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Internal Ratings, Non-Performing Loans, and Bank Opacity: Evidence from Analysts' Forecasts

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Internal Ratings, Non-Performing Loans, and Bank Opacity: Evidence from Analysts' Forecasts

Brunella Bruno♣, Immacolata Marino♥, and Giacomo Nocera♦

Abstract
We use a panel data set of large listed European banks to evaluate the effect of the usage of internal ratings-based (IRB) models on bank opacity. We find that a more intensive implementation of these models is associated with lower absolute forecast error and disagreement among analysts about bank earnings per share. The results are stronger in banks adopting the advanced version of IRB models. In these banks the negative effect of non-performing loans on bank transparency is mitigated. We deal with concerns regarding omitted variables and reverse causality using an instrumental variables approach. Our results are driven by the more in-depth disclosure of the credit risk exposures that follows the adoption of IRB models.

JEL Classification: G20; G21; G28

Keywords: Bank regulation, Basel II, risk-weighted assets, transparency

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1. Introduction

An important, but unexplored topic is whether the usage of internal ratings, i.e., a bank's internal assessment of risk exposures for the computation of minimum capital requirements, accentuate or mitigate bank opacity.

A large literature in banking has studied the critical question of bank opacity (in particular: Morgan, 2002; Flannery et al., 2004; and Hirtle, 2006). It is conventional wisdom that banks, owing to their particular asset and liability composition, are informationally opaque institutions by their own nature. As for the asset side, theory predicts that bank loans are opaque because bank insiders may possess valuable private information about the borrowers' creditworthiness or the bank's monitoring efforts (Campbell and Kracaw, 1980). On the liability side, high leverage, combined with a large proportion of insured liabilities (which reduce creditors' incentives to monitor banks' behavior), increases information asymmetry and raises moral hazard concerns. This induces agency costs in the form of a higher external funding premium (Bernanke and Gertler, 1995). By making bank funding more expensive, opaque assets may also impair banks' core functions such as the supply of credit to the real economy. For these reasons, bank balance sheet transparency is at center of the debates on bank fragility and regulation (Goldstein and Sapra, 2014).

In this study, we present the first empirical analysis of the impact that the usage of internal ratings has on bank opacity. We address this issue by looking at the absolute forecast error and the disagreement among equity analysts about the expected earnings per share (EPS) as measures of bank opacity. Specifically, we investigate whether and to what extent the intensity of internal rating implementation influences the analysts' assessment of bank performance. Previous works have shown that analysts' earnings forecasts can be used to derive independent (external) assessment of firm opacity (Flannery et al. 2004). *Ceteris paribus*, larger analyst absolute forecast errors or greater disagreement among analysts' forecasts implies that the firm is harder to assess.

There are two contrasting views of the potential effect of internal ratings on bank opacity. In principle, the usage of internal ratings may prove useful in reducing uncertainty around bank balance sheets because of two favorable mechanisms commonly associated with IRB adoption: more effective risk management and enhanced information disclosure requirements. As for the first mechanism, better risk models and management practices could lead to more accurate loan loss provisioning and pricing schemes. This would make future earnings more stable and predictable. As for the second mechanism, since IRB banks (i.e., banks adopting IRB models) 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 could result in more accurate earnings forecasts. However, since the global financial crisis, the validity of internal ratings has been at the core of market scrutiny as regards potential opportunistic risk reporting and miscalculation of capital requirements. At that time, several IRB banks, although complying with the minimum regulatory requirements, were found to be inadequately capitalized. Banks reported wide variation in risk weighted assets (RWAs). Where IRB models were implemented more comprehensively, banks and banking systems disclosed relatively lower RWA densities (i.e., the share of RWA over total assets) (Le Leslè and Avramova, 2012). Several studies corroborated the existence of strategic risk-modelling in IRB banks (Mariathasan and Merrouche, 2014; Behn et al., 2016; Berg and Koziol, 2017).

Against this background, we exploit the institutional features of IRB implementation among European banks from 2008 to 2015 to understand how internal ratings influence bank opacity. The focus on Europe and this specific time horizon provide an insightful setting for several reasons.

IRB models have been adopted in Europe by a wider array of banks than in the US where they are used only by top tier institutions.[1] Released in 2004, the Basel II rules that introduced internal ratings were accepted at the European Union (EU) level in 2006. Nevertheless, widespread IRB implementation occurred only two years later. The adoption has been gradual and uneven among banks. Before the introduction of the Single Supervisory Mechanism in late 2014, the lack of transparency and comparability across banks has made Pillar III reporting particularly valuable for market participants.

We proceed in four steps. Drawing on previous research on the determinants of bank opacity, we first check the validity of our transparency measures by testing how asset composition, funding structure and macroeconomic variable indicators affect analysts' forecast of bank earnings. As expected, we find absolute forecast errors and dispersion to rise when the share of the most opaque components of loan portfolio (i.e., non-performing loans (NPLs) and corporate loans) increases;[2] when the "plain" (i.e., non-risk-weighted) capital ratio decreases; and during economic downturns.

Second, in our main analysis, we enrich the explanatory variables of our econometric model with several measures of IRB model implementation in order to exploit the gradual and heterogeneous IRB adoption by European banks. Our primary variables of interest include both an indicator variable denoting the adoption of internal ratings by a bank, for an extensive margin analysis, and a continuous variable (i.e., the share of credit exposures evaluated with the IRB approach), to account for the impact of different degrees in IRB implementation. We also introduce an "advanced" version of the same variables to account for the *advanced* version of the model (the AIRB approach) and to capture its higher degree of sophistication in measuring credit risk. We

[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.

[2] This result is consistent with the findings in Campbell and Kracaw (1980), Arnould et al. 2020), and Flannery et al. (2004).

expect any effect on analysts' forecasts to be stronger when banks adopt (more intensively) the advanced as opposed to the *foundation* IRB (FIRB) approach since the former models are more granular and risk-sensitive.[3] In addition, banks adopting AIRB models are required to release even more information on their internal risk parameters.[4] We also look at the number and the type of credit portfolios (corporate, retail, and government) under internal ratings. This analysis is important to account for the heterogenous implementation of IRB models across banks and over time.

Overall, we find that it is not the adoption *per se*, but the intensity of internal ratings usage that impacts and reduces bank opacity. Moreover, banks are more transparent when they apply the IRB models to all their credit portfolios as opposed to a single portfolio. Bank transparency benefits from the adoption of IRB models especially if they are used to assess corporate credit portfolios. All these results are statistically and economically stronger for banks that implement the advanced IRB model.

To alleviate the concern that the IRB variable is not fully exogenous to bank opacity, we implement a two-stage least-square regression, in which we employ the average IRB adoption of other banks in the country as an instrument for the IRB variable. The instrumental variable results confirm that IRB usage is negatively and significantly associated with our measures of bank opacity.

As a third step, we investigate whether and to what extent the usage of an IRB model mitigates the intrinsic opacity of non-performing loans. Loans that are past due or unlikely to be repaid, i.e.,

[3] In the FIRB approach, banks only estimate the borrowers' probability of default, whereas AIRB banks also measure expected recoveries on impaired loans and changes in exposure in case of default.
[4] Pillar III reports in AIRB banks provide details on, e.g., the loss rates experienced on past defaulted loans, which provide a useful benchmark against which current loan loss provisions can be set. They also contain information on loan portfolios broken down by industry and geography for both performing and non-performing exposures.

NPLs, are not only risky, but also highly opaque assets according to banking authorities (ESRB, 2017; EBA, 2019). Our results show that advanced IRB models mitigate the opacity-increasing effect of NPLs. Specifically, we determine that the negative impact of NPLs on bank opacity is neutralized when at least 21% of bank credit exposures are assessed under the advanced approach.

Lastly, we explore the mechanism through which the usage of the IRB approach translates into higher transparency. Our findings suggest that the more likely mechanism by which IRB models enhance bank transparency lies in their wider and deeper informational disclosure.

The paper contributes to various strands of literature. To the best of our knowledge, this is the first study investigating the nexus between internal ratings and bank opacity. We extend research on the effects of internal ratings by providing a novel perspective on the benefits and potential misuses of IRB implementation. By showing the overall benefits of IRB adoption in terms of reduced opacity, the paper addresses some potential regulatory and supervisory concerns about whether and to what extent the internal rating models should be allowed.

We also contribute to the analyst forecast literature as we show that IRB information can be a useful input in analysts' forecasting process mainly due to the disclosure of more granular data. In this respect, our findings contribute to the debate on the cost of compliance with supervisory reporting (EBA, 2021), providing evidence of the beneficial effects of enhanced public disclosure practices.

This paper offers another important contribution concerning our evidence pertaining to the discussion on NPLs. Problem loans have recently become a first-order priority for European banking authorities who are concerned that high levels of NPLs would increase systemic risk and impair the supply of credit to the real economy (ESRB, 2017; ESRB, 2019). By making bank assets harder to assess, NPLs could increase funding costs, impair funding capacity and, thus, threaten banks' ability to make loans. Understanding how banks can mitigate the negative effect of NPLs on bank transparency could help design more calibrated measures to cope with problem loans.

Our paper is structured as follows. Section 2 illustrates the institutional background and develops the main hypotheses. Section 3 discusses the data and the empirical methodology. Section 4 presents the empirical results and their economic interpretation, and Section 5 examines the mechanisms that might explain the observed results. Section 6 concludes.

2. Institutional background and hypotheses development

In this section we start by providing some background information on the objective and institutional details of the IRB approach. The institutional framework sheds light on potential implications of IRB models, suggesting that both "opportunistic" and "transparency-enhancing" usages of IRB models are plausible. We then formulate hypotheses about whether and how IRB implementation influences bank opacity.

2.1. Institutional background

2.1.1. IRB models and capital regulation

The usage of internal ratings

Prudential regulation requires banks to hold a minimum amount of their own funds ("regulatory capital") to absorb unexpected losses that may originate from risky investments. The riskier the banking activity, the higher the amount of capital banks must set aside to comply with the minimum requirements. Therefore, capital holdings are required to increase proportionally to the bank's RWAs.

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

In the IRB approach, four variables define the credit risk of an exposure: the borrower's probability of default (PD); the loss given default (LGD); the exposure size at default (EAD); and the life-to-maturity. While PDs are borrower specific, LGD and EAD reflect certain characteristics of the transaction such as loan facility, loan seniority and collateral.[5] In its basic formulation, the FIRB approach requires banks to estimate internally only the PD of each borrower and to employ this estimate to quantify the capital absorbed by each exposure. A bank adopting the "advanced" (AIRB) approach estimates all four parameters internally.

The assessment of these parameters requires extensive historical data on borrowers' past defaults and transaction-specific factors as well as complex methodologies to calibrate risk parameters. To draw out meaningful results, banks need robust systems in place to validate the accuracy and consistency of rating systems, processes, and estimates of risk components. This means, for example, that banks must regularly compare realized default rates with estimated PDs

[5] For example, the LGD is expected to be low if the exposure is secured by high-quality collateral and the EAD is expected to increase if the borrower draws additional credit lines. Long-term, large exposures with high PD and LGD convert into higher risk-weighted assets and therefore into larger capital absorption (Resti, 2016).

and demonstrate that realized default rates are within the expected range for that grade.[6] 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.

The temporary and permanent partial usage of IRB

To avoid cherry picking and minimize capital arbitrage strategies, the IRB approach must apply to all bank exposures. However, implementation occurs gradually over time, according to a procedure that is known as the partial usage of IRB. Commonly, banks start applying IRB to loan portfolios with extensive historical data in active businesses. Then, IRB models roll out across different exposures and business units according to a plan agreed between the bank and the national supervisors.[7]

Besides the temporary partial usage during the implementation phase, the Basel rules allow banks to follow the standardized approach permanently for certain *non-material* exposures, such as exposures to non-major operational units and insignificant counterparties in terms of size and level of risk for which IRB implementation would be both statistically unreliable and too costly.

The 2004 Basel II rules were transposed at the EU level in 2006,[8] with some relaxation of the terms of the original framework. In particular, contrary to the materiality criterion, the EU Capital requirement regulation allowed national competent authorities the discretion to authorize the

[6] According to banking rules, these comparisons must make use of historical data that are over as long a period as possible. Methods and data used in such comparisons must be updated at least annually.
[7] Section IAI in the Internet Appendix describes an example of IRB gradual adoption by a bank in our sample.
[8] See the Capital Requirements Directive (2006/48/EC and 2006/49/EC) (CRD).

permanent partial usage even for "domestic" sovereign exposures (CRR, art. 148 and 150). These are euro-denominated exposures to EU central governments and central banks to which a 0% risk weight can be applied, regardless of the actual credit risk of the sovereign.[9]

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

Beyond capital requirements: risk management practices and disclosure requirements

The scope of application of internal ratings goes beyond the calculation of capital requirements. The banking regulators argued that IRB models have so many managerial applications that using them for the sole purpose of calculating the capital requirement would be considered "unacceptable" (BCBS, 2006).

In many banks, internal ratings form an integral part of management information about the quality structure of the loan portfolio, which allows for close monitoring of its risk composition, the aggregated exposure for all rating grades, and the limits assigned. Rating information serves as a basis for a bank's provisioning and loan loss reserve policy. It is also an input for loan pricing in the loan origination process and for profitability analysis. In particular, the greater granularity of risk weights and risk sensitivity of IRB models as opposed to the standardized approach enable banks to price their loans more efficiently, thus mitigating adverse selection issues. In more sophisticated banks, the results of the rating processes provide the basis for economic capital allocation systems.[10] Overall, previous work on the impact of IRB models on risk management, loan pricing and bank profitability supports the view that internal ratings strengthen incentives for

[9] Because of the currency union, the exemption is automatically applicable to all banks within the euro area holding euro-denominated government debt, leading to preferential treatment of the respective bonds despite the differences in credit risk among governments (Deslandes and Magnus, 2019).

[10] "Most of the advantages will come from the management and operating results obtained from the systematic application of the new methodologies that should make it possible to improve risk management and control capabilities as well as increase the efficiency and effectiveness of customer service". ISP Pillar III, 2008.

banks to manage risk more effectively. Repullo and Suarez (2004) show that low-risk firms obtain lower loan rates by borrowing from banks adopting the IRB approach. Cucinelli et al. (2018) reveal that IRB banks' credit risk increased less in the aftermath of the global financial crisis than banks that adopted the standardized approach. Mascia et al. (2019) find that IRB models improve credit risk-management and banks' profit margin due to higher investment in interest-earning assets and lower funding costs.

IRB adoption provides another potential benefit. Since IRB models require a large amount of qualitative and quantitative information on borrowers, collateral, and loan facilities, IRB banks have, in principle, an information competitive advantage over banks with less sophisticated approaches. Interestingly, IRB banks make this information advantage available to their investors as a result of the Pillar III disclosure requirements. In fact, under Pillar III rules, banks are asked to disclose relevant data and information about their risk exposures and risk management approach, which are more detailed in IRB banks (as opposed to banks adopting the standardized model), and even more so when the advanced approach is in place (as opposed to the foundation approach).[11] Greater disclosure would make market participants (investors, financial analysts, rating agencies, etc.) better able to exert market discipline.

Criticisms of internal ratings

Despite these potential benefits, the shift towards the IRB approach came at a cost. The greater granularity and complexity of internal rating systems (especially in the advanced version) made

[11] Quantitative details can be provided in terms of amounts of exposures, PD and LGD, with a breakdown by type of exposure and geography.

external scrutiny more difficult and provided IRB banks the incentive to capital arbitrage by manipulating risk weights. [12]

In fact, the adoption of IRB coincided with a substantial increase in capital ratios for many banks and a suspiciously wide variability in large banks' RWAs. This impaired comparability of capital ratios and raised doubts on the credibility of risk-based capital measures (Le Leslè and Avramova, 2012; Bastos e Santos, et al. 2020). Investors started arguing that banks might not be as capitalized as suggested by risk-based measures (Barclays Capital, 2011; Masters, 2012).[13] Several studies investigated the extent to which discrepancies in risk weights could be justified by differences in underlying portfolios and business models (see Bruno et al., 2017 and the literature review therein). Consistent with a strategic usage of IRB, academic research found evidence of intentionally biased risk estimates to lower regulatory capital requirements, calling for simpler rules to increase the efficacy of financial regulation (Mariathasan and Merrouche, 2014; Behn et al., 2016; Abbassi and Schmidt, 2018; Plosser and Santos, 2018; Bastos e Santos et al., 2020).

Basel III, the third international accord on bank capital agreed in late 2010, provided the first regulatory response to curb biases due to opportunistic or flawed internal ratings, by e.g., introducing a non-risk-adjusted minimum capital ratio. In December 2017, the Basel Committee introduced revisions to the Basel III rules in order to restore credibility to the calculation of RWAs and improve the comparability of banks' capital ratios. The reforms constrain the usage of advanced internal models; enhance the risk sensitivity of the standardized approaches; increase the

[12] In some authors' view (Haldane and Madouros, 2012), the inappropriate regulatory framework, by providing an explicit capital incentive to pursue internal models, effectively provided a subsidy to complexity.

[13] The large gap between RWAs and total assets, combined with the wide risk weight heterogeneity across IRB banks, fed mistrust in internal ratings and undermined confidence in risk-weighted capital ratios also among market participants (Barclays Capital, 2011).

leverage ratio requirement for global systemically important institutions; and introduce an aggregate output floor to RWA based on the standardized approaches (BCBS, 2017).

2.2. Hypotheses development

2.2.1. IRB models and bank opacity

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 internal ratings-based models affects bank opacity.

On the one hand, a more intensive usage of internal ratings may entail more accurate provisioning and more timely NPL recognition, making balance sheets more reliable. Also, better risk models and practices could help stabilize banks' profits. All these effects, which we refer to as the "risk management mechanism", would make it easier for market analysts to predict bank earnings. Furthermore, IRB adoption requires the release of more accurate information to market participants. Hence, a greater adoption of the IRB approach would reduce bank opacity, suggesting a "transparency-enhancing" usage of IRB models. We refer to this effect as the "information disclosure mechanism".

On the other hand, IRB banks could manipulate risk weights, making their key performance indicators less reliable. In this view, the more intensive application of internal ratings would increase bank opacity, leading to an "opportunistic" usage of IRB models.

These contrasting arguments show that the net effect of the usage of internal ratings on bank opacity is ambiguous and hard to predict. Therefore, whether the net change in opacity is positive or negative for the average bank raises an empirical question which constitutes our two first opposing testable hypotheses:

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

or

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

For the reasons explained in the institutional section (Section 2.1.1), 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.*

2.2.2. IRB models, NPLs, and bank opacity

Banking literature (Arnould et al., 2020) has identified asset quality as an important source of bank opacity. A common indicator of asset quality lies in the amount of non-performing loans, that is loans that are either more than 90 days past their repayment date or loans that are unlikely to be repaid in full. NPLs have recently become a key priority for prudential authorities in Europe because of their multiple negative externalities (ESRB, 2019).[14]

NPLs increase bank balance sheet opacity for many reasons. First, NPLs generate cash flows that are unstable and hard to predict. Second, a greater amount of NPLs are often associated with increasing loan loss provisions (LLPs). Because LLPs are discretionary, bank managers may

[14] NPLs in European banks, that skyrocketed to unprecedented levels in the wake of the global financial crisis and the euro sovereign crisis, have decreased only recently thanks in part to the pressure of the European supervisors. According to the EBA, the NPL ratio of European Union (EU) financial institutions has decreased on average from 6% as of mid-2015 to 3% as of mid-2020. However, discrepancies across banks and countries remain significant. As for the recent scenario, tightening financial conditions, slowing GDP growth, inflation and supply-chain bottlenecks may reverse the NPLs downtrend.

provision more or less than necessary in order to smooth income and capital. This would introduce discretionary modifications to earnings and reduce comparability across firms as found in previous literature (Walter, 1991). Third, high NPL ratios can also distort bank managers' incentives, increase moral hazard and promote excessive risk-taking by eroding bank capital (Bruno and Marino, 2018). In turn, this would make bank profits even more unstable.

If banks use IRB models opportunistically, those with a larger share of NPLs would have even more incentives to manipulate risk weights strategically. If instead IRB models are beneficial to bank transparency, due to the risk management and/or the information disclosure mechanism, the effect of NPLs on balance sheet opacity would be mitigated in IRB banks. Thus, implementation of IRB models would either reinforce or alleviate the detrimental effect of NPLs on bank opacity depending on whether banks use internal ratings opportunistically or not. This constitutes our third hypothesis:

H3*: The effect of NPLs on bank opacity depends on the usage of internal ratings-based models, in line with H1a or H1b.*

3. Data and empirical methodology

3.1. Sample and data sources

We build a cross-country sample of large listed European banking groups. 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 countries.[15] Italy, the country with the largest number of observations, generates about 17% of the

[15] Table A.1, in the Appendix, lists the 43 banks in the sample.

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. We collected information from several sources: I/B/E/S for analysts' forecasts; Moody's Analytics BankFocus for annual consolidated balance sheet data; and banks' 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 EAD) for which the IRB approach is used; the retail vs the corporate component of the loan portfolio; and the Tier 1 capital ratio. Although compulsory for most banks, Pillar III reports did not follow a standard structure as a common reporting template was only introduced in 2019. Hence, we had to extract and reconcile data items by hand. In our sample 34 banks used internal models to assess credit risk during the entire sample period, two banks started using them in 2011 and 2013, respectively, and only seven banks did not use them at all.

3.2. Methodology

To evaluate the effect of the usage of IRB (AIRB) models on bank opacity and test the first two hypotheses, 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:

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

Following Flannery et al. (2004) and Anolli et al. (2014),[16] we measure the dependent variable, *OPACITY*, in terms of *MAFE* (Median Absolute Forecast Error) and *Dispersion* of bank *i* in year *t*. *MAFE* 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 guess. *Dispersion* indicates the cross-sectional standard deviation of EPS forecasts, computed only for banks with more than one analyst. This functions 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, *IRB dummy* (*AIRB dummy*), takes value 1 if the share of credit exposures, in terms of EAD, covered by (advanced) internal ratings-based models exceeds zero. This variable represents our extensive margin measure of (A)IRB usage. The continuous variable, *IRB weight* (*AIRB weight*), measures the degree of IRB models' usage to assess credit risk by a bank as it is defined as the share of credit exposures, in terms of EAD, covered by (advanced) internal ratings-based models.[17] We use these variables to test *H1* and *H2*. In particular, the comparison between the impact of *IRB dummy* and *IRB weight* vs *AIRB dummy* and *AIRB weight* on *OPACITY* allows us to test *H2*.

The vector $X_{i,t\text{-}1}$ of bank level controls includes variables that, according to previous studies, can affect bank balance sheet transparency. We measure bank characteristics at *t*-1 to mitigate endogeneity concerns.

[16] All variable definitions and sources are reported in Table A.2, in the Appendix.
[17] To the best of our knowledge the existing empirical analysis on the usage of IRB models has been based on the *IRB dummy* variable only. The difference in the degree of usage of such models and the role of their advanced version has been previously taken into account only by Ferri and Pesic (2016).

Based on bank opacity literature, we expect asset composition and asset quality to affect analysts' ability to predict banks' earnings. If analysts' predictions reflect opacity, they should vary systematically across banks with different balance sheet compositions. We measure asset composition by using the share of loans to total assets (*Loans)* and the share of corporate loans to total loans (*Corporate ratio*). The literature on banks as information producers (Rajan, 1992; Parlour and Plantin, 2008) states that loans are rather opaque assets that are harder for external observers to value than investment securities. This assumes that lending generates proprietary information about the borrower. Furthermore, it asserts that an important part of the information that a bank acquires in order to originate and monitor the firm cannot be credibly communicated to outsiders. The bank-borrower relationship plays a significant role in this process of gathering and producing information. This type of information remains essentially soft, and often acquired by the loan officer through ongoing personal interaction with the corporate management. Consistent with this view, more confidential information is contained in corporate loans than is embedded in standardized contracts such as mortgages, which makes the former harder to assess than the latter.

Among bank balance sheet items, problem loans are possibly even more difficult to assess (see the discussion in Section 2.2.2), 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. We therefore include the share of non-performing loans over total gross loans (*NPL*).

Bank valuation also depends on the level of capitalization that influences a bank's moral hazard and risk-taking behavior, which in turn can affect the volatility of earnings. The banking literature has extensively investigated the effect of undercapitalization on bank behavior. The theoretical literature suggests that high leverage and information asymmetries produce agency problems and moral hazard (Jensen and Meckling, 1976). In particular, undercapitalized banks are more prone to gamble for resurrection, and thus increase the riskiness of their loan portfolio compared to stronger banks (Peek and Rosengren, 2005; Caballero et al., 2008; Schivardi et al., 2017). Moreover, financially weaker banks may have a greater incentive to engage in balance sheet window-dressing by under-reporting problem loans (Ristolainen, 2018).

In light of the debate on the reliability of risk-based capital ratios (see our discussion in Section 2), we use two main measures of bank capitalization: a pure, un-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 factors that might potentially influence banks' earnings forecasts: funding structure (*Deposits*, 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). Funding structure is critically important because banks with a larger share of demandable debt may be more exposed to market discipline compared to banks that rely less on deposits (Calomiris and Kahn, 1991). Moreover, since the global financial crisis, short-term, wholesale-funded banks have been found to be less resilient and more unstable than those mainly funded through traditional deposits (Altunbas et al., 2011), making their returns harder to predict. Consequently, one may expect greater transparency, the higher the reliance on customer deposits.

Finally, drawing on the extant analyst forecast literature (Hutton et al., 2012), we employ macro-level variables: the GDP annual real growth rate (*ΔGDP)* and the return rate of the stock market (*Stock market return*) as we expect the forecasts' accuracy to be affected by macroeconomic and financial market conditions. All dependent variables are measured at time *t* and independent variables (except *ΔGDP* and *Stock market return*) are measured at *t*-1.

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). This estimator, by computing a separate intercept for each bank, strips out cross-sectional variation before estimating the slope coefficients. This approach is, therefore, well suited to identify variations in bank opacity over time.

Our third hypothesis, *H3*, suggests a heterogeneous effect of NPLs on bank opacity that depends on the usage of IRB models. As discussed previously, in the traditional banking literature, loans are illiquid, and untraded contracts generate cash flows that are hard to predict (Diamond and Dybvig, 1983). NPLs are especially hard to value for an outsider and significantly increase uncertainty as to a bank's fair value (Ciavoliello et al., 2016). To test this hypothesis, we add the interacted term *NPL*×*IRB* to our specification and employ the following regression equation:

$$\begin{aligned} OPACITY_{i,t} = \alpha + \beta_1\, IRB_{i,t-1} + \beta_2\, NPL_{i,t-1} + \beta_3\, NPL_{i,t-1} \times IRB_{i,t-1} + \\ + \psi' \mathbf{\Phi}_{i,t-1} + \gamma\, \Delta GDP_{i,t} + \theta\, Stock\ market\ return_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \end{aligned} \qquad (2)$$

where $\mathbf{\Phi}_{i,t-1}$ is the new vector of controls, similar to $\mathbf{X}_{i,t-1}$, except that *NPL* has been removed as it enters the equation separately. In this specification, the coefficient β_3 captures whether and to what extent a more intensive usage of (advanced) internal models enhances or alleviates the detrimental effect of NPLs on bank transparency.

3.3. Descriptive statistics

Table 1 presents sample descriptive statistics for the main variables used in our analysis. 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 internal ratings-based models to evaluate the credit risk of (at least part of) their exposures. The average share of credit exposures assessed with (advanced) IRB models accounts for 54% (47%) of the sample. The average (and the median) bank implements an internal ratings-based model to evaluate risk in two different credit portfolios. IRB models are used more (less) intensively for the retail (government) portfolio, with an average share of EAD measured by advanced internal ratings models equal to 62% (23%).

Figure 1 reports the number of banks adopting the IRB approach and the evolution of the average *IRB weight* and *AIRB weight* from 2008 to 2014. While seven banks have used the standardized approach throughout the entire sample period, 31 have started using the IRB models since 2008 and two have started using them during the sample period. The increasing degree of IRB usage and, especially AIRB models, introduces heterogeneity in the time series, that – along with the cross-sectional variation in banks' usage of IRB models – calls for a panel fixed effects model estimation.

Insert Table 1 approximately here

Insert Figure 1 approximately here

4. Empirical results

4.1. Validation test

Table 2 illustrates our preliminary investigation into the relationship between internal rating usage and bank opacity. We estimate a simplified version of Equation (1) as we exclude the *IRB* variable and focus the analysis on bank level controls that according to the extant literature should influence bank opacity. While we do not find a significant relationship between bank opacity and the share of total loans to total assets, we find that analysts' forecasts are less accurate and more dispersed when the share of corporate loans and NPLs increase. The results are significant and stable across specifications.

As expected, capitalization and funding structure are important explanatory factors for bank opacity. As for capitalization, we find that opacity is positively associated with the Tier 1 ratio and negatively associated with the pure leverage ratio. This discrepancy brings into question the reliability of risk-based capital ratios as opposed to a plain leverage indicator, as discussed in Section 2, and supports the idea that markets are skeptical about the reliability of risk-based capital ratios (Haldane and Madouros, 2012). Our results also reveal the importance of funding structure, as both *MAFE* and *Dispersion* improve in banks that rely more on stable sources of funding such as customer deposits.

Finally, we find that opacity decreases in better times when economic and financial market conditions improve. The coefficient of the *Sovereign crisis* dummy variable in both columns 3 and 6 is positive and statistically significant at the 5% level. This result supports the view that bank balance sheets become increasingly opaque under stress. One plausible explanation could be that under uncertain times analysts' forecasts are more difficult to set. Another explanation could be that during poor economic periods banking supervisors are more lenient and bank managers are more prone to discretionary behaviors (i.e., to under provision and/or overstating the value of distressed assets), as found in previous literature (Huizinga and Laeven, 2012), which would make analysts' assessments less precise and more misaligned.

Insert Table 2 approximately here

4.2. Internal ratings-based models and bank opacity

4.2.1. Baseline analysis

Table 3 shows the results of *t*-tests for the equality of means of the main characteristics of banks adopting the internal ratings-based approach (IRB banks) and banks adopting the standardized approach (S banks) [Columns 1-3]; and banks with an *IRB weight* above (High IRB banks) and below (Low IRB banks) the median value (0.629) [Columns 4-6]. In terms of our opacity measures, the banks that adopted the IRB models are not statistically different from the banks that kept using the standardized approach, albeit the former 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 shown by lower customer deposit ratio and loan ratios). When comparing banks that use IRB models more vs less intensively (i.e., whose IRB weight is above vs below the median), the previous differences are confirmed. Moreover, the two groups differ also in terms of opacity: more intensive users of IRB models exhibit statistically lower average values of both *MAFE* and *Dispersion*. Altogether, the differences among these groups highlight the importance of controlling for these variables in a regression setup.

Insert Table 3 approximately here

Table 4 reports the results of estimating Equation (1) using ordinary least squares regressions to test *H1* and *H2*.[18] In columns 1 to 4, we estimate the impact of the usage of (advanced) internal ratings-based models on *MAFE*; columns 5 to 8 show a similar relation with respect to *Dispersion*. The usage of IRB (AIRB) is observed in terms of both a dummy variable (*Dummy*) in columns 1-

[18] Hereinafter, to ease the representation of the results, we do not show the coefficients of the control variables in our tables. Their values and their significances are aligned with those presented in Table 2 and discussed in Section 4.1.

2 and 5-6; and a continuous variable (*Weight*) in columns 3-4 and 7-8. The dummy variables identify banks that rely on an (advanced) internal ratings-based model to determine at least part of their risk-weighted assets. The continuous variables, defined on the [0, 1] interval, contain additional information as they measure the relative importance of the usage of internal ratings in the risk assessment (and minimum capital requirement computation) exercise.

The estimated coefficients of all the IRB variables are negative, but only those of the continuous variables in columns 3-4 and 7-8 are statistically significant. These findings suggest that the mere adoption of the IRB model *per se* does not affect bank opacity, but it is the degree of implementation that matters and has a significant negative impact on bank opacity. Therefore, the findings on the specifications of Equation (1) with the continuous variables support hypothesis *H1a*. These findings are consistent and economically significant across our two alternative opacity measures. Specifically, a one-standard deviation increase in *IRB weight* (30.6 percentage points) is associated with a decrease in *MAFE* of 12.7 percentage points (54.7% of its mean) and a decrease in *Dispersion* of 5.2 percentage points (44.2% of its mean).

Moreover, both statistical and economic significance strengthens when we consider the effect of the advanced models' usage, supporting hypothesis *H2*. The results in specifications with *Weight AIRB* (columns 4 and 8) are stronger than with *Weight IRB* (columns 3 and 7). In terms of economic significance, a one-standard deviation increase in *AIRB weight* (30.4 percentage points) corresponds to a 20.7 percentage points decrease in *MAFE* (88.6% of its mean) and a 9.3 percentage points decrease in *Dispersion* (78.5% of its mean).

In summary, our empirical analysis shows that a more intensive usage of internal ratings-based models translates into lower levels of bank opacity. This effect is more pronounced if banks adopt advanced internal ratings-based models.

Table IA.1 of the Internet Appendix replicates the results of the specifications in Table 4 with the continuous (*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 4.

Insert Table 4 approximately here

4.2.2. Dealing with endogeneity

The estimates in Table 4 include bank fixed effects and year fixed effects. Thus, the results cannot be explained by unobserved, time-invariant, cross-sectional differences in users and non-users of IRB models, nor by time-varying differences in IRB adoption and opacity for all banks in our sample. In addition, our measures of IRB adoption are lagged one year, which further mitigates the potential role of reverse causality in explaining our results. Finally, we include a set of time-variant bank measures of the asset quality and composition that are more likely 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 is 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 variable 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).[19] This instrument should satisfy the exclusion restriction because the average IRB usage of the other banks in the country is unlikely to be related to a given bank's level of opacity. Moreover, by construction, the instrument accounts for the variation in the IRB usage in a given country and year due to unobserved variables, just as a country by year fixed effects approach would control for unobserved factors that are common in a given country and year.[20] This is important in our setting where differences in IRB usage may be due to heterogeneity among national banking authorities in authorizing the IRB adoption and implementation. Table 5 shows the results of both the first- and the second-stage regression estimation for *MAFE* (columns 1 and 2) and *Dispersion* (columns 3 and 4). In columns 1 and 3, we regress the *IRB weight* variable on the instrument. 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 4. More specifically, we find a negative coefficient, which is statistically significant in the regression on *Dispersion*.

Overall, we believe that the instrumental variables approach supports our ordinary least squares estimations. In fact, the most significant results of the OLS counterpart (Table 4) occur when the usage of internal ratings is measured by the *AIRB weight* variable, whereas the coefficient of the *IRB variable* is statistically significant only at the 10% level. Unfortunately, due to lack of data on

[19] 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.

[20] In fact, estimations with country × year fixed effects are implausible in our setup, due to the limited number of banks in each country-year cell, which severely limits the within-country-and-year variation.

the average *AIRB weight* at the country level, we were unable to construct a similar instrument for the *AIRB weight* variable.

Insert Table 5 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 lack of significance of the coefficients of the IRB variables in the specifications of Equation (1) with *IRB dummy* and *AIRB dummy* suggests that the adoption of IRB methods affects bank opacity at the intensive margin only. In other words, our analysis shows that it is not the adoption but the degree of implementation of internal rating models that affects bank opacity. In this section we investigate this finding more explicitly.

As discussed in Section 2.1.1, even if the IRB approach must be implemented to all bank exposures, IRB implementation tends to occur gradually. Banks may also be allowed to permanently continue using the standardized approach for certain exposures. Hence, IRB adoption is not a truly binary event, and some (even relevant) credit exposures could be excluded from the IRB method. Therefore, given that a roll-out plan may be in place, the continuous (A)IRB variables might capture the impact on bank opacity of various degrees of (A)IRB usage (different type and/or different amount of credit exposures) that the dummy variables are unable to grasp.

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. This allows us to observe and analyze the effects of heterogenous behaviors in internal rating adoption. As discussed in Section 3.3, some banks used the standardized approach throughout the entire sample period, while others started using the IRB models from the beginning, and still others started using them at some point during the sample period. Additionally, we observe heterogeneity not only in the amount but also in the *types* of credit exposures under IRB models. More specifically, along with the *(A)IRB weight* variables that refer to the entire credit risk portfolio of the bank, we define three additional continuous variables for (A)IRB usage: *(A)IRB Corporate weight*, *(A)IRB Retail weight*, and *(A)IRB Government weight* that measure the share of credit exposures, in terms of EAD, covered by (advanced) internal ratings-based models for the three main bank credit portfolios. We also define three corresponding dummy variables to capture the (A)IRB usage at the extensive margin: *(A)IRB Corporate dummy*, *(A)IRB Retail dummy*, and *(A)IRB Government dummy*.[21]

Built on this more granular information, Figure 2 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. Finally, 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 intensity (A)IRB usage for the government exposures could be due to the permanent partial usage allowed by national regulators in the EU for "domestic" sovereign exposures.

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

Insert Figure 2 approximately here

We exploit this additional information to test whether the implementation of (A)IRB models to different number and different types of credit exposures affects bank opacity 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 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 6 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 (columns 1 and 7) and under AIRB (columns 2 and 8) on *MAFE* and *Dispersion*, respectively. We find that the major contribution to the decrease of bank opacity occurs when banks adopt AIRB models across all the three portfolios. The coefficient of the *AIRB 3 portfolios* dummy variable is the only one to be statistically significant (and negative) in both the specifications with *MAFE* and *Dispersion*. We find that opacity, when measured in terms of the absolute forecast error, decreases even when the AIRB is applied on two portfolios (column 2), and a similar result occurs in the more general specification with IRB (column 1). In columns 3-4 and 9-10 we test if the implementation of (A)IRB models to some specific types of credit exposures affects bank opacity and replace the three *IRB j_portfolios* (or *AIRB j_portfolios*) variables with the (*A)IRB Corporate*, (*A)IRB Retail*, and (*A)IRB Government* dummies. We find that it is the application of the advanced IRB approach to the corporate portfolio that contributes to enhance bank transparency. These findings are confirmed when these dummy variables are substituted with the corresponding continuous variables in columns 5-6 and 11-12. The beneficial effect of internal ratings on bank opacity increases as the share of corporate exposures under (A)IRB models rises, consistent with the idea that corporate loans are customized and high-information content facilities, as opposed to retail loans that are standardized and easy-to-assess contracts (Boot, 2000).[22]

Insert Table 6 approximately here

To further isolate the effect in the intensive margin, in Table IA.2 of the Internet Appendix, we replicate the results of Table 6 on the subsample of (A)IRB banks. In this case, in the specifications 1-2 and 7-8, we omit the *IRB 1portfolios* (*AIRB 1portfolios*) dummy variable. The results are consistent with the findings in Table 6.

4.2.4. IRB models and bank opacity in highly leveraged banks

Overall, our results highlight one beneficial aspect of the IRB approach. In this section, we test whether our results hold in case of low-capital banks in periods of shortage of long-term and equity financing. In this case, following the discussion in Section 2.1.2, poorly capitalized banks may find it advantageous to manipulate risk weights to artificially increase their regulatory capital ratios

[22] Typically, for risk assessment purposes, retail exposures are not managed individually in a way comparable to corporate exposures, but rather as part of a portfolio segment or pool of exposures with similar risk characteristics.

(Bastos e Santos et al., 2020).[23] If this is true, the transparency-enhancing effect of the usage of IRB models in those banks may be less pronounced, or even inexistent.

To investigate how IRB adoption affects balance sheet opacity in poorly capitalized banks in harsh times, we conduct an additional test and include in our baseline specification an interaction between the *AIRB weight* variable and *Low Tier 1 in 2008*, a dummy variable indicating banks below the median of Tier 1 ratio distribution in 2008 (8.6%). By adding this interaction term, we attempt to verify if the impact of the usage of AIRB models on opacity was affected by the capitalization level of the bank at the beginning of the observation period. The time frame of our analysis includes two subsequent crises when raising capital was particularly expensive and meeting the regulatory capital requirements was more challenging. Table 7 presents results from this specification. The coefficient of the interaction term is negative and statistically significant at 10%. This result together with the result of the *F*-test on the sum of this coefficient and the one of AIRB weight variable suggest that the transparency-enhancing effect of AIRB models holds in poorly capitalized banks. However, it is significantly attenuated compared to the result for better-capitalized banks.

In Table IA.3 in the Internet Appendix, we show that these results are confirmed when we replace the *Low Tier 1 in 2008* dummy variable with the value of the bank Tier 1 ratio at the beginning of the sample period, *Tier 1 ratio in 2008*.[24]

[23] This conjecture also is supported by the evidence in Begley et al. (2017), who find that banks underreport the risk especially when they have lower equity capital, and in Berg and Koziol (2017), who find that banks with the lowest capital adequacy ratios are those most likely to underreport the credit risk of their loan portfolio.

[24] In this case, as the model includes a multiplicative interaction model, the magnitude and significance of the coefficients of both the key explanatory variables, *AIRB weight* and *Tier 1 ratio in 2008* × *AIRB weight*, are substantively uninformative. Therefore, in line with the approach followed later in Section 4.3, the estimated marginal effects of the usage of AIRB models on opacity over all the observed range of Tier 1 ratio in 2008 are plotted in Figure IA.1. The figure shows that the transparency-enhancing effect of usage of AIRB increases with the value of the bank Tier 1 ratio measured in 2008. The usage of AIRB models does not significantly affect bank opacity in banks with lower initial values of the Tier 1 ratio (below 7.7% and 6.9%, when bank opacity is measured by *MAFE* and

Insert Table 7 approximately here

We interpret these findings as follows. For the average bank in our sample, the usage of AIRB models improves transparency. However, low-capital banks are expected to be more inclined to use (advanced) internal ratings-based models opportunistically and to manipulate risk weights, especially in economically challenging times as those covered in our analysis. Consequently, in line with our expectations, the usage of AIRB models for such banks may have a weaker or even no favorable effect on transparency. This result concurs with the research that has documented how banks have exploited Basel II to engage in regulatory arbitrage (e.g., Mariathasan and Merrouche, 2014; Behn et al., 2016; Ferri and Pesic, 2016; Begley et al., 2017, Berg and Koziol, 2017; Bruno et al., 2017).

4.3. Internal ratings, NPLs, and bank opacity

Hypothesis *H3* posits that the effects of NPLs on bank opacity may depend on the bank's usage of (A)IRB models. In Table 8, we formally test this hypothesis and estimate Equation (2). We look at the interaction among two results from the previous analyses: (*i*) the positive relation between bank opacity and the weight of NPLs and (*ii*) the negative relation between opacity and the usage of IRB models. As before, we measure opacity through both *MAFE* (columns 1 to 3) and *Dispersion* (columns 4 to 6).

Consistent with results in Tables 2 and 4, the coefficients of *NPL* and the *AIRB weight* variables are significant with positive and negative signs, respectively. The negative coefficient for the *NPL×AIRB weight* interacted term suggests that a more widespread AIRB implementation

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Dispersion, respectively). Conversely, when the value of *Tier 1 ratio in 2008* increases, the marginal effect of AIRB on opacity is negative (that is: transparency-enhancing) as we found in our main analysis.

mitigates the increased opacity due to a larger NPL portfolio. This reinforces the view that AIRB models are associated with better risk management practices (including more accurate NPL recognition and more timely provisions) and/or with richer and deeper information disclosure.

Insert Table 8 approximately here

This empirical exercise is based on a multiplicative interaction model (Equation 2). As noted by Brambor et al. (2006), in applications with interacted variables, it is possible to obtain statistical significance for a range of values of the interacted variable despite the lack of significance of the reported coefficient. Similarly, the absence of statistical significance for a range of values of the interacted variable is also possible despite the significance of the reported coefficient. To shed light on the relations among the NPLs, AIRB usage, and opacity, Figure 3 provides a graphical assessment of the marginal effect of NPLs on opacity over different ranges of the interacted variable *AIRB weight*. The solid line indicates how the marginal effect of NPLs on opacity changes with AIRB usage: such first partial derivative, $\frac{\partial OPACITY}{\partial NPL}$, is given by $\beta_2 + \beta_3 \cdot AIRB\ weight$. The left panel of Figure 3 contains estimates of the marginal effect of *NPL* on *MAFE*, while the right panel shows a similar relation for the *Dispersion* variable.

The negative slope in both specifications implies that the detrimental effect of NPLs on bank transparency declines as AIRB usage increases. Indeed, the lower confidence band shows that, as *AIRB weight* reaches around 21%, the relation between *NPL* and *OPACITY* is no longer statistically significant at 1% (although the upper confidence band suggests that it may remain positive also for heavy AIRB users).

Insert Figure 3 approximately here

In columns 2 and 5 of Table 8, we substitute *AIRB weight* with *AIRB loans*. *AIRB weight* is the share of all the bank's credit exposures, in terms of EAD, measured by advanced internal ratings models. However, a bank might have a high *AIRB weight* even though the share of its loans evaluated with (advanced) internal ratings models could be relatively lower. If so, the hypothesized beneficial effect of the internal ratings models on the NPL opacity would depend on the degree of IRB implementation to evaluate the bank's loans rather than on the more general IRB implementation for the evaluation of *all* the bank's credit exposures. We therefore introduce a new variable, *AIRB loans*, defined as $(Corporate\ ratio \times AIRB\ Corporate\ weight) + (Retail\ ratio \times AIRB\ Retail\ weight)$, where $Corporate\ ratio = \frac{Corporate\ loans}{Retail\ loans + Corporate\ loans}$ and $Retail\ ratio = \frac{Retail\ loans}{Retail\ loans + Corporate\ loans}$.

We define *AIRB loans* as the average of *AIRB Corporate AIRB* and *AIRB Retail AIRB* (the share of corporate and retail credit exposures evaluated with advanced internal models, respectively), weighted with the share of corporate loans and retail loans over total loans. *AIRB loans* is a closer proxy for the share of the loans' credit exposure evaluated with internal advanced internal models. Although in this specification the coefficient of the *NPL×AIRB loans* interacted term is not significant, the graphical description of the marginal effect of *NPL* on opacity for different levels of *AIRB loans* illustrates that the level of *AIRB loans* did play a role in conditioning the relation between *NPL* and opacity. Specifically, Figure 4 shows that as the share of loan risk exposure evaluated with internal ratings model increases, the impact of the NPLs on bank opacity decreases and, when *AIRB loan* exceeds about 32% and 37% (for *MAFE* and *Dispersion*, respectively), the relation between NPLs and bank opacity becomes statistically insignificant.

Insert Figure 4 approximately here

Finally, as previous results show that corporate loans are the most opaque loan portfolio component, in columns 3 and 6, we replicate our analysis by distinguishing the intensity of the AIRB usage in the corporate, retail, and government portfolios. Therefore, we replace the *AIRB weight* variable with the *AIRB Corporate weight*, *AIRB Retail weight*, and *AIRB Government weight* variables and we interact the first variable with *NPL*. We find that the coefficients of *AIRB Corporate weight* are statistically significant (and negative), whereas those of *AIRB Retail weight* and *Government Retail weight* are not statistically different from zero. Although consistent with previous findings (see Table 6, columns 5 and 10), the result has now a slightly different meaning. In fact, the coefficients of *AIRB Corporate* (*Retail*/*Government*) *weight* in Table 8 summarize the relation between the relevance of IRB models in the corporate and retail portfolios and bank opacity when *NPL* = 0. Figure 5 shows the importance of the conditional relation between *NPL* and the intensity of AIRB usage for the evaluation of the corporate credit exposures. The detrimental effect of the NPLs on bank opacity becomes statistically insignificant as the AIRB adoption for the corporate exposures exceeds a certain threshold (which is around 53% for *MAFE* and 56% for *Dispersion*).

Insert Figure 5 approximately here

These findings are confirmed when we replace the continuous AIRB variables (*AIRB weight* and *AIRB Corporate weight*) with the corresponding dummy variables (*AIRB dummy* and *AIRB Corporate dummy*, with the latter that equals one if bank *i* in year *t* evaluates the credit risk of its corporate portfolio with AIRB models).[25] The results (reported in Table IA.4 in the Internet

[25] We do not include in this robustness a specification with the *AIRB loans dummy* (i.e., a dummy that equals one if the corresponding continuous variable of Table 8, *AIRB loans*, takes any positive value) as this variable, in our sample, corresponds to *AIRB dummy*. As shown in Panel *B* of Figure 2, all the AIRB banks in our sample have implemented the advanced model on at least the retail and/or the commercial portfolio.

Appendix) confirm those in Table 8: NPLs correlate positively with bank opacity only in banks that do no adopt the *advanced* IRB models; on the contrary, the NPLs-bank opacity relationship is statistically insignificant in AIRB banks, as implied by the result of the *F* test on the sum of the coefficients of the *NPL* and *NPL × AIRB dummy* (*NPL × AIRB Corporate dummy*) variables.

5. Exploring the mechanism

Our results so far indicate that a more intensive usage of IRB models corresponds to lower bank opacity, but they do not clarify which channel makes this relationship work. In fact, our results are consistent with two (not mutually exclusive) arguments, the risk management mechanism and the information disclosure mechanism, described in Section 2.1.2. According to the former, IRB models may be associated with better risk management practices (including more accurate NPL recognition and less discretionary provisions), which may translate into more reliable and more predictable earnings. The latter posits that IRB adoption entails additional disclosure requirements, which may result in more valuable information (in particular: that included in banks' Pillar III reports) that may decrease informational asymmetries and improve the accuracy of analysts' forecasts.

5.1. Tests for the risk management mechanism

5.1.1. IRB models and earnings volatility

To assess if the risk management mechanism effect is at work, we first 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 should report lower earnings volatility.

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.

Table 9 reports the results. The coefficient of our explanatory variable is not statistically significant in any of the nine specifications. This means that a wider usage of AIRB models does not translate into a reduction of earnings volatility.

Insert Table 9 approximately here

5.1.2. IRB models and discretionary loan loss provisioning

To further establish whether the adoption of IRB models improves the effectiveness of the bank risk management systems, we define another specification of model (1) with a measure of the discretionary loan loss provisioning (LLP) as the dependent variable. We follow Beatty and Liao (2014) and compute the *ABSDLLP*(*j*) variable (with *j* = *a*, *b*, *c* or *d*), that is the absolute value of discretionary loan loss provisions, calculated as the absolute value of the residual from one of four different regression models described in the Internet Appendix (Section IA.II). Our line of reasoning is the following. As clarified by the banking authority (see our discussion in Section 2.1.2), IRB models should be used not only for capital requirements calculation but also for improving risk management practices. A major benefit of implementing IRB models resides in reducing discretionary managerial practices in loan loss provisioning.

LLP is the periodic assessment of expected credit losses associated with a given credit exposure, allowing banks to recognize the estimated loss even before the actual loss can be determined with accuracy and certainty. LLP is a key accounting policy choice that directly influences the volatility and cyclicality of bank earnings. It also affects the ability to interpret information in banks' financial reports with respect to their loan portfolios' risk attributes (Bushman and William, 2015). Despite the accounting rules, however, the complexity of loan portfolios allows scope for discretion. Because LLPs are expense items on the Profit and Loss account, banks have the incentive to set provisions, not on the basis of credit risk management considerations, but to pursue other managerial objectives such as income smoothing and capital management (Alessi et al. 2021, and literature therein). To counter this incentive, the adoption of internal rating models would enable banks to provide more accurate LLP estimates, e.g., because of a better quality of the underlying data that generates provisions. In addition, bank supervisors' expectations on the scope of application of internal ratings (as discussed in Section 2.1.2) would further persuade banks to use the granular assessment of credit risk parameters allowed by IRB models (especially the advanced version of internal ratings) for setting more timely and accurate loan loss provisions. Should this be the case, one would expect lower discretionary provisioning in banks adopting internal ratings more broadly. However, the results of our analysis, reported in Table 10, do not provide any significant association between the degree of AIRB usage and discretionary LLP.

Insert Table 10 approximately here

Overall, our results do not support the risk management mechanism. More precisely, even if our findings do not allow us to rule out the idea that AIRB models are associated with better risk management practices (Cucinelli et al., 2018 and Mascia et al., 2019), we can still exclude that the reduced analyst forecast error and disagreement across analysts' forecasts are due to lower bank earnings dispersion induced by the usage of internal models. We can also exclude that the practice of discretionary loan loss provisioning is less frequent and/or pronounced in IRB banks, as one would expect in case IRB models were indicative of better risk management practices.

5.2. Tests for the information disclosure mechanism

The alternative explanation of our main result may therefore rely on the information disclosure mechanism, i.e., the idea that a more intensive usage of internal ratings implies the disclosure of additional information. If such information were relevant and valuable, financial analysts' forecasts would be more accurate. Yet, the difficulty to isolate and quantify such incremental information presents an obstacle to a direct test of the impact of greater disclosure on forecast estimates. We address this issue by relying on qualitative and quantitative information contained in the Pillar III public disclosure document. In fact, there is anecdotal evidence that the implementation of (especially advanced) internal ratings-based models – or their extension to additional credit exposures (like other portfolios or other subsidiaries within a banking group) usually goes along with the release of additional information in the Pillar III report.[26] For this mechanism to be active, we should at least observe a positive relation between the usage of (A)IRB models and the information released. To empirically test the existence of this relationship, we estimate the coefficients of the following fixed effects panel regression:

$$PILLAR3\ INFO_{i,t} = \alpha + \beta\ IRB_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \quad (3)$$

[26] An example is reported in Session I of the Internet Appendix, that describes the application of the IRB approach Intesa Sanpaolo.

where *PILLAR3 INFO* is either the number of pages of the Pillar III report (*PIII pages*) or the number of pages in the same document specifically devoted to the credit and counterparty risk (*PIII credit risk pages*). *IRB* is alternatively defined as (*i*) *(A)IRB dummy*, (*ii*) *(A)IRB weight*, and (*iii*) *No of (A)IRB portfolios*. It is worth noting that, different from the previous analyses, we test a correlation rather than a causal relation, hence both the explanatory and the dependent variable are measured at year *t*. We include bank fixed effects (δ_i), to control for time-invariant, unobserved bank country 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 *PILLAR3 INFO* variables used in the analysis have important limitations. First, they can signal the release of additional information than the one implied by the usage of IRB models (this is especially true for the *PIII pages* variable). Second, they depend on idiosyncratic factors such as the “informative reporting style” of each bank that the inclusion of bank fixed effects can capture only in part. Nonetheless, the results of our analysis, reported in Table 11, support the information disclosure mechanism. We find a positive and significant correlation between the number of pages in the Pillar III report (especially the parts describing the exposure to credit and counterparty risk) and the adoption of internal models (especially the advanced ones).

Insert Table 11 approximately here

6. Conclusions

This paper contributes to the institutional and academic literature on the benefits and challenges of bank internal ratings by uncovering a positive effect (i.e., the transparency-enhancing role of

IRB models) that has not been investigated by previous studies. We also contribute to the recent policy debate on impaired loans by showing that a greater usage of IRB can mitigate certain negative externalities of NPLs.

We document 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. More specifically, this paper establishes five novel and interrelated empirical facts. First, we find that 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, we determine that 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. Fourth, the absence of any significant relationship between the usage of IRB models and earnings volatility suggests that the most plausible explanation of our result relies in the more detailed disclosure of their loan portfolios which is required for users of advanced internal ratings. Fifth, the fact that the AIRB model usage-opacity relationship is not significant for low-capital banks makes our results consistent with the existing empirical evidence (Mariathasan and Merrouche, 2014) affirming that weakly capitalized banks are more likely to use their AIRB models opportunistically for risk weight manipulation.

Together, the empirical facts established in this paper suggest that the disclosure requirements imposed by the implementation of IRB models enhance the transparency of bank balance sheets and especially of opaque items such as corporate loans and problem loans. The additional reporting effort requested of IRB banks does not appear to be excessive and irrelevant as some within the banking industry has feared.[27]

By showing the overall benefits of IRB adoption in terms of reduced opacity, the paper also addresses some potential concerns about whether and to what extent internal rating models should be allowed or further promoted. Our findings on the combined effect of NPLs and IRB adoption on bank transparency are of particular interest also given the relevance of the NPL issue in the European policy agenda.

[27] See Ralph (2015).

Appendix A. Banks in the sample

Bank	Country
Dexia SA	BELGIUM
KBC Groep NV/ KBC Groupe SA-KBC Group	BELGIUM
Danske Bank A/S	DENMARK
Jyske Bank A/S	DENMARK
OP Corporate Bank plc-OP Yrityspankki Oyj	FINLAND
BNP Paribas	FRANCE
Crédit Agricole S.A.	FRANCE
Crédit Industriel et Commercial SA - CIC	FRANCE
Société Générale SA	FRANCE
Commerzbank AG	GERMANY
Deutsche Bank AG	GERMANY
Alpha Bank AE	GREECE
Eurobank Ergasias SA	GREECE
National Bank of Greece SA	GREECE
Piraeus Bank SA	GREECE
OTP Bank Plc	HUNGARY
Bank of Ireland-Governor and Company of the Bank of Ireland	IRELAND
BPER Banca S.P.A.	ITALY
Banca Carige SpA	ITALY
Banca Monte dei Paschi di Siena SpA-Gruppo Monte dei Paschi di Siena	ITALY
Banca Popolare di Milano SCaRL	ITALY
Intesa Sanpaolo	ITALY
UniCredit SpA	ITALY
Unione di Banche Italiane Scpa-UBI Banca	ITALY
ING Groep NV	NETHERLANDS
DnB ASA	NORWAY
Powszechna Kasa Oszczednosci Bank Polski SA - PKO BP SA	POLAND
Banco Comercial Português, SA-Millennium bcp	PORTUGAL
Banco Bilbao Vizcaya Argentaria SA-BBVA	SPAIN
Banco Santander SA	SPAIN
Banco de Sabadell SA	SPAIN
Bankinter SA	SPAIN
Caixabank, S.A.	SPAIN
Skandinaviska Enskilda Banken AB	SWEDEN
Svenska Handelsbanken AB	SWEDEN
Swedbank AB	SWEDEN
Credit Suisse Group AG	SWITZERLAND
UBS AG	SWITZERLAND
Barclays Plc	UNITED KINGDOM
HSBC Holdings Plc	UNITED KINGDOM
Lloyds Banking Group Plc	UNITED KINGDOM
Royal Bank of Scotland Group Plc (The)	UNITED KINGDOM
Standard Chartered Plc	UNITED KINGDOM

Appendix B. Variable definitions

Variables	Definition	Source
MAFE	Median of the analysts' absolute EPS forecast error, divided by the share price at the start of the fiscal year.	I/B/E/S
Dispersion	Cross-sectional standard deviation of analysts' EPS forecasts.	I/B/E/S
IRB dummy	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	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)	
AIRB dummy	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)	
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
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
AIRB loans	= Corporate ratio × AIRB Corporate weight + Retail ratio × AIRB Retail weight.	Banks' Pillar III reports
Loans	= Total loans/Total assets.	BankFocus
NPL	= Impaired loans/Total gross loans.	BankFocus
Corporate ratio	= Corporate loans/(Corporate loans + Retail loans).	Banks' Pillar III reports
Equity ratio	= Total equity/Total assets.	BankFocus
Tier 1 ratio	= Tier 1 capital/Risk weighted assets.	Banks' Pillar III reports
Deposits	= Customer deposits/Total assets.	BankFocus
ROA	Return on Assets.	BankFocus
Size	= ln(Total assets).	BankFocus
ΔGDP	Growth rate of the country's annual real gross domestic product.	World Bank
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
Sovereign crisis	Dummy variable taking value 1 if the observation refers to the 2010-2012 years.	
ROA volatility (1, 2, and 3 years)	Standard deviation of the ROA calculated over the quarters of the year, those of the year and the year after, and those of the year and the two years after.	Bloomberg

ROE volatility (1, 2, and 3 years)	Standard deviation of the ROE calculated over the quarters of the year, those of the year and the year after, and those of the year and the two years after.	Bloomberg
EBPT ratio volatility (1, 2, and 3 years)	Standard deviation of the ratio of Earnings before provisions and taxes over Total assets calculated over the quarters of the year, those of the year and the year after, and those of the year and the two years after.	Bloomberg
ABSDLLP(a)	Absolute value of discretionary loan loss provision, calculated as the absolute value of the residual from the regression model (IA.1a): $LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \beta_5 Size_{i,t-1} + \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \beta_8 Real\ estate\ return_{i,t} + \beta_9 \Delta Unemployment_{i,t} + \varepsilon_{it}$.	Authors' calculations
ABSDLLP(b)	Absolute value of discretionary loan loss provision, calculated as the absolute value of the residual from the regression model (IA.1b): $LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \beta_5 Size_{i,t-1} + \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \beta_8 Real\ estate\ return_{i,t} + \beta_9 \Delta Unemployment_{i,t} + \beta_{10} LLA_{i,t-1} + \varepsilon_{it.}$	Authors' calculations
ABSDLLP(c)	Absolute value of discretionary loan loss provision, calculated as the absolute value of the residual from the regression model (IA.1c): $LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \beta_5 Size_{i,t-1} + \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \beta_8 Real\ estate\ return_{i,t} + \beta_9 \Delta Unemployment_{i,t} + \beta_{10} Charge\ offs_{i,t} + \varepsilon_{it}$.	Authors' calculations
ABSDLLP(d)	Absolute value of discretionary loan loss provision, calculated as the absolute value of the residual from the regression model (IA.1d): $LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \beta_5 Size_{i,t-1} + \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \beta_8 Real\ estate\ return_{i,t} + \beta_9 \Delta Unemployment_{i,t} + \beta_{10} LLA_{i,t-1} + \beta_{11} Charge\ offs_{i,t} + \varepsilon_{it}$.	Authors' calculations
LLP	Loan loss provisions divided by lagged total loans.	BankFocus
ΔNPL	Change in non-performing loans divided by lagged total assets.	BankFocus
ΔLoans	Change in total loans divided by lagged total loans	BankFocus
Real estate return	Return on the house price index over the year.	OECD
ΔUnemployment	Change in the unemployment ratio over the year.	World Bank
Charge offs	Net charge offs divided by lagged total loans.	BankFocus
LLA	Loan loss allowances divided by total loans.	BankFocus
PIII pages	Number of pages of the Pillar III report.	
PIII credit risk pages	Number of pages of the part of the Pillar III report devoted to credit and counterparty risk.	

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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 B.

	Mean	St. dev.	p10	p25	p50	p75	p90	N
Opacity measures								
MAFE	0.071	0.140	0.001	0.005	0.015	0.048	0.259	289
Dispersion	0.036	0.049	0.004	0.011	0.017	0.031	0.113	287
Internal rating model usage (lagged)								
IRB dummy	0.810	0.393	0	1	1	1	1	289
IRB weight	0.542	0.306	0	0.412	0.629	0.773	0.856	289
No. of IRB portfolios	1.983	1.101	0	2	2	3	3	289
AIRB dummy	0.792	0.406	0	1	1	1	1	289
AIRB weight	0.470	0.304	0	0.238	0.524	0.722	0.810	289
No. of AIRB portfolios	1.779	1.154	0	1	2	3	3	289
IRB Corporate weight	0.623	0.362	0	0.516	0.752	0.898	0.982	289
IRB Retail weight	0.617	0.364	0	0.423	0.765	0.903	0.967	289
IRB Government weight	0.246	0.369	0	0	0	0.550	0.911	289
AIRB Corporate weight	0.466	0.397	0	0	0.648	0.841	0.923	289
AIRB Retail weight	0.617	0.364	0	0.423	0.765	0.903	0.967	289
AIRB Government weight	0.231	0.367	0	0	0	0.539	0.911	289
AIRB loans	0.559	0.337	0	0.341	0.664	0.827	0.926	289
Balance sheet items (lagged)								
Loans	54.09	16.96	28.31	42.00	58.58	67.64	74.19	289
Corporate ratio	52.60	13.64	35.36	42.52	53.06	61.51	67.69	289
NPL	7.305	7.474	0.938	2.561	5.212	9.115	16.53	289
Tier 1 ratio	11.74	3.687	7.860	9.460	11.60	13.50	16.10	289
Equity ratio	5.755	2.659	3.096	4.241	5.570	7.130	9	289
Total assets (m EUR)	575,651	621,163	44,861	82,007	275,416	992,856	1,653,000	289
Deposits	51.93	14.95	34.36	41.99	51.77	61.27	69.61	289
ROA	8.137	138.0	-83.30	3	26.60	57.10	81.10	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	4.360	14.80	20.96	289
Pillar III report variables (lagged)								
PIII pages	88.43	57.25	31	44	74	120	161	271
PIII credit risk pages	33.34	21.61	11	17	28	44	59	270

Table 2. Bank opacity and balance sheet items

This table reports the coefficient estimates of an OLS regression of bank opacity on various balance sheet items. 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 (*MAFE*), in columns 1-3, and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*), in columns 4-6. Explanatory variables are defined in Appendix B. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects. All specifications except those in columns 3 and 6 contain 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)
		$MAFE_t$			**$Dispersion_t$**	
$Loans_{t-1}$	-0.001	0.000	0.000	-0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Corporate $ratio_{t-1}$	0.002	0.002*	0.002*	0.001*	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
NPL_{t-1}	0.005***	0.006***	0.006***	0.002***	0.002***	0.002***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Tier 1 $ratio_{t-1}$	0.005	0.009**	0.014***	0.000	0.001	0.002**
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
Equity $ratio_{t-1}$		-0.024**	-0.017**		-0.007***	-0.006***
		(0.009)	(0.007)		(0.002)	(0.002)
$Deposits_{t-1}$	-0.005**	-0.003**	-0.003**	-0.001***	-0.001**	-0.001**
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.015	-0.001	-0.012	-0.007	-0.002	-0.004
	(0.010)	(0.012)	(0.012)	(0.004)	(0.004)	(0.003)
$Size_{t-1}$	-0.036	-0.031	-0.005	-0.006	-0.004	-0.001
	(0.058)	(0.054)	(0.056)	(0.028)	(0.027)	(0.023)
ΔGDP_t	-0.008**	-0.007**	-0.003	-0.005***	-0.005***	-0.003***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Stock market $return_t$	-0.002	-0.003**	-0.001**	-0.000	-0.000*	-0.000*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Sovereign crisis			0.029**			0.010**
			(0.014)			(0.004)
Intercept	0.484	0.348	0.009	0.111	0.066	0.036
	(0.737)	(0.697)	(0.760)	(0.364)	(0.353)	(0.324)
No. of obs.	289	289	289	287	287	287
No. of banks	43	43	43	42	42	42
Adj. R^2	0.244	0.278	0.226	0.367	0.399	0.355

Table 3. Bank characteristics of more and less intensive users of internal ratings-based models

This table reports the mean and the standard deviation (in parenthesis) of characteristics of banks adopting the internal ratings-based approach (IRB banks, column 1) and banks adopting the standardized approach (S banks, column 2) and banks with IRB weight above (High IRB banks, column 4) and below (Low IRB banks, column 5) the median value (0.629). Consistent with the main empirical setting, opacity measures are observed at year *t*, accounting measures are observed at year *t*-1, and bank classification (into IRB-S banks and High-Low IRB banks) is based on IRB values observed at year *t*-1. All variables are defined in Appendix B. Column 3 and 6 report the difference between the means (in parentheses the *t*-test) between IRB banks and S banks and between High IRB banks and Low IRB banks, respectively. ∗, ∗∗, and ∗∗∗ denotes significance at the 10%, 5%, and 1% level, respectively.

	(1) IRB banks$_{t-1}$	(2) S banks$_{t-1}$	(3) = (2)-(1)	(4) High IRB banks$_{t-1}$	(5) Low IRB banks$_{t-1}$	(6) = (5)-(4)
MAFE$_t$	0.07	0.09	0.03	0.05	0.10	0.05**
	(0.14)	(0.16)	(1.18)	(0.10)	(0.17)	(2.97)
Dispersion$_t$	0.03	0.04	0.01	0.03	0.05	0.02***
	(0.05)	(0.05)	(1.37)	(0.04)	(0.06)	(3.43)
Loans$_{t-1}$	50.33	70.10	19.77***	45.52	62.60	17.08***
	(16.38)	(7.30)	(13.59)	(15.96)	(13.26)	(9.89)
Corporate ratio$_{t-1}$	0.53	0.51	-0.02	0.54	0.52	-0.02
	(0.14)	(0.11)	(-1.32)	(0.13)	(0.14)	(-1.23)
NPL$_{t-1}$	6.06	12.61	6.55***	4.13	10.46	6.33***
	(6.09)	(10.12)	(4.61)	(3.38)	(8.96)	(7.96)
Tier 1 ratio$_{t-1}$	12.22	9.70	-2.52***	13.48	10.00	-3.48***
	(3.52)	(3.70)	(-4.58)	(3.24)	(3.27)	(-9.08)
Equity ratio$_{t-1}$	5.11	8.51	3.40***	4.71	6.79	2.09***
	(1.82)	(3.73)	(6.58)	(1.460)	(3.14)	(7.26)
Deposits$_{t-1}$	49.43	62.56	13.13***	49.43	54.41	4.98**
	(13.84)	(14.94)	(5.95)	(14.74)	(14.78)	(2.87)
ROA$_{t-1}$	0.08	0.08	-0.01	0.22	-0.06	-0.29
	(1.05)	(2.33)	(-0.02)	(0.46)	(1.89)	(-1.77)
Size$_{t-1}$	12.92	10.91	-2.01***	13.18	11.90	-1.28***
	(1.16)	(0.37)	(-22.23)	(1.05)	(1.25)	(-9.40)
No. of obs.	234	55		144	145	

Table 4. Usage of internal ratings-based 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 (*MAFE*, 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). Control variables (not reported for brevity) are the same as in Table 2, columns 2 and 5. 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)
	MAFE$_t$				**Dispersion$_t$**			
	IRB	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*
Dummy$_{t-1}$	-0.035	-0.031			-0.001	-0.002		
	(0.028)	(0.035)			(0.019)	(0.013)		
Weight$_{t-1}$			-0.127*	-0.207***			-0.052*	-0.093***
			(0.064)	(0.050)			(0.026)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.277	0.277	0.283	0.308	0.397	0.397	0.409	0.461

Table 5. Usage of internal ratings-based 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 (*MAFE*, 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, columns 2 and 5. 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 MAFE	(3) First stage IRB weight$_{t-1}$	(4) Second stage Dispersion
IVIRB weight$_{t-1}$	0.691*** (0.0602)		0.690*** (0.0603)	
IRB weight$_{t-1}$		-0.169 (0.131)		-0.0909** (0.0380)
Controls	Yes	Yes	Yes	Yes
No. of obs.	289	289	287	287
No. of banks	43	43	42	42
F stat	131.51		130.93	

Table 6. Usage of internal ratings-based 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 (*MAFE*, 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 3portfolios*, columns 2 and 8); three dummy variables variable 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 variable 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, columns 2 and 5. 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)
	MAFE$_t$						**Dispersion$_t$**					
	IRB	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*
1portfolios$_{t-1}$	-0.007	0.007					0.008	0.012				
	(0.034)	(0.029)					(0.021)	(0.012)				
2portfolios$_{t-1}$	-0.053*	-0.062**					-0.009	-0.015				
	(0.031)	(0.030)					(0.014)	(0.009)				
3portfolios$_{t-1}$	-0.188**	-0.147***					-0.033	-0.049**				
	(0.087)	(0.049)					(0.030)	(0.020)				
Corporate dummy$_{t-1}$			-0.068	-0.081***					-0.030**	-0.029***		
			(0.043)	(0.027)					(0.013)	(0.010)		
Retail dummy$_{t-1}$			-0.038	-0.018					-0.001	0.004		
			(0.047)	(0.041)					(0.015)	(0.013)		
Government dummy$_{t-1}$			-0.010	-0.037					0.017*	-0.027		
			(0.023)	(0.038)					(0.009)	(0.022)		
Corporate weight$_{t-1}$					-0.172**	-0.142***					-0.061***	-0.054***
					(0.072)	(0.035)					(0.020)	(0.015)
Retail weight$_{t-1}$					0.002	0.013					-0.005	0.002
					(0.051)	(0.042)					(0.015)	(0.011)
Government weight$_{t-1}$					0.012	-0.019					0.002	-0.020
					(0.036)	(0.030)					(0.021)	(0.015)
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	0.286	0.306	0.295	0.301	0.306	0.306	0.400	0.445	0.402	0.438	0.424	0.454

Table 7. Internal ratings-based models and initial capitalization levels on bank opacity

This table reports the coefficient estimates of an OLS regression of bank opacity on the use of advanced internal ratings-based models under different levels of the bank capitalization at the beginning of sample period. 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 (*MAFE*, in columns 1 and 2) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in column 3 and 4). The main explanatory variables are: the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*); and the interaction between *AIRB weight* and a dummy variable taking value 1 if the Tier 1 capital over Risk weighted assets in 2008 is below the median [8.6%] (*Low Tier 1 in 2008*). The other explanatory variables are defined in Appendix B. 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. *F*-test tests the hypothesis that the sum of the coefficients for *AIRB weight* and the interaction term *Low Tier 1 in 2008* × *AIRB weight* equals zero. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) **MAFE$_t$**	(2) **Dispersion$_t$**
AIRB weight$_{t-1}$	-0.240***	-0.124***
	(0.060)	(0.035)
Low Tier 1 in 2008 × AIRB weight$_{t-1}$	0.132*	0.072*
	(0.071)	(0.038)
Loans$_{t-1}$	-0.000	-0.000
	(0.002)	(0.000)
Corporate ratio$_{t-1}$	0.002	0.001**
	(0.001)	(0.000)
NPL$_{t-1}$	0.006***	0.002***
	(0.002)	(0.000)
Equity ratio$_{t-1}$	-0.020**	-0.007***
	(0.009)	(0.002)
Deposits$_{t-1}$	-0.004**	-0.001***
	(0.002)	(0.000)
ROA$_{t-1}$	0.000	0.000
	(0.000)	(0.000)
Size$_{t-1}$	-0.056	-0.015
	(0.051)	(0.023)
ΔGDP$_t$	-0.007**	-0.005***
	(0.003)	(0.001)
Stock market return$_t$	-0.003***	-0.001**
	(0.001)	(0.000)
Intercept	0.923	0.278
	(0.706)	(0.318)
No. of obs.	289	287
No. of banks	43	42
Adj. R^2	0.286	0.461
F-test	11.77***	13.60***

Table 8. Advanced internal ratings-based models and impact of NPLs on bank opacity

This table reports the coefficient estimates of an OLS regression of bank opacity on the share of non-performing loans under different levels of advanced internal ratings-based model usage. 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 (*MAFE*, in columns 1-3) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 4-6). The main explanatory variables are: the share of impaired loans over total gross loans (*NPL*); the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*, columns 1 and 4); the average of the share of corporate and retail credit exposures covered by advanced internal ratings-based models, weighted with the share of corporate loans and retail loans over total loans, respectively (*AIRB loans*, columns 2 and 5); the share of corporate (retail) [government] credit exposures evaluated with advanced internal models (*AIRB Corporate* (*Retail*) [*Government*] *weight*, columns 3 and 6); and the interaction between *NPL* and either *AIRB weight*, *AIRB loans*, or *AIRB Corporate weight*. Control variables (not reported for brevity) are the same as in Table 2, columns 2 and 5. 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)
		$MAFE_t$			**$Dispersion_t$**	
NPL_{t-1}	0.007***	0.007***	0.007***	0.002***	0.002***	0.002***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
AIRB $weight_{t-1}$	-0.154***			-0.071***		
	(0.053)			(0.022)		
AIRB $loans_{t-1}$		-0.160***			-0.067***	
		(0.059)			(0.022)	
AIRB Corporate $weight_{t-1}$			-0.123***			-0.047***
			(0.035)			(0.016)
NPL_{t-1}×AIRB $weight_{t-1}$	-0.008*			-0.003**		
	(0.004)			(0.002)		
NPL_{t-1}×AIRB $loans_{t-1}$		-0.003			-0.001	
		(0.004)			(0.001)	
NPL_{t-1}×AIRB Corporate $weight_{t-1}$			-0.003			-0.001
			(0.003)			(0.001)
AIRB Retail $weight_{t-1}$			0.013			0.002
			(0.044)			(0.012)
AIRB Government $weight_{t-1}$			-0.012			-0.018
			(0.029)			(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	289	289	289	287	289	287
No. of banks	43	43	43	42	43	42
Adj. R^2	0.312	0.308	0.306	0.472	0.308	0.306

Table 9. Usage of advanced internal ratings-based models and earnings volatility

This table reports the coefficient estimates of an OLS regression of earnings volatility on the usage of advanced internal ratings-based models. The dependent variables are the standard deviation of the ROA (*ROA volatility*, in columns 1-3) and ROE (*ROE volatility*, in columns 4-6), computed over: the quarters of the year (columns 1 and 4), those of the year and the year after (columns 2 and 5), and those of the year and the two years after (columns 3 and 6). The main explanatory variable is the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*). Control variables (not reported for brevity) are the same as in Table 2, columns 2 and 5. 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)
	ROA volatility$_t$			**ROA volatility$_t$**			**EBPT ratio volatility$_t$**		
AIRB weight	-0.037	-0.259	-0.211	1.058	-2.613	-4.640	-0.004	0.010	0.009
	(0.171)	(0.188)	(0.217)	(4.878)	(5.344)	(3.242)	(0.014)	(0.024)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	263	268	269	263	268	269	265	268	270
No. of banks	39	39	39	39	39	39	39	40	40
Adj. R^2	0.514	0.599	0.594	0.073	0.054	0.111	0.026	0.134	0.140

Table 10. Usage of advanced internal ratings-based models and discretionary LLPs

This table reports the coefficient estimates of an OLS regression of the discretionary loan loss provisions on the usage of advanced internal ratings-based models. The dependent variable is the absolute value of discretionary loan loss provisions, calculated as the absolute value of the residual from one of the four regression models (IA.1*j*) described in Session IA.II of the Internet Appendix, that is *ABSDLLP*(*j*) (with *j* = *a*, *b*, *c* or *d*) in columns a, b, c and d, respectively. The main explanatory variable is the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*). Control variables (not reported for brevity) are the same as in Table 2, columns 2 and 5. 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.

	(a)	(b)	(c)	(d)
AIRB weight	-0.663	-0.664	-0.182	-0.197
	(2.377)	(2.431)	(2.244)	(2.273)
Controls	Yes	Yes	Yes	Yes
No. of obs.	252	251	252	251
No. of banks	44	44	44	44

Table 11. Usage of internal ratings-based models and length of Pillar III report

This table reports the coefficient estimates of an OLS regression of the number of pages in pillar III reports and the usage of advanced internal ratings-based models. The dependent variables are: the number of pages of the pillar III report (*PIII pages*, Panel A) and the number of pages of the part of pillar III report devoted to credit and counterparty risk (*PIII credit risk pages*, Panel B). 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*, in column 1); 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 column 2); the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*IRB weight*, in column 3); the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*, in column 4); the number of portfolios in which the bank uses the IRB approach (*No. of IRB portfolios*, in column 5); and the number of portfolios in which the bank uses the IRB approach (*No. of IRB portfolios*, in column 6). All specifications include bank fixed effects and year fixed effects. Standard errors are shown in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) IRB dummy	(2) AIRB dummy	(3) IRB weight	(4) AIRB weight	(5) No. of IRB portfolios	(6) No. of AIRB portfolios
Panel A						
PIII pages	20.757	23.783**	17.616	39.491**	5.537	13.497**
	(12.742)	(9.917)	(14.781)	(18.539)	(4.105)	(6.048)
No. of obs.	271	271	271	271	271	271
No. of banks	42	42	42	42	42	42
Adj. R^2	0.420	0.428	0.417	0.425	0.418	0.426
Panel B						
PIII credit risk pages	5.833	8.379**	12.688**	16.580**	2.739*	5.621***
	(4.586)	(3.562)	(5.256)	(6.632)	(1.468)	(2.163)
No. of obs.	270	270	270	270	270	270
No. of banks	42	42	42	42	42	42
Adj. R^2	0.189	0.203	0.204	0.206	0.196	0.207

Figure 1. Usage of (A)IRB approach

This figure shows the evolution over the 2008-2014 period of (*i*) the number of banks in the sample adopting the IRB and the Standardized approach (bars, left-hand scale) and (*ii*) the average credit exposures, in terms of EAD, covered by internal ratings-based models (*IRB weight*) and by advanced internal ratings-based models (*AIRB weight*) (lines, right-hand scale).

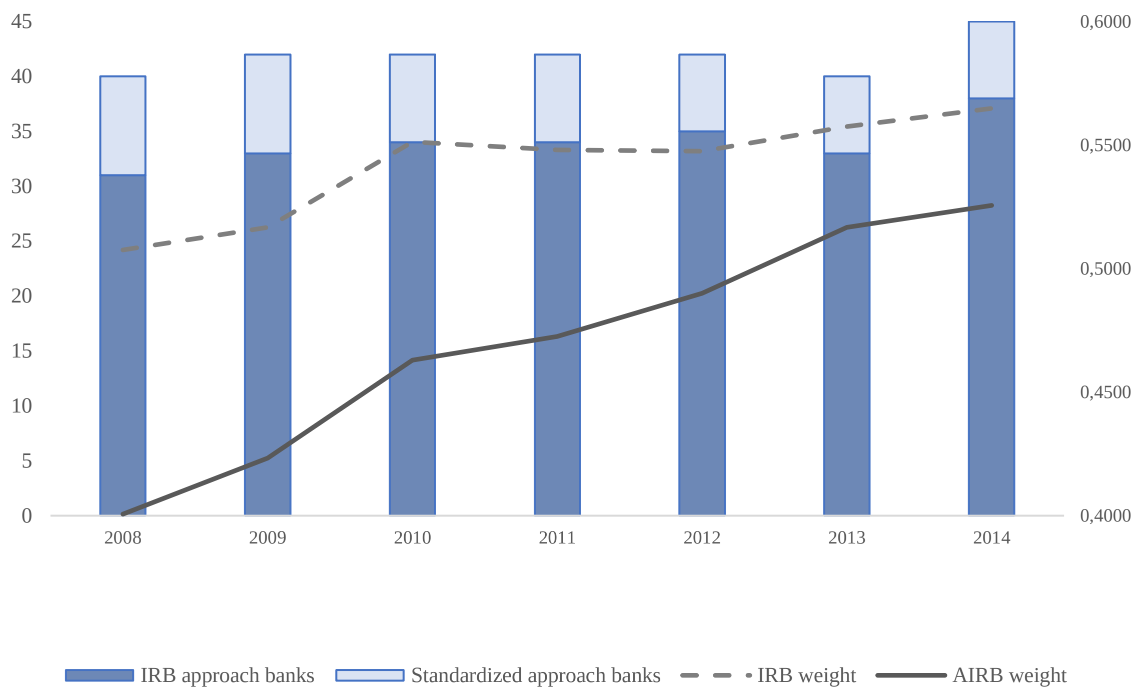


Figure 2. Number and type of portfolios under the (A)IRB approach

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

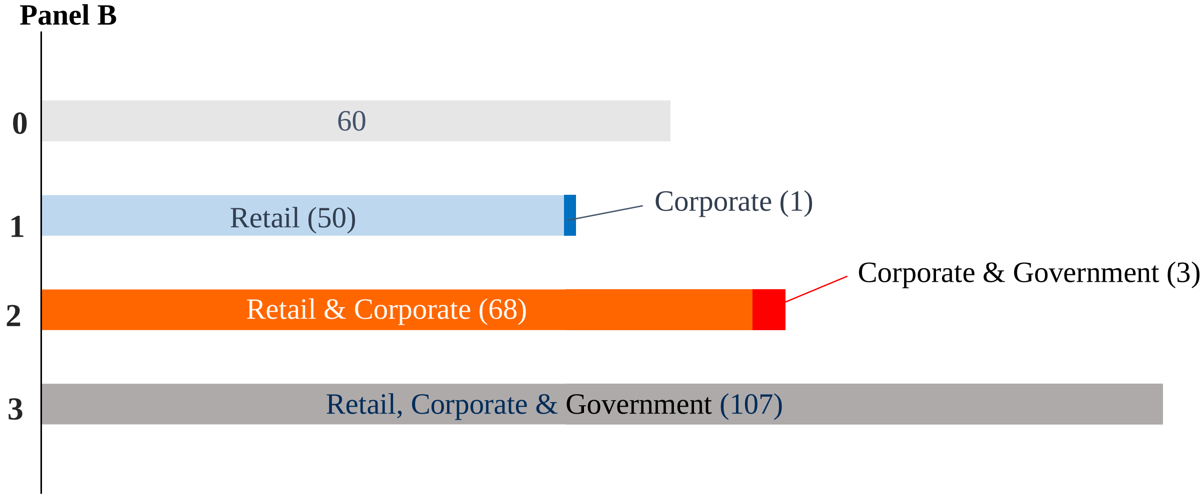


Figure 3. Marginal effect of *NPL* on opacity for different levels of *AIRB weight*

This figure contains the point estimates (solid line) and 90% and 99% confidence intervals (dotted and dashed lines, respectively) for the estimates of the marginal effect of *NPL* on banks' opacity - *MAFE* (left panel) and *Dispersion* (right panel) - according to *AIRB weight* as in regressions 1 and 4 of Table 8.

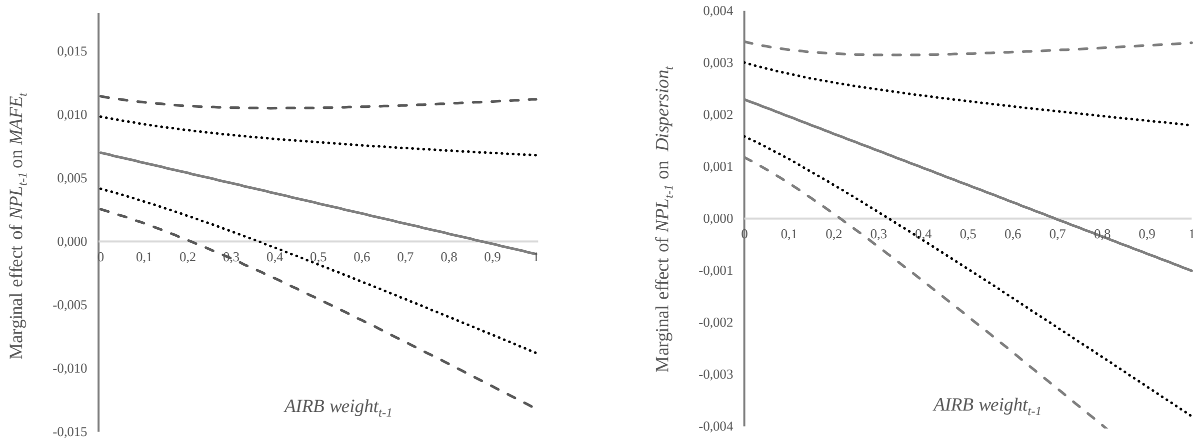


Figure 4. Marginal effect of *NPL* on opacity for different levels of *AIRB loans*

This figure contains the point estimates (solid line) and 90% and 99% confidence intervals (dotted and dashed lines, respectively) for the estimates of the marginal effect of *NPL* on banks' opacity - *MAFE* (left panel) and *Dispersion* (right panel) - according to *AIRB loans* as in regressions 2 and 5 of Table 8.

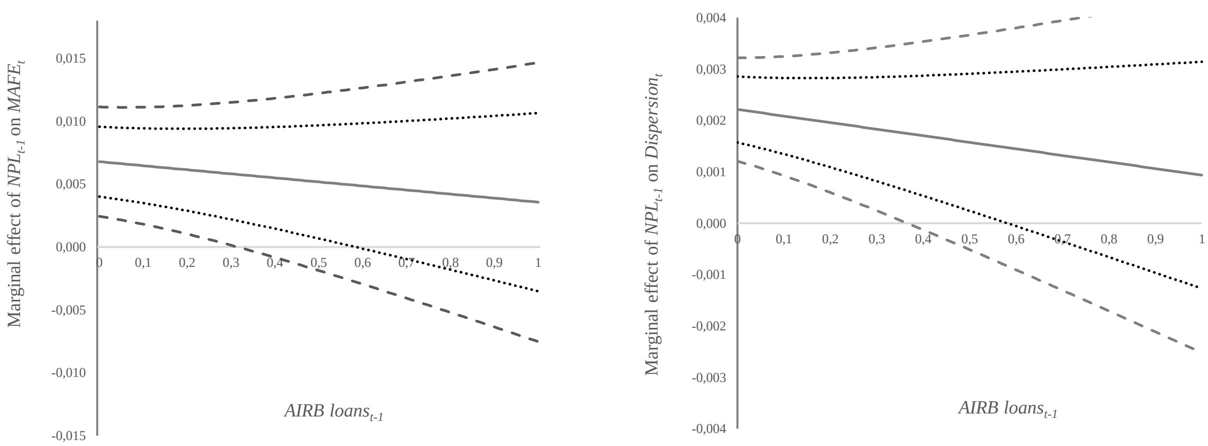
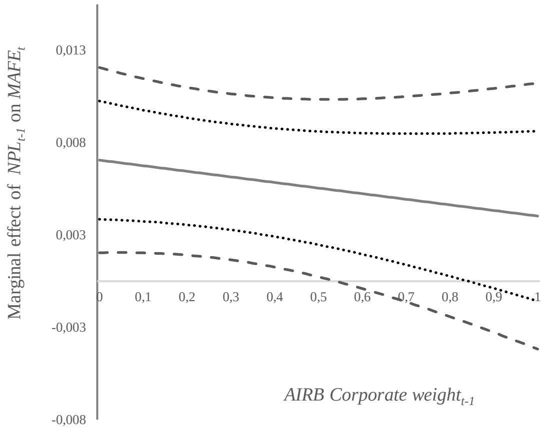
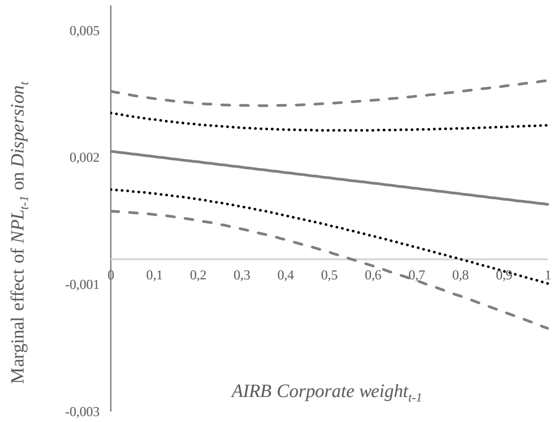


Figure 5. Marginal effect of *NPL* on opacity for different levels of *AIRB Corporate weight*

This figure contains the point estimates (solid line) and 90% and 99% confidence intervals (dotted and dashed lines, respectively) for the estimates of the marginal effect of *NPL* on banks' opacity - *MAFE* (left panel) and *Dispersion* (right panel) - according to *AIRB Corporate weight* as in regressions 3 and 6 of Table 8.





Internal Ratings, Non-Performing Loans, and Bank Opacity: Evidence from Analysts' Forecasts (Internet appendix)

Brunella Bruno

Immacolata Marino

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IA.I. The implementation of the IRB approach and the evolution of the IRB indicators: the Intesa Sanpaolo (ISP) case

In 2008, the Intesa Sanpaolo Group began the approval process for the adoption of the advanced approach within the “Basel 2 Project”. With regards to credit risk, the plan distinguished between the Italian subsidiaries belonging to an “initial scope” for which IRB models adoption was carried over a period of six years (2009-2014) and those (Italian and foreign) subsidiaries for which models were adopted at a later date.

The roll-out plan did not include certain exposures for which the permanent partial use of the standardized approach was requested: exposures to central governments and central banks; exposures to the banking group; exposures to minor operational units; and non-significant exposure classes in terms of size and risk level (e.g., loans to non-bank financial institutions). As such, in our dataset, the amount of credit risk exposure under (A)IRB for the government portfolio is zero during the whole sample period.

For the “initial scope” companies, the ISP Group was authorized to use the IRB Foundation approach for the corporate portfolio starting from its report as of 31 December 2008.

Accordingly, the IRB variables in 2008 in our dataset take the following values:

- IRB dummy = 1 (AIRB dummy = 0)
- IRB weight = 0.26 (AIRB weight = 0)
- number of portfolios under IRB = 1 (number of portfolios under AIRB = 0);
- IRB corporate = 60% (AIRB corporate = 0);
- (A)IRB retail = 0;[1]
- IRB government = 0.

[1] For retail exposures managed in pool there is no distinction between IRB and AIRB.

In 2010 the roll-out plan entailed the following steps:

- transitions to the AIRB approach for the corporate portfolio and for certain retail exposures (i.e., "exposures secured by residential property");
- transitions to the IRB approach for the "other retail exposures".

Accordingly, in our dataset the main IRB usage variables in 2010 are the following:

- IRB dummy = 1 (AIRB dummy = 1)
- IRB weight = 0.39 (AIRB weight = 0.35)
- number of portfolios under IRB = 2 (number of portfolios under AIRB = 2);
- IRB corporate = 78% (AIRB corporate = 69%);
- (A)IRB retail = 42%;
- IRB government = 0.

Following the gradual adoption of AIRB models, the ISP Group started disclosing in 2010 Pillar III report additional qualitative and quantitative information on new risk parameters. For example, a new column (with the weighted average LGD by rating class) was added in the tables reporting the amount and probability of default of the exposures under the advanced model (i.e., "exposures secured by residential property" and "exposures to or secured by corporates").

IA.II. The absolute value of discretionary loan loss provisions

ABSDLLP(j) (with $j = a$, b, c or d) is the absolute value of discretionary loan loss provisions, calculated as the absolute value of the residual from one of the following four regression models (IA.1j) adopted by Beatty and Liao (2014):

$$LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \\ + \beta_5 Size_{i,t-1} + \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \\ + \beta_8 Real\ estate\ return_{i,t} + \beta_9 \Delta Unemployment_{i,t} + \varepsilon_{it}. \tag{IA.1a}$$

$$LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \\ + \beta_5 Size_{i,t-1} + \ \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \\ + \beta_8 Real\ estate\ return_{i,t} + \beta_9 \Delta Unemployment_{i,t} + \beta_{10} LLA_{i,t-1} + \\ + \varepsilon_{it}. \tag{IA.1b}$$

$$LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \\ + \beta_5 Size_{i,t-1} + \ \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \\ + \beta_8 Real\ estate\ return_{i,t} + \beta_9 \Delta Unemployment_{i,t} + \\ \beta_{10} Charge\ offs_{i,t} + + \varepsilon_{it}. \tag{IA.1c}$$

$$LLP_{it} = \alpha + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \\ + \beta_5 Size_{i,t-1} + \ \beta_6\ \Delta Loans_{i,t-1} + \beta_7\ \Delta GDP_{i,t} + \\ + \beta_8 Real\ estate\ return_{i,t} + \ \beta_9 \Delta Unemployment_{i,t} + \beta_{10} LLA_{i,t-1} + \\ + \beta_{11} Charge\ offs_{i,t} + \varepsilon_{it}. \tag{IA.1d}$$

where, for every bank *i* at time *t* (*t*-1), *LLP* is loan loss provisions scaled by lagged total loans; *NPL* is non-performing loans divided by lagged total loans; *Size* is the natural log of total assets; *Loans* is total loans divided by lagged total loans; *GDP* is the country's annual real gross domestic product; *Real estate return* is the return on the house price index over the year; *Unemployment* is the country's unemployment rate; *LLA* is loan loss allowances divided by total loans; *Charge offs* is net charge-offs; and Δ denotes change.

Tables and figures

Table IA.1. Usage of internal ratings-based models and bank opacity in (A)IRB banks

This table reports the coefficient estimates of an OLS regression of bank opacity on the usage of internal ratings-based models. The analysis is performed on the subsample of all banks adopting IRB models (in columns 1 and 3) and AIRB models (in columns 2 and 4). 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 (*MAFE*, in columns 1-2) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 3-4). The main explanatory variables are: the share of credit exposures, in terms of EAD, covered by internal ratings-based models (*IRB weight*, columns 1 and 3) and the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*, columns 2 and 4). Control variables (not reported for brevity) are the same as in Table 2, columns 2 and 5. 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)
	MAFE$_t$		**Dispersion$_t$**	
	IRB	*AIRB*	*IRB*	*AIRB*
Weight	-0.112	-0.191**	-0.079**	-0.117***
	(0.126)	(0.073)	(0.034)	(0.029)
Controls	Yes	Yes	Yes	Yes
No. of obs.	200	195	199	194
No. of banks	36	36	35	35
Adj. R^2	0.407	0.446	0.518	0.602

Table IA.2. Usage of internal ratings-based models across different credit exposures and bank opacity in (A)IRB banks

This table reports the coefficient estimates of an OLS regression of bank opacity on various measures of usage of internal ratings-based models. The analysis is performed on the subsample of all banks adopting IRB models (in odd-numbered columns) and AIRB models (in odd-numbered columns). 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 (*MAFE*, in columns 1-6) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 7-12). The main explanatory variables are: two dummy variables taking value 1 if the bank has two/three portfolio(s) with a share of credit exposures, in terms of EAD, covered by internal ratings-based models higher than zero (*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 3portfolios,* columns 2 and 8); three dummy variables variable 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 variable 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, columns 2 and 5. 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)
	$MAFE_t$						$Dispersion_t$					
	IRB	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*	*IRB*	*AIRB*
$2portfolios_{t-1}$	-0.051	-0.063*					-0.020	-0.032**				
	(0.047)	(0.033)					(0.015)	(0.013)				
$3portfolios_{t-1}$	-0.147	-0.130***					-0.035	-0.062***				
	(0.089)	(0.042)					(0.036)	(0.021)				
Corporate $dummy_{t-1}$			-0.168***	-0.091**					-0.087***	-0.040**		
			(0.027)	(0.035)					(0.011)	(0.015)		
Retail $dummy_{t-1}$			-0.060	-0.121					-0.016	-0.039		
			(0.047)	(0.090)					(0.013)	(0.030)		
Government $dummy_{t-1}$			0.005	-0.011					0.025***	-0.015		
			(0.028)	(0.038)					(0.009)	(0.020)		
Corporate $weight_{t-1}$					-0.201**	-0.134***					-0.069**	- 0.060***
					(0.096)	(0.047)					(0.027)	(0.018)
Retail $weight_{t-1}$					-0.016	-0.006					-0.018	-0.024
					(0.059)	(0.087)					(0.017)	(0.019)
Government $weight_{t-1}$					0.083	0.003					0.014	-0.019
					(0.063)	(0.082)					(0.035)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	200	195	200	195	200	195	199	194	199	194	199	194
No. of banks	36	36	36	36	36	36	35	35	35	35	35	35
Adj. R^2	0.414	0.448	0.417	0.451	0.435	0.444	0.505	0.576	0.530	0.577	0.539	0.589

Table IA.3. Internal ratings-based models and initial capitalization levels on bank opacity

This table reports the coefficient estimates of an OLS regression of bank opacity on the usage of advanced internal ratings-based models under different levels of the bank capitalization at the beginning of sample period. 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 (*MAFE*, in columns 1 and 2) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in column 3 and 4). The main explanatory variables are: the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*) and the interaction between *AIRB weight* and the ratio of Tier 1 capital over Risk weighted assets in 2008 (*Tier 1 ratio in 2008*). The other explanatory variables are defined in Appendix B. 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) **MAFE$_t$**	(2) **Dispersion$_t$**
AIRB weight$_{t-1}$	0.459	0.124
	(0.404)	(0.143)
Tier 1 ratio in 2008 × AIRB weight$_{t-1}$	-0.075	-0.025
	(0.049)	(0.018)
Loans$_{t-1}$	-0.000	-0.000
	(0.002)	(0.000)
Corporate ratio$_{t-1}$	0.176	0.0091**
	(0.139)	(0.040)
NPL$_{t-1}$	0.005***	0.002**
	(0.002)	(0.000)
Equity ratio$_{t-1}$	-0.020***	-0.007***
	(0.009)	(0.002)
Deposits$_{t-1}$	-0.004**	-0.001***
	(0.002)	(0.000)
ROA$_{t-1}$	0.008	0.000
	(0.013)	(0.004)
Size$_{t-1}$	-0.049	-0.012
	(0.051)	(0.023)
ΔGDP$_t$	-0.006**	-0.004***
	(0.003)	(0.001)
Stock market return$_t$	-0.003***	-0.001***
	(0.001)	(0.000)
Intercept	0.855	0.253
	(0.695)	(0.318)
No. of obs.	289	287
No. of banks	43	42
Adj. R^2	0.292	0.460

Table IA.4. Advanced internal ratings-based models and impact of NPLs on bank opacity

This table reports the coefficient estimates of an OLS regression of bank opacity on the share of non-performing loans in banks using advanced internal rating 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 (*MAFE*, in columns 1-3) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 4-6). The main explanatory variables are: the share of impaired loans over total gross loans (*NPL*); a dummy variable taking value 1 if the share of credit exposures, in terms of EAD, covered by (advanced) internal ratings-based models exceeds zero (*AIRB dummy*, columns 1 and 3); dummy variable taking value 1 if the share of corporate credit exposures, in terms of EAD, covered by (advanced) internal ratings-based models exceeds zero (*AIRB Corporate dummy*, columns 2 and 4); and the interaction between *NPL* and either *AIRB dummy* (columns 1 and 3) or *AIRB Corporate dummy* (columns 2 and 4). Control variables (not reported for brevity) are the same as in Table 2, columns 2 and 5. 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. *F*-test tests the hypothesis that the sum of the coefficients for *NPL* and the interaction term *NPL × AIRB dummy* (columns 1 and 3) and *NPL × AIRB Corporate dummy* (columns 2 and 4) equals zero. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	MAFE$_t$		**Dispersion$_t$**	
NPL$_{t-1}$	0.007***	0.007***	0.002***	0.002***
	(0.001)	(0.002)	(0.000)	(0.000)
AIRB dummy$_{t-1-1}$	-0.020		0.001	
	(0.042)		(0.015)	
AIRB Corporate dummy$_{t-1}$		-0.067**		-0.024**
		(0.026)		(0.010)
NPL$_{t-1}$×AIRB dummy$_{-1}$	-0.002		-0.001	
	(0.003)		(0.001)	
NPL$_{t-1}$×AIRB Corporate dummy$_{t-1}$		-0.003		-0.001
		(0.003)		(0.001)
AIRB Retail dummy$_{t-1}$		-0.013		0.006
		(0.041)		(0.012)
AIRB Government dummy$_{t-1}$		-0.025		-0.022
		(0.039)		(0.022)
Controls	Yes	Yes	Yes	Yes
No. of obs.	289	289	287	287
No. of banks	43	43	42	42
Adj. R^2	0.277	0.301	0.396	0.440
F-test	1.76	1.86	1.96	1.34

Figure IA.1. Marginal effect of *AIRB weight* on opacity for different levels of Tier 1 ratio in 2008

This figure contains the point estimates (solid line) and 95% confidence intervals (dotted lines) for the estimates of the marginal effect of *AIRB weight* on banks' opacity – *MAFE* (left panel) and *Dispersion* (right panel) – according to bank's *Tier 1 ratio in 2008* as in regressions 1 and 2 of Table IA.3.