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

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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 usage of these models is associated with lower forecast error and disagreement among analysts about bank earnings per share. These results seem to be driven by the more detailed disclosure of loan portfolios required of IRB users, and 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. However, the transparency-enhancing role of IRB models fades in low-capital banks, suggesting that capital constraints could favor an opportunistic usage of internal ratings that counterbalances their beneficial effect on bank transparency.

JEL Classification: G20; G21; G28.

Keywords: Banks; Opacity; Internal Ratings-Based (IRB) approach; NPLs; Analysts' forecasts.

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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 usage of these models is associated with lower forecast error and disagreement among analysts about bank earnings per share. These results seem to be driven by the more detailed disclosure of loan portfolios required of IRB users, and 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. However, the transparency-enhancing role of IRB models fades in low-capital banks, suggesting that capital constraints could favor an opportunistic usage of internal ratings that counterbalances their beneficial effect on bank transparency.

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1. Introduction

An important, but rather unexplored, topic in the banking literature is whether internal ratings accentuate or mitigate bank opacity. We address this issue by looking at the forecast error and the disagreement among equity analysts about the banks' expected earnings per share (EPS) as measures of bank opacity. Specifically, we investigate whether and to what extent a more intensive usage of such models helps analysts assess banks' performance more accurately.

A large literature in banking has studied the critical question of bank opacity (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, raises information asymmetry and moral hazard concerns that entail 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).

Despite their relevance for regulators, the implications of internal ratings for bank opacity are not clear a priori. Internal ratings, i.e., a bank's internal assessment of counterparties and exposures, were first introduced in the Basel II Capital Accord (2003) as an alternative, and ideally more accurate, way to assess bank riskiness and hence, to calculate risk-weighted capital requirements. They were considered an improvement over existing risk weights based on external ratings released by credit rating agencies. In the regulators' view (BIS, 2001), the superiority of internal ratings would lie in two distinctive features. The first is an additional risk sensitivity: internal ratings-based (IRB) capital requirements are supposed to be more sensitive to the drivers of credit risk and economic loss in a bank's portfolio. The second is an incentive compatibility, as an appropriately structured internal ratings system is expected to improve banks' risk management practices.

In this view, internal ratings may prove useful in reducing uncertainty around bank balance sheets because of two favorable channels: more appropriate risk models and higher disclosure requirements. Better risk models and management practices could in principle lead to more accurate loan loss provisioning and pricing schemes. This would make future earnings more stable and predictable. At the same time, since IRB banks (i.e., banks adopting IRB models) are required to disclose details on their risk parameters in the so-called Pillar III report, investors and analysts could benefit from a richer information set that could result in more homogeneous earnings forecasts.

Unexpectedly, however, since the global financial crisis the usage 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. A range of studies reported a wide variation in risk weighted assets (RWAs) across banks, with relatively lower RWA densities (i.e., the share of RWA over total assets) found at banks and in banking systems where the adoption of IRB models was more comprehensive (Le Leslè and Avramova, 2012). 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 among market participants (Barclays Capital, 2011).

Several studies have 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). The main findings corroborate the existence of strategic risk-modelling, calling for simpler rules to increase the efficacy of financial regulation (Mariathasan and Merrouche, 2014; Behn et al., 2016; Berg and Koziol, 2017).

Against this background, we aim to assess the implication of IRB usage on bank opacity. We proceed in four steps. We first check the validity of our transparency measures by testing how asset composition, asset quality, funding structure and macro variable indicators affect analysts' forecast of banks' earnings. Previous work on bank opacity (Flannery et al. 2004) has shown that analysts' earnings forecasts provide an independent (external) measure of firm opacity. *Ceteris paribus*, larger analyst forecast errors or greater disagreement across analysts' forecasts implies that the firm is harder to understand. As expected, we find forecast errors and dispersion to increase during economic downturns; when the share of the most opaque components of loan portfolio (i.e., non-performing loans (NPLs) and corporate loans) increases; and when the "plain" (i.e., non-risk-weighted) capital ratio decreases.

Second, in our main analysis, we enrich the explanatory variables of our econometric model with a measure of the intensity of usage of IRB models. Our primary variable of interest is the share of credit exposures evaluated with the IRB approach. Alternatively, we construct a measure based on the value of the exposures under the *advanced* version of the model (the AIRB approach) to capture its higher degree of sophistication in measuring credit risk. We expect any effect on analysts' forecasts to be stronger when banks adopt the advanced as opposed to the *foundation* IRB approach since the former models are more granular and risk-sensitive.[1] In addition, banks adopting AIRB models are required to release even more information on their internal risk parameters including, for example, the loss rates experienced on past defaulted loans, which provide a useful benchmark against which current loan loss provisions can be evaluated. Finally, we include indicators of the share of corporate and retail loans under the advanced approach. These additional variables enable us to account for the different informational content attached to relatively more tailor-made loans (namely, those granted to corporates) as opposed to standardized contracts (namely, retail loans, such as mortgages and consumer credits), in line with relationship banking literature (Boot, 2000). We find that a greater usage of IRB models is associated with lower forecast error and disagreement among analysts. This result is statistically and economically more relevant for banks adopting the advanced approach (the coefficient associated with the AIRB adoption variable in our model is 8 percentage points greater than the coefficient associated with the IRB adoption variable). Interestingly, this result does not hold for low-capital banks, suggesting that weaker banks have a greater incentive to use internal models opportunistically.

Third, we investigate more explicitly whether and to what extent the usage of an IRB model mitigates the intrinsic opacity of NPLs. NPLs, that is, loans that are past due or unlikely to be repaid, are not only risky but also highly opaque assets which have recently become a supervisory priority in Europe (ESRB, 2017; EBA, 2019). Our results show that advanced IRB models mitigate the opacity-increasing effect of NPLs. Specifically, the negative impact of NPLs on bank opacity is neutralized for banks in our sample with at least 21% of their credit exposures managed under the advanced approach.

[1] In the foundation internal ratings-based (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.

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 is through the wider and deeper informational disclosure they entail.

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 adoption. We also contribute to the analyst forecast literature as we show that IRB information is a useful input in analysts' forecasting process mainly due to the disclosure of more granular data.

Another important contribution is that the paper provides new evidence for the discussion on NPLs. Problem loans have recently become a first-order priority for banking authorities in Europe, 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). One of the channels by which NPLs could impair bank lending is by making bank asset values harder to assess. This would 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 is important to design more calibrated measures to cope with problem loans.

Finally, the paper carries important policy implications. To the extent that bank opacity is detrimental to bank stability (Fosu et al., 2017, and the discussion therein), improving bank balance sheet transparency is a relevant supervisory and regulatory objective (Goldstein and Sapra, 2014). By showing the overall benefits of IRB adoption in terms of reduced opacity, the paper also addresses some potential regulatory and supervisory concerns about whether and to what extent internal rating model should be allowed.

The 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. Section 5 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 applications of IRB models, suggesting that both "opportunistic" and "transparency-enhancing" uses of IRB models are plausible. We then formulate hypotheses about whether and how IRB adoption influences bank opacity.

2.1. Institutional background

2.1.1. IRB models and capital regulation

Prudential regulations require banks to hold a minimum amount of own funds ("regulatory capital") to absorb unexpected losses that may originate from risky investments. Therefore, capital holdings must increase proportionally to the bank's RWAs.

The 2004 Basel II agreement introduced a major innovation in capital requirement and risk-weight calculation as banks were asked to choose between two approaches: the standardized approach based on external agencies' ratings, and the IRB approach based on the assessment of credit risk provided by the banks themselves. In the IRB approach four key parameters are needed to capture the credit risk of an exposure: the borrower's probability of default (PD); the loss given default (LGD), i.e., the loss rate in the event of a default; the exposure size at default (EAD); and the life-to-maturity. While PDs are borrower specific, LGD and EAD reflect certain characteristics of the loan facility such as the loan seniority and type of collateral.[2] 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. When all four parameters are estimated internally, a bank is said to follow the "advanced" (AIRB) approach. Banks develop complex models to estimate these parameters, which need to be validated by the competent national authority in order for banks to employ their internal estimates to quantify risk weights and hence, the regulatory capital required to cover each exposure.

The shift towards the IRB approach (as opposed to pre-set risk weights as in Basel I or in the Basel II standardized approach) that was motivated by the need to enhance the risk sensitivity of capital ratios came at a cost. The first side effect of the IRB framework was that its greater granularity could compromise comparability in capital requirements across banks. The second potential flaw concerned the complexity of internal rating systems (especially in the advanced

[2] 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).

version). By making external scrutiny more difficult, the IBR approach could increase the incentive to capital arbitrage through risk weight manipulation.

Since 2004 the IRB approach has been adopted by a growing number of banks, many of which achieved substantial benefits in terms of lower capital requirements. The wide variation in RWAs at large banks adopting different approaches (Le Leslè and Avramova, 2012) impaired comparability of capital ratios and raised doubts on the credibility of risk-based capital measures. The 2007-2009 global financial crisis reinforced the belief that RWAs may have helped banks disguise a rising credit bubble by keeping their stated capital ratios artificially high. Consequently, investors started arguing that banks may not be as capitalized as suggested by risk-based measures (Barclays Capital, 2011; Masters, 2012). Further doubts on the reliability of RWAs stemmed from academic studies that found evidence of intentionally biased risk estimates to lower regulatory capital requirements (Mariathasan and Merrouche, 2014; Abbassi and Schmidt, 2018; Behn et al., 2016; Plosser and Santos, 2018).[3] Market participants lose faith in RWAs given the excessive complexity of internal ratings that could make monitoring harder and, thus, provide banks with the incentive to manipulate risk weights in order to relax capital constraints.[4]

Basel III, the third international accord on bank capital agreed in late 2010, provided the first regulatory response to curb biases due to opportunistic/flawed internal ratings. 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 leverage ratio requirement for global systemically important institutions; and introduce an aggregate output floor to RWA based on the standardized approaches (BCBS, 2017).

2.1.2. Internal ratings: risk management practices and disclosure requirements

The scope of application of internal ratings goes beyond calculating a bank's capital requirement. As argued by the banking regulator (BCBS, 2006), internal ratings-based models have so many managerial applications that using IRB for the sole purpose of calculating the capital requirement would be considered "unacceptable".

[3] See also Bruno et al. (2017), and the literature review therein.

[4] 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.

In many banks, internal ratings are 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 used as 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.

Moreover, IRB banks could have an information advantage over banks adopting less sophisticated approaches since IRB models require a large amount of qualitative and quantitative information on borrowers, collateral, and loan facilities. Under Pillar III rules, banks are asked to disclose relevant data and information on their risk exposures and risk management approach, which are more detailed in IRB banks (as opposed to banks adopting the standard model), and the more so when the advanced approach is adopted (as opposed to the foundation approach). Sharing this information with market participants (investors, financial analysts, rating agencies, etc.) would enable them to exert market discipline. They could reward through reduced cost of funding those banks that are managed effectively while penalizing with a higher cost of funding those whose management is weak.

Overall, previous work on the impact of internal ratings-based models on risk management, loan pricing and bank profitability supports the view that IRB can strengthen incentives for banks to behave in a prudent and efficient manner. 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.

2.2. Hypotheses development

2.2.1. IRB models and bank opacity

Based on these research results, it is difficult to establish a priori whether and how a more intense adoption of internal ratings-based models affects bank opacity.

On the one hand, according to the discussion in Section 2.1.1, IRB models could lend themselves to misuse and distorted incentives, making banks' key performance indicators unreliable. In this view, the more intensive application of internal ratings would increase bank opacity, pointing to an "opportunistic" usage of IRB models.

On the other hand, based on the discussion in Section 2.1.2, a more intensive usage of internal ratings could help stabilize banks' profits through more appropriate risk models and practices (effective risk management channel) and/or by releasing more accurate information (enhanced disclosure channel). Hence, a greater adoption of the IRB approach would reduce bank opacity, suggesting a "transparency-enhancing" usage of IRB models.

The above arguments demonstrate that the net effect of the usage of internal ratings-based (IRB) models on bank opacity is ambiguous. Therefore, whether the net change in opacity is positive or negative for the average bank is an empirical question which constitutes our first testable hypothesis:

H1*: The net effect of the usage of internal ratings-based models on bank opacity can be positive or negative.*

For the reasons explained in the institutional section, any such effect would be more pronounced in banks adopting the advanced version of IRB models more intensively. 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 is 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).[5]

NPLs increase bank balance sheet opacity for many reasons. First, NPLs generate cash flows that are unstable and hard to predict. Second, higher NPLs are often associated with increasing loan loss provisions (LLPs). Because LLPs are at the discretion of bank managers, there is potential for banks to provision more or less than necessary in order to smooth their 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 in that troubled loans may increase moral hazard and promote excessive risk-taking by eroding bank capital (Bruno and Marino, 2018), which would in turn make bank profits even more unstable.

If IRB models are used opportunistically, banks 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, one may expect the effect of NPLs on balance sheet opacity to be mitigated in IRB banks. This would be due to either better risk management practices or better information associated with IRB adoption. Thus, adoption of IRB models would either reinforce or mitigate the detrimental effect of NPLs on bank opacity depending on whether internal ratings have been used opportunistically or not. This constitutes our third hypothesis:

H3*: The effect of NPLs on bank opacity depends on the use of internal ratings-based models.*

3. Data and empirical methodology

3.1. Sample and data sources

We build a cross-country sample of large listed European banking groups. Europe provides an interesting setting as IRB models have been adopted by a wider array of banks than in the US where they are used only by top tier institutions.[6] Starting with the top 50 listed groups by total

[5] NPLs in European banks skyrocketed to unprecedented levels in the wake of the global financial crisis and 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. What is worse, the COVID-19 pandemic and associated economic recession are expected to reignite the NPL problem: according to ECB estimates, in a severe scenario NPLs in euro area banks could surpass the levels of the financial and sovereign debt crises.

[6] 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.

assets and 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.[7] The country with the largest number of observations is Italy with about 17% of the total, followed by Spain and the UK (each with about 12% of the total). Our sample covers more than 60% of the European banks' total assets overall.

The data cover the period 2008-2015 which are the years prior to the Basel Committee's reforms introduced in 2017-2019 to prevent misuse of internal models. We collect 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 were using 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 that extends conventional analyzes on the determinants of bank opacity with the addition of measures of usage of IRB models:

$$OPACITY_{i,t} = \alpha + \beta \cdot IRB_{i,t-1} + \xi' \mathrm{X}_{i,t-1} + \gamma \cdot GDP\ growth_{i,t} + \\ + \theta \cdot Stock\ market\ return_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \tag{1}$$

The dependent variable, *OPACITY*, is alternatively measured in terms of either: *Forecast error* or *Dispersion* of bank *i* in year *t*, as defined in Flannery et al. (2004) and Anolli et al. (2014).[8] *Forecast error* is defined as the median absolute EPS forecast error, divided by the share price at

[7] Table A.1, in the Appendix, lists the 43 banks in the sample.
[8] All variable definitions and sources are reported in Table A.2, in the Appendix.

the start of the fiscal year. It provides us with an *ex post* measure of opacity, suggesting whether EPS proved easy or hard to guess. *Dispersion* is the cross-sectional standard deviation of EPS forecasts, computed only for banks with more than one analyst. This is an *ex ante* measure of opacity, suggesting stronger/weaker agreement among market participants.

β is the coefficient of interest that identifies the role played on bank opacity by our key explanatory variable, *IRB* – the intensity of IRB models' usage to assess credit risk by a bank in the previous fiscal year. *IRB* can be either *IRB weight* (the share of credit exposures, in terms of EAD, covered by internal ratings-based models), or *AIRB weight* (the share covered by advanced IRB models only). We use the two IRB variables to test *H1* and *H2*. In particular, the comparison between the impact of *IRB weight vs AIRB weight* on *OPACITY* gives us insights to test *H2*.

The vector $X_{i,t-1}$ of bank level controls includes variables that according to previous studies can affect bank balance sheet transparency. Bank characteristics are measured at *t*-1 to mitigate endogeneity concerns. 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*). 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 and captures the intuition 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 informational content is impounded 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 estimate (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 largely 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, unrisk-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 as potentially important influences on 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 core deposits.

Finally, drawing on the extant analyst forecast literature (Hutton et al., 2012), we employ macro-level variables: the GDP annual real growth rate (*GDP growth)* and the return rate of the stock market ($Stock\ market\ return$), as we expect the forecasts' accuracy to be affected by macroeconomic and financial markets conditions.[9] To account for the effect of a negative macro scenario more explicitly, we also include the sovereign debt crisis dummy that equals one in 2010-2012. All dependent variables are measured at time t and independent variables (except *GDP growth* and $Stock\ market\ return$) are measured at t-1.

[9] In untabulated analyzes, our main findings are confirmed if the year fixed effect and the *GDP growth* variables are replaced by year×country fixed effects.

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, 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 include the interacted term *NPL×IRB* to our analysis and employ the following regression equation:

$$OPACITY_{i,t} = \alpha + \beta_1 \cdot IRB_{i,t-1} + \beta_2 \cdot NPL_{i,t-1} + \beta_3 \cdot NPL_{i,t-1} \times IRB_{i,t-1} + \psi' \mathbf{\Phi}_{i,t-1} + \\ + \gamma \cdot GDP\ growth_{i,t} + \theta \cdot Stock\ market\ return_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

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, all dependent variables in this table are measured at time *t* and independent variables are measured at time *t*-1. The mean value of the *Forecast error* is 7.1%, with a high degree of heterogeneity across banks: the standard deviation is about two times its mean (14%) and the variable ranges from a p10 of 0.1% to a p90 of 25.9%. The average value of *Dispersion* is 3.6%, with a standard deviation of around 5%, indicating that this measure is less volatile relative to the *Forecast error*. As far as the key explanatory variables, the average values of *IRB weight* and *AIRB weight* in our sample are 54% and 47%, respectively.

Figure 1 reports the evolution of the average *IRB weight* and *AIRB weight* for the banks in our sample from 2008 to 2014. The increasing use of IRB and, especially, AIRB models shows the importance of some heterogeneity in the time series, that – along with the cross-sectional variation in banks' use of IRB models – calls for a panel fixed effects model estimation.

Total loans account for about 54% of the average bank's total assets, which records an average of annual €57 billion (*Size* is measured as the log of total assets). Our measure of asset quality, NPLs (as percentage of total gross loans) has a mean value of 7.3% with a standard deviation of similar size (7.43%). Equity capital stands at 5.7% of total assets, on average, and the mean value of *Tier 1 ratio* is 11.72%. These variables, including ROA, exhibit moderate levels of heterogeneity. We use all these balance sheet items, lagged one period, as controls in our specifications.

Insert Table 1 approximately here

Insert Figure 1 approximately here

4. Empirical results

4.1. Validation test

A preliminary investigation into the relationship between internal rating usage and bank opacity is illustrated in Table 2.

In Table 2 we test whether analysts' earnings forecasts reflect the information asymmetries impounded in the asset portfolios of our sample banks. Overall, we find this is the case. While the share of total loans to total assets seems unrelated to opacity, opacity increases when the share of corporate loans increases. Moreover, analysts' forecasts are less accurate and more dispersed the higher the share of NPLs. The result is 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. To further investigate the impact of the different measures of capitalization on bank opacity, we replace *Tier 1 ratio* and *Equity ratio* with a new variable (*Undercapital*) that summarizes their informational contents. *Undercapital* is the difference between the standardized values of *Tier 1 ratio* and *Equity ratio*. Banks with a positive (negative) *Undercapital* amount have *relative* values of *Tier 1 ratio* higher (lower) than their *relative Equity ratio* values, that is, they have a higher (lower) risk-weighted leverage ratio than the corresponding pure leverage ratio. A (high) positive value of *Undercapital* is associated with banks that appear to be better capitalized if assets are evaluated in their risk-weighted dimension than in absolute terms. When risk weights (especially if based on internal ratings models) are less credible, this seems to signal higher opacity. These findings support the idea (Haldane and Madouros, 2012) that markets are skeptical about the reliability of risk-based capital ratios, the more so the wider the gap between the pure leverage ratio and the risk-based capital ratio.

Funding structure is also important as our results reveal that analysts' forecasts improve along both dimensions 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. Consistently, the coefficient of the *Sovereign crisis* dummy variable in Columns 5 and 10 is negative 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 in bad times banking supervisors are more lenient and bank managers are more prone to discretionary behaviors (i.e., to underprovision and/or overstate the value of distressed assets), as found in previous literature (Huizinga and Laeven, 2012).

Insert Table 2 approximately here

4.2. Internal ratings-based models and bank opacity

To shed some light on the differences between banks with a different usage intensity of IRB models, in Table 3 we perform *t*-tests for the equality of means of High IRB banks versus Low IRB banks, that is the banks with above and below the median value of IRB exposures (63%), respectively. The results show that banks adopting more intensively IRB models are significantly less opaque in terms of forecast error and dispersion. This highlights the importance of obtaining a panel dataset with values for banks' opacity and usage of IRB models, and of employing a fixed effects approach to control for endogeneity in the cross section. There are other significant differences between more and less intense IRB users. High IRB banks are larger and relatively less oriented to traditional commercial banking, and report higher Tier 1 ratios, although combined on average with lower non-risk-weighted capital ratios. They also show better loan portfolio quality and lower earnings volatility (measured in terms of both ROA and ROE over different quarters).

Insert Table 3 approximately here

Table 4 reports the results of estimating equation (1) using ordinary least squares regressions to test *H1* and *H2*. The dependent variable is *Forecast error* (columns 1 to 3) and *Dispersion* (columns 4 to 6). IRB usage is captured by *IRB weight* in columns 1 and 4, by *AIRB weight* in columns 2 and 5, and by *AIRB corporate* and *AIRB retail* in columns 3 and 6.

Starting with the control variables, as in the previous test, we observe that a higher weight of corporate loans and NPLs corresponds to higher opacity levels. Tier 1 ratios are associated with greater opacity, while plain equity ratios reduce disagreement among analysts. Finally, a larger deposit base (indicative of a more traditional business model), a more favorable economic cycle and higher stock market return contribute positively to bank transparency by reducing forecast error and dispersion.

As for the link between internal ratings and bank opacity, the coefficient of *IRB weight* is negative although slightly statistically significant (columns 1 and 4). Results gain significance at 1% level when we replace *IRB weight* with *AIRB weight* (columns 2 and 5). These findings are consistent and economically significant across our two alternative opacity measures. For example, a one-standard deviation increase in *IRB weight* (30.6 percentage points) is associated with a decrease in *Forecast error* of 12.7 percentage points (55% of its mean) and a decrease in *Dispersion* of 5.2 percentage points (44% of its mean). The economic significance strengthens when we consider the effect of the advanced models' usage. A one-standard deviation increase in *AIRB weight* (30.4 percentage points) corresponds to a 20.7 percentage points decrease in *Forecast error* (89% of its mean) and a 9.3 percentage points decrease in *Dispersion* (79% of its mean).

In columns 3 and 6, we replace the *AIRB weight* variable with *AIRB corporate* and *AIRB retail* to analyze more in depth the impact of the usage of AIRB models. These variables represent the share of corporate and retail credit exposures, respectively, evaluated with advanced internal models. Not surprisingly, we find that the effect of the usage of AIRB models is fully driven by the *AIRB corporate* component. This finding is 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. As such, the opacity mitigating effect of internal ratings is greater, the larger the share of corporate exposures under AIRB models.

Insert Table 4 approximately here

4.3. Internal ratings, NPLs, and bank opacity

The results in Table 4 show that the usage of internal ratings models is associated with a lower degree of bank opacity. In this section, we take a step forward and explore one mechanism through which a more intensive adoption of internal models may result in lower opacity. Because the opacity mitigating effect of internal ratings is stronger if advanced models are used, the rest of the analysis focuses on the role played by the *AIRB weight* variable.

Hypothesis *H3* suggests heterogeneous effects of NPLs on bank opacity are conditional on the bank's use of (A)IRB models. In Table 5, we formally test this hypothesis using Equation (2). Specifically, we look at the interaction among two results from the previous analysis: (*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 *Forecast error* (columns 1 to 3) and *Dispersion* (columns 4 to 6).

Consistent with results in Table 4, the coefficients of *NPL* and the *AIRB weight* variables are significant with positive and negative signs, respectively. The size of the coefficient associated with the NPL variable is similar to the one in the baseline specification (Table 4, columns 2 and 5). However, the magnitude (in absolute terms) of the *AIRB weight* coefficients decreases from 0.207 and 0.093 (Table 4, columns 2 and 5) to 0.154 and 0.071 (Table 5, columns 1 and 4), indicating an average negative effect of 66% for the *Forecast error* and 60% for *Dispersion*. The negative coefficient for the *NPL×AIRB weight* interacted term suggests that more widespread AIRB usage mitigates the increased opacity due to a larger NPL portfolio. This is consistent with 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 5 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 it is also possible despite the significance of the reported coefficient. To shed light on the relations among the NPLs, AIRB usage, and opacity, Figure 2 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 2 contains estimates of the marginal effect of *NPL* on *Forecast Error*, 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 2 approximately here

In columns 2 and 5 of Table 5, 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,* but the share of its loans evaluated with (advanced) internal ratings models could be relatively lower. As a matter of fact, the conjectured beneficial effect of the internal ratings models on the NPL opacity would depend on the intensity of their adoption for the loan evaluation, rather than the more general internal ratings model adoption for the evaluation of *all* the bank's credit exposures. We therefore introduce a new variable, $AIRB\ \ loans$, defined as $AIRB\ loans = (corporate\ weight \times AIRB\ corporate) + (retail\ weight \times AIRB\ retail)$, where $corporate\ weight = \frac{corporate\ loans}{retail\ loans + corporat\ \ loans}$ and $retail\ weight = \frac{retail\ loans}{retail\ loans + corporat\ \ loans}$.

AIRB loans is the average of *AIRB corporate* and *AIRB retail* (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 loan* interacted term is not significant, the graphical description of the marginal effect of *NPL* on opacity for different levels of *AIRB loans* documents that the level of *AIRB loan* did play a role in conditioning the relation between *NPL* and opacity. Specifically, Figure 3 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 *Forecast error* and *Dispersion*, respectively), the relation between NPLs and bank opacity becomes statistically insignificant.

Insert Figure 3 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 both corporate and retail portfolios. The *AIRB weight* variable is therefore replaced with the *AIRB corporate* and the *AIRB retail* variables, both interacted with *NPL*. We find that the coefficients of *AIRB corporate* are statistically significant (and negative), whereas those of *AIRB retail* are not statistically different from zero. Although consistent with previous findings (see Table 4, columns 3 and 6), the result has now a slightly different meaning. In fact, the coefficients of *AIRB corporate* and *AIRB retail* in Table 5 summarize the relation between the relevance of IRB models in the corporate and retail portfolios and bank opacity when *NPL*=0. Figure 4 shows the importance of the conditional relation between *NPL* and the intensity of AIRB usage for the evaluation of the retail (left panels) and corporate (right panels) credit exposures, respectively. The detrimental effect of the NPLs on bank opacity becomes statistically insignificant as the AIRB adoption, for both the corporate and retail exposures, exceeds a certain threshold (which is around 22% for *Forecast Error* and 30% for *Dispersion*).

Insert Figure 4 approximately here

4.4. Further analyses

4.4.1. IRB model usage and earnings forecasts: exploring the mechanism

Our results in Table 4 indicate that a more intensive usage of IRB models corresponds to lower bank opacity, but they do not clarify which mechanism makes this relation work. In fact, our results are consistent with two possible (not mutually exclusive) arguments. According to the first one, the "risk management mechanism", IRB models may be associated with better risk management practices (including more accurate NPL recognition and more timely, non-discretionary provisions), which may translate into more stable (hence, more predictable) earnings. The second argument, the "information disclosure mechanism", 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.

To assess if the risk management mechanism effect is also at work, we estimate a fixed effects panel regression model similar to Equation (1), where the dependent variable is bank earnings volatility. We argue that if the risk management mechanism is in place, banks adopting IRB models more intensively should report lower earnings volatility.

Following De Hann and Poghosyan (2012), we proxy bank earnings volatility by the variation in either banks' return on assets (ROA) or their return on equity (ROE). Earnings volatility for bank i in year t is defined as the standard deviation of its ROA (ROE) calculated over year t's four quarters. As a robustness check, we also take the standard deviation of ROA (ROE) over the 8 (over years t and t+1) and 12 (over years t to t+2) quarters to calculate volatility.

Table 6 reports the results. The coefficient of our explanatory variable is not statistically significant in any of the six specifications. This means that a more intensive usage of AIRB models does not translate into a reduction of earnings volatility. 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. Overall, our analysis supports the information disclosure mechanism.

Insert Table 6 approximately here

4.4.2. Low-capital banks and opportunistic usage of IRB models

Overall, our results highlight the "bright side" of the IRB approach (Cucinelli et al., 2018), despite the heavy criticism that IRB models have faced especially in the aftermath of the global financial crisis. However, one may argue that the incentives to capital arbitrage through risk weight manipulation triggered by the adoption of IRB models may be stronger for banks in weak financial conditions. Namely, poorly capitalized banks, especially during periods of shortage of long-term financing, may find some advantage in manipulating risk weights to artificially enhance their regulatory capital ratios.[10] If this is true, the transparency-enhancing effect of the usage of IRB models may be less pronounced, or even inexistent, for low-capital banks.

To investigate how IRB adoption affects balance sheet opacity in poorly capitalized banks, we conduct an additional test and include in our baseline specification an interaction between the *AIRB weight* variable and a *Tier 1 ratio in 2008* variable that assigns, to all observations of a bank, the value of its *Tier 1 ratio* at the beginning of our sample period. By adding this interaction term, we attempt to verify if the impact of the usage of AIRB models on opacity during the sample period was affected by the capitalization of the bank at the beginning of the observation period. This period included two subsequent crises when raising capital was particularly expensive and meeting the regulatory capital requirements was more challenging.

The results of this analysis are presented in Table 7. As the tested 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. In fact, the (statistically non-significant positive) coefficient of *AIRB weight* expresses the marginal effect of the usage of AIRB models on opacity when the conditioning variable, *Tier 1 ratio in 2008*, is zero, which does not correspond to any real-word situation.[11] Similarly, as pointed out by Brambor et al (2006), there is no way of knowing, from the sign and

[10] This conjecture 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.
[11] *Tier 1 ratio in 2008* values range from 5.13 to 13.3.

significance of the coefficients of *Tier 1 ratio in 2008* × *AIRB weight* in Table 7, what the impact of the usage of AIRB models is when the 2008 *Tier 1 ratio* is greater than zero.

Insert Table 7 approximately here

Therefore, in line with the recommendations in Brambor et al. (2006), we plot the estimated marginal effects of the usage of AIRB models on opacity (solid lines) and their 95% confidence intervals (dotted lines) over all the observed range of *Tier 1 ratio in 2008*, in Figure 5. The left panel of Figure 5 contains estimates of the marginal effects of *AIRB weight* on *Forecast Error* computed on the estimates in column 1 of Table 7, while the right panel shows a similar relation for the *Dispersion* variable and values are computed on the estimates in column 2. 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 (as demonstrated by the negative slope of the marginal effects in both panels). Both panels show that 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 *Forecast error* and *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.

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 not have any 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; Bruno et al., 2017; Behn et al., 2016; Ferri and Pesic, 2016; Begley et al., 2017, Berg and Koziol, 2017).

Insert Figure 5 approximately here

5. Conclusions

This paper contributes to the institutional and academic literature on the benefits and challenges of bank internal ratings by uncovering a positive side 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.

The evidence in this paper documents a relation between the use of IRB models and bank opacity as measured by the 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 relation is stronger the more the IRB models are adopted in their "advanced" version and especially if they are applied to the corporate component of the bank's loan portfolio. Third, we show 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 cope with, and provide a clearer picture of, their NPL portfolios. Fourth, the absence of any significant relation between the use 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. Five, the fact that the AIRB model usage-opacity relation is not significant for low-capital banks makes our results compatible 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 adoption of internal ratings-based models contribute to enhance the transparency of bank balance sheets and especially their more opaque items such as corporate loans and problem loans.

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 model 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.

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Appendix

Table A.1. Banks in the sample

Bank	Country
Alpha Bank AE	Greece
BNP Paribas	France
BPER Banca S.P.A.	Italy
Banca Carige SpA	Italy
Banca Monte dei Paschi di Siena SpA	Italy
Banca Popolare di Milano SCaRL	Italy
Banco Bilbao Vizcaya Argentaria SA-BBVA	Spain
Banco Comercial Português, SA-Millennium bcp	Portugal
Banco Santander SA	Spain
Banco de Sabadell SA	Spain
Bank of Ireland-Governor and Company of the Bank of Ireland	Ireland
Bankinter SA	Spain
Barclays Plc	United Kingdom
Caixabank, S.A.	Spain
Commerzbank AG	Germany
Credit Suisse Group AG	Switzerland
Crédit Agricole S.A.	France
Crédit Industriel et Commercial SA – CIC	France
Danske Bank A/S	Denmark
Deutsche Bank AG	Germany
Dexia SA	Belgium
DnB ASA	Norway
Eurobank Ergasias SA	Greece
HSBC Holdings Plc	United Kingdom
ING Groep NV	Netherlands
Intesa Sanpaolo	Italy
Jyske Bank A/S	Denmark
KBC Group	Belgium
Lloyds Banking Group Plc	United Kingdom
National Bank of Greece SA	Greece
OP Corporate Bank plc	Finland
OTP Bank Plc	Hungary
Piraeus Bank SA	Greece
Powszechna Kasa Oszczednosci Bank Polski SA	Poland
Royal Bank of Scotland Group Plc (The)	United Kingdom
Skandinaviska Enskilda Banken AB	Sweden
Société Générale SA	France
Standard Chartered Plc	United Kingdom
Svenska Handelsbanken AB	Sweden
Swedbank AB	Sweden
UBS AG	Switzerland
UniCredit SpA	Italy
Unione di Banche Italiane Scpa-UBI Banca	Italy

Table A.2. Variable definition

Variables	Definition	Source
Forecast error	The 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	The cross-sectional standard deviation of analysts' EPS forecasts.	I/B/E/S
IRB weight	The share of credit exposures, in terms of EAD, covered by internal ratings-based models.	Banks' Pillar III reports
AIRB weight	The share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models.	Banks' Pillar III reports
AIRB loans	= Corporate weight × AIRB corporate + Retail weight × AIRB retail.	Banks' Pillar III reports
AIRB corporate	The share of corporate credit exposures evaluated with advanced internal models.	Banks' Pillar III reports
AIRB retail	The share of retail credit exposures evaluated with advanced internal models.	Banks' Pillar III reports
Loans	= Total loans/Total assets.	BankFocus
Corporate weight	= Corporate loans/(Corporate loans + Retail loans).	Banks' Pillar III reports
Retail weight	= Retail loans/(Corporate loans + Retail loans).	Banks' Pillar III reports
NPL	= Impaired loans/Total gross loans.	BankFocus
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
Size	= ln(Total assets).	BankFocus
ROA	Return on Assets.	BankFocus
GDP growth	The growth rate of the annual gross domestic product.	World Bank
Stock market return	The 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
ROA volatility (1, 2, and 3 years)	The 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)	The 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

Tables and figures

Table 1. Descriptive statistics

This table reports summary statistics for the characteristics of the banks in the sample.

	Mean	St. dev.	p10	p25	p50	p75	p90	N
Opacity measures								
Forecast error	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 weight	0.542	0.306	0	0.412	0.629	0.773	0.856	289
AIRB weight	0.470	0.304	0	0.238	0.524	0.722	0.810	289
AIRB loans	0.559	0.337	0	0.341	0.664	0.827	0.926	289
AIRB corporate	0.466	0.397	0	0	0.648	0.841	0.923	289
AIRB retail	0.617	0.364	0	0.423	0.765	0.903	0.967	289
Balance sheet items (lagged)								
Loans	54.09	16.96	28.31	42.00	58.58	67.64	74.19	289
NPL	7.305	7.474	0.938	2.561	5.212	9.115	16.53	289
Size	12.54	1.317	10.71	11.31	12.53	13.81	14.32	289
Corporate weight	0.526	0.136	0.354	0.425	0.531	0.615	0.677	289
Deposits	51.93	14.95	34.36	41.99	51.77	61.27	69.61	289
ROA	0.081	1.380	-0.833	0.0300	0.266	0.571	0.811	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
GDP growth	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
Earnings volatility measures								
ROA volatility – 1 year	0.318	0.758	0.0263	0.0438	0.0863	0.240	0.728	263
ROE volatility – 1 year	3.967	7.276	0.343	0.745	1.497	3.920	10.05	263
ROA volatility – 2 years	0.479	1.022	0.0414	0.0686	0.143	0.421	0.966	268
ROE volatility – 2 years	6.728	15.73	0.806	1.246	2.348	7.446	13.16	268
ROA volatility – 3 years	0.568	1.090	0.0539	0.0943	0.177	0.479	1.138	269
ROE volatility – 3 years	8.080	16.91	1.041	1.772	3.314	8.674	17.89	269

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 (*Forecast error*), in columns 1-4, and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*), in columns 5-8. Explanatory variables are defined in Table A.2. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects. All specifications except those in columns 4 and 8 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)	(7)	(8)
	Forecast error$_t$				**Dispersion$_t$**			
Loans$_{t-1}$	-0.001	0.000	0.000	0.000	-0.001	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Corporate weight$_{t-1}$	0.205	0.231*	0.241*	0.248*	0.090*	0.097**	0.098**	0.088**
	(0.143)	(0.128)	(0.128)	(0.138)	(0.048)	(0.045)	(0.043)	(0.043)
NPL$_{t-1}$	0.005***	0.006***	0.006***	0.006***	0.002***	0.002***	0.002***	0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Equity ratio$_{t-1}$	-	-0.024**	-	-0.017**	-	-0.007***	-	-0.006***
		(0.009)		(0.007)		(0.002)		(0.002)
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)
Undercapital$_{t-1}$	-	-	0.042**	-	-	-	0.009**	-
			(0.015)				(0.004)	
Deposits$_{t-1}$	-0.005**	-0.003**	-0.004**	-0.003**	-0.001***	-0.001**	-0.001**	-0.001**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
ROA$_{t-1}$	-0.015	-0.001	-0.010	-0.012	-0.007	-0.002	-0.007**	-0.004
	(0.010)	(0.012)	(0.009)	(0.012)	(0.004)	(0.004)	(0.003)	(0.003)
Size$_{t-1}$	-0.036	-0.031	-0.029	-0.005	-0.006	-0.004	-0.002	-0.001
	(0.058)	(0.054)	(0.056)	(0.056)	(0.028)	(0.027)	(0.027)	(0.023)
GDP growth$_t$	-0.008**	-0.007**	-0.007**	-0.003	-0.005***	-0.005***	-0.005***	-0.003***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Stock market return$_t$	-0.002	-0.003**	-0.002**	-0.001**	-0.000	-0.000*	-0.000	-0.000*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Sovereign crisis				0.029**				0.010**
				(0.014)				(0.004)
Intercept	0.531	0.388	0.371	0.018	0.127	0.079	0.056	0.044
	(0.760)	(0.722)	(0.754)	(0.754)	(0.379)	(0.368)	(0.357)	(0.317)
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	0.244	0.278	0.273	0.226	0.367	0.399	0.384	0.355

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

This table reports summary statistics (mean and standard deviation) for bank characteristics of banks with a share of credit exposures, in terms of EAD, covered by internal ratings-based models (*IRB weight*) equal or higher than (*High IRB banks*) and below (*Low IRB banks*) the median value (62.9%). All bank characteristics but *Forecast error* and *Dispersion* are lagged one period. All variables are defined in Table A.2. Column 5 reports the difference between the means and column 6 reports the *t*-test for the difference in means.

∗, ∗∗, and ∗∗∗ denotes significance at the 10%, 5%, and 1% level, respectively.

	High IRB banks		**Low IRB banks**		**Difference in Mean Low IRB – High IRB**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	St. dev.	Mean	St. dev.	(3) – (1)	*t*-test
Forecast error$_t$	0.05	0.10	0.10	0.17	0.05**	(2.97)
Dispersion$_t$	0.03	0.04	0.05	0.06	0.02***	(3.43)
Loans$_{t-1}$	45.52	15.96	62.60	13.26	17.08***	(9.89)
Corporate weight$_{t-1}$	0.54	0.13	0.52	0.14	-0.02	(-1.23)
NPL$_{t-1}$	4.13	3.38	10.46	8.96	6.33***	(7.96)
Equity ratio$_{t-1}$	4.71	1.46	6.79	3.14	2.09***	(7.26)
Tier 1 ratio$_{t-1}$	13.48	3.24	10.00	3.27	-3.48***	(-9.08)
Deposits$_{t-1}$	49.43	14.74	54.41	14.78	4.98**	(2.87)
ROA$_{t-1}$	0.22	0.46	-0.06	1.89	-0.29	(-1.77)
Size$_{t-1}$	13.18	1.05	11.90	1.25	-1.28***	(-9.40)
ROA volatility$_t$ – 1 year	0.10	0.11	0.51	1.00	0.41***	(4.82)
ROE volatility$_t$ – 1 year	2.79	4.40	5.00	8.97	2.21*	(2.57)
ROA volatility$_t$ – 2 years	0.14	0.14	0.79	1.34	0.66***	(5.74)
ROE volatility$_t$ – 2 years	3.73	5.30	9.47	20.82	5.74**	(3.13)
ROA volatility$_t$ – 3 years	0.16	0.13	0.94	1.40	0.79***	(6.58)
ROE volatility$_t$ – 3 years	4.14	5.22	11.65	22.25	7.51***	(3.86)
No. of obs.	144		145		289	

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 model. The dependent variables are the median of the analysts' absolute EPS forecast error, divided by the share price at the start of the fiscal year (*Forecast error*, in columns 1-3) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 3-6). 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 4); or the share of credit exposures, in terms of EAD, covered by advanced internal ratings-based models (*AIRB weight*, columns 2 and 5); or the share of corporate (retail) credit exposures evaluated with advanced internal models (*AIRB corporate* (*AIRB retail*), columns 3 and 6). Control variables are defined in Table A.2. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Forecast error$_t$			**Dispersion$_t$**		
IRB weight$_{t-1}$	-0.127*	-	-	-0.052*		-
	(0.064)			(0.026)		
AIRB weight$_{t-1}$	-	-0.207***	-	-	-0.093***	-
		(0.050)			(0.023)	
AIRB corporate$_{t-1}$	-	-	-0.146***	-	-	-0.059***
			(0.034)			(0.017)
AIRB retail$_{t-1}$	-	-	0.013	-	-	0.002
			(0.043)			(0.012)
Loans$_{t-1}$	-0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)
Corporate weight$_{t-1}$	0.234*	0.248**	0.258**	0.099**	0.104**	0.109**
	(0.122)	(0.117)	(0.118)	(0.042)	(0.040)	(0.041)
NPL$_{t-1}$	0.006***	0.006***	0.006***	0.002***	0.002***	0.002***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Equity ratio$_{t-1}$	-0.026***	-0.028***	-0.028***	-0.008***	-0.009***	-0.009***
	(0.009)	(0.009)	(0.009)	(0.002)	(0.002)	(0.002)
Tier 1 ratio$_{t-1}$	0.009**	0.011***	0.011***	0.001	0.002*	0.002*
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Deposits$_{t-1}$	-0.003*	-0.003**	-0.003**	-0.001**	-0.001**	-0.001**
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
ROA$_{t-1}$	0.001	0.002	0.001	-0.002	-0.001	-0.001
	(0.012)	(0.012)	(0.012)	(0.004)	(0.004)	(0.004)
Size$_{t-1}$	-0.042	-0.048	-0.036	-0.008	-0.011	-0.007
	(0.052)	(0.047)	(0.049)	(0.026)	(0.023)	(0.024)
GDP growth$_t$	-0.007**	-0.007**	-0.008**	-0.005***	-0.005***	-0.005***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Stock market return$_t$	-0.003**	-0.003***	-0.003***	-0.000*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Intercept	0.610	0.665	0.475	0.170	0.207	0.130
	(0.705)	(0.639)	(0.673)	(0.349)	(0.316)	(0.336)
No. of obs.	289	289	289	287	287	287
No. of banks	43	43	43	42	42	42
Adj. R^2	0.283	0.308	0.308	0.409	0.461	0.452

Table 5. 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 internal ratings 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 (*Forecast error*, in columns 1-3) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in columns 3-6). 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 advance internal ratings-based models (*AIRB weight*, columns 1 and 4); or 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); or the share of corporate (retail) credit exposures evaluated with advanced internal models (*AIRB corporate* (*AIRB retail*), columns 3 and 6); and the interaction between *NPL* and either *AIRB weight*, *AIRB loans*, or *AIRB corporate* and *AIRB retail*. Control variables are defined in Table A.2. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Forecast error$_t$			**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$_{t-1}$	-	-	-0.126***	-	-	-0.051***
			(0.040)			(0.019)
AIRB retail$_{t-1}$	-	-	0.016	-	-	0.004
			(0.058)			(0.018)
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$_{t-1}$	-	-	-0.003	-	-	-0.001
			(0.008)			(0.002)
NPL$_{t-1}$×AIRB retail$_{t-1}$	-	-	-0.001	-	-	-0.000
			(0.009)			(0.003)
Loans$_{t-1}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Corporate weight$_{t-1}$	0.220*	0.226*	0.240*	0.092**	0.098**	0.102**
	(0.124)	(0.125)	(0.135)	(0.039)	(0.040)	(0.041)
Equity ratio$_{t-1}$	-0.028***	-0.030***	-0.028***	-0.009***	-0.010***	-0.009***
	(0.010)	(0.010)	(0.009)	(0.002)	(0.003)	(0.002)
Tier 1 ratio$_{t-1}$	0.011***	0.012***	0.011***	0.002*	0.003**	0.002*
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Deposits$_{t-1}$	-0.003**	-0.003*	-0.003**	-0.001**	-0.001**	-0.001**
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
ROA$_{t-1}$	0.001	0.001	0.001	-0.001	-0.002	-0.001
	(0.012)	(0.012)	(0.012)	(0.004)	(0.004)	(0.004)
Size$_{t-1}$	-0.059	-0.053	-0.040	-0.016	-0.013	-0.009
	(0.044)	(0.044)	(0.045)	(0.021)	(0.023)	(0.024)
GDP growth$_t$	-0.007**	-0.007**	-0.008**	-0.005***	-0.005***	-0.005***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Stock market return$_t$	-0.003**	-0.003***	-0.003***	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Intercept	0.830	0.727	0.543	0.275	0.229	0.160
	(0.616)	(0.609)	(0.639)	(0.292)	(0.317)	(0.335)
No. of obs.	289	289	289	287	287	287
No. of banks	43	43	43	42	42	42
Adj. R^2	0.312	0.308	0.306	0.472	0.454	0.452

Table 6. 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 use of advanced internal ratings model. 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 are defined in Table A.2. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		ROA volatility$_t$			**ROE volatility$_t$**	
	1 year	2 years	3 years	1 year	2 years	3 years
AIRB weight$_{t-1}$	-0.037	-0.259	-0.211	1.058	-2.613	-4.640
	(0.171)	(0.188)	(0.217)	(4.878)	(5.344)	(3.242)
Loans$_{t-1}$	-0.005	-0.012	-0.020*	0.045	0.111	0.045
	(0.009)	(0.011)	(0.012)	(0.116)	(0.228)	(0.192)
Corporate weight$_{t-1}$	-0.554	-0.145	0.231	-3.900	-15.565	8.432
	(0.615)	(0.627)	(0.590)	(12.734)	(20.970)	(11.730)
NPL$_{t-1}$	-0.007	-0.027**	-0.060***	0.198	-0.201	-0.578
	(0.010)	(0.013)	(0.016)	(0.144)	(0.394)	(0.564)
Equity ratio$_{t-1}$	0.096**	0.034	0.045	-0.038	-0.959	-0.733
	(0.044)	(0.060)	(0.050)	(0.731)	(0.802)	(0.819)
Tier 1 ratio$_{t-1}$	-0.002	0.001	-0.009	0.183	-0.145	0.052
	(0.021)	(0.032)	(0.026)	(0.181)	(0.377)	(0.381)
Deposits$_{t-1}$	-0.014**	-0.009	0.001	0.008	-0.239	-0.006
	(0.006)	(0.008)	(0.006)	(0.105)	(0.270)	(0.111)
ROA$_{t-1}$	-0.304***	-0.314***	-0.203***	0.121	-1.039	-1.886
	(0.056)	(0.067)	(0.062)	(0.585)	(2.836)	(2.385)
Size$_{t-1}$	0.160	0.167	0.041	7.800	2.637	6.744
	(0.269)	(0.270)	(0.333)	(5.003)	(6.121)	(5.358)
GDP growth$_t$	-0.139***	-0.164***	-0.118***	-0.965	-0.770	-0.760
	(0.041)	(0.049)	(0.034)	(0.684)	(0.779)	(1.182)
Stock market return$_t$	0.003	-0.003	-0.001	-0.014	-0.029	0.040
	(0.004)	(0.005)	(0.005)	(0.068)	(0.100)	(0.130)
Intercept	-1.396	-1.256	0.646	-100.390	-9.395	-77.718
	(4.121)	(3.889)	(4.719)	(68.063)	(92.244)	(76.655)
No. of obs.	263	268	269	263	268	269
No. of banks	39	39	39	39	39	39
Adj. R^2	0.514	0.599	0.594	0.073	0.054	0.111

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 model 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 (*Forecast error*, in column 1) and the cross-sectional standard deviation of analysts' EPS forecasts (*Dispersion*, in column 2). The main explanatory variables are: the share of credit exposures, in terms of EAD, covered by advance internal ratings-based models (*AIRB weight*); the ratio of Tier 1 capital over Risk weighted assets in 2008 (*Tier 1 ratio in 2008*); and the interaction between *AIRB weight* and the ratio of Tier 1 capital over Risk weighted assets in 2008 (*Tier 1 ratio in 2008*).
Control variables are defined in Table A.2. All bank-level explanatory variables are lagged one period. All specifications include bank fixed effects and year fixed effects. Robust standard errors are clustered at the bank level and are shown in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) **Forecast error**	(2) **Dispersion**
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 weight$_{t-1}$	0.176	0.091**
	(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)
GDP growth$_{t}$	-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

Figure 1. Usage of internal ratings

This figure shows the evolution over the 2008-2014 period of the share of credit exposures, in terms of EAD, covered by internal ratings-based models (*IRB weight*) and by advanced internal ratings-based models (*AIRB weight*) for the banks in the sample.

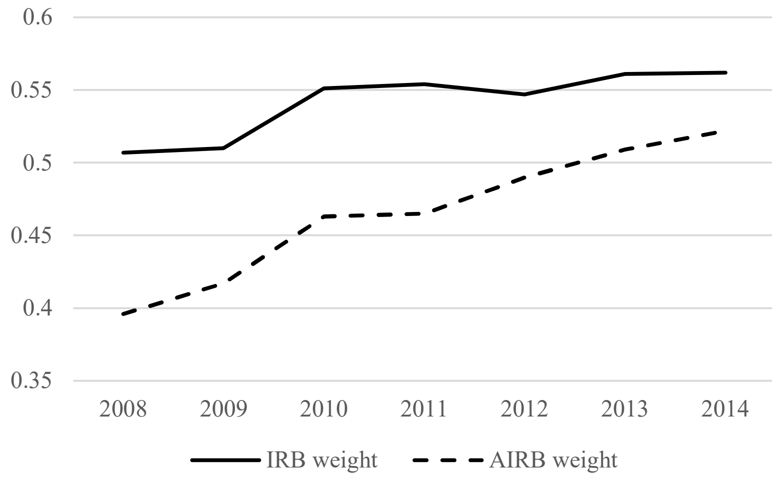

Figure 2. Marginal effect of *NPL* on opacity for different levels of *AIRB weight*

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 - *Forecast error* (left panel) and *Dispersion* (right panel) - according to *AIRB weight* as in regressions 1 and 4 of Table 5.

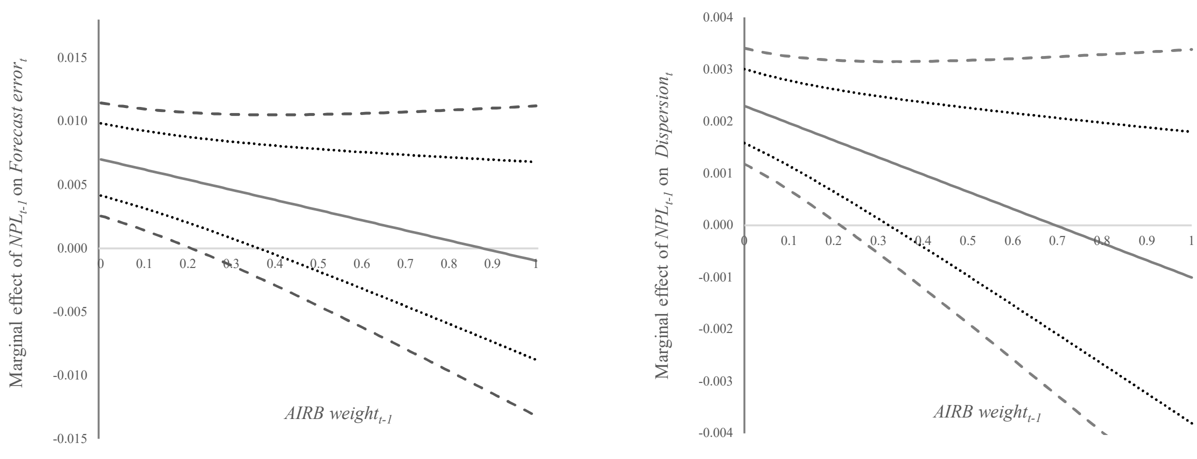

Figure 3. Marginal effect of *NPL* on opacity for different levels of *AIRB loans*

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 - *Forecast error* (left panel) and *Dispersion* (right panel) - according to *AIRB loans* as in regressions 2 and 5 of Table 5.

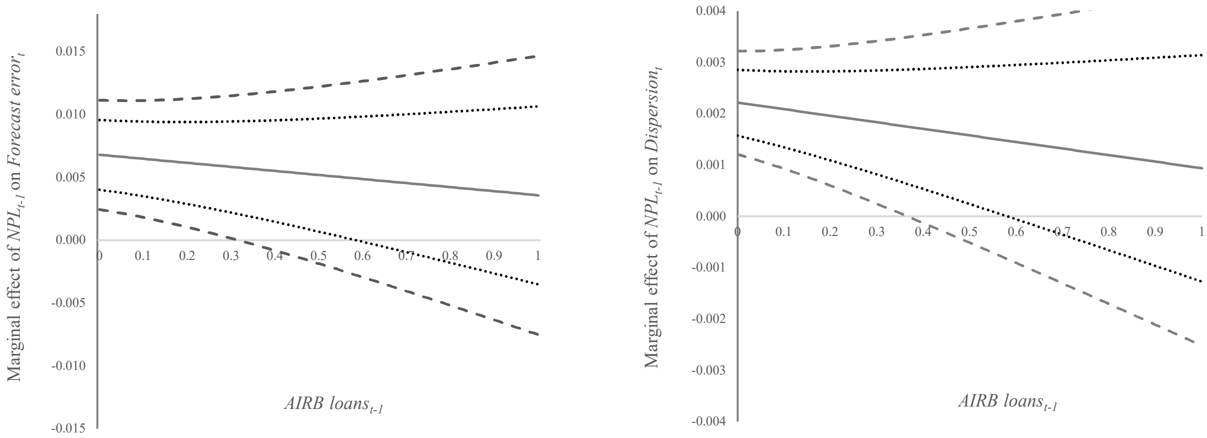

Figure 4 (*a*). Marginal effect of *NPL* on opacity (*Forecast Error*) for different levels of *AIRB*

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 - *Forecast error* - according to *AIRB retail* (left panel) and *AIRB corporate* (right panel) as in regression 3 of Table 5.

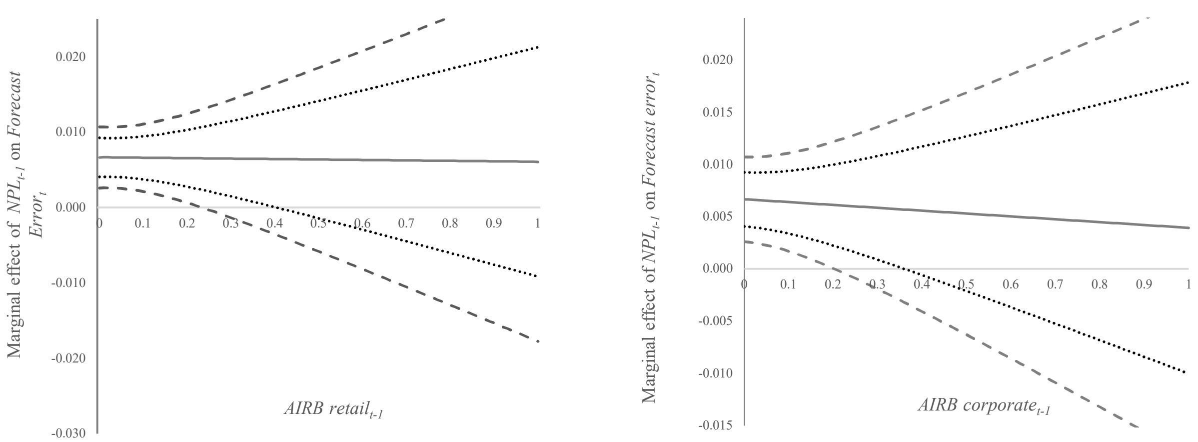

Figure 4 (*b*). Marginal effect of *NPL* on opacity (*Dispersion*) for different levels of *AIRB*

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 - *Dispersion* - according to *AIRB retail* (left panel) and *AIRB corporate* (right panel) as in regression 6 of Table 5.

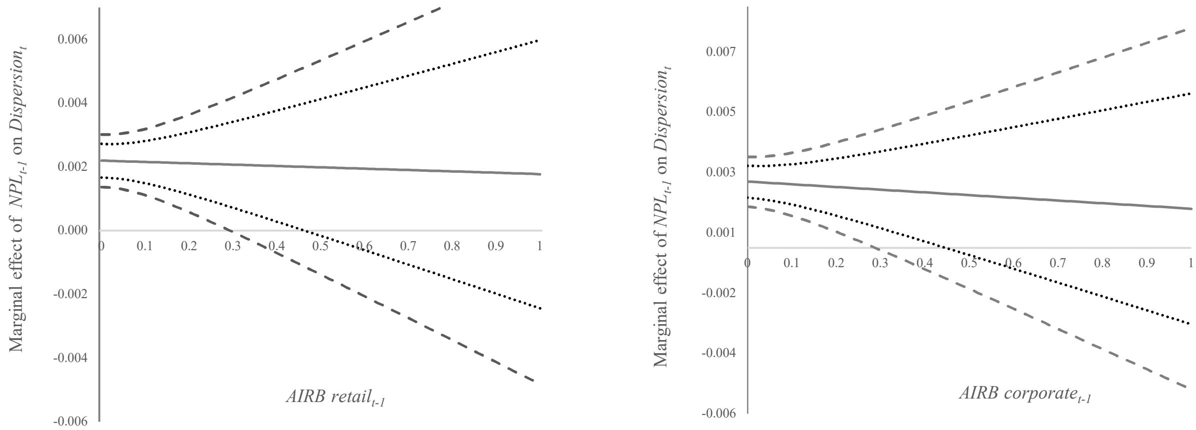

Figure 5. Marginal effect of *AIRB weight* on opacity for different levels of *Tier 1 ratio* in 2008

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 - *Forecast error* (left panel) and *Dispersion* (right panel) - according to bank's *Tier 1 ratio in 2008* as in regressions 1 and 2 of Table 7.