level, our findings contribute to the corporate disclosure and analyst behavior literature. We provide empirical support to theoretical works on the benefits of Pillar III reporting (Vauhkonen, 2012). As such, our paper has implications for the ongoing policy discussion on the cost of compliance with supervisory reporting (Enria, 2016; EBA, 2021), providing further evidence of the beneficial effects of enhanced public disclosure practices.

Overall, our findings are consistent with the idea that banks respond to multiple stakeholders including regulators and markets. While internal ratings may distort incentives and promote regulatory arbitrage, they still provide valuable information to the market through better risk management and the additional disclosure they require.

2. Institutional background and hypotheses development

In this section we first provide background information on the objective and institutional details of the IRB approach. Then, we formulate hypotheses about whether and how IRB implementation influences bank opacity.

2.1. Institutional background: IRB models and capital regulation

Prudential regulation requires banks to fund their activity through a minimum amount of capital to absorb unexpected losses that may originate from risky investments. Capital is required to increase proportionally to the bank's risk-weighted assets (RWAs).

The 2004 Basel II agreement introduced a major innovation in the capital requirement and credit risk-weight calculations as, for the first time, risk weights were based upon credit ratings either provided by external agencies (the standardized approach - SA) or produced by banks internally (the IRB approach). Although regulators asked banks to choose between the two approaches (BIS, 2001), they considered internal ratings better for two reasons. First, IRB capital requirements have greater sensitivity to the drivers of credit risk in a bank's portfolio. This means that the capital absorption of credit exposures for high (low)-risk borrowers can be higher (lower) for IRB than for SA banks. Second, an appropriately structured IRB system can incentivize banks to improve their risk management practices.

In addition, banks adopting internal ratings can choose between the AIRB and the FIRB approaches that differ in the amount of data collected, the risk parameters calculated internally and the sophistication of the model. The AIRB approach is more complex, requires more data entry, and generates more granular and risk-sensitive outcomes than the FIRB approach. Internet Appendix Section IA.1 provides details on the differences between the two options.

As a final step, banks willing to adopt internal ratings for regulatory purposes must adhere to minimum requirements for risk management and control methodologies to be validated by the national competent authority. Because collecting high quality data and implementing robust internal ratings system is a cumbersome and costly process, only the largest banks have implemented internal rating systems for regulatory purposes.

To avoid cherry picking and minimize capital arbitrage strategies, the IRB approach must apply to all bank exposures. Moreover, implementation occurs gradually over time. For certain exposures, banks may be permitted to use permanently the standardized approach. Internet Appendix Sections IA.2 and IA.3 provide details on the permanent partial usage of IRB in Europe and an example of IRB gradual adoption by a bank in our sample, respectively.

2.2. Internal ratings: scope of application, potential benefits, and criticisms

2.2.1. IRB and credit risk management

Banking authorities consider that IRB models have so many managerial applications that using them solely for calculating the capital requirement would be "unacceptable" (BCBS, 2006). As such, in many banks, internal ratings form an integral part of the management information about the quality of the loan portfolio. They allow for close monitoring of its risk composition, the aggregated exposure for all rating grades, and the limits assigned. Rating information serves not only as a basis for a bank's provisioning and loan loss reserve policy but also a valuable input for loan pricing. In particular, the greater granularity of risk weights and risk sensitivity of IRB models as opposed to the standardized approach enables banks to price their loans more efficiently. In more sophisticated institutions, the results of the internal rating processes provide the basis for more efficient capital management, e.g., by enabling them to reallocate credit from riskier to safer assets to exploit savings in capital charges.

Previous research on the impact of IRB models on risk management, loan pricing and bank profitability supports the view that internal ratings strengthen incentives for banks to manage risk more effectively (Repullo and Suarez, 2004; Bruno et al., 2017; Cucinelli et al. 2018; Gallo, 2021). Overall, these findings suggest that the reduction in capital requirements often achieved through the implementation of internal ratings is not solely due to more accurate risk measurement, but also to more effective risk management.

2.2.2. IRB and Pillar III disclosure requirements

A further implication of IRB adoption is that banks must disclose information on the way they calculate credit risk internally. Since IRB models require a large amount of qualitative and quantitative information about, e.g., borrowers, collateral, and loan facilities, IRB banks have, in principle, an information competitive advantage over banks with less sophisticated approaches. IRB banks make this information advantage available to their investors as a result of the Pillar III disclosure requirements.

Pillar III can be regarded as mandatory disclosure of *regulatory* data that complements accounting-based information, whose aim is to enhance market discipline and corporate governance by providing market participants with "*unique* information, not already available elsewhere" (ESRB, 2013). Under Pillar III rules, banks are asked to disclose relevant data and information about their risk exposures and risk management approach. Quantitative details can be provided, for example, in terms of amounts of exposures, probability of default and recovery rates, with a breakdown by type of exposure and geography. Consequently, disclosed information tends to be more detailed in IRB banks compared to SA banks, and this is further amplified when the advanced approach is implemented instead of the FIRB approach.

Prior to the introduction of the Single Supervisory Mechanism in late 2014, the lack of transparency and comparability across banks made Pillar III reporting particularly valuable for market participants.

2.2.3. Criticisms of internal ratings

Despite the potential benefits, the shift towards the IRB approach has sparked controversy, with the main concern being that the complexity of internal rating systems, especially in the advanced version, could hinder external scrutiny and make banks more inclined to engage in capital arbitrage (Haldane and Madouros, 2012). Indeed, the adoption of IRB in the aftermath of the global financial crisis coincided with a significant increase in capital ratios and a wide variability in RWAs for many banks (Le Leslè and Avramova, 2012; Turk-Ariss, 2017). These developments raised doubts about the credibility of risk-based capital measures among market participants (Barclays Capital, 2011; Masters, 2012). Consistent with a strategic usage of IRB, academic research found evidence of risk under-reporting to improve capital ratios artificially, highlighting the perils of regulation premised on self-reporting (Mariathasan and Merrouche, 2014; Behn et al., 2022; Abbassi and Schmidt, 2018; Plosser and Santos, 2018; Bastos e Santos et al., 2020).

In response, Basel III, the third international accord on bank capital agreed in late 2010, introduced a non-risk-adjusted minimum capital ratio to mitigate biases arising from opportunistic or flawed internal ratings. In December 2017, the Basel Committee introduced revisions to the Basel III rules to enhance the credibility of RWAs and improve the comparability of bank capital ratios.[2]

[2] The reforms constrain the usage of advanced internal models; enhance the risk sensitivity of the standardized approaches; increase the leverage ratio requirement for global systemically important institutions; and introduce an aggregate output floor to RWA based on the standardized approaches (BCBS, 2017).

2.3. Hypotheses development

Based on the discussion of the benefits and criticisms of internal ratings, it is difficult to establish *a priori* whether and how a more thorough implementation of IRB models would impact bank opacity.

On the one hand, IRB models can serve as transparency-enhancing tools due to two mutually beneficial mechanisms. First, more intensive usage of internal ratings has the potential to enhance risk modelling and risk management practices (risk management mechanism). For instance, it could lead to improved borrower screening and monitoring, more accurate provisioning, and more timely recognition of NPLs, thus contributing to stabilizing banks' profits and making balance sheets more reliable. These effects can enhance the quality of bank earnings, make them more informative, and, consequently, improve market analysts' forecasts. Second, IRB adoption requires the disclosure of granular information regarding bank risks and their computation to market participants (information disclosure mechanism). Therefore, a broader adoption of internal ratings can reduce bank opacity by expanding the analysts' information through regulatory data.

In contrast, bank opacity could increase due to an "opportunistic" use of IRB approaches. The complexity of internal ratings, along with the discretion permitted by the IRB approach, may create the incentive to underreport risk as found in Begley et al. (2017) and Plosser and Santos (2018), among others, ultimately resulting in a more uncertain balance sheet.

These contrasting arguments indicate that the effect of internal ratings on bank opacity is ambiguous and challenging to predict. Moreover, since banks respond to multiple stakeholders, including regulators and markets, IRB model regulations may encourage regulatory arbitrage while at the same time providing valuable information to the market through the additional disclosure they require. Therefore, whether the overall net change in opacity is negative or positive for the average IRB bank constitutes an empirical question, forming the basis of our first two opposing hypotheses:

H1a*: The usage of internal ratings-based models has a net beneficial effect on bank opacity*;

or

H1b*: The usage of internal ratings-based models has a net detrimental effect on bank opacity.*

For the reasons explained in Section 2.1, any such effect would be more pronounced in banks adopting the advanced version of IRB models. This constitutes our second hypothesis:

H2*: The net effect of the usage of internal ratings-based models on bank opacity becomes stronger if banks adopt* advanced *internal ratings-based models.*

3. Data and empirical methodology

3.1. Sample and data sources

We build a cross-country sample of large listed European banking groups. We collect information from several sources: I/B/E/S for analysts' forecasts; Moody's Analytics BankFocus for annual consolidated balance sheet data; and Pillar III reports for banks' usage of IRB models. Information retrieved from Pillar III reports includes the share of credit exposures (measured as the bank's estimate of the likely exposure at default) for which the IRB approach is used; the retail vs the corporate component of the loan portfolio; and the Tier 1 capital ratio. Despite being mandatory, Pillar III reports did not adhere to a standardized structure until the introduction of a common reporting template in 2019. As a result, we had to manually extract and reconcile data items.

Starting with the top 50 listed groups by total assets, then dropping those with incomplete data (e.g., lacking I/B/E/S forecasts), we obtain a final sample of 289 bank-year observations from 43 banks chartered in 17 European countries (Internet Appendix Table IA.1 lists the sample banks). Italy, the country with the largest number of observations, generates about 17% of the total, followed by Spain and the UK (each with about 12% of the total). Our sample covers more than 60% of the European banks' total assets overall. The data cover the period 2008-2015 prior to the Basel Committee's reforms introduced in 2017-2019 to prevent misuse of internal models.

3.2. Methodology

To evaluate the effect of the usage of internal ratings on bank opacity, we estimate the coefficients of the following fixed effects panel regression. This extends conventional analyses of the determinants of bank opacity with the addition of measures of usage of IRB models:

$$\begin{aligned} OPACITY_{i,t} = \alpha + \beta\, IRB_{i,t-1} + \xi' \mathrm{X}_{i,t-1} + \gamma\, \Delta GDP_{i,t} + \\ + \theta\, Stock\ market\ return_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

We measure the dependent variable, *OPACITY*, in terms of *Forecast Error* and *Dispersion* of bank *i* in year *t*. *Forecast Error* is the median absolute EPS forecast error, divided by the share price at the start of the fiscal year. It serves as an *ex post* measure of opacity, indicating whether EPS proved easy or hard to estimate. *Dispersion* refers to the cross-sectional standard deviation of EPS forecasts, computed exclusively for banks with more than one analyst covering them. This acts as an *ex ante* measure of opacity, signaling stronger/weaker agreement among market participants.

β is the coefficient of interest that identifies the relation between bank opacity and our key explanatory variable, *IRB*, alternatively defined as either a dummy or a continuous variable. The dummy variable, *(A)IRB dummy*, takes value 1 if the share of credit exposures, in terms of Exposure at Default (EAD), covered by (advanced) internal ratings-based models exceeds zero. This variable represents our extensive margin measure of (A)IRB usage. The continuous variable, *(A)IRB weight*, is defined as the share of credit exposures, in terms of EAD, covered by (advanced) internal ratings-based models. It measures the degree of usage of (A)IRB models to assess credit risk. We use these variables to test *H1* and *H2*. Specifically, we test *H2* by comparing the impact on *OPACITY* of the *IRB* variables as opposed to the *AIRB* variables (which account for the usage of the advanced version of internal ratings).

The vector $X_{i,t-1}$ of bank level controls includes variables that are expected to impact bank balance sheet transparency. Based on bank opacity literature (e.g., Flannery et al., 2004 and 2013), we expect asset composition to affect analysts' ability to predict earnings. If analysts' predictions reflect opacity, they should vary systematically across banks with different asset compositions, reflecting the information asymmetries impounded in their asset mix and asset quality. We identify six variables to measure asset composition: loans to total assets (*Loans/TA)*; corporate credit exposures to the sum of corporate and retail credit exposures (*Corporate exposure ratio*); liquid assets to total assets (*Liquid assets/TA*); securities to total assets (*Securities/TA*); trading and fair value assets to total securities (*Trading assets/Securities*); and derivatives to total assets (*Derivatives/TA*). Among bank balance sheet items, problem loans are possibly even more difficult to assess (see the discussion in Section 4.2.4). We therefore include the share of non-performing loans over total gross loans (*NPLs/Loans*).

Bank valuation also depends on the level of capitalization, which influences a bank's moral hazard and risk-taking behavior (Jensen and Meckling, 1976; Peek and Rosengren, 2005). In addition, low-capital banks may have an incentive to bias risk estimates they report to regulators

(Plosser and Santos, 2018). In light of the debate on the reliability of risk-based capital ratios (as discussed in Section 2), we use two measures of bank capitalization: a pure, non-risk-weighted leverage ratio (*Equity ratio*, the equity to total asset ratio) and a risk-based capital ratio (*Tier 1 ratio*, the ratio of Tier 1 capital to risk-weighted assets).

We also control for other banks' characteristics that are likely to influence earnings forecasts: funding structure (*Deposits/TF*, measured as the percentage of customer deposits to total funding); profitability (*ROA*, the net income to average total asset ratio); and *Size* (the natural logarithm of total assets). In addition, we include the GDP annual real growth rate (*ΔGDP)* and the return rate of the stock market (*Stock market return*) as we expect the forecast accuracy to be affected by macroeconomic and financial market conditions.

The dependent variables are measured at time *t* and the independent variables (except *ΔGDP* and *Stock market return*) are measured at *t*-1 to mitigate endogeneity concerns. We present all variable definitions and sources in Appendix A. In Internet Appendix Section IA.4 we discuss in detail how these variables are expected to affect bank opacity according to theoretical and empirical literature and we comment on the results of a validation test of a simplified version of Equation (1) where we exclude the *IRB* variable.

In all specifications we include bank fixed effects (δ_i) to control for unobserved bank heterogeneity caused by bank-level factors that remain constant across the sample period. To capture any further time-specific events, we also include year fixed effects (μ_t). Standard errors are clustered at the bank level (results are robust to clustering at the country level or to using no clustering at all).

3.3. Descriptive statistics

Table 1 presents descriptive statistics for the main variables used in our analysis.[3] To ensure consistency with the regression analysis, we measure bank-specific explanatory variables at time *t*-1. On average, around 80% of the sample banks use IRB models to evaluate the credit risk of (at least part of) their exposures. The average share of credit exposures assessed with IRB models accounts for 54% of the sample. The average number of credit portfolios under internal ratings is two. IRB models are used more (less) intensively for the corporate (government) portfolio, with an average share of EAD measured by advanced internal ratings models equal to 62% (25%). The number of banks adopting the IRB approach and the share of credit exposures under (especially advanced) internal ratings increased over our sample period. Some banks started using the IRB models from the beginning, others started using them at some point during the sample period, while still others used the standardized approach throughout the entire sample period (Internet Appendix Figure IA.1).

Insert Table 1 approximately here

Internet Appendix Table IA.2 summarizes the results of *t*-tests for the equality of means of the main characteristics of *(i)* IRB banks and banks adopting the standardized approach and *(ii)* banks with an *IRB weight* above and below the median value (62.9%). IRB banks are, on average, significantly larger, more capitalized in terms of Tier 1 ratio (but less capitalized, if the equity to total asset ratio is considered) and characterized by less traditional business models, as indicated by the lower customer deposit ratio and loan ratio, and by the higher share of securities.

[3] Further descriptive statistics are reported in Internet Appendix Table IA.2.

Overall, the heterogeneity in the time series, along with the cross-sectional variation in banks' usage of IRB models, calls for a panel fixed effects model estimation.

4. Empirical results

4.1. The determinants of IRB adoption

Before testing the impact of IRB model adoption on bank opacity, it is worth exploring a related question: what factors drive the adoption of IRB models? This question is particularly relevant in addressing concerns of reverse causality, where more (or less) opaque banks may be more inclined to adopt these models. To answer this question, we use the Cox (1972) proportional hazard model to estimate the propensity of a bank to adopt the IRB approach in any given year during our sample period, based on the bank's characteristics as of the year prior to the IRB model adoption. Banks remain in the sample until they adopt the IRB approach, or throughout the sample period if they never adopt it. The model allows the estimates to account for the adjustment of the propensity to adopt the IRB approach to the time varying characteristics of banks over the sample period.

We report the estimates of the Cox proportional hazard model in Internet Appendix Table IA.3. Our analysis shows that the level of bank opacity prior to the IRB adoption does not exhibit a significant difference between IRB and SA banks. The characteristics that significantly impact the propensity of a bank in our sample to adopt the IRB approach are size (positively) and the share of non-performing loans (negatively). This is not surprising. First, internal models are costly to implement, making larger banks the natural candidates to adopt them (as found in previous literature, e.g., Behn et al., 2022). Second, given their greater risk sensitivity, the switch to IRB models would entail, by definition, higher capital charges for banks with riskier portfolios (Gallo, 2021). *Ceteris paribus*, this would make it less likely for banks with higher NPLs to adopt IRB models. These results are confirmed when testing for the propensity of a bank to adopt the IRB approach for the most opaque credit portfolio, i.e., the corporate portfolio.

4.2. IRB models and bank opacity

4.2.1. Baseline analysis

Table 2 reports the results of estimating Equation (1) using ordinary least squares regressions to test *H1* and *H2*. In columns 1 to 4, the dependent variable is *Forecast Error* whereas in columns 5 to 8 the dependent variable is *Dispersion*. The usage of (advanced) IRB models is observed in terms of both a dummy variable, *(A)IRB dummy*, in columns 1-2 and 5-6; and a continuous variable, *(A)IRB weight*, in columns 3-4 and 7-8.

The estimated coefficients of all the IRB variables are negative, but only those of the continuous variables are statistically significant across all the specifications. The coefficients of the dummy variables are statistically significant (at the 10% level) only when the opacity dimension is captured by *Forecast Error*. Overall, these findings support hypothesis *H1a* and suggest that the degree of implementation, rather than the mere adoption, of the IRB model affects bank opacity. Specifically, the results regarding the specifications of Equation (1) with the continuous variables are consistent and economically significant across our two alternative opacity measures. A one-standard deviation increase in *IRB weight* is associated with a 64.2% decrease in *Forecast Error* and a 50.6% decrease in *Dispersion* relative to their means.

Furthermore, both the statistical and economic significance are strengthened when considering the effect of advanced model usage, providing support for hypothesis *H2*. The results in specifications with *AIRB weight* (columns 4 and 8) are stronger than those with *IRB weight* (columns 3 and 7). In terms of economic significance, a one-standard deviation increase in *AIRB weight* corresponds to a decrease in *Forecast Error* and *Dispersion* equal to 89% and 81% of their means.

The values and the significance of the control variables are aligned with those presented and discussed in Internet Appendix Section IA.4. Internet Appendix Table IA.5 replicates our analysis with the continuous (*IRB weight* and *AIRB weight*) variables on the subsample of banks adopting the IRB (or the AIRB) only. Overall, the results are in line with those we found in Table 2.

As our opacity measures can take only positive values, their distributions are positively skewed. To check whether the non-normality of these variables affects our results, we replicated the estimations in Table 2 by substituting the dependent variables with their logarithmic transformations. The results, not reported for brevity, align with our main findings. Additionally, an unreported comparison of the distributions of *Forecast Error* and *Dispersion* across the quartiles of the IRB variables reveals that the extreme values of bank opacity are not concentrated in banks with limited or no reliance on internal ratings.

Insert Table 2 approximately here

4.2.2. Dealing with endogeneity

The estimates in Table 2 include bank fixed effects and year fixed effects. Therefore, the results cannot be attributed to unobserved, time-invariant, cross-sectional differences between users and non-users of IRB models, nor by time-varying disparities in IRB adoption and opacity among all banks in our sample. Furthermore, our measures of IRB adoption are lagged by one year to reduce concerns about reverse causality explaining our results. Finally, we include a set of time-variant bank measures of the asset quality and composition that are more likely to be associated with bank opacity.

Despite the usage of such fixed effects and bank-specific variables, our estimates could be potentially biased if the IRB adoption were more likely for banks holding assets that are fundamentally easier to assess to external observers. In other words, there may be other unobserved drivers of bank opacity in IRB banks. We deal with this issue by adopting an instrumental variables approach that exploits the exogenous variation in IRB implementation arising from common practices in the country where the banks are located.

As an instrument for the *IRB weight* variable of a given bank, we take the weighted average *IRB weight* of all *other* banks in the same country and year (*IVIRB weight* variable).[4] Table 3 shows the results of both the first- and the second-stage regression estimates for *Forecast Error* (columns 1 and 2) and *Dispersion* (columns 3 and 4).[5] The significant positive coefficient of the *IVIRB weight* variable and the high values of the *F*-statistic show that our instrument is relevant and not weak. The sign of the coefficients of the *IRB weight* variable in the second-stage regressions (columns 2 and 4) is consistent with the corresponding one of the OLS estimations found in columns 3 and 7 of Table 2. Specifically, we find a negative coefficient that is statistically significant in the regression on *Dispersion*. Overall, the results of the instrumental variables approach are qualitatively similar to our ordinary least squares (OLS) estimations. Unfortunately, due to a lack of data regarding the average AIRB weight at the country level, we

[4] A similar instrument is used by Laeven and Levine (2009) and Garcia-Appendini et al. (2023). To construct the *IVIRB weight* variable, we collected data on total assets and average *IRB weight* at the country level, from the ECB statistical Data Warehouse and, when unavailable, directly from the national regulatory authorities' websites. Unfortunately, due to a lack of data regarding the average usage of advanced internal rating models at the country level, we were unable to construct a similar instrument for the *AIRB weight* variable, for which the results in Table 2 are statistically more significant.

[5] Hereinafter, to simplify the representation of the results, we do not show the coefficients of the control variables in our tables.

are unable to construct a similar instrument for the *AIRB weight* variable, which yields the most significant results in the OLS analysis (Table 2).

For *IVIRB weight* to be a valid instrument, the exclusion restriction should be satisfied. This means that the average IRB usage of other banks in the country should relate to the bank opacity only through its effect on the bank's own choice of the internal rating approach. This condition would be violated if the financial analysts' EPS forecasts (which serve as the basis for opacity measures) for bank *i* in country *c* were influenced by the extent of IRB model adoption by the other banks in that country. This could happen if, for example, a high adoption of IRB models at the country level would allow analysts covering multiple banks to better evaluate common factors and risks that affect the earnings of all banks within that country.

While we cannot completely rule out this possibility, we believe it is unlikely that the *IVIRB weight* variable captures the feedback between the bank and its country peers. This is because, in our sample, the average analyst covers five banks, with only 2.5 of them belonging to the same country. To further address this concern, we conduct an unreported analysis where we calculate a new specification of our opacity measures for a given bank *i* in country *c* in year *t*. These measures are derived from earnings forecasts provided by analysts who exclusively cover bank *i* and do not cover any other bank in country *c* during the same year *t* in our sample. We then use these more restricted opacity measures, specifically based on forecasts from the "one-bank-of-one-country analysts", to replicate the estimations presented in Table 2 and Table 3. The results, available upon request, are consistent with our main findings.

Another valuable characteristic of our instrument is that, by design, it captures the variation in IRB usage within a specific country and year caused by unobserved factors, similar to how a country-by-year fixed effects approach controls for unobserved factors shared by a particular country and year. Estimates using country×year fixed effects are not fully consistent with our setup due to the limited number of banks in each country-year combination. Our instrument mitigates this concern. This is particularly relevant in our context, where differences in IRB usage can be attributed to variations among national banking authorities in authorizing and implementing the IRB framework.[6]

Insert Table 3 approximately here

4.2.3. The gradual and partial adoption of IRB models

The results from the OLS strategy with the continuous variables *IRB weight* and *AIRB weights*, and those from the IV estimations with *IRB weight* support hypotheses *H1a* and *H2*. However, the statistical significance of the coefficients of the *(A)IRB dummy* variables in Equation (1) (at 10% only in the specifications with *Forecast Error*), suggests that bank opacity is influenced by the extent of internal model implementation, rather than just adoption. In other words, the IRB method adoption primarily affects bank opacity at the intensive margin. In this section we explore this finding further.

As discussed in Section 2.1 (and in Internet Appendix Section IA.2), the application of the IRB approach, even though it is required for all bank exposures, tends to occur gradually. Banks may also be allowed to permanently continue using the standardized approach for certain exposures. Therefore, because IRB adoption is not a truly binary event, the continuous (A)IRB variables may capture the impact on bank opacity resulting from varying degrees of internal

[6] Nonetheless, to validate the robustness of our results, we replicate the estimations presented in Tables 2 and 3 with country×year fixed effects. These additional results are very similar to our previous findings. They are provided in Internet Appendix Table IA.6 and IA.7.

ratings usage, whether by type or amount of credit exposures, which the dummy variables are less capable of capturing.

One of the advantages of our empirical setting is that the sample period covers the first years of the entry into force of Basel II and the first adoption of the IRB approach for risk-weight and capital requirement calculation by large European banks. We observe heterogeneity not only in the amount but also in the *types* of credit exposures under IRB models.[7]

Figure 1 reports the number and the type of credit risk exposures evaluated according to the (A)IRB approach for the 289 bank-year observations of our main empirical analysis. Out of the 81% (79%) of bank-year observations that exhibit some IRB (AIRB) usage, 4% (22%) have only one portfolio; 46% (31%) have two portfolios; and 50% (47%) have three portfolios covered – at least partially – by (advanced) internal ratings. Among observations with positive values of *IRB weight* (*AIRB weight*), 99% (78%) apply IRB (AIRB) to their corporate exposures; 96% (98%) to their retail exposures; and only 51% (48%) to their government portfolio. The lower usage of internal ratings for the government exposures could be due to the permanent partial usage allowed by national regulators in the EU for "domestic" sovereign exposures.

Insert Figure 1 approximately here

We exploit this additional information to test whether the implementation of internal ratings to different numbers and different types of credit exposures affects bank opacity.

We do so by estimating a modified version of Equation (1), where we replace the key *IRB* variable with one of the following sets of three variables: (*i*) three dummy variables; *IRB j_portfolios* (*AIRB j_portfolios*) (with *j*=1, 2, 3), which equal one if the bank uses the (A)IRB

[7] Internet Appendix Section IA.3 shows how these IRB variables evolve over time following the implementation of the plan for the progressive roll-out of the IRB approach for a bank in our sample.

approach on 1, 2 or 3 portfolios, respectively, and zero otherwise; (*ii*) three dummy variables, (*A)IRB Corporate dummy*, (*A)IRB Retail dummy*, and (*A)IRB Government dummy*, which equal one if at least a portion of the corporate, retail, and government portfolio, respectively, is assessed through the (A)IRB method, and zero otherwise; and (*iii*) three continuous variables, (*A)IRB Corporate weight*, (*A)IRB Retail weight*, and (*A)IRB Government weight*, which measure the share of corporate, retail, and government credit exposures, respectively, evaluated with (advanced) internal ratings models.

Table 4 reports the results of this analysis. In columns 1-2 and 7-8 we estimate the impact of the number of credit exposures evaluated under IRB models (columns 1 and 7) and under AIRB models (columns 2 and 8) on *Forecast Error* and *Dispersion*, respectively. We observe that opacity decreases when internal ratings are applied on at least two portfolios, although the most significant reduction in bank opacity occurs when banks adopt advanced models across three portfolios (columns 2 and 8).

In columns 3-4 and 9-10 we test if the implementation of internal ratings to specific types of credit exposures affects bank opacity and replace the three *(A)IRB j_portfolios* variables with the (*A)IRB Corporate*, (*A)IRB Retail*, and (*A)IRB Government* dummies. We find that the application of the advanced IRB approach to the corporate portfolio enhances bank transparency at the extensive margin (columns 4 and 10). When the dummy variables are replaced with the corresponding continuous variables (columns 5-6 and 11-12), the beneficial effect of internal ratings on bank opacity increases as the share of corporate exposures under IRB models rises, especially in their advanced version. This aligns with the notion that corporate loans are customized and high-information content facilities, in contrast to retail loans, which are standardized and easy-to-assess contracts (Boot, 2000).

Insert Table 4 approximately here

To further isolate the effect on the intensive margin, in Internet Appendix Table IA.8, we replicate the results of Table 4 using a subsample of (A)IRB banks. In this case we omit the *IRB 1portfolios* (*AIRB 1portfolios*) dummy variable. The results are consistent with the findings in Table 4.

4.2.4. IRB models, low-capital banks, and NPLs

In this section, we first exploit the heterogeneity in our sample to investigate the effect of IRB models on bank opacity in low-capital banks. We then assess if the intrinsic opacity of NPLs is affected by IRB model adoption. As our baseline results are stronger in the case of AIRB models, in these extensions we focus on the impact of the advanced approach.

IRB models and bank opacity in low-capital banks

Motivated by research on the strategic usage of internal ratings and risk under-reporting (Plosser and Santos, 2018; Behn et al., 2022), we test whether our results hold in case of low-capital banks in periods of shortage of long-term and equity financing, as during the years covered by our analysis. We argue that poorly capitalized banks may find it advantageous to misrepresent riskiness to artificially increase their regulatory capital ratios, as discussed in Section 2.2, especially during economically tough times when raising capital is particularly expensive and meeting the regulatory capital requirements is more challenging. We find that, while the usage of AIRB models improves transparency for the average bank in our sample, it has a weaker or even no favorable effect for low-capital banks. We provide details on the estimation procedure in Internet Appendix Section IA.5.1. This result concurs with the research on the flaws of model-based regulation (Behn et al., 2022; Begley et al., 2017; Plosser and Santos, 2018).

IRB models, non-performing loans, and bank opacity

Banking authorities (ESRB, 2019; Enria, 2016) and academics (Flannery et al. 2004) have identified poor asset quality, as proxied by the share of NPLs, as a major source of bank opacity. NPLs contribute to increased opacity in bank balance sheets for several reasons. First, they generate cash flows that are unstable and hard to predict, as the uncertainty pertains to several aspects of the contract from the amount and timing of cash flows to the efficiency and effectiveness of the recovery procedure (Ciavoliello et al., 2016). Second, they are often associated with discretionary accruals such as loan loss provisions that bank managers may manoeuvre in order to smooth income and capital, as found in previous literature (Beatty and Liao, 2014). Third, high NPL ratios can distort bank managers' incentives, increase moral hazard, and promote excessive risk-taking by eroding bank capital (Peek and Rosengren, 2005). Consequently, all these factors make bank earnings even more unstable and uncertain.

As our analysis has shown that IRB models are beneficial to bank transparency, we expect that the detrimental effect of NPLs on balance sheet opacity should be mitigated in IRB (and especially AIRB) banks. In Internet Appendix Section IA.5.2, we empirically demonstrate that this is the case. In particular, we document that the impact of NPLs on bank opacity is neutralized when at least 13% of bank credit exposures are assessed under the advanced approach. This reinforces the view that AIRB models may be associated with better risk management practices, including more accurate NPL recognition and more timely provisions, and/or with richer and deeper information disclosure.

5. How do IRB models affect bank opacity?

Our results so far indicate that a more intensive usage of IRB models corresponds to lower bank opacity, but they do not clarify whether the risk management or the information disclosure mechanisms underlie this relationship. In theory, both are consistent. According to the former, IRB models may be associated with better risk management practices, potentially leading to more informative and less volatile earnings. The latter posits that IRB adoption also entails additional disclosure requirements included in banks' Pillar III reports, which may result in more valuable information on bank risk. Taken together, these two mechanisms may decrease informational asymmetries and enhance the accuracy of analysts' forecasts.

5.1. Risk management mechanism

5.1.1. Are IRB banks' earnings *more informative*?

We first investigate whether IRB usage affects earnings quality and, more broadly, balance sheet reliability. To test this hypothesis, we draw upon the literature on earnings quality, its determinants, and consequences (see Dechow et al., 2010, and the literature review therein). Among the factors influencing earnings quality, governance and controls serve as internal mechanisms that may mitigate managers' incentives for opportunistic earnings management. Therefore, when effective controls are in place, discretionary accruals and accounting misstatements should be less likely. Similarly, internal rating models that are crucial components of a bank's internal controls and governance procedures can contribute to enhancing the reliability of bank balance sheets. This, in turn, enhances earnings quality and improves forecast accuracy.

To assess the information content of banks' earnings and whether it differs between IRB and SA banks, we use the short-term equity market responses to earnings announcements to infer earnings quality (Teoh and Wang, 1993). Such inferences are based on the significance of the slope coefficient (β) in a linear regression model like $CAR_{i,t} = \alpha + \beta\, Surp_{i,t} + \varepsilon_{i,t}$, where $CAR_{i,t}$ is the cumulative absolute return for the firm *i* in time *t*, and $Surp_{i,t}$ is a measure of the earnings surprise and ε_t a random disturbance term. The coefficient β, commonly defined as the earnings response coefficient (ERC), serves as a measure of earnings quality.

This measurement is rooted in the idea that investors' response to an earnings surprise depends on the perceived credibility of the earnings report. To test if IRB banks exhibit better earnings quality than SA banks, we introduce the interacted term *Surp*×*IRB* into the previous specification and employ the following regression equation:

$$\begin{aligned} CAR_{i,t} = \alpha + \beta_1\, Surp_{i,t} + \beta_2\, IRB_{i,t-1} + \beta_3\, Surp_{i,t} \times IRB_{i,t-1} + \\ + \upsilon' \mathbf{\Phi}_{i,t-1} + \delta_i + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

CAR_{it} is the sum of bank *i* daily abnormal stock returns from day 1 before and day 1 after the announcement of earnings for year *t*. We employed an estimation window of 260 trading days (-261, -2) for the market model and adopted the MSCI World and the MSCI Europe as proxies for the market portfolio. *Surp* is the earnings surprise, defined as the I/B/E/S actual earnings per share minus the last mean analyst consensus forecast before the earnings-announcement date, scaled by the stock price 5 trading days before the announcement. *IRB* is either *IRB* or *AIRB dummy*. The vector $\mathbf{\Phi}_{i,t-1}$ of bank level controls includes *Size*, *Equity ratio*, the equity to total asset ratio, and *ROA*. β_3 is the coefficient of interest and captures whether *ERC* is different for (A)IRB banks. Table 5 reports the results. The coefficient of the multiplicative term variable *Surp*×*IRB* is positive and statistically significant in all the specifications, revealing that the earnings of adopters of (A)IRB models are more informative.

Insert Table 5 approximately here

5.1.2. What makes IRB banks' earnings more informative?

As risk management tools, IRB models implementation should lead to improved screening and monitoring of borrowers, as well as more timely and precise credit risk reporting. Consequently, IRB banks' financial statements should result more accurate and more informative.

IRB models and loan loss provisioning

The adoption of internal rating models may counter the incentive for strategic loan loss provisioning, thereby improving earnings quality. This improvement can be attributed to the higher quality of the underlying data used to calculate provisions. Additionally, bank supervisors expect banks to utilize these detailed data to achieve more timely and accurate provisioning. Given these considerations, we anticipate lower discretionary provisioning in banks that adopt internal ratings more extensively. To test this hypothesis, we define another specification of model (1) with a measure of the *discretionary* loan loss provisions as the dependent variable, as described in Section IA.6 of the Internet Appendix. The analysis, reported in Internet Appendix Table IA.13, indicates that there is no significant association between the degree of AIRB usage and discretionary provisioning for loan losses.

IRB models and NPL recognition

Previous research (Cucinelli et al., 2018) has demonstrated that IRB banks are better equipped to measure credit risk and differentiate among borrowers, leading to lower NPL ratios. In line with this finding, the enhanced granularity and risk sensitivity of internal ratings should improve banks' ability to identify problem loans as borrower creditworthiness deteriorates. Consequently, the reported amounts of NPLs should more accurately reflect the actual credit risk in IRB banks compared to SA banks.

To test this hypothesis, we exploit the first Asset Quality Review (AQR) conducted by the European Central Bank in 2014. The primary objective of this exercise was to enhance transparency and comparability of balance sheets across banks in preparation for the introduction of the single supervisory mechanism. As part of the review, banks were required to adjust the amount of NPLs based on a new, stricter, and standardized definition of non-performing exposures.[8] The banks under review were also subject to close supervisory scrutiny. The AQR resulted in a total increase of €136 billion (+18%) in NPLs, with over 12% of originally classified performing debtors requiring reclassification as non-performing. Bruno and Marino (2018) provide a comprehensive description of the institutional details of the AQR.

Out of the 43 banks in our sample, 24 underwent the AQR exercise. In 2013, the fiscal year to which the first AQR referred, 19 of these 24 banks were IRB banks, while the remaining 5 were SA banks. We employ the AQR adjustment of the NPL ratio (*ΔNPE*) from ECB data as a measure of balance sheet inaccuracy to gauge the discrepancy between the bank's financial statements information and a more objective assessment provided by the supervisor (ECB, 2014). Internet Appendix Table IA.14 shows the results of *t*-tests for the equality of the means of three different indicators of balance sheet inaccuracy. Overall, we observe lower NPL adjustments in IRB banks compared to SA banks. While not conclusive, this evidence supports the argument that IRB banks may demonstrate greater accuracy in reporting NPLs, suggesting

[8] The European Banking Authority (EBA) definition of NPE is broader than the one used in our paper, which focuses on NPL (Non-Performing Loans). According to the EBA, NPE includes any exposure that meets any of the following criteria: (1) every material exposure that is 90 days past its due date, even if not recognized as defaulted or impaired; (2) every impaired exposure; and (3) every exposure that is in default according to capital requirements regulation, indicating that the debtor is "unlikely to pay".

that their financial statements could provide a more precise representation of the bank's financial position and performance.

5.1.3. Are IRB banks' earnings *less volatile*?

We estimate a fixed effects panel regression model similar to Equation (1), where the dependent variable is bank earnings volatility. We argue that if the risk management mechanism is in place, banks implementing IRB models more widely could report less volatile earnings, along with better quality earnings. It follows that analysts' forecasts could improve not only because of greater informativeness but also due to the greater stability of IRB banks' earnings.

We proxy bank earnings volatility by the variation in banks' return on assets (ROA), or their return on equity (ROE), as in De Hann and Poghosyan (2012), or their Earnings before provisions and taxes over Total assets (EBPT ratio). We define earnings volatility for bank *i* in year *t* as the standard deviation of its ROA (ROE) [EBPT ratio] calculated, alternatively, over year *t*'s four quarters, or the 8 (over years *t* and *t*+1), or 12 (over years *t* to *t*+2) quarters to calculate volatility.

The explanatory variable in all the specifications is *AIRB weight*, the most relevant of all IRB measures according to our baseline analysis. Internet Appendix Table IA.15 reports the results. The coefficient of our explanatory variable is not statistically significant in all but one of the nine specifications. This means that a wider usage of AIRB models does not translate into a reduction of earnings volatility. It also suggests that internal ratings influence analyst forecasts by making bank balance sheets *more reliable* and not by rendering bank performance *less volatile*.

5.2. Information disclosure mechanism

An alternative (but not mutually exclusive) explanation of our main results lies in the idea that a more intensive usage of internal ratings implies the disclosure of relevant information in the Pillar III report.[9] This mandatory disclosure complements accounting-based information and regulators expect it to facilitate "assessment of the bank by others, including…analysts" (ESRB, 2013).

The difficulty in isolating and quantifying such incremental information makes a direct test of the impact of greater disclosure on forecasts challenging. In fact, the complementary (although mandatory) character of Pillar III has led national supervisors to adopt a non-prescriptive approach regarding Pillar III disclosure practices, resulting in differences in timeliness, presentation formats, and verification of disclosures.

For the information disclosure mechanism to be active, however, we should observe at least a positive relation between the usage of (A)IRB models and the amount of information released. To empirically test the existence of this relationship, we rely on qualitative and quantitative information contained in the Pillar III report and estimate the coefficients of the following fixed effects panel regression:

$$PILLAR3\ INFO_{i,t} = \alpha + \beta\ IRB_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \tag{4}$$

where *PILLAR3 INFO* is either the number of pages of the Pillar III report (*PIII pages*); the number of pages in the credit risk section (i.e., the part of the document specifically devoted to the credit and counterparty risk) (*PIII credit risk pages*); or the number of words and numbers in

[9] There is anecdotal evidence that the implementation of IRB models, or their extension to additional credit exposures like other portfolios or other subsidiaries within a banking group, goes along with the release of additional information in the Pillar III report. An example is provided in Internet Appendix Section IA.3.

this credit risk section (*PIII credit risk words*). *IRB* is alternatively defined as (*i*) *(A)IRB dummy*; (*ii*) *(A)IRB weight*; and (*iii*) *No of (A)IRB portfolios*.

We include bank fixed effects (δ_i), to control for time-invariant, unobserved bank characteristics that may simultaneously affect the IRB usage or degree of implementation and amount of information, and year fixed effects (μ_t), to control for time-specific events. The inclusion of bank fixed effects is particularly relevant for capturing idiosyncratic factors such as the "reporting style" of each bank.

Despite the limitation of the *PILLAR3 INFO* variables, notably their ability to signal the release of additional information *beyond* what is implied by the usage of IRB models, the results of our analysis support the information disclosure mechanism. In Table 6, we observe a positive and significant correlation between the size (length) of Pillar III (especially the "number of pages" and the "number of words and numbers" in the sections of the report describing the exposure to credit and counterparty risk) and the adoption of internal models, particularly the advanced ones.

Insert Table 6 approximately here

6. Conclusion

This paper contributes to the literature on the benefits and challenges of bank internal ratings by uncovering a positive effect that has not been explored before, namely the transparency-enhancing role of IRB models.

We examine the relationship between the usage of IRB models and bank opacity as measured by the absolute forecast error and the disagreement among equity analysts about the banks' expected earnings per share. Specifically, this paper presents five novel and interrelated empirical results. First, a more intensive usage of IRB models reduces errors in forecasting bank earnings per share and increases agreement among analysts. Second, this relationship strengthens the more the IRB models are implemented in their "advanced" version, and especially if they are applied to the corporate component of the bank's loan portfolio. Third, the most plausible explanations for our results are based on the greater informativeness of earnings and the more detailed disclosure of loan portfolios required for users of advanced internal ratings. Fourth, the usage of AIRB models mitigates the negative effect on bank opacity of problem loans. This finding in particular suggests that, *ceteris paribus*, AIRB users are better equipped to manage, and provide a clearer picture of, their NPL portfolios. This is significant not only due to the negative externalities typically associated with NPLs (Peek and Rosengren, 2005), but also considering the relevance of the NPL issue in the European policy agenda in recent years (ESRB, 2019). Fifth, the lack of a significant relationship between AIRB model usage and opacity in low-capital banks is consistent with existing empirical evidence suggesting that weakly capitalized banks are more prone to using internal ratings opportunistically (Plosser and Santos, 2018).

Together, our findings suggest that the implementation of IRB models enhances the transparency of bank balance sheets, especially of more opaque items such as corporate loans and problem loans. They also suggest that the additional reporting effort requested of IRB banks does not appear to be excessive and irrelevant as some within the banking industry have feared (Ralph, 2015). In doing so, the paper addresses potential concerns regarding the further promotion of internal rating models.

Appendix A

Variable definitions

Variables	Unit	Definition	Source
AIRB dummy	0/1	Dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models is higher than zero.	Banks' Pillar III reports
AIRB weight	%	Share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models.	Banks' Pillar III reports
AIRB *j*_portfolios		Dummy variable taking value 1 if the bank has *j* portfolio(s) with a share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models higher than zero (*j*=1, 2 or 3).	Banks' Pillar III reports
AIRB Corporate weight	%	Share of corporate credit exposures, in terms of EAD, evaluated with advanced internal models.	Banks' Pillar III reports
AIRB Retail weight	%	Share of retail credit exposures, in terms of EAD, evaluated with advanced internal models.	Banks' Pillar III reports
AIRB Government weight	%	Share of government credit exposures, in terms of EAD, evaluated with advanced internal models.	Banks' Pillar III reports
CAR	%	Cumulative abnormal returns for a 3-day event window (-1, 1) centered on the earnings announcement day with using an estimation window of 260 trading days (-261, -2) for the market model.	Bloomberg
Corporate exposure ratio	%	= Corporate credit exposures /(Corporate credit exposures + Retail credit exposures).	Banks' Pillar III reports
Deposits/TF	%	= Customer deposits/Total funding	BankFocus
Derivatives/TA	%	= Derivatives/Total assets,	BankFocus
Dispersion	%	Cross-sectional standard deviation of analysts' EPS forecasts.	I/B/E/S
Equity ratio	%	= Total equity/Total assets.	BankFocus
Forecast Error	%	Median of the analysts' absolute EPS forecast error, divided by the share price at the start of the fiscal year.	I/B/E/S
IRB dummy	0/1	Dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by internal ratings-based models is higher than zero.	Banks' Pillar III reports
IRB weight	%	Share of credit exposures, in terms of EAD, covered by internal ratings-based models.	Banks' Pillar III reports
IRB *j*_portfolios	0/1	Dummy variable taking value 1 if the bank has *j* portfolio(s) with a share of credit exposures, in terms of EAD, covered by internal ratings-based models higher than zero (*j* =1, 2 or 3).	Banks' Pillar III reports
IVIRB weight	%	Weighted (by total assets) average IRB weight of all other banks in the same country and year.	ECB statistical Data Warehouse and national regulatory authorities' websites
Liquid assets/TA	%	= Liquid assets/Total assets.	BankFocus
Loans/TA	%	= Total loans/Total assets.	BankFocus
NPLs/Loans	%	= Impaired loans/Total gross loans.	BankFocus
PIII pages		Number of pages of the Pillar III report.	Banks' Pillar III reports
PIII credit risk pages		Number of pages of the part of the Pillar III report devoted to credit and counterparty risk.	Banks' Pillar III reports
PIII credit risk words		Number of words and numbers in the part of the Pillar III report devoted to credit and counterparty risk.	Banks' Pillar III reports
Real estate return		Return on the house price index over the year.	OECD
ROA	%	Return on Assets.	BankFocus
Securities/TA	%	= Total securities/Total assets.	BankFocus
Size		= ln(Total assets).	BankFocus
Stock market return	%	Growth rate of the annual average stock market index (The annual average stock market index is constructed by taking the average of the daily stock market indexes available at Bloomberg).	www.theglobaleconomy.com
Surp	%	I/B/E/S actual earnings per share minus the last mean analyst consensus forecast before the earnings-announcement date, scaled by the stock price 5 trading days before the announcement.	I/B/E/S and Bloomberg
Trading assets/Securities	%	= Trading and fair value assets/Total securities	BankFocus
Tier 1 ratio	%	= Tier 1 capital/Risk weighted assets.	Banks' Pillar III reports
ΔGDP	%	Growth rate of the country's annual real gross domestic product.	World Bank

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Tables and figures

Table 1. Descriptive statistics

This table reports summary statistics for the main characteristics of the banks in the sample. Variables are defined in Appendix A.

	Unit	Mean	St. dev.	p10	p25	p50	p75	p90	N
Opacity measures									
Forecast Error	%	7.102	13.993	0.113	0.568	1.507	4.830	25.894	289
Dispersion	%	3.566	4.926	0.448	1.056	1.687	3.057	11.335	287
Internal rating model usage (lagged)									
IRB dummy	0/1	0.810	0.393	0	1	1	1	1	289
AIRB dummy	0/1	0.792	0.406	0	1	1	1	1	289
IRB weight	%	54.195	30.600	0.000	41.248	62.852	77.279	85.601	289
AIRB weight	%	47.020	30.444	0	23.761	52.416	72.163	80.994	289
No. of IRB portfolios		1.983	1.101	0	2	2	3	3	289
No. of AIRB portfolios		1.779	1.154	0	1	2	3	3	289
IRB Corporate dummy	0/1	0.789	0.409	0	1	1	1	1	289
IRB Retail dummy	0/1	0.779	0.416	0	1	1	1	1	289
IRB Government dummy	0/1	0.415	0.494	0	0	0	1	1	289
AIRB Corporate dummy	0/1	0.619	0.486	0	0	1	1	1	289
AIRB Retail dummy	0/1	0.779	0.416	0	1	1	1	1	289
AIRB Government dummy	0/1	0.381	0.486	0	0	0	1	1	289
IRB Corporate weight	%	62.280	36.177	0	51.609	75.238	89.809	98.204	289
IRB Retail weight	%	61.714	36.416	0	42.276	76.462	90.285	96.746	289
IRB Government weight	%	24.626	36.934	0	0	0	54.955	91.135	289
AIRB Corporate weight	%	46.599	39.741	0	0	64.829	84.066	92.303	289
AIRB Retail weight	%	61.714	36.416	0	42.276	76.462	90.285	96.746	289
AIRB Government weight	%	23.125	36.702	0	0	0	53.925	91.135	289
Balance sheet items (lagged)									
Loans/TA	%	54.089	16.956	28.306	41.9970	58.576	67.638	74.190	289
Corporate exposure ratio	%	52.596	13.641	35.356	42.518	53.065	61.509	67.693	289
NPLs/Loans	%	7.305	7.474	0.938	2.561	5.212	9.115	16.530	289
Securities/TA	%	18.717	7.431	9.893	14.169	17.817	21.804	28.293	289
Trading assets/Securities	%	40.704	28.060	4.505	14.507	39.501	64.624	81.214	289
Liquid assets/TA	%	12.266	7.033	4.826	7.068	10.374	15.566	22.403	289
Derivatives/TA	%	8.869	9.663	0.940	2.032	5.723	10.384	24.242	289
Deposits/TF	%	51.930	14.947	34.360	41.990	51.770	61.270	69.610	289
Tier 1 ratio	%	11.738	3.687	7.860	9.460	11.600	13.500	16.100	289
Equity ratio	%	5.755	2.659	3.096	4.241	5.570	7.130	9.000	289
ROA	%	8.137	138.029	-83.300	3.000	26.600	57.100	81.100	289
Total assets	€ mn	575,651	621,163	44,861	82,007	275,416	992,856	1,653,220	289
Country-level variables									
ΔGDP	%	0.088	3.310	-4.248	-1.841	0.778	1.949	2.864	289
Stock market return	%	1.659	18.25	-23.05	-11.48	4.36	14.80	20.96	289

Table 2. Usage of IRB models and bank opacity

This table reports the coefficient estimates of an OLS regression of bank opacity on the usage of internal ratings-based models. The dependent variables are the median of the analysts' absolute EPS forecast error, divided by the share price at the start of the fiscal year (*Forecast Error*, in columns 1-4) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 5-8). The main explanatory variables are: a dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by internal ratings-based models is higher than zero (*IRB dummy*, in columns 1 and 5); a dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models is higher than zero (*AIRB dummy*, in columns 2 and 6); the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*IRB weight*, in columns 3 and 7); and the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*, in columns 4 and 8). Variables are defined in Appendix A. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Forecast Error (*t*)				Dispersion (*t*)			
IRB dummy (*t*-1)	-5.088*				-0.688			
	(2.624)				(1.821)			
AIRB dummy (*t*-1)		-5.783*				-1.136		
		(3.182)				(1.275)		
IRB weight (*t*-1)			-0.149**				-0.059**	
			(0.060)				(0.026)	
AIRB weight (*t*-1)				-0.208***				-0.095***
				(0.052)				(0.024)
Loans/TA (*t*-1)	-0.005	-0.009	-0.001	0.054	-0.034	-0.035	-0.038	-0.016
	(0.241)	(0.241)	(0.243)	(0.234)	(0.061)	(0.060)	(0.058)	(0.051)
Corporate exposure ratio (*t*-1)	0.206	0.222*	0.205	0.222*	0.083*	0.086**	0.083**	0.089**
	(0.127)	(0.126)	(0.122)	(0.120)	(0.042)	(0.042)	(0.038)	(0.036)
NPLs/Loans (*t*-1)	0.581**	0.575**	0.577**	0.566**	0.166***	0.164***	0.162***	0.157***
	(0.219)	(0.220)	(0.218)	(0.215)	(0.054)	(0.054)	(0.052)	(0.052)
Securities/TA (*t*-1)	-0.026	-0.008	-0.007	0.029	0.001	0.006	0.015	0.033
	(0.216)	(0.209)	(0.205)	(0.205)	(0.037)	(0.035)	(0.033)	(0.033)
Trading assets/Securities (*t*-1)	-0.152**	-0.163**	-0.156**	-0.138**	-0.028	-0.030	-0.031	-0.023
	(0.064)	(0.067)	(0.064)	(0.064)	(0.021)	(0.022)	(0.020)	(0.019)
Liquid assets/TA (*t*-1)	0.018	0.006	0.065	0.063	-0.094	-0.098*	-0.077	-0.075
	(0.225)	(0.222)	(0.216)	(0.217)	(0.057)	(0.056)	(0.053)	(0.055)
Derivatives/TA (*t*-1)	0.141	0.174	0.199	0.205	0.119	0.127	0.147*	0.151**
	(0.294)	(0.297)	(0.291)	(0.292)	(0.074)	(0.077)	(0.078)	(0.073)
Tier 1 ratio (*t*-1)	0.847**	0.858**	0.877**	1.059***	0.135	0.138	0.147	0.221*
	(0.383)	(0.379)	(0.389)	(0.390)	(0.127)	(0.126)	(0.121)	(0.130)
Equity ratio (*t*-1)	-2.388**	-2.448**	-2.521***	-2.701***	-0.726***	-0.743***	-0.801***	-0.894***
	(0.908)	(0.910)	(0.912)	(0.911)	(0.205)	(0.201)	(0.204)	(0.222)
Deposits/TF (*t*-1)	-0.356**	-0.328*	-0.363**	-0.367**	-0.095**	-0.088**	-0.096**	-0.099***
	(0.172)	(0.172)	(0.173)	(0.166)	(0.039)	(0.040)	(0.038)	(0.035)
ROA (*t*-1)	-0.001	-0.001	0.001	0.001	-0.002	-0.002	-0.002	-0.001
	(0.012)	(0.012)	(0.012)	(0.012)	(0.004)	(0.004)	(0.004)	(0.004)
Size (*t*-1)	-2.290	-1.917	-3.286	-3.831	-0.652	-0.575	-1.123	-1.440
	(5.575)	(5.562)	(5.315)	(4.868)	(2.575)	(2.544)	(2.410)	(2.110)
ΔGDP (*t*)	-0.588**	-0.608**	-0.566**	-0.582**	-0.444***	-0.450***	-0.443***	-0.450***
	(0.283)	(0.280)	(0.279)	(0.275)	(0.094)	(0.093)	(0.092)	(0.083)
Stock market return (*t*)	-0.294***	-0.291***	-0.302***	-0.313***	-0.050**	-0.050*	-0.054**	-0.060**
	(0.107)	(0.108)	(0.107)	(0.108)	(0.025)	(0.025)	(0.025)	(0.026)
No. of obs.	289	289	289	289	287	287	287	287
No. of banks	43	43	43	43	42	42	42	42
Adj. R^2	0.284	0.286	0.291	0.313	0.406	0.408	0.421	0.472

Table 3. Usage of IRB models and bank opacity: Instrumental variables estimations

This table reports the first-stage (in columns 1 and 3) and the second-stage (in columns 2 and 4) coefficient estimates of instrumental variables regressions of bank opacity on the usage of internal ratings-based models. The dependent variable of the first stage regression is the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*IRB weight*); the instrument *IVIRB weight* is – for a bank *i* – the weighted (by total assets) average *IRB weight* of all other banks in the same country and year as bank *i*. The dependent variables of the second-stage regressions are: the median of the analysts' absolute EPS forecast error, divided by the share price at the start of the fiscal year (*Forecast Error*, in column 2) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in column 4). *IRB weight* has been instrumented using *IVIRB weight*. Control variables (not reported for brevity) are the same as in Table 2. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses. The last row contains the *F* -test for the null hypothesis that our instrument is week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) **First stage** **IRB weight (*t*-1)**	**(2)** **Second stage** **Forecast Error (*t*)**	**(3)** **First stage** **IRB weight (*t*-1)**	**(4)** **Second stage** **Dispersion (*t*)**
IVIRB weight (*t*-1)	0.674*** (0.060)		0.672*** (0.060)	
IRB weight (*t*-1)		-0.209 (0.134)		-0.0909** (0.039)
Controls	Yes	Yes	Yes	Yes
No. of obs.	289	289	287	287
No. of banks	43	43	42	42
F stat	122.51		121.68	

Table 4. Usage of IRB models across different credit exposures and bank opacity

This table reports the coefficient estimates of an OLS regression of bank opacity on various measures of usage of internal ratings-based models. The dependent variables are the median of the analysts' absolute EPS forecast error, divided by the share price at the start of the fiscal year (*Forecast Error*, in columns 1-6) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 7-12). The main explanatory variables are: three dummy variables taking value 1 if the bank has one/two/three portfolio(s) with a share of credit exposures, in terms of EAD, covered by internal ratings-based models higher than zero (*IRB 1portfolios*, *IRB 2portfolios*, and *IRB 3portfolios*, columns 1 and 7); three dummy variables taking value 1 if the bank has one/two/three portfolio(s) with a share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models higher than zero (*AIRB 1portfolios*, *AIRB 2portfolios*, and *AIRB* 3*portfolios*, columns 2 and 8); three dummy variables taking value 1 if the share of corporate/retail/government credit exposures, in terms of EAD, covered by internal ratings-based models is higher than zero (*IRB Corporate dummy*, *IRB Retail dummy*, *IRB Government dummy*, columns 3 and 9); three dummy variables taking value 1 if the share of corporate/retail/government credit exposures, in terms of EAD, covered by advanced internal ratings-based models is higher than zero (*AIRB Corporate dummy*, *AIRB Retail dummy*, *AIRB Government dummy*, columns 4 and 10); the share of corporate (retail) [government] credit exposures, in terms of EAD, evaluated with internal models (*IRB Corporate*(*Retail*)[*Government*] *weight*, columns 5 and 11); and the share of corporate (retail) [government] credit exposures, in terms of EAD, evaluated with advanced internal models (*AIRB Corporate*(*Retail*)[*Government*] *weight*, columns 6 and 12). Control variables (not reported for brevity) are the same as in Table 2. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Forecast Error (*t*)						**Dispersion (*t*)**					
	IRB	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*
1portfolios (*t*-1)	-1.693	-2.901					0.509	0.073				
	(2.463)	(2.933)					(1.739)	(1.309)				
2portfolios (*t*-1)	-8.991**	-8.481**					-2.194*	-2.404**				
	(3.763)	(3.248)					(1.178)	(0.922)				
3portfolios (*t*-1)	-24.415**	-18.658***					-5.195*	-6.262***				
	(9.435)	(5.077)					(2.829)	(1.930)				
Corporate dummy (*t*-1)			-6.954	-6.813**					-3.061**	-2.733**		
			(4.993)	(3.272)					(1.497)	(1.203)		
Retail dummy (*t*-1)			-6.884	-5.438					-1.098	-0.619		
			(4.594)	(4.268)					(1.547)	(1.393)		
Government dummy (*t*-1)			-2.208	-5.231					1.100	-3.064		
			(2.546)	(4.133)					(0.796)	(2.183)		
Corporate weight (*t*-1)					-0.156**	-0.130***					-0.055**	-0.052***
					(0.069)	(0.039)					(0.021)	(0.017)
Retail weight (*t*-1)					-0.036	-0.026					-0.018	-0.010
					(0.048)	(0.042)					(0.015)	(0.013)
Government weight (*t*-1)					0.020	-0.014					0.006	-0.017
					(0.036)	(0.033)					(0.019)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	289	289	289	289	289	289	287	287	287	287	287	287
No. of banks	43	43	43	43	43	43	42	42	42	42	42	42
Adj. R^2	0.299	0.315	0.294	0.311	0.303	0.312	0.418	0.459	0.416	0.453	0.437	0.464

Table 5. Usage of IRB models and the informational content of bank earnings

This table reports the coefficient estimates of an OLS regression of investors' response on the unexpected earnings. The dependent variable is the bank cumulative abnormal return (*CAR*) for a 3-day event window (-1, 1) centered on the earnings announcement day, computed using either the MSCI World (in columns 1-4) or the MSCI Europe (in columns 5-8) as proxy for the market portfolio. The main explanatory variables are: the I/B/E/S actual earnings per share minus the last mean analyst consensus forecast before the earnings-announcement dates, scaled by the stock price 5 trading days before the announcement (*Surp*); a dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by internal ratings-based models in year *t*-1 is higher than zero (*IRB dummy*, in columns 1, 3, 5, and 7); a dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models in year *t*-1 is higher than zero (*AIRB dummy*, in columns 2, 4, 6, and 8); and the interaction between *Surp* and either *IRB dummy* or *AIRB dummy*. Control variables (in specifications 3-4 and 7-8) include *Equity ratio*, *ROA* and *Size* (defined in Appendix A) and are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR (*t*) (Market index: MSCI World)				**CAR (*t*) (Market index: MSCI Europe)**			
Surp (*t*)	0.052**	0.051**	0.055***	0.054***	0.061**	0.060**	0.062***	0.061***
	(0.022)	(0.022)	(0.019)	(0.019)	(0.023)	(0.023)	(0.022)	(0.022)
IRB dummy (*t*-1)	0.176		0.160		0.616		0.597	
	(1.243)		(1.292)		(1.230)		(1.296)	
$Surp_t$ × IRB dummy (*t*-1)	0.230**		0.222**		0.203*		0.213*	
	(0.105)		(0.108)		(0.113)		(0.114)	
AIRB dummy (*t*-1)		-0.260		-0.272		0.197		0.178
		(1.050)		(1.078)		(1.015)		(1.047)
$Surp_t$ × AIRB dummy (*t*-1)		0.232**		0.224**		0.205*		0.215*
		(0.106)		(0.109)		(0.113)		(0.114)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
No. of obs.	282	282	282	282	282	282	282	282
No. of banks	42	42	42	42	42	42	42	42
Adj. R^2	0.060	0.060	0.051	0.051	0.041	0.040	0.034	0.033

Table 6. Usage of IRB models and Pillar III report size

This table reports the coefficient estimates of an OLS regression of the size (in terms of number of pages and words) of the Pillar III reports on the usage of internal ratings-based models. The dependent variables are: the number of pages of the Pillar III report (*PIII pages*, in column 1); the number of pages in the section of the Pillar III report dedicated to credit and counterparty risk (*PIII credit risk pages*, in column 2); and the number of 'words and numbers' in the same credit risk part of the Pillar III report (*PIII credit risk words*, in column 3). The explanatory variables are: a dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by internal ratings-based models is higher than zero (*IRB dummy*); a dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models is higher than zero (*AIRB dummy*); the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*IRB weight*); the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*); the number of portfolios in which the bank uses the IRB approach (*No. of IRB portfolios*); and the number of portfolios in which the bank uses the AIRB approach (*No. of AIRB portfolios*). All specifications include bank fixed effects and year fixed effects. The standard errors of the coefficients and the adjusted R^2 of the regressions are shown in brackets and in parentheses, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

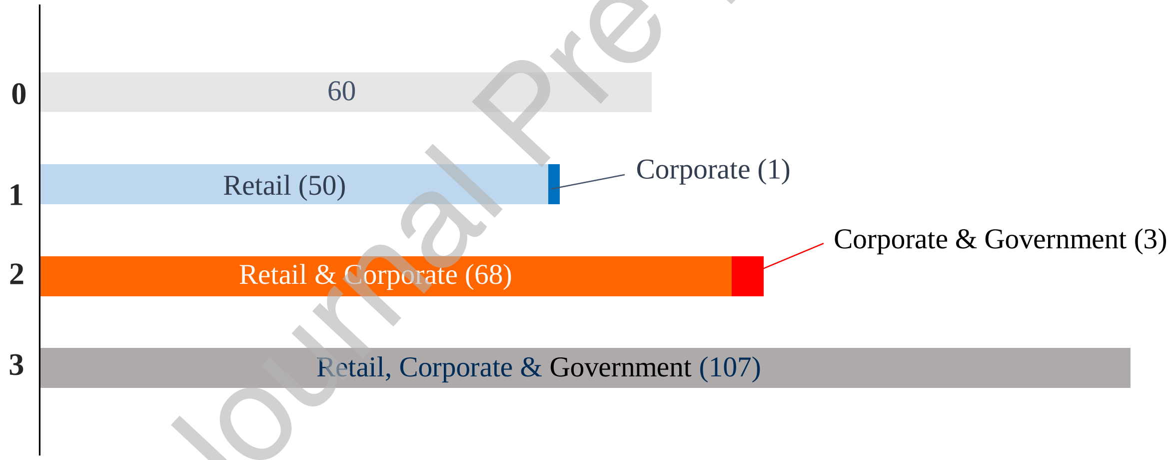
	(1) **PIII pages**	(2) **PIII credit risk pages**	(3) **PIII credit risk words**
IRB dummy	22.62*	6.368	4,214***
	(12.54)	(4.484)	(1,342)
	[0.509]	[0.323]	[0.386]
AIRB dummy	22.65**	7.400**	3,359***
	(9.361)	(3.346)	(1,005)
	[0.514]	[0.331]	[0.389]
IRB weight	0.433**	0.169***	52.48**
	(0.180)	(0.064)	(19.47)
	[0.514]	[0.336]	[0.379]
AIRB weight	0.230	0.144***	45.21***
	(0.144)	(0.051)	(15.39)
	[0.508]	[0.339]	[0.383]
No. of IRB portfolios	13.68**	5.396**	1,862***
	(5.859)	(2.085)	(631.4)
	[0.514]	[0.336]	[0.383]
No. of AIRB portfolios	6.235	2.887**	1,009**
	(4.008)	(1.425)	(432.1)
	[0.507]	[0.329]	[0.375]
No. of obs.	289	289	289
No. of banks	43	43	43

Figure 1. Number and type of portfolios under the (A)IRB approach

This figure shows the number (and the type) of credit risk exposures evaluated according to the IRB approach (Panel *A*) and the AIRB approach (Panel *B*) for the 289 bank-year observations of the main analysis.

Panel A

Panel B



CRediT author statement

Brunella Bruno: Conceptualization, Writing - Original Draft, Writing - Review & Editing
Immacolata Marino: Software, Formal analysis, Data Curation
Giacomo Nocera: Resources, Conceptualization, Methodology