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WORKING PAPER NO. 576

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June 2020

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ISSN. 2240-9696

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Do Internal Rating Models Mitigate Bank Opacity? Evidence from Analysts' Forecasts

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Abstract
Based on a sample of large European banks, we test whether the usage of internal rating models for regulatory purposes affects bank opacity. We find that a more intensive use of advanced internal rating models is associated with lower forecast error and disagreement across analysts on bank earnings per share. We also find that these models alleviate the negative effect of non-performing loans on bank transparency.

JEL Classification: G20; G21; G28

Keywords: Banks; Opacity; Internal Rating-Based (IRB) approach

Acknowledgements: For their helpful comments, we would like to thank Stephen Gates and Marco Troiano.

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Table of contents

1. Introduction

The internal ratings-based (IRB) approach allows banks to estimate the risk of their loan portfolio based on their own credit scores. It was introduced in the Basel 2 accord (2003) to make the calculation of capital requirements more risk-sensitive and promote sounder risk management. However, since the peak of the global financial crisis it has been widely questioned by academics and policy makers, as it may have been used to deplete capital levels and increase leverage.

In this paper we explore the link between internal rating models and bank opacity by investigating whether a more intensive usage of such models helps analysts assess banks' performance more accurately. This is an unexplored topic, as most studies on IRB models have focused on whether risk weight variability across banks is motivated by opportunistic goals (with internal ratings being manipulated by capital-constrained institutions) as opposed to differences in, for example, business models or underlying portfolios (Le Leslé and Avramova, 2012; Mariathasan and Merrouche, 2014; Behn et al., 2016; Ferri and Pesic, 2016).

The relationship between IRB models and bank opacity is indeed ambiguous. On the one hand, they are complex and hard to monitor, hence – as noted above – they can be used to manipulate risk weights in order to relax capital constraints (Haldane and Madouros, 2012). As a result, bank stakeholders became skeptical about reported risk-weighted capital ratios.[1] Consistent with this view, one may expect a greater adoption of IRB models to be associated with a lower degree of transparency.

On the other hand, there are at least two reasons why internal ratings may still prove useful in reducing uncertainty around bank balance sheets. First, the use of internal rating models for regulatory purposes provides banks with an incentive to invest more in better risk management practices, leading to more accurate loan provisioning and pricing schemes (Cucinelli et al., 2018; Mascia et al., 2019). This makes future earnings more stable and predictable.[2] Second, since IRB banks are required to disclose details on their risk parameters in the so-called Pillar 3 report, investors benefit from a richer information set and earnings forecasts provided by different analysts may end up being more homogeneous.

Such an effect can be expected to be stronger when banks adopt the so-called *advanced* internal rating-based (AIRB) approach, as opposed to the *foundation* (FIRB) approach, as the former entails more sophisticated and risk-sensitive models.[3] In addition, banks adopting AIRB models ("AIRB banks") 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.

To assess whether and how the usage of internal ratings affects bank opacity, we look at the forecast error and the disagreement among equity analysts about the banks' expected earnings per share (EPS). We find that a more widespread adoption of AIRB models is associated with lower forecast error and disagreement; we also find that advanced internal rating models mitigate the opacity-increasing effect of non-performing loans.

2. Data and empirical methodology

We build a cross-country sample of large listed European banking groups. Europe provides an interesting setting, as IRB models are adopted by a wider array of banks than, say, in the US (where they may be used only by top tier institutions).[4] Starting with the top 50 listed groups by total assets and dropping those with

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[1] The excessive variability found in bank practices led the Basel Committee (BCBS, 2017) to introduce new constraints in the way internal ratings are built and used.

[2] Accurate loan pricing may occur even if capital computations may be tweaked to minimize the final requirements, as found in Behn et al. (2016).

[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] 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.

incomplete data (e.g., lacking I/B/E/S forecasts), we obtain an unbalanced panel of 41 banks from 16 countries. Our sample covers more than 60% of the overall European banks' total assets.

Data refer to the period 2008-2015, the years leading up 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), Orbis Banks Focus (for annual consolidated balance sheet data), and Pillar 3 reports. Information taken from Pillar 3 reports includes the Tier 1 capital ratio and the share of credit exposures (measured as the bank's estimate of the likely exposure at default, EAD) for which the IRB approach (foundation or advanced) is used. Although they are compulsory for most banks, Pillar 3 reports did not follow a standard structure, as a common reporting template was only introduced in 2019. Hence, we had to extract data items (and reconcile them across banks) by hand. Our sample provides a good balance between IRB users and non-users, as the average bank uses internal models to assess credit risk on roughly 50% of its assets (with a standard deviation of 31%).

To assess the link between bank opacity and IRB usage, we estimate the following baseline specification:

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

where $OPACITY_{i,t}$ is alternatively measured in terms of: *i*) *Forecast error* and *ii*) *Dispersion* of bank i in year t, as defined in Flannery et al. (2004). The analysts' forecast error is the median absolute EPS forecast error, divided by the share price at the start of the fiscal year: it provides us with an *ex post* measure of opacity (suggesting whether EPS proved easy/hard to guess). Dispersion of analysts' earnings forecasts is the cross-sectional standard deviation of EPS forecasts, computed only for firms with more than one analyst: this is an *ex ante* measure of opacity, suggesting stronger/weaker agreement among market participants. Intuitively, greater bank opacity would be associated with both greater forecast errors and stronger disagreement among analysts.

IRB is a continuous variable, which can be either *IRB weight* (the share of credit exposures, in terms of EAD, covered by internal rating models), or *AIRB weight* (the share covered by advanced IRB models only).

Control variables, $\mathbf{X}_{i,t-1}$, include: *Tier1 ratio*, the ratio of Tier 1 capital to risk weighted assets; *Equity ratio*, the equity to total asset ratio; *NPL*, the share of non-performing loans over total gross loans; *Size*, the natural logarithm of total assets; *Loans*, the ratio of net loans over total assets; *Deposits*, the fraction of customer deposits over total funding; and *ROA*, the net income to average total asset ratio. Bank characteristics are measured at t-1 to mitigate endogeneity concerns.

We also control for the GDP annual real growth rate, *GDP growth*, to account for movements in credit quality over the business cycle.[5] To capture any further bank-specific characteristics or time-specific events, we also include fixed effects for banks (δ_i) and years (μ_t). Standard errors are clustered at the bank level (our results are robust to clustering at the country level or to using no clustering at all).

In this specification, the main coefficient of interest is β, denoting how bank opacity changes with IRB usage.

Among bank balance sheet items, non-performing loans (NPLs) have become an important source of concern for banking authorities, also for their potential effect on bank opacity. In the traditional banking literature, loans are illiquid, and untraded contracts generate cash flows that are hard to predict. NPLs are especially hard to value for an outsider and significantly increase uncertainty as to a bank's fair value (Ciavoliello et al., 2016). We therefore extend our analysis and include the interacted term *NPL×IRB* to investigate how NPLs affect bank opacity conditional on IRB usage. Our additional specification becomes:

$$\begin{aligned} OPACITY_{i,t} = \alpha + \beta_1 \cdot IRB_{i,t-1} + \beta_2 \cdot NPL_{i,t-1} + \beta_3 \cdot NPL_{i,t-1} \times IRB_{i,t-1} + \\ + \psi' \cdot \mathbf{\Phi}_{i,t-1} + \gamma \cdot GDP\ growth_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

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

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

3. Main findings

Table 1 reports our main findings for the two measures of bank opacity described above, i.e., *Forecast error* (Columns 1 to 3) and *Dispersion* (Columns 4 to 6). IRB usage is captured by *IRB weight* in Columns 1 and 4, and by *AIRB weight* in all other specifications.

Starting with the control variables, we observe that stronger Tier 1 ratios are associated with greater opacity, while plain (non-risk weighted) equity ratios reduce disagreement among analysts. Overall, this evidence supports the idea that markets do not trust risk-based capital indicators, but rather rely on pure leverage measures. As expected, higher NPLs increase opacity: this result is strongly significant across specifications. Finally, a larger deposit base (indicative of a more traditional business model), a more favourable economic cycle and, to a lesser extent, higher profitability, 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 but not statistically significant (Columns 1 and 4). Results gain significance 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 *AIRB weight* (31%) corresponds to a 0.04 decrease in *Forecast error* (i.e., 71% of its mean) and a 0.026 decrease in *Dispersion* (i.e., 77% of its mean). This confirms that the use of advanced IRB models provides a stronger incentive for banks to invest in better risk management practices and forces them to disclose more information on the riskiness of their assets.

Columns 3 and 6 report results for Equation (2). The negative coefficients for the *NPL×AIRB weight* interacted term suggest that a more widespread AIRB usage mitigates the increase in opacity due to a larger NPL portfolio: this is consistent with the fact that IRB models may help banks perform a more timely identification (and a more accurate valuation) of impaired loans, somewhat reducing the risk of unexpected losses arising from non-performing exposures.

	(1)	(2)	(3)	(4)	(5)	(6)
		Forecast error			Dispersion	
Irb weight$_{t-1}$	-0.057	-	-	-0.046	-	-
	(0.070)			(0.031)		
Airb weight$_{t-1}$	-	-0.158**	-0.087*	-	-0.088***	-0.060***
		(0.063)	(0.047)		(0.026)	(0.021)
Tier1 ratio$_{t-1}$	0.008**	0.010***	0.010***	0.002	0.002**	0.003**
	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Equity ratio$_{t-1}$	-0.007	-0.009	-0.010	-0.005***	-0.006***	-0.007***
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.002)
NPL$_{t-1}$	0.005**	0.005**	0.006***	0.002***	0.002***	0.002***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
NPL$_{t-1}$ × Airb weight$_{t-1}$	-	-	-0.012***	-	-	-0.005***
			(0.004)			(0.001)
Size$_{t-1}$	-0.042	-0.050	-0.064	-0.010	-0.013	-0.018
	(0.064)	(0.056)	(0.051)	(0.027)	(0.023)	(0.020)
Loans$_{t-1}$	-0.002	-0.002	-0.002	-0.001	-0.000	-0.001
	(0.002)	(0.001)	(0.001)	(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$_{t-1}$	-0.015	-0.015	-0.015	-0.005*	-0.005*	-0.005
	(0.012)	(0.011)	(0.012)	(0.003)	(0.003)	(0.003)
GDP growth$_t$	-0.009**	-0.009**	-0.009**	-0.006***	-0.006***	-0.006***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.001)	(0.001)
Intercept	0.764	0.893	1.045	0.251	0.296	0.354
	(0.899)	(0.772)	(0.705)	(0.348)	(0.303)	(0.269)
No. of obs.	279	279	279	277	277	277
No. of banks	41	41	41	40	40	40
Adj. R^2	0.249	0.269	0.284	0.379	0.428	0.451
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered by banks in parenthesis.

*** p<0.01; ** p<0.05; * p<0.1.

Table 1. Usage of internal ratings and bank opacity.

In the spirit of Brambor et al. (2006), Figure 1 sheds more light on the relationship among the NPLs, AIRB usage and opacity. 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 $\beta_1 + \beta_3 \cdot AIRB\ weight$.

The negative slope implies that the (positive) impact of NPLs on opacity declines as AIRB usage increases: indeed, the lower confidence band shows that, as *AIRB weight* reaches 11% (for *Forecast error*) or 22% (for *Dispersion*), the relation between *NPL* and *OPACITY* is not statistically significant anymore at 1% (although the upper confidence band suggest that it may remain positive also for heavy AIRB users).

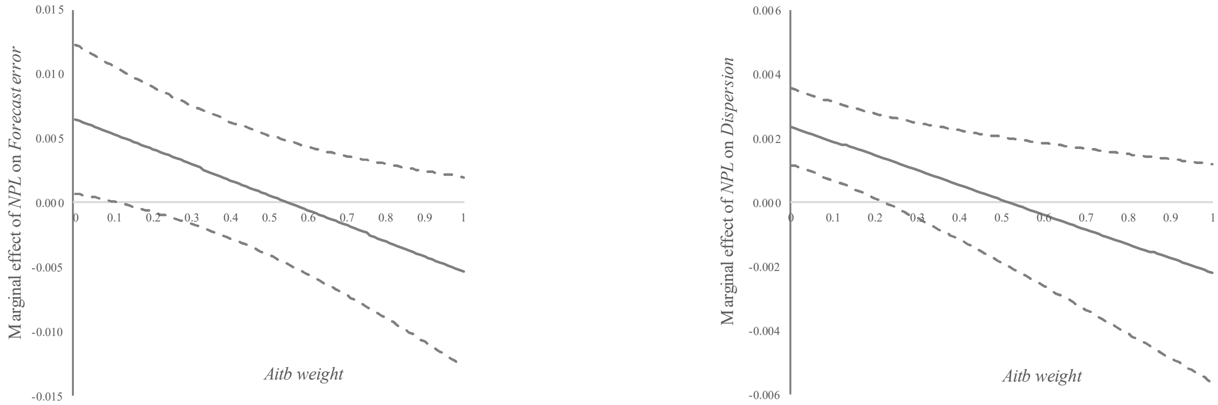

Figure 1. Marginal effect of *NPL* on opacity for different levels of *Airb weight*.
This figure contains the point estimates (solid line) and 99% confidence intervals (dashed lines) for the estimates of the marginal effect of *NPL* on banks' opacity - *Forecast error* (left panel) and *Dispersion* (right panel) - according to *Airb weight* as in regressions 3 and 6 of Table 1.

4. Conclusions

This paper contributes to the institutional and scientific literature on the benefits and challenges of internal ratings, by shedding light on a positive side effect that has not been investigated by previous studies. We find that a more intensive usage of advanced internal rating models reduces errors in forecasting bank earnings per share and increases agreement among analysts. There are two possible explanations for our results. On the one hand, the use of AIRB models for regulatory purposes provides stronger incentives to invest in better risk management practices, leading to more stable and predictable earnings. On the other hand, AIRB banks disclose more details on their loan portfolio to market participants. The paper also contributes to the recent policy debate on impaired loans, by suggesting that, *ceteris paribus*, AIRB users are better equipped to cope with, and provide a clearer picture of, their NPL portfolios.

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