Elsevier Editorial System(tm) for Journal of Banking and Finance

Manuscript Draft

Manuscript Number: JBF-D-17-00246R3

Title: Credit risk in European banks: The bright side of the Internal Ratings Based approach

Article Type: Full Length Article

Keywords: Internal Ratings Based approach; credit risk; prudential regulation; dynamic panels; state dependent endogenous dummy; System GMM

Corresponding Author: Professor Laura Nieri,

Corresponding Author's Institution: Università di Genova

First Author: Doriana Cucinelli

Order of Authors: Doriana Cucinelli; Maria Luisa Di Battista; Malvina Marchese; Laura Nieri

Credit risk in European banks:

The bright side of the Internal Ratings Based approach

This version: 28th May 2018

Abstract

This paper investigates the accuracy of internal rating based (IRB) models in measuring credit risk. We contribute to the growing debate on the current prudential regulatory framework by investigating the use of validated IRB models in promoting efficient risk management practises. Our empirical analysis is based on a novel panel data set of 177 Western European banks observed from 2008 to 2015, in the aftermath of the financial and economic crisis. We find that IRB banks were able to curb the increase in credit risk driven by the macroeconomic slowdown better than banks under the standardized approach. This suggests that the introduction of the internal ratings based approach by Basel II has promoted the adoption of stronger risk management practices among banks, as meant by the regulators.

Keywords: Internal Ratings Based approach; credit risk; prudential regulation; dynamic panels; state dependent endogenous dummy; System GMM.

JEL code: G21; C23.

Genoa, 28th May 2018

Ref: R&R Review of "Credit risk in European banks: The bright side of the IRB approach"
Ms. Ref. No.: JBF-D-17-00246

Dear Reviewer #2,

Thank you for your attentive reading of the paper and for your further comments. We are happy that you appreciate our efforts to follow your guidance. We are very grateful for your suggestions and we have tried to implement as many as we could in this latest version of the paper.

In what follows we explain how we revised the paper on the base of your comments, highlighting the major changes with respect to its previous version. We also discuss how we accounted for those comments that we could not investigate directly due to data availability.

We wish to thank you very much for guiding us through this extensive revision process and particularly for directing our efforts towards a justifiable econometric approach to support our findings.

Best regards,

The Authors

1. *First, in the intro, I would tone down the method approach as a contribution, though you might discuss that you rule out other plausible alternatives.*

We have removed the emphasis on the method approach as a contribution, focusing instead on the actual contribution to the risk literature. In the introduction we briefly discuss the econometric approach that we use in addressing the empirical question in term of model, estimation strategy and standard errors calculations for inference. We felt that this would help the reader to get a clear picture of the methodology together with the research question from the outset.

2. *Second, I would spend some more time on how to package the results in the best way. The manuscript still feels more like a rough draft than a finished product.*

We have re written the comments on our empirical findings, in the attempt to make them better structured and more extensive. We have highlighted how they support our original hypothesis, hopefully increasing the clarity of our contribution. We have also modified the Conclusions section following your suggestion on the need to indicate further directions for work on which others can build (as discuss below in more details).

In details, in the introductory Section we have modified a paragraph as follows (for the sake of simplicity, the new parts are in *Italics*):

> "We find that IRB banks did face a lower credit risk increase in the aftermath of the great financial crisis. This evidence suggests that IRB banks were better able to select and manage credit risk and that, despite the potential heterogeneity and discretionality in the validation process, *validated IRB models and procedures are superior. Furthermore, since to obtain validation and enjoy the capital savings steaming from IRB risk weights, banks undergo massive investments in terms of data collection, risk management tools and procedures and human capital, we pose that* the adoption of the IRB approach by regulators has contributed to spur the use of stronger credit risk management practices among banks."

In Section 5 (Results) we have widened the general comments of our results and we have put more emphasis on our findings concerning the IRB dummy variable and the inverse Mills ratio.

In particular, we have highlighted the following aspects:

> “The superiority of IRB banks in managing risk, supported by our outcome equation findings, is a consequence of their increased risk management capabilities, as the Mills ratio significance and sign suggest. *Such improvements in turn arise from the effort in terms of data, tools, procedures and human capital that banks must make in order to obtain IRB validation.*”

> “*The increasing number of IRB banks coupled with the evidence on the effectiveness of IRB models in managing credit risk* suggest that the introduction of the IRB approach by regulators has enhanced the diffusion of sound and robust credit risk management procedures and tools among banks. *Thus, our findings contribute to the existing literature on risk-sensitive regulation by showing that there is a ‘bright’ side of the internal rating-based approach..”*

3. *Third, I would put some thought into the mechanism(s) behind why the IRB approach is helpful. Are the models superior or does the firm actually learn more about or focus more on risk management under the IRB regime? I wonder if you can use your data, even descriptively, to shed some light on this issue. For example, do you see any evidence that firms get better at managing risk the longer they use the IRB approach? Some discussion on this issue could be useful at the end of the paper and could be useful for others building on this work.*

This is a very interesting question and, as you suggest, a very relevant direction for future work. The light we can shed on this point is based on our results on the significance of the Mills ratio in the continuous outcome equation. We have tried to express this with more clarity in Section 5.1 where, upon commenting the significance of the Mills ratio we write

> “This endogeneity is due to latent factors that impact both on the IRB propensity of adoption and on the NPL ratio. We conjecture that these factors are related to the quality of the risk management of a bank which affects both the outcome of the validation process and its screening and monitoring abilities which eventually impact on the level of credit risk.”

Moreover, we have rephrased some parts of our work and added new elements to clearly convey our hypothesis and our contribution, i.e. The use of IRB models for regulatory purposes allows for capital savings and represent an incentive for banks to improve their risk management skills in order to achieve IRB models validation. We assess the superiority of validated models in controlling credit risk, thus supporting the view that a more risk-sensitive regulation (i.e. the IRB approach introduced by Basel II) has spurred the use of more accurate and effective risk management tools and procedures among banks.

However our data set does not allow us to shed any light on whether there is an improvement over time at managing risk the longer a bank is in the IRB regime. If we had a longer time span of available data we could consider two subsample of IRB banks and test if there is a significant difference in the Mills ratios.

As you recommend we include a discussion on this issue in the Conclusion, suggesting which type of data could help in addressing it:

> "*An interesting issue that we do not address is whether the overall bank risk management effectiveness improves after the validation of its internal rating models. As a matter of fact, the authorization to use IRB models for regulatory purposes may concern only a share of the loan portfolio, e.g. portfolios including only retail or corporate exposures or mortgages, etc.. As the bank risk management tools and procedures become more accurate, supervisors may allow the bank to shift from SA to IRB other shares of the loan portfolio and may also allow for a shift from Foundation IRB (F-IRB) to Advanced IRB (A-IRB). Further research may shed light on this issue by accounting more specifically for the adoption of F-IRB vs A-IRB over time and for the shares of loan portfolios under either of these models*."

*Title Page (with authors and affiliations)

"Credit risk in European banks: The bright side of the Internal Ratings Based approach"

Doriana Cucinelli*
Università di Milano-Bicocca

Maria Luisa Di Battista♦
Università Cattolica del Sacro Cuore

Malvina Marchese♣
City University

Laura Nieri♠
Università di Genova.

This version: 28th May 2018

* School of Economics and Statistics,Via Bicocca degli Arcimboldi, 8, 20126 Milan, Italy. doriana.cucinelli@unimib.it
♦ Faculty of Economics, Via Emilia Parmense , 84, 29100 Piacenza, Italy. marialuisa.dibattista@unicatt.it .
♣ Cass Business School, 106 Bunhill Row, EC1Y 8TZ, London, UK. malvina.marchese@city.ac.uk
♠ **Corresponding author**. Department of Economics, Via Vivaldi 5, 16126 Genova. (Tel. +39.010.2095223) laura.nieri@unige.it

Credit risk in European banks:

The bright side of the Internal Ratings Based approach

This version: 28th May 2018

Abstract

This paper investigates the accuracy of internal rating based (IRB) models in measuring credit risk. We contribute to the growing debate on the current prudential regulatory framework by investigating the use of validated IRB models in promoting efficient risk management practises. Our empirical analysis is based on a novel panel data set of 177 Western European banks observed from 2008 to 2015, in the aftermath of the financial and economic crisis. We find that IRB banks were able to curb the increase in credit risk driven by the macroeconomic slowdown better than banks under the standardized approach. This suggests that the introduction of the internal ratings based approach by Basel II has promoted the adoption of stronger risk management practices among banks, as meant by the regulators.

Keywords: Internal Ratings Based approach; credit risk; prudential regulation; dynamic panels; state dependent endogenous dummy; System GMM.

JEL code: G21; C23.

1. Introduction

Risk-sensitive capital ratios are the cornerstone of bank prudential regulatory framework. Banks are required to hold regulatory capital as a percentage of their total risk-weighted assets (RWAs). Since the enforcement of Basel II, banks calculate their minimum capital requirements under Pillar I using either risk weights provided by regulators (the standardised approach (SA)) or risk weights based on their internal risk models (the internal ratings based approach (IRB)). In the regulators' intentions, the introduction of IRB models was aimed at i) improving the risk-sensitivity and the soundness of minimum capital charges, ii) promoting the adoption of stronger risk management practices by banks, iii) aligning managerial and supervisory perspective, thus reducing the scope for potential arbitrage (BCBS, 2000 and 2006). To promote IRB adoption, the new framework ensures that capital requirements are lower under the IRB than the SA approach (BCBS, 2006). The aftermath of the publication of Basel II has witnessed a growing debate on the reliability of IRB models and on the desirability of such a sophisticated model-based regulation. (Haldane, 2011). Despite a general agreement on its validity, quite a few aspects of the new regulatory framework have been questioned so far (BCBS, 2013; EBA, 2013). A number of authors suggests that validated IRB models may bring negative implications, such as : i) opacity in credit risk measurement and lack of comparability of RWAs across banks; ii) incentives and opportunities for risk weights manipulation and regulatory arbitrage; and iii) a bias in asset allocation and a pro-cyclical effect on banks lending policy (Arroyo et al., 2012; Mariathasan and Merrouche, 2014; Bruno et al., 2015; Ferri and Pesic, 2016; Beltratti and Palladino, 2016; Behn et al., 2016a; Pèrez Montes et al., 2016; Berg and Koziol, 2017). While the negative implications of the IRB framework have been thoroughly discussed in the literature, few studies have indirectly investigated whether such models accurately measure risk and contribute to the adoption of stronger risk management practices among banks,thus improving banks' resilience, as meant by the regulators (Mariathasan and Merrouche, 2014; Mascia et al., 2016; Behn et al., 2016b; Bruno et al., 2016).

The use of IRB models to compute the minimum capital requirement is allowed only after validation by the supervisory authorities. During the validation period, which can take up to several years, a bank is required to implement in its internal models any change requested by the supervisors, to provide clear evidence of the robustness of such models and to demonstrate their relevance in the day-by-day risk management and in its own risk culture. For all these reasons, we expect validated IRB models to display strong accuracy and effectiveness in measuring risk as meant by the regulators.

The aim of this paper is to verify if this expectation is supported by the data. We investigate whether banks with validated internal models (henceforth IRB banks) are more effective in managing credit risk, thus supporting the hypothesis that the IRB regulatory framework has promoted stronger risk management practises and enhanced banks resilience.

Evaluating banks credit risk management effectiveness is a rather difficult task for an external analyst since it requires data which are not publicly available and it might be affected by discretionality. We assess the effectiveness of risk management procedures by looking at the risk management output, i.e. the level of risk borne by a bank. We proxy credit risk by the ratio of non-performing loans to total gross loans (the so-called NPL ratio). Our analysis focuses on the European banking system and employs a novel panel data set of 177 banks from 14 countries observed during the period following the Basel II enforcement (2008-2015). This period captures the immediate aftermath of the great financial crisis, which saw a prolonged negative economic cycle and a fast and marked increase in credit risk levels. We believe that it offers an excellent setup to assess whether banks with validated IRB models were able to curb the increase in credit risk driven by the macroeconomic slowdown better than banks under the standardized approach (SA banks).

We contribute to the credit risk literature by evaluating the impact of validated IRB models on efficient risk management and by investigating which factors drive IRB adoption at bank level. The accuracy of IRB models has been discussed by few authors indirectly (Mariathasan and Merrouche, 2014; Mascia et al., 2016; Behn et al., 2016b; Bruno et al., 2016) but, to our knowledge, the only paper assessing their direct impact on credit risk is Erdinc and Gurov's (2016). These scholars find a negative and significant impact of validated IRB models on asset quality at country level. We improve on their findings by testing the impact of IRB on loan portfolio deterioration at bank level and by considering a longer time span that includes the whole economic slowdown following the great financial crisis.

We address the research question in the context of dynamic panels with endogenous dynamic binary treatment. Estimation methods for dynamic panel models with sample selection are well established in the literature (Kyriziadou 2001; Semykina and Wooldridge 2013) for the case of a static and a dynamic selection equation. Methods for dynamic panels with a dynamic, state dependent, endogenous binary treatment have not received much attention in the econometric literature so far. We implement an empirical strategy based on a dynamic panel Probit equation and a dynamic panel continuous outcome equation. Estimation is conducted using System GMM methods with Heckman-type correction for endogeneity. To account for the distortion introduced by the generated regressor , we compute the main equation standard errors by bootstrap.

We find that IRB banks did face a lower credit risk increase in the aftermath of the great financial crisis. This evidence suggests that IRB banks were better able to select and manage credit risk and that, despite the potential heterogeneity and discretionality in the validation process, validated IRB models and procedures are superior. Furthermore, since to obtain validation and enjoy the capital savings steaming from IRB risk weights, banks undergo massive investments in terms of data collection, risk management tools and procedures and human capital, we pose that the adoption of the IRB approach by regulators has contributed to spur the use of stronger credit risk management practices among banks.

The remainder of the paper is organized as follows: Section 2 presents the main features of the IRB validation process and surveys the relevant literature; Section 3 describes our data; Section 4 illustrates our empirical strategy and econometric methodology. Section 5 offers some discussion of our empirical findings and robustness checks and, finally, Section 6 concludes.

2. The regulatory use of the IRB approach and literature review

2.1 The introduction of IRB models in the European banking system

The IRB approach was introduced in 2004 by the Second Accord of the Basel Committee on Banking Supervision (Basel II) as an alternative to the standardized approach (SA). In Europe the use of IRB approach for regulatory purposes was allowed since June 2006 by the Capital Requirements Directive; its adoption by banks started to spread from 2008 onwards.

While according to the SA approach banks must use risk weights provided by the regulators, under the IRB approach they use their own internal rating models to estimate the different components of the expected loss. Under Foundation IRB, banks determine internally the probability of default (PD) only, under Advanced IRB, they define internally the loss given default (LGD), the exposure at default (EAD) and the maturity (M) as well. As a consequence, IRB banks may benefit from a more granular credit risk measurement that brings lower risk weights and ultimately implies lower capital charges.

The use of IRB models is conditional on supervisory authorities' validation. In Europe, validation of the models used to be granted by national supervisors since the end of 2014, when the Single Supervisory Mechanism established that IRB models of 'significant' banks must be validated by the European Central Bank.

To validate the models, supervisors rely on quite stringent criteria and guidelines covering several aspects of the bank rating system, ranging from statistical methodologies to 'processes, controls, data collection and IT systems that support the assessment of credit risk, the assignment of internal risk ratings, and the quantification of default and loss estimates' , assessed on an ongoing base (BCBS, 2006). In the overall, IRB validation is a long process which requires a massive effort and a significant modification of a bank's risk management practises and models.

Since its adoption is not mandatory in the European banking system, only banks that anticipate substantial net benefits from the IRB approach are likely to apply for it. More specifically, banks decide to enter a validation process on the base of a cost-benefit analysis. Compliance costs associated with validation are mostly fixed costs of significant magnitude making the IRB adoption more convenient for large rather than small banks. Moreover, in order to be approved, internal models must pass a 'data quality check' and a 'replication exercise' (Arroyo et al., 2012) which require wide and accurate databases, that may not be available for small banks. The most significant advantage in the use of internal models is the lower risk weights arising from a more granular credit risk measurement, that in turn allow for savings in capital requirements. The relation between PD and risk weights is concave: very steep for low PD values and flatter for high PD values (Behn et al., 2016a). Thus, the highest benefits in terms of risk weight reduction are associated with low-PD exposures, although also large and highly risky exposures, which tend to absorb large amount of capital, may generate sizable savings. These benefits represent an incentive for banks, especially for the less capitalised or fast-growing ones, to apply for validation of their IRB models.

Once internal models are validated, exit from the IRB framework must be approved by the supervisors and, as stated in Basel II (2006), "A voluntary return to the standardised or foundation approach is permitted only in extraordinary circumstances".

Data on the use of validated IRB models are rather scant and display significant heterogeneity across countries. According to national supervisory authorities' data[1], at the end of 2013, 46% of the overall capital that European banks were required to hold was generated using the IRB approaches (Resti, 2016). In some countries like Austria, Greece, Italy and Portugal, internal

[1] Data refer to a sample of 105 banks from 21 European countries and account for around 70% of total European banking assets.

models accounted for less than 33% of the total capital requirements, in Denmark, the Netherlands and Sweden they exceeded 70%.

Using data from the EBA transparency exercise (June 2015) on credit risk only (which accounts for 85% of total RWAs), Turk-Ariss (2017) finds a high dispersion of IRB adoption across European banks. While more than 90% of banks in Northern European countries use the IRB approach, the large majority of banks in few countries such as Cyprus, Latvia and Poland adopts the SA framework.

2.2 The IRB approach in the literature

Since its introduction, scholars and authorities have given rise to an intense debate on the effectiveness and reliability of the IRB approach. In particular this regulatory framework has been questioned for its high complexity and the strong degree of discretionality allowed to banks. The sophistication of internal risk models makes risk estimates and RWAs comparison difficult across different banks, unless a host of detailed information, often not publicly available, is taken into account (Haldane, 2010; Arroyo et al., 2012; Ledo, 2011; Cannata et al. 2012). Empirical studies suggest that such degree of discretionality, coupled with the opportunity for capital savings, generate incentives for regulatory arbitrage and capital requirements manipulation especially for capital constrained banks (Mariathasan and Merrouche, 2014; Plosser and Santos, 2014; Pèrez Montes et al.2016; Ferri and Pesic, 2016; Berg and Koziol, 2017)[2].

It has been argued that, heterogeneous risk weights and discrepancies in RWAs may also stem from differences in the validation process itself (Le Leslè and Avramova, 2012; Arroyo et al., 2012; Ledo, 2011; EBA, 2013; EBA, 2016, Bruno et al., 2016; BCBS, 2016 and 2016b) and/or from a different 'supervisory pressure' (Arroyo et al., 2012; Mariathasan and Merrouche, 2014). These

[2] These potential flaws have been addressed by the Basel Committee on Banking Supervision that in 2010 has issued a revised regulatory framework (also known as Basel III) and at the end of 2017 has finalized another set of reforms that aim at improving the comparability of capital ratios across banks and limiting the strategic use of internal risk models.

differences may be exacerbated by the use of different models to measure different component of the overall credit risk. The flexibility allowed by regulators, justified by the willingness to align regulation to banks risk management practices, is itself an implicit source of model risk, i.e. different risk models may generate different results given the same underlying risk[3].

The banking authorities (BCBS, 2016; EBA, 2016; ECB Banking Supervision, 2017) have already addressed these criticisms and in the overall there is a general consensus on the validity of the IRB framework as a risk-sensitive way to measure capital requirements (Barakova and Palvia, 2014; Colliard, 2015; Resti, 2016; Huizinga, 2016).

The alleged manipulation of risk weights represents a potential flaw in risk reporting, which is a different issue with respect to the effectiveness and accuracy of validate internal models. A bank may have a sophisticated and accurate internal risk model and choose to underreport its own risk.

As previously discussed, the ability of IRB models to measure risk and discriminate among borrowers and the effectiveness and robustness of IRB banks risk management practices have been investigated only indirectly in the literature. Behn et al. (2016b) analyse a sample of German banks and find that single loans and loan portfolios under the IRB approach have lower PD and RWA but higher actual default rate and loan loss rate. While this result supports the hypothesis of underreporting, the authors find also that, despite the low PD, the interest rates associated with these portfolios and loans are higher, suggesting that validated internal models have high discriminatory power and do allow for an accurate risk measurement. Mariathasan and Merrouche (2014) use bank-level data show that weakly capitalized banks report RWAs values not consistent with their riskiness and find evidence that under-reporting is due to a strategic manipulation of risk weights rather than to the use of flawed internal models. Finally, a number of studies show that during the negative economic cycle in the aftermath of the great financial crisis, European IRB banks reallocated credit from riskier to safer borrowers (Mascia et al., 2016; Behn et al., 2016a, 2016b;

[3] These differences tend to amplify i) in time of crisis, when markets are more volatile, and ii) for credit risk models, due to the scarcity of public data about borrowers (Danielsson, 2002; Danielsson et al. 2015)

Bruno et al., 2016), which supports the hypothesis that IRB banks managed to select their borrowers accurately and curb the undesired increase in credit risk.

The aim of this paper is to contribute to the debate on the effectiveness of the current prudential regulatory framework by investigating the regulatory use of the IRB approach. Considering that i) the introduction of the IRB approach is aimed at promoting the adoption of stronger risk management practices; ii) the validation occurs once banks have modified their models according to the prescription of supervisors and have proven their accuracy and robustness; and iii) the validation process may be affected by discretionality, we assess if IRB models are more accurate in managing credit risk than non-validated models used by SA banks. To this end, we investigate if, during the recession period that followed the great financial crisis, IRB banks managed to curb the deterioration of their loan portfolio better than SA banks.

3. Data and descriptive statistics

3.1 The sample and variables

Our empirical analysis is based on a balanced panel of 177 banks from 14 Western European countries[4], accounting for about 63% of the banking system total assets of these countries. We focus on the parent banks of banking groups at the country level[5], since credit risk and the ensuing capital policies are usually envisaged and managed mainly at the group level. The initial sample consisted of 341 banks and was selected according to the availability of information on the bank's regulatory approach (the standardized (SA) or the validated IRB approach) obtained from the SNL Unlimited data-base. We restrict our analysis to commercial banks, cooperative banks, savings banks, real estate banks and bank holdings, to focus on banks types most exposed to credit risk. In line with De Haas and Van Lelyveld (2014), we drop from the sample banks with total assets of less than 10

[4]Austria, Belgium, German, Denmark, Spain, Finland, France, UK, Ireland, Italy, Netherlands, Norway, Portugal and Sweden.

[5] For banking groups that operate in more than one country, we identified the parent company at the country level – i.e. the company that is at the highest level among those of each specific country - and used its the consolidated financial statements. Thus, we can control for the macroeconomic context at the country level.

billion euro in 2015[6] and banks with an annual growth of total earning assets greater than 75%, to control for the effects of mergers and acquisitions. Our data set is built using different sources: macroeconomic data are collected from the IMF, the World Bank and the Eurostat databases, and bank-specific data are drawn from Bankscope, we use consolidated financial statement data at the country level and we use unconsolidated data for independent banks (no shareholder recorded with more than 50% of direct ownership).

Our panel consists of yearly observations over the period 2008-2015[7], accounting for the whole economic slowdown which occurred in most European countries in the aftermath of the international financial crisis.

We proxy credit risk by the ratio of gross non-performing loans (NPLs) to gross loans (NPL_GL), which is a common measure of the level of credit risk in bank loan portfolios. This accounting variable has been widely used in other relevant studies as an ex-post measure of the credit risk accumulated by a bank (Salas and Saurina, 2002; Jimenez and Saurina, 2006; Hess et al., 2009; Boudriga et al., 2009; Louzis et al., 2011; Beck et al., 2015; Gosh, 2015)[8]. In order to distinguish between IRB banks and SA banks, we use a dummy variable (IRB) that equals 1 if the bank uses the IRB approach to calculate the regulatory minimum capital requirement[9].

The wide literature on credit risk and NPLs suggests that the deterioration of bank loan portfolios is determined by macroeconomic and bank-specific variables. It is well established that NPLs

6 Smaller banks, i.e. banks with total assets under 10 billion euro, were dropped from the sample because financial data were in most case incomplete. However, since our analysis is performed at the group-level, using consolidated financial statements, smaller banks that are part of a group are indirectly represented in our sample. .

7 We restricted our analysis to the period starting from 2008 because, even if Basel II was enacted in 2004, only from 2008 most of European supervisory authorities had started to validate the IRB models.

8 We are aware that NPLs may be affected by differences in the accounting policies adopted across Europe. Only in 2013 did the EBA publish a common definition of non-performing loans; before this date, European countries used different classifications of problem loans. Despite potential inhomogeneity, it is deemed the best proxy of credit risk that is publicly available.

9 As for the method used to calculate the regulatory minimum capital requirement, the SNL Unlimited data base reports one of the following items of information for each bank and each year: ‘Standardized’, when the bank/banking group adopts the standardized approach for the whole loan portfolio; ‘Foundation IRB’ and ‘Advanced IRB’ when the respective approach is used for the whole bank loan portfolio; ‘Mixed’ when, referring to different segments of the loan portfolio, either the standardized and the IRB approach are contemporarily used, or Foundation IRB and Advanced IRB are contemporarily used. Our dummy is equal to 1 when the bank adopts a ‘Mixed’ or a pure IRB approach and zero when it uses the ‘Standardized’ approach.

increase during a negative economic cycle (Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Marcucci and Quagliariello, 2009; Bofondi and Ropele, 2011; Glen and Mondragon-Velèz, 2011; Farhan et al., 2012; Beck et al., 2015). We control for the growth rate of real GDP (GDP), the unemployment rate (UN) and the level of house prices and the interest rate (HPI).

As for the bank-specific variables, a number of studies highlight that credit risk and NPLs are driven by three different factors: i) the quality of management; ii) the bank capitalization, and iii) the stance of the bank lending policy (Salas and Saurina, 2002; Boudriga et al., 2009; Louzis et al., 2011, Glen and Mondragon-Velez, 2011; Makri et al., 2014; Chaibi and Ftiti, 2015; Ghosh, 2015; Zhang et al., 2016; Dimitrios et al., 2016; Chaibi, 2016). In line with the literature, we proxy the quality of management by the Return on Equity (ROE) and cost to income ratio (C_I). According to the so called "bad management hypothesis" (Berger and De Young, 1997; Podpiera and Weill, 2008; Louzis et al., 2011; Klein, 2013 and Chaibi, 2016) low profitability and efficiency are due to poor management quality, which implies a scant ability in screening and monitoring loans, which to a large extent eventually become NPLs. On the other hand, the "skimping hypothesis" (Berger and De Young, 1997) suggests that a high cost efficiency hides the deployment of scarce resources to manage risks, deteriorating loan quality.

We control for the level of bank capitalization using the banks' leverage ratio (E_TA, i.e. Equity on total assets). Thus, we account for the hypothesis that banks may have different incentive to take more/less risk depending on their capitalization. Several studies, mostly focusing on the period pre-Basel II, find evidences of a negative and significant relationship between banks capitalization and their level of NPLs (Keeton and Morris, 1987; Berger and DeYoung, 1997; Jimenez and Saurina, 2006; Klein, 2013; Makri et al., 2014, and Chaibi, 2016). However, since the current prudential regulation tries to curb moral hazard incentives by imposing risk-sensitive capital requirement, we would expect that only well capitalized banks might afford a higher risk appetite and profile. These banks need higher returns to compensate their shareholders for the higher riskiness of their investment, which implies a positive and significant relationship between the banks' capitalization and their NPLs, as found by Macit (2012) and Ghosh (2015). In some of the specifications of our baseline model, we proxy banks' risk attitude with the Loan Premium (LP), defined as the difference between the bank average interest rate applied on bank loans[10] and the interest rate on 10-years Government Bond of the respective country. This variable is a proxy of the average risk premium applied by the bank to its loans[11]. We posit that a bank that voluntarily lends money to riskier borrowers charges a higher risk premium, hence we expect a positive relation between NPL ratio and LP.

Finally, we proxy the bank lending policy by the rate of growth of gross loans (GLGR), consistently with the empirical evidence that faster loan growth leads to higher loan losses in the following years (up to four years) (Radlet and Sachs, 1998, Keeton, 1999, Ranjan and Dhal, 2003 and Foos et al., 2010). To account for the apparent positive relation between loan portfolio deterioration and the relevance of lending activity for a bank (IMF, 2015; ECB, 2015), we use two well-established proxies of the bank business model: the ratio of Gross Loans to Total Assets (GL_TA) and the ratio of Interest Income to Gross Revenues (II_GR). Finally, in two specifications of our baseline model we include a dummy variable (DREC) that equals 1 in the years 2013, 2014 and 2015, i.e. the years during which the NPL ratio of European banks begins to decrease, after peaking in 2012, and the quality of loans portfolios starts to recover.

Table 1 provides reports details of our variables calculations, our information sources and the variables expected signs.

< Table 1 approximately here >

3.2 Descriptive statistics

[10] Proxied by the interest income on gross loans divided by the average of gross loans at time t-1 and t.

[11] We are aware that this proxy of risk premium is rather rough and does not take into account other variables that may affect the level of bank interest rate and the overall interest income, such as the cost of funding or the cost of equity, etc.

Banks in our sample are quite heterogeneous. Descriptive statistics (Table 2) show high in sample variability in terms of size (proxied by total assets), profitability, riskiness and regulatory (IRB vs. SA) approach. We observe across time an increase in the proportion of IRB vs SA banks: by the end of 2015 most banks in the sample adopt the IRB approach (Table 3). In line with previous studies (Erdinc and Gurov, 2016; Resti, 2016; Turk-Ariss, 2017), we find that the use of internal models varies across countries and it is slightly lower for the Southern European banking systems.

< Table 2 and 3 approximately here >

To describe the features and the differences between SA and IRB banks, Table 4 reports descriptive statistics for the subsamples of respectively IRB- and SA-banks. The data are in line with Behn at al. (2016)[14] and show that IRB banks have considerably larger size, higher profitability (ROAE) and a slightly higher efficiency (C_I). They also have a better quality of their credit portfolio (in term of NPL ratio and LLP ratio), suggesting the existence of a correlation between the use of validated IRB models and the quality of banks loan portfolio. Our hypothesis is that IRB adoption promotes stronger risk management practices among banks and that as consequences IRB banks achieve a lower level of NLPs *ceteris paribus*. In addressing this question, we face a self-selection issue: banks with more sophisticated management capabilities are very likely to self-select into IRB.

We first investigate the determinants of IRB adoption and assess whether the differences in size, profitability and efficiency found at sample level are significant at population level. We then study the impact of IRB adoption on the levels of banks' NPLs, controlling for macroeconomic and bank specific variables and the unobserved endogeneity. Finally, we run several checks on a number of contingency variable to assess the robustness of our findings[12].

[12] To shed more light on this issue we have also computed descriptive statistics for six subsets of IRB and SA banks; these subsets include banks that show values below or above the median of the following three variables: the size, as proxied by total assets, the original riskiness, as measured by the NPL ratio at 2007, and the lending policy, proxied by the rate of growth of gross loan. We find that IRB banks, regardless of their size, original riskiness and

4. The empirical strategy

Our empirical setting is that of a continuous outcome equation (the credit risk equation) with an endogenous binary treatment (the IRB dummy). The IRB dummy is a binary treatment that takes value 1 once a bank's IRB model gets validated by the supervising authority, and zero otherwise. The treatment dummy might be endogenous in the credit risk equation since the IRB adoption/validation itself might be driven by some or all the variables relevant to the risk process. Failure to account for this potential source of endogeneity is well known to lead to inconsistent estimates of the behavioral parameters of interest, as these are confounded with parameters that determine the probability of entry into the treatment. To control for it, we estimate the treatment probability from the first stage equation and then we use it as an instrument in the continuous outcome equation. If the treatment is endogenous we expect to find a significant coefficient of the treatment probability in our main equation.

Further sources of concern in the empirical analysis are the time persistence of the outcome equation dependent variable (NLPs) and the state dependence of the treatment dummy (IRB). The significant time persistence of NPLs is well documented in the empirical literature on credit risk determinants and it strongly supported by our data[13]. It is well known that when the data generating process is dynamic, the consistency of the static fixed effect methods breaks down because of the non-zero correlation between the lagged dependent variable and the differenced error term (Matyas and Sevestre, 2008). Thus, we model the credit risk process with a dynamic panel equation. Finally, since the current regulatory framework strongly discourages exit from a validated IRB framework, we use a dynamic Probit equation with state dependence to model the IRB validation process. Our system of equations is:

---

lending policy, display a lower level of credit risk (NPL ratio and LLP ratio) than their peers. Satistics are available upon requests.

[13] The Arellano Bond (1991) test for serial correlation shows rejection of the null hypothesis of no time dependence at 10 %, 5 % and 1% significance levels.

$$NPL_{GL_{it}} = \rho NPL_{GL_{it-1}} + \boldsymbol{x'}_{it}\boldsymbol{\beta} + \theta IRB_{it-1} + \alpha_i + \varepsilon_{it} \quad i = 1, \dots, N \; t = 1, \dots, T \qquad (1)$$

$$IRB_{it} = 1(\delta IRB_{it-1} + \boldsymbol{z'_{it}}\boldsymbol{\gamma} + \eta_i + u_{it} > 0), \qquad (2)$$

where Equation (1) is the main outcome/second stage equation and Equation (2) is the first stage/ treatment equation where the IRB dummy, defined through the indicator function $1(.)$, depends on a linear index, on an unobserved time-constant additive individual effect and on its own state persistence. We seek to estimate the treatment effect θ. The vectors $\boldsymbol{x}_{it}$ and $\boldsymbol{z_{it}}$ are vectors of strictly exogenous explanatory variables with possibly common elements, including both time variant and time invariant variables, a constant term, time and country individual effects. Although $\boldsymbol{x}_{it}$ and $\boldsymbol{z_{it}}$ may contain common variables, the identification by exclusion restriction scheme requires equation (2) to contain at least one variable which is not included in the main equation and displays a significant time variability (Matyas and Sevestre, 2008; Semykina and Wooldridge 2013;). In equation (1) $\boldsymbol{x}_{it}$ contains the macro and bank specific controls discussed in the previous Section, time and country individual effects. We set the lag orders of the dependent and independent variables by minimizing the Modified BIC criterion of Han, Phillips and Sul (2017). Consistently with the credit risk determinants literature (Bofondi and Ropele, 2011), we find that macro and bank specific variables should be included with a one year lag. The IRB dummy enters in the outcome equation at lag t-1 considering that NPLs do not arise in the same year as the loan has been granted. We choose the predictors to include in the treatment equation by means of a general to specific exercise: $\boldsymbol{z_{it}}$ might contain all the regressors of the primary equation, and other factors that affect the IRB selection but do not affect NPLs. The α_i and η_i are unobserved time invariant individual specific effects, possibly correlated with each other. The ε_{it} and u_{it} are unobserved disturbances, and the endogenous selection implies that in general $\alpha_i + \varepsilon_{it}$ and $\eta_i + u_{it}$ are correlated.

Our estimation strategy is fully parametric. In the first stage we estimate a dynamic random effect Probit model by quasi maximum likelihood methods, using the DBP (Dynamic Binary

Probit) Gretl function package with the linearized index initial condition of Heckman (1981)[14]. This first stage equation is relevant in itself since it sheds some lights on the determinants of the IRB validation process at bank level. Using the first stage results we construct the dynamic Mills ratios at every t:

$$\lambda_{it}^{d} = \frac{\phi(\hat{\delta}IRB_{it-1} + \boldsymbol{z}'_{\boldsymbol{it}}\widehat{\boldsymbol{\gamma}})}{1 - \Phi(\hat{\delta}IRB_{it-1} + \boldsymbol{z}'_{\boldsymbol{it}}\widehat{\boldsymbol{\gamma}})},$$

where $\phi()$ and $\Phi()$ denote respectively the pdf and CDF of a standard normal distribution. We include the inverse of the dynamic Mills ratios in our outcome equation and estimate the behavioral parameters with the System GMM estimator. We are not concerned with the weak instrument problem since the AR(1) coefficient of the NPL equation is significant but not close to unity and our regressors display sufficient time variability.

At this stage we address the correction of the main equation estimated standard errors. The need for such correction arises from the introduction of one predicted (generated) regressor, the inverse dynamic Mills ratio, obtained in the auxiliary equation, in the main equation. It is well known that two stage procedures yield consistent estimate of the second stage parameters but the second step standard errors and related test statistics based on two these procedures are incorrect because of the sampling error introduced by the predicted regressor (Wooldrige, 2002). While the correct form of the asymptotic covariance matrix is well known in the case of dynamic panels with sample selection case (Kyriazidou 1997; Semykina and Wooldrige 2013), to the best of our knowledge this is not the case for dynamic panels with endogenous binary treatment. Here we follow the common practice of applied econometrics and obtain the corrected standard errors via bootstrap[15]. We implement a parametric bootstrap scheme with 5,000 replications. To simulate the probit pseudo-dataset, we initialize the value of IRB to zero and the predictors at their 2008 values, and generate 1000 random draws from a standard Normal. We estimate the propensity to adopt IRB on the pseudo dataset with

[14] For a complete reference on the DBP estimation package we refer the reader to Lucchetti and Pigini (2017).

[15] The validity of bootstrapping techniques to obtain bias-corrected confidence intervals and standard errors is well established in econometric research (Hall, 2002).

the DPM algorithm. We then simulate the main equation dataset and include the generated Mills ratio obtained in the first bootstrap stage in the dynamic panel estimation. We reiterate this procedure 5000 times and obtain the bootstrapped p-values.

5. Results

5.1 Discussion of results

Panel A of Table 4 reports the results of the dynamic selection equation with the best predictive likelihood[16]. Note that identification of model (1)-(2) by exclusion restrictions is ensured by the inclusion in the first stage equation of the variable size, proxied by natural logarithm of Total Assets (SIZE), and by the inclusion of the squares of the credit risk determinants that impact on IRB adoption. It is standard practice in the applied treatment literature to strengthen identification by including non-linear functions of the significant regressors. Our main instrument, SIZE, displays a significant time variability and does not impact on NPLs[17], as established in the credit risk determinants literature. We expect this instrument to be an important determinant of validation of IRB models: as previously mentioned, compliance costs associated with the validation process and the unavailability of large loan-datasets may act as a deterrent for small banks to apply for validation.

In the equation, together with the variables ensuring identification, we include all the relevant credit risk drivers and two specific variables that might predict IRB adoption: RWA density (RWA_TA) and Total Capital Ratio (TCR), a measure of bank capitalization. These controls

[16] Panel A reports the dynamic equation with the best likelihood and includes IRB specific variables that do not impact on NPLs and those NPLs determinants which are significant for the IRB adoption. At the bottom of the Table we report the LogLikelihood of the models, their standard information criteria, AIC and BIC, and the Wald test for the joint significance of the explanatory variables. Estimation output for the general specification is not reported but available upon request from the authors.

[17] In our data set the sample correlation between size and NPLs is not significant at any level. To assess size validity as an instrument, we estimate all the models specifications including size in the main equation and find that it is never statistically significant, implying that it does not impact on NPLs. The estimation results are available upon request.

account for the fact that banks that are less capitalized and riskier have stronger incentives to use internal models. Both are included at t-1 to avoid any potential reverse causality issue[18].

In the overall, all the specifications of the selection equation display strong predictive power. Bearing in mind that equation (1) is a reduced form highly non-linear equation that we estimate for the purpose of controlling for endogeneity in the outcome equation, we notice anyhow that the significant coefficient associated with IRB confirms the state-dependent nature of our treatment.

As expected and in line with previous evidence (Behn et al., 2016), the size (SIZE) displays a strong predictive power, confirming that large banks are more successful in obtaining validation. Moreover, the significant coefficients of cost to income (C_I) and ROAE suggest that more efficient and profitable banks, i.e. better managed banks, are more likely to obtain validation. We also find that the use of IRB models is more likely for less capitalized (E_TA and TCR) and fast growing banks (GLGR) and banks with a business models more oriented towards credit intermediation (GL_TA), i.e. those banks that may enjoy greater benefits in terms of capital savings thank to the use of IRB based risk weights. Moreover, the negative coefficient of RWA density (RWA_TA) shows that validation is more probable for less risky banks; this result may be explained by the greater incentives for these banks to shift from SA to IRB due to the higher reduction of risk weights associated with low-PD exposures.

Panel B of Table 4 reports the System GMM estimates of the main equation for different specifications of our baseline model. We work with log differences of the variables and interpret the coefficients as percentage variations. The bootstrap corrected p-value of the Sargan and Hansen tests rule out the problem of instruments over proliferation, the bootstrap corrected p-value of the Arellano Bond (1991) test for first and second order residuals serial correlations confirm that no time dependence is left unaccounted for. In the overall, all models are statistically significant.

< Table 4 Panel A and B approximately here >

[18] RWA density and TCR values are influenced by the use of the IRB approach.

The most interesting results are the negative and significant coefficients of the IRB dummy and of the dynamic inverse Mills ratio. The IRB dummy 1% significance supports our research hypothesis that, in the aftermath of the financial crisis, banks with validated IRB risk-management procedures, curbed the increase in credit risk driven by the macroeconomic slowdown better than SA banks. The use of IRB validated models has, *ceteris paribus*, reduced the NPL ratio by 11%. This evidence suggests that validated internal rating models and procedures are more effective in selecting less risky counterparts and in managing credit risk when it materializes.

The significance of the inverse Mills ratio coefficient confirms the presence of a selection type endogeneity in our sample. Its sign is by definition the sign of the correlation between the disturbances of the outcome and of the selection equations, implying that we are accounting for a negative potential source of endogeneity. This endogeneity is due to latent factors that impact both on the IRB propensity of adoption and on the NPL ratio. We conjecture that these factors are related to the quality of the risk management of a bank which affects both the outcome of the validation process and its screening and monitoring abilities which eventually impact on the level of credit risk. The superiority of IRB banks in managing risk, supported by our outcome equation findings, is a consequence of their increased risk management capabilities, as the Mills ratio significance and sign suggest. Such improvements in turn arise from the effort in terms of data, tools, procedures and human capital that banks must make in order to obtain IRB validation. So while our results support the ‘bad management’ hypothesis (Berger and De Young, 1997) and confirm that the overall quality of bank management, proxied by bank profitability (ROAE) and efficiency (C_I), affect the level of NPLs, they furthermore show the relevance of risk management skills and abilities as a specific means to control credit risk. The increasing number of IRB banks coupled with the evidence on the effectiveness of IRB models in managing credit risk suggest that the introduction of the IRB approach by regulators has enhanced the diffusion of sound and robust credit risk management procedures and tools among banks. Thus, our findings contribute to the existing literature on risk-sensitive regulation by showing that there is a ‘bright’ side of the internal rating-based approach.

In line with previous studies (Salas and Saurina, 2002; and Foos et al., 2010), our analysis suggests that the increase in credit risk is boosted by the adoption of an expansive lending policy, hinting at the adverse selection issues associated with a fast growth of loans. We also find evidence that banks with a stronger risk appetite, proxied by higher interest rates for customer loans (i.e. loan premia), and with a business model more oriented towards credit intermediation are more prone to loan portfolio deterioration.

Finally, in line with the current literature, we find that macro variables, such as GDP, unemployment and, to a lesser extent, house prices, impact significantly on NPLs (Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Marcucci and Quagliariello, 2009; Bofondi and Ropele, 2011; Glen and Mondragon-Velèz, 2011; Farhan et al., 2012; Beck et al., 2015). Business cycles recessionary phases decrease borrowers' ability to repay their debts and reduce the value of collaterals and act as the strongest driver of bank loan portfolios deterioration.

5.2. Robustness checks

In this section we address a number of potential concerns that may hinder the validity of our findings.

It is well known that the amount of NPLs reported in bank balance sheet may be affected by differences in the accounting policies and in the definitions of default adopted across Europe. Furthermore, while NPLs capture the most severe and the largest part of credit risk, they disregard the credit risk embodied in exposures that are not deteriorated. However, the risk associated with non-deteriorated exposures influences RWAs and capital ratios and may represent an incentive for a bank to ask for validation of internal models. Not accounting for this component of credit risk may bias our analysis. Therefore, as a first robustness check, we estimate our model using an alternative proxy of credit risk, the loan loss provision ratio (LLP_GL) i.e. LLPs to gross loans. The advantage of this variable over the NPL ratio is that it captures the credit risk embodied in performing loans.

Its main drawback is that it reacts more quickly to the deterioration of loan portfolio and might be more volatile. Table 5 reports the main equation results for all model specifications[19].

<Table 5 approximately here>

The results confirm the negative sign and the strong statistical significance of the Mills ratio and the IRB dummy coefficients. The coefficients of both variables are very close to their NLP ratio counterparts: the use of validated IRB models implies a 11% decrease in credit risk at bank level. This evidence further supports our hypothesis that IRB-banks managed credit risk better than SA-banks showing that our findings are robust to the proxy of credit risk used.

Our second robustness check addresses the potential issue of bank size. As previously argued, large banks may have a stronger incentive to apply for IRB validation. This intuition is to some extent supported by the significance of the predictor SIZE in the full sample treatment equation results (Table 4 Panel A). We thus estimate our model on a subsample made of the 'large banks', i.e. those banks that display a value of their total assets over the sample median. Results are reported in Table 6 and are in line with our main findings[20]. We find that IRB banks of the same size-class display a superior ability in managing credit risk, thus discarding the concern that other unobserved factors driven by bank size may bias our conclusions.

<Table 6 approximately here>

We are also concerned about the possibility that IRB banks enjoy a lower increase in credit risk because they are more risk adverse than SA banks. It might be that an initial better quality of their loan portfolio has allowed them to better weather the recession. To investigate the validity of this concern, we split our sample according to the level of the NPL ratio at 2007, i.e. year zero, before the beginning of the observation period. Thus, we isolate 'less risky banks', i.e. banks with a NPL ratio under the median value. Our estimates are reported in Table 7 and confirm the significance

[19] We do not report the selection equation results for the robustness check, but they are available upon request.

[20] We have also performed the same analysis on the subsample of 'smaller banks', but due to the low frequency of IRB banks in this subsample we are not able to identify the Mills ratio from the selection equation where the dependent variable is almost always zero.

and the negative sign of the IRB dummy coefficient on this subsample thus providing evidence that IRB validation did make a significant difference among banks with low risk attitude and a high quality loan portfolio as well.

<Table 7 approximately here>

A number of studies have analyzed the impact of business cycle and credit cycle on credit risk (Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Quagliarello and Marcucci, 2009) finding significant evidences that credit risk reacts differently to the same drivers during downturns and expansions. Our sample statistics (Table 2) show that IRB banks on average display a lower loans growth rate over the whole sample period and this evidence raises concern as to whether the lower increase in credit risk experienced by IRB banks may be due to the credit cycle phase. To address the potential business cycle driven asymmetric effect, we split our observation period into two sub-periods. The first one goes from 2008 to 2013 and the second one from 2014 to 2015. Starting from 2014 we observe a recovery in loan growth in the European banking system[21], therefore the first sub-period identifies the negative part of the credit and economic cycle, while the second sub-period captures the recovery of credit and economic cycle. We report results for the recession period only since the recovery phase is too short to obtain significant estimates. In line with the credit cycle literature, Table 8 confirms that the impact of macro variables on credit risk during a recession is much stronger. However, the Mills ratio and IRB dummy are significant and negative and display both a small increase with respect to the whole period, which suggest that when the general economic context deteriorates, validated internal models displays a greater effectiveness and accuracy.

<Table 8 approximately here>

[21] See ECB Economic Bullettin, n.4/2017, p.29 "The recovery in loan growth to the private sector observed since the beginning of 2014 is proceeding…". Besides, according to CEPR Euro Area Business Cycle Dating Committee Announcements "the trough of the recession that started after the 2011Q3 peak has been reached in 2013Q1". This means that 2014 is a turning –point also for the economic cycle.

In order to deepen our understanding of the impact of the credit cycle and of the lending behavior on credit risk we test our model also on two subsamples of banks constructed on the base of the stance of their lending policy during the negative phase of the credit cycle. We divide the 'more conservative banks', i.e. banks with average growth rate of gross loans (GLGR) over the period 2008-2013 below the sample median, from the 'less conservative banks', i.e. banks with values above the sample median (Table 9). As previously mentioned, during this period banks have reduced their credit supply due to the negative economic context and the expected increase in credit risk. We may therefore suspect that IRB banks have not avoided a sharp increase in credit risk because of their stronger ability in selecting and managing credit risk, but simply because they have been more conservative and have diminished their credit supply. Our results show that even comparing banks with similar lending policies, IRB banks enjoy a lower increase in NPL ratio, thus supporting the view that validated internal models are indeed more effective. The hypothesis that IRB banks have identified and selected their borrowers more accurately and have granted new loans only to safer customers thanks to the higher discriminatory power of IRB models, is consistent with Mascia et al. (2016) and Bruno et al. (2016), who find that during the crisis IRB banks have moved towards safer borrowers, according to a "fly to quality" strategy. Finally, this finding is also consistent with those of Behn et al. (2016) who find that during the recent financial crisis German IRB banks reduced their credit offer more than SA banks.

<Table 9 approximately here>

Finally, the IRB adoption process is a time consuming process which takes on average several years. Clearly, this implies that IRB is not a sharp treatment. The timing of the treatment might be difficult to identify since there is no information available in public sources on whether a bank has initiated the validation process. The validation process itself is latent: we can only assume that during the period that goes from the application for validation until the validation itself the quality of the internal models may increase gradually. We address the concern on the non-sharp nature of the treatment by identifying the significance of IRB models using between banks variation only. We estimate the models on the restricted sample of banks which do not switch from the SA approach to the IRB approach during the period of interest[22]. Thus, we eliminate any potential noise arising in the sample by the efficiency improvement of the switching banks and we rely only on between banks variations. Note that none of the SA banks considered in this subsample obtains IRB in 2016. Our estimates are reported in Table 10 and confirm the robustness of the previous findings: the coefficient of the IRB dummy is significant and has a similar magnitude also for this sub sample of banks. This evidence confirms that IRB banks face a lower deterioration of their loan portfolio and that IRB validated models are superior.

<Table 10 approximately here>

6. Conclusions

The introduction of risk-sensitive capital charges and the possibility for banks to use internal ratings (IRB) models to calculate risk weights represent one of the more important novelties in banking prudential regulation. Since the introduction of the IRB regulatory framework, several issues on its design and implementation have been raised, urging regulators to revise technical features of the validation process.

While a growing body of literature discusses the alleged flaws of the IRB regulation, the ability of validated internal models to contribute to the adoption of stronger risk management practices has not been thoroughly investigated. This paper addresses such question and investigates whether, as meant by regulators, the introduction of the IRB approach has promoted the diffusion of stronger risk management practices among banks. We assess banks credit risk management accuracy and effectiveness by looking at risk management output, i.e. the level of risk borne by a bank, proxied by the NPL ratio and we provide an empirical investigation based on a novel panel data set of 177

[22] In our sample only 23 banks out of 177 switch from SA to IRB during the period under analysis (Table 3).

Western European banks for the 2008-2015 period. Our empirical strategy relies on a dynamic two stage Heckman procedure. We control for the potential endogeneity arising from the IRB dummy in the credit risk equation with an inverse Mills ratio obtained from a dynamic Probit first stage equation. The significance of the IRB dummy in the credit risk equation supports our research hypothesis: in the period under analysis, the use of validated IRB models allowed banks to curb the deterioration of their loan portfolio, limiting the negative impact of the economic downturn that followed the great financial crisis. IRB banks managed to adopt more conservative lending policies by selecting their borrowers more accurately and granting new loans to safer customers. IRB models have thus been accurate and effective in managing credit risk. The significance of the inverse Mills ratio confirms that this result is due to the adoption of sounder and more robust credit risk management procedures among banks as meant by Basel II. Our analysis sheds also light on the validation process, confirming that large and more efficient and profitable banks are more likely to obtain validation.

Overall, our results contribute to the growing debate on the use of the IRB approach by regulators and support the hypothesis that validated IRB models are accurate and robust in the evaluation of credit risk. Our conclusions are in line with the view of the European banking authorities who have reiterated that risk-sensitive internal models should remain the first driver of capital requirements and have issued a plan of technical adjustments aimed at restoring the reliability and consistency of the IRB approach. Finally, our findings suggest that the huge investments required to a bank in terms of data, risk management tools and procedures and human capital to obtain the validation of its internal models may be justified not only by a capital saving for low-risk exposures, but also by a more accurate credit risk evaluation and eventually a lower burden of NPLs.

An interesting issue that we do not address is whether the overall bank risk management effectiveness improves after the validation of its internal rating models. As a matter of fact, the authorization to use IRB models for regulatory purposes may concern only a share of the loan portfolio, e.g. portfolios including only retail or corporate exposures or mortgages, etc.. As the bank risk management tools and procedures become more accurate, supervisors may allow the bank to shift from SA to IRB other shares of the loan portfolio and may also allow for a shift from Foundation IRB (F-IRB) to Advanced IRB (A-IRB). Further research may shed light on this issue by accounting more specifically for the adoption of F-IRB vs A-IRB over time and for the shares of loan portfolios under either of these models.

Bibliography

Arellano, M., Bond, S. (1991) Some tests of specifications for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic .Stud*ies Vol 58, No 3, pp277-297.

Arroyo J. M., Colomer I., Garcia-Baena R., Gonzalez-Mosquera L. (2012) Comparing risk-weighted assets: the importance of supervisory validation processes. Banco de Espana, Estabilidad Financiera, num. 22.

Barakova I., Palvia A. (2014) Do banks' internal Basel risk estimates reflect risk? *Journal of Financial Stability*, Vol. 13, pp. 167-179.

Basel Committee on Banking Supervision (2000) Range of Practice in Banks' Internal Ratings Systems, Discussion paper, Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision (2006) International convergence of capital measurement and capital standards – A revised framework. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision (2013 and 2016) Regulatory consistency assessment programme (RCAP): Analysis of risk-weighted assets for credit risk in the banking book. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision, (2016b) Reducing variation in credit risk-weighted assets – constraints on the use of internal model approaches. Basel, Switzerland: Bank for International Settlements.

Beck R., Jakubik P., Piloiu A. (2015) Key determinants of Non-performing loans: new evidence from a Global sample. *Open Economic Review*, Vol. 26, pp. 525-550.

Berg T., Koziol P. (2017) An Analysis of the Consistency of Banks Internal Ratings. *Journal of Banking and Finance*, doi: 10.1016/j.jbankÞn.2017.01.013

Berger A., DeYoung R. (1997) Problem loans and cost efficiency in commercial banks. *Journal of Banking and Finance*, Vol. 21, 849–870.

Beltratti A., Paladino G. (2016) Basel II and regulatory arbitrage. Evidence from financial crises. *Journal of Empirical Finance*, n. 39, pp. 180-196.

Bhen M.,Haselmann R., Wachtel P. (2016a) Procyclical capital regulation and lending. *Journal of Finance*, Vol LXXI, No 2, pp.919-956.

Bhen M., Haselmann R., Vig V. (2016b) The limits of model-based regulation. Working paper series, European Central Bank, n. 1928/July 2016.

Bikker J.A., P.A.J. Metzemakers (2005) Bank provisioning behaviour and procyclicality. *Journal of International Financial Markets, Institutions and Money*, Vol. 15, pp. 141-157.

Bofondi M., Ropele T. (2011) Macroeconomic determinants of bad loans: evidence from Italian banks, Occasional Paper, Questioni di Economia e Finanza, Banca d'Italia.

Boudriga, A., Boulila, N., Jellouli, S. (2009) Does bank supervision impact nonperforming loans: cross-country determinants using aggregate data? MPRA Paper No. 18068.

Bruno, B., Nocera, G., Resti, A. (2015) The credibility of european banks'risk-weighted capital: structural differences or national segmentations? BAFFICAREFIN Centre Res., 2015–2019.

Bruno, B., Nocera, G., Resti, A. (2016) Are risk-based capital requirements detrimental to corporate lending? Evidence from Europe, unpublished working paper, June 29, 2016, Bocconi University, Milano.

Chaibi H. (2016) Determinants of problem loans: non-performing loans vs loan quality deterioration. *International Business Research*, Vol. 9, No 10, pp. 86-93.

Chaibi H., Ftiti Z. (2015) Credit risk determinants: evidence form a cross-country study. *Research in International Business and Finance*, Vol. 33, pp. 1-16

Colliard, J. E. (2018) Strategc selection of risk models and bank capital. Management Science

De Haas R., Lelyveld I. I. (2014) Multinational banks and the global financial crisis: weathering the perfect storm? *Journal of Money, Credit and banking*, Vol. 46, No 1, pp. 333-364.

Dimitrios A., Louri H., Tsionas M. (2015) Determinants of non-performing loans: evidence form Euro-area countries. *Finance Research Letters*, Vol. 18, pp. 116-19.

EBA (2013). Summary report on the comparability and pro-cyclicality of capital requirements under the Internal Ratings Based Approach in accordance with Article 502 of the Capital Requirements Regulation.

EBA (2015) Future of the IRB approach. Discussion Paper, EBA/DP/2015/01.

EBA (2016) The EBA's regulatory review of the IRB approach. Conclusions from the consultation on the discussion paper on the 'Future of the IRB approach'.

EBA (2016b) Final Draft Regulatory Technical Standards on the specification of the assessment methodology for competent authorities regarding compliance of an institution with the requirements to use the IRB Approach in accordance with Articles 144(2), 173(3) and 180(3)(b) of Regulation (EU) No 575/2013.

European Central Bank (2015) *Financial Stability Review*, n. 2/15.

European Central Bank (2017) Guide for the Targeted Review of Internal Models, Banking Supervision.

Erdinc D., Gurov A. (2016) The effect of regulatory and risk management advancement on Non performing loans in European Banking, 2000-2011. *International Advances in Economic Research*, Vol. 22, pp. 249-262.

Farhan, M., Sattar A., Chaudhry A. H., Khalil F. (2012) Economic determinants of non-performing loans: perceptions of Pakistani bankers. *European Journal of Business and Management*, Vol. 4, No 19, 87-100.

Ferri G., Pesic V. (2016) Bank regulatory arbitrage via risk weighted assets dispersion. *Journal of Financial Stability*, http://dx.doi.org/10.1016/j.jfs.2016.10.006.

Foos D., Norden L., Weber M. (2010) Loan growth and riskiness of banks. *Journal of banking and*

Finance, Vol. 34, pp. 2929-2940.

Ghosh A. (2015) Banking-industry specific and regional economic determinants of non-performing loans: evidence from US states. *Journal of Financial Stability*, Vol. 20, pp. 93-104

Glen J., C. Mondragón-Vélez C. (2011) Business Cycle Effects on Commercial Bank Loan Portfolio Performance in Developing Economies, International Finance Corporation, World Bank Group.

Han C., Phillips C. B., Sul D. (2017) Lag length selection in panel autoregression. Econometric Review, vol. 36(1-3).

Heckman J. J. (1981) Heterogeneity and State Dependence. In Studies in Labor Market, Sherwin Rosen ed. ISBN 0-226-72628-2.

Hess K., Grimes A., Holmes M. (2009) Credit losses in Australasian banking. *Economic Record,* Vol. 85, pp. 331-343.

Huizinga H. (2016) Banks' internal rating models – time for change? The "system of floors" as proposed by the Basel Committee. European Parliament.

International Monetary Fund (2015), A Strategy for Resolving Europe's Problem Loans, IMF Staff Discussion Note 15/19

Jimenez, G., Saurina, J. (2006) Credit cycles, credit risk, and prudential regulation. *International Journal of Central Banking*, Vol. 2, pp. 65-98.

Keeton W. (1999) Does faster loan growth lead to higher loan losses. Federal Reserve Bank of Kansas City Economic Review 1999 (2nd quarter), 57–75.

Keeton, W., Morris C. (1987) Why Do Banks' Loan Losses Differ?, Federal Reserve Bank of Kansas City, *Economic Review*, May, pp. 3–21.

Klein N. (2013) Non-performing loans in CESEE: determinants and impact on macroeconomic performance, IMF Working paper. WP/13/72.

Kyriazidou, E. (1997). Estimation of a panel data sample selection model. *Econometrica: Journal of the Econometric Society*, 1335-1364.

Kyriazidou, E. (2001). Estimation of dynamic panel data sample selection models. *The Review of Economic Studies*, *68*(3), 543-572.Laeven L., Majnoni G. (2003) Loan Loss provisioning and economic slowdowns: too much, too late? *Journal of Financial Intermediation*, Vol. 12, pp. 178-197.

Ledo M. (2011) Towards more consistent, albeit diverse, risk-weighted assets across banks, Banco d'Espana, Estabilidad Financiaria, num. 21.

Le Leslé V. and Avramova S. (2012) Revisiting Risk-Weighted Assets, IMF Working Paper, n. 90.

Louzis, D.P., Vouldis A. T., Metaxas V. L. (2011) Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance*.

Lucchetti and Pigini (2017) DPB: Dynamic Panel Binary Data Models in gretl. *Journal of Statistical Software.* Vol. 79(8).

Macit F. (2012) What determines the non-performing loans ratio: evidence from Turkish commercial banks. *Cea Journal of Economics*, Vol. 7, No 1, pp. 33-40.

Makri V., Tsagkanos A., Bellas A. (2014) Determinants of non-performing loans: the case of Eurozone. *Panoeconomicus,* Vol. 2, pp. 193-206.

Marcucci J., M. Quagliariello (2009) Asymmetric effects of the business cycle on bank credit risk. *Journal of Banking and Finance,* Vol. 33, pp. 1624-1635.

Mariathasan M., Merrouche O. (2014) The manipulation of basel risk-weights. *Journal of Financial Intermediation,* Vol. 23, pp. 300-321.

Mascia D. V., Keasey K., Vallascas F. (2016) Did Basel II Affect Credit Growth to Corporate Borrowers During the Crisis?, S.P.S. Rossi, R. Malavasi (eds.). *Financial Crisis, Bank Behaviour and Credit Crunch*, Contributions to Economics, Springer International Publishing Switzerland.

Matyas L, Sevestre P (eds) (2008) The econometrics of panel data. Springer, Berlin, Third completely new edition.

Perèz Montes, C., Trucharte Artigas, C., Cristófoli, M. E., & San Segundo, N. L. (2016) The impact of the IRB approach on the risk weights of European banks. *Journal of Financial Stability*, http://dx.doi.org/10.1016/j.jfs.2016.11.004

Podpiera, J., Weill, L. (2008) Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability*, Vol. 4, pp. 135–148.

Plosser M. C., Santos J. A. (2018) Banks' Incentives and Inconsistent Risk Models, *The Review of Financial Studies*, forthcoming .

Radlet S., Sachs J. (1998) The onset of the east Asian financial crisis, Nber working paper series.

Rajan R., Dhal S. C. (2003) Nonperforming Loans and Terms of Credit of Public Sector Banks in India: An Empirical Assessment. *Reserve Bank of India Occasional Papers*, Vol. 24, pp. 81–121.

Resti, A. (2016) Bank internal ratings: are capital floors a suitable tool to restore their credibility? *Journal of Financial Management, Markets and Institutions*, Vol. 2, pp 179-194.

Salas V., Saurina J. (2002) Credit Risk in Two Institutional Regimes: Spanish Commercial and Saving Banks. *Journal of Financial Services Research*, Vol. 22-0, pp. 203-224.

Semykina A., Wooldrige J. M. (2013) Estimation of dynamic panel data models with sample selection. *Journal of Applied econometrics,* vol. 28(1), pp. 47-61.

Turk-Assis (2017) Heterogeneity of Bank Risk Weights in the Eu: Evidence by asset class and country of counterparty exposure. IMF Working Paper. WP 17/137.

Wooldridge, J.M. (2002) *Econometrics Analysis of Cross Section and Panel Data*. MIT Press

Zhang D., Cai J., Dickinson D. G., Kutan A. M. (2016) Non-performing loans, moral hazard and regulation of the Chinese commercial banking system. *Journal of Banking and Finance*, 63, pp. 48-60

Table 1

Variables, their definition, source and expected sign

Name	Description	Source	Expected sign
NPL_GL	Non-performing loans on gross loans as measure of bank's asset quality	Bankscope	/
LLP_GL	Loan loss provisions on gross loans as measure of bank's asset quality	Bankscope	/
IRB	Dummy variable that equals 1 if bank uses validated IRB model	SNL Unlimited	Negative
ROAE	Return over average equity as measure of banks' profitability	Bankscope	Negative
C_I	Total operating costs over total operating income as measure of cost efficiency	Bankscope	Positive/Negative
E_TA	Equity over total assets as measure of banks' capitalization	Bankscope	Positive/negative
GLGR	Growth rate of Gross Loans as measure of propensity to offer loans.	Bankscope	Negative
LP	Loan premium, calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country.	Bankscope and European Central Bank (Statistical Data Warehouse)	Positive
GL_TA	Gross Loans over Total Assets as measure of banks' business model	Bankscope	Positive
II_GR	Interest Income over Gross Revenues as measure of banks' business model	Bankscope	Positive
RWA	Risk weighted assets on total assets as measure of risk appetite as measure of banks' risk appetite	Bankscope	
TCR	Total capital ratio as measure of banks' capitalization	Bankscope	
SIZE	Natural logarithm of total assets as measure of banks' size	Bankscope	
DREC	Dummy variable that equals 1 for years from 2013 to 2015, i.e. years when the aggregate level of NPL fro European banks has started to decrease		Positive
GDP	Growth of GDP at the bank's country-level	Eurostat	Negative
HPI	House price index at the bank's country-level	Eurostat	Negative
UN	Unemployment rate at the banks' country level	Eurostat	Positive

This Table reports the variables used in our analysis, their meaning, the source and the sign expected. Where the expected sign is not reported, it means that the variable is used only in the Probit regression and not in the GMM.

Table 2

Descriptive statistics of the total sample and the two subsamples IRB and SA Banks (2008-2015)

	N. OBSERVATIONS			MEAN			MEDIAN			SD		
	TOT	**SA**	**IRB**	**TOT**	**SA**	**IRB**	**TOT**	**SA**	**IRB**	**TOT**	**SA**	**IRB**
IRB	1,412	-	-	0.6339	-	-	1	-	-	0.4819	-	-
LLP_GL (%)	1,385	497	883	0.7137	0.8141*	0.6564*	0.3911	0.55	0.34	1.722	1.215	1.952
NPL_GL (%)	1,353	468	880	5.215	6.644***	4.453***	3.217	4.16	2.87	5.956	7.402	4.855
ROAE (%)	1,387	500	883	1.99	0.7731*	2.673*	5.173	15.31	21.69	19.61	3.894	5.833
C_I (%)	1,363	490	866	64.15	66.54***	62.85***	62.28	65.65	60.17	23.7	25.03	22.91
E_TA (%)	1,391	501	886	6.45	6.358	6.497	5.991	6.27	5.879	3.377	2.677	3.715
GRGL (%)	1,371	490	877	3.818	4.78*	3.273*	2.594	3.08	2.407	15.96	17.86	14.82
LP (%)	1,359	489	861	0.533	0.3483**	0.6388**	0.630	0.6203	0.6376	2.085	1.86	2.2
GL_TA (%)	1,382	494	884	63.43	67.75***	61.01***	66.82	71.45	63.84	18.83	18.22	18.73
II_GR (%)	1,364	485	872	68.27	70.33	67.14	65.46	69.34	62.49	38.93	38.81	39.12
RWA (%)	1,298	486	808	44.7	53.45***	39.35***	43.45	58.38	38.78	18.18	19.01	15.32
TCR (%)	1,285	482	799	15.57	14.26***	16.37***	14.07	12.95	14.7	7.527	7.114	7.674
TA (bn. Euro)	1,395	503	888	192.92	36.543***	282.026***	39.22	17.675	84.490	384.83	47.837	457.765
GDP (%)	1,062	-	-	1.569	-	-	1.7	-	-	3.388	-	-
UN (%)	1,416	-	-	5.281	-	-	5.1	-	-	2.229	-	-
HPI	1,342	-	-	101.9	-	-	100.7	-	-	10.23	-	-

This Table reports the descriptive statistics for the total sample and for the subsamples of IRB- and SA-banks, during the period 2008-2015. IRB is a dummy variable equal to 1 if banks adopt IRB model, 0 otherwise; TA is the total assets of banks as measure of size (expressed in billions euro); LLP_GL is the loan loss provisions on gross loans (%) and NPL_GL is the non-performing loans on gross loans (%); ROAE the return on average equity (%); C_I is the cost income ratio (%); E_TA is the equity on total assets (%); GRGL is the growth of gross loans year on year (%); LP is the loan premium (%) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; GL_TA is the gross loans on total assets (%) and II_GR is the interest income on gross revenues (%); RWA is the risk weighted assets on total assets (%); TCR is the total capital ratio (%); TA is the total assets expressed in billions of euro. The macroeconomic variables are: GDP that is the growth gross domestic product (%), the unemployment rate (UN) (%) and the house price index (HPI).

***, ** and * indicate that the differences between the two means are statistically significant at the 1%, 5% and 10% levels respectively.

Table 3

IRB vs. SA approach. Number of banks in the full sample and divided by year and country.

	2008	2009	2010	2011	2012	2013	2014	2015	Sample total assets/Total Asset of banking system (% at 31/12/2015)
TOTAL	**177**	**177**	**177**	**177**	**177**	**177**	**177**	**177**	**62.62**
SA	75	70	67	65	64	60	60	56	
IRB	98	107	110	112	113	117	117	121	
Austria	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**72.61**
SA	7	7	7	7	7	6	6	5	
IRB	3	3	3	3	3	4	4	5	
Belgium	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**96.78**
SA	1								
IRB	7	8	8	8	8	8	8	8	
Denmark	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**72.87**
SA	3	3	3	3	3	3	3	3	
IRB	7	7	7	7	7	7	7	7	
Finland	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**41.37**
SA	2	2	2	2	2	2	2	1	
IRB	2	2	2	2	2	2	2	3	
France	**41**	**41**	**41**	**41**	**41**	**41**	**41**	**41**	**86.46**
SA	7	5	4	4	4	4	4	4	
IRB	32	36	37	37	37	37	37	37	
Germany	**22**	**22**	**22**	**22**	**22**	**22**	**22**	**22**	**63.57**
SA	12	12	12	11	11	10	10	10	
IRB	9	10	10	11	11	12	12	12	
Great Britain	**17**	**17**	**17**	**17**	**17**	**17**	**17**	**17**	**45.69**
SA	7	7	7	7	7	7	7	6	

IRB	10	10	10	10	10	10	10	11	
Ireland	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**83.36**
SA	2	2	2	2	2	2	2	2	
IRB	2	3	3	3	3	3	3	3	
Italy	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**74.98**
SA	23	22	22	21	20	18	18	17	
IRB	4	5	5	6	7	9	9	10	
Netherland	**7**	**7**	**7**	**7**	**7**	**7**	**7**	**7**	**37.54**
SA	2	2	1	1	1	1	1	1	
IRB	5	5	6	6	6	6	6	6	
Norway	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**83.48**
SA	3	3	2	2	2	2	2	2	
IRB	6	6	7	7	7	7	7	7	
Portugal	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**51.04**
SA	4	3	3	3	3	3	3	3	
IRB	1	2	2	2	2	2	2	2	
Spain	**6**	**6**	**6**	**6**	**6**	**6**	**6**	**6**	**41.49**
SA	2	2	2	2	2	2	2	2	
IRB	4	4	4	4	4	4	4	4	
Sweden	**6**	**6**	**6**	**6**	**6**	**6**	**6**	**6**	**91.87**
IRB	6	6	6	6	6	6	6	6	

Note: SA = Banks that compute regulatory capital requirement using the standardized approach; IRB = Banks that compute regulatory capital requirement using their validated internal models

Table 4

Panel A – Propensity to adopt validated IRB

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
IRB_{t-1}	0.769***	0.802***	0.791***	0.776***	0.790***	0.783***	0.764***	0.755***
$ROAE_{t-1}$	0.021**	0.018*	0.020**	0.020**	0.016**	0.022**	0.023**	0.019*
$ROAE^2_{t-1}$	0.004*	0.003*	0.007*	0.006*	0.004*	0.007*	0.007*	0.009*
C_I_{t-1}	-0.263***	-0.287**	-0.275**	-0.257***	-0.285**	-	-0.262*	-
$C\_I^2_{t-1}$	-0.111***	-0.116**	-0.111**	-0.109**	-0.112**		-0.113**	
E_TA_{t-1}	-0.145***	-0.151**	-0.155***	-0.157**	-0.158***	-0.053***	-0.148**	-0.162**
$E\_TA^2_{t-1}$	-0.021*	-0.033*	-0.032*	-0.030**	-0.030*	-0.036*	-0.028*	-0.027*
$GLGR_{t-1}$	-	0.001*	0.007*	-	0.003*	0.003*	-	0.002*
$GLGR^2_{t-1}$	-	0.003*	0.005*	-	0.006*	0.003*	-	0.005*
LP_{t-1}	-	-	-	0.019*	0.022*	-	-	-
LP^2_{t-1}				0.011*	0.009			
GL_TA_{t-1}	0.056**	0.052**	0.053**	0.054**	0.055**	-	0.053**	-
$GL\_TA^2_{t-1}$	0.013*	0.011*	0.015*	0.014**	0.007*		0.012*	
II_GR_{t-1}	-	-	-	-	-	0.023*	-	0.022*
$II\_GR^2_{t-1}$						0.008*		0.006*
GDP_{t-1}	0.002*	0.004*	0.001	0.003*	0.005*	0.003*	0.007*	0.002
RWA_TA_{t-1}	-0.046**	-0.048**	-0.052**	-0.048**	-0.055**	-0.052**	-0.051***	-0.053***
TCR_{t-1}	-0.027**	-0.022**	-0.032**	-0.031**	-0.028*	-0.024**	-0.031*	-0.028**
$SIZE_{t-1}$	0.036**	0.033**	0.037**	0.035**	0.041**	0.038***	0.040**	0.043***
N: obs.	1239	1239	1239	1239	1239	1239	1239	1239
Log-Likelihood	-17843.05	-16574.33	17054.21	16885.53	-18993.34	-17654.23	-16567.20	-17111.28

Panel B - Determinants of NPL ratio

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NPL_GL_{t-1}	0.283***	0.289**	0.301***	0.278**	0.311***	0.299**	0.312***	0.275***
	(0.000)	*(0.024)*	*(0.005)*	*(0.030)*	*(0.005)*	*(0.026)*	*(0.004)*	*(0.007)*
IMR_{t-1}	-0.022***	-0.021***	-0.022***	-0.018***	-0.020***	-0.023***	-0.011***	-0.026***
	(0.000)	*(0.000)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.001)*	*(0.005)*	*(0.000)*
IRB_{t-1}	-.111***	-.112***	-.116***	-.111**	-0.110***	-.106***	-.113**	-.108***
	(0.005)	*(0.000)*	*(0.000)*	*(0.021)*	*(0.000)*	*(0.005)*	*(0.013)*	*(0.000)*
$ROAE_{t-1}$	-0.045*	-0.046**	-0.043**	-0.047**	-0.046*	-0.045*	-0.040*	-0.042**
	(0.062)	*(0.040)*	*(0.041)*	*(0.042)*	*(0.084)*	*(0.067)*	*(0.086)*	*(0.048)*
C_I_{t-1}	0.320***	0.318**	0.311***	0.315**	0.316***	-	0.322***	-
	(0.004)	*(0.020)*	*(0.000)*	*(0.032)*	*(0.003)*		*(0.001)*	
E_TA_{t-1}	0.225***	0.234**	0.274**	0.256**	0.233***	0.238***	0.227***	0.230**
	(0.005)	*(0.027)*	*(0.013)*	*(0.028)*	*(0.004)*	*(0.000)*	*(0.000)*	*(0.039)*
$GLGR_{t-1}$	-	0.070***	0.071**	-	0.073**	0.068**	-	0.070***
		(0.007)	*(0.017)*		*(0.031)*	*(0.035)*		*(0.009)*
LP_{t-1}	-	-	-	0.133**	0.130**	-	-	-
				(0.027)	*(0.025)*			
GL_TA_{t-1}	0.044**	0.041**	0.040**	0.045**	0.046**	-	0.045**	-
	(0.043)	*(0.036)*	*(0.041)*	*(0.047)*	*(0.048)*		*(0.042)*	
II_GR_{t-1}	-	-	-	-	-	0.065**	-	0.061**
						(0.027)		*(0.036)*
GDP_{t-1}	-0.324***	-0.389***	-0.337***	-0.342***	-0.334***	-0.324***	-0.385***	-0.333***
	(0.001)	*(0.005)*	*(0.009)*	*(0.003)*	*(0.006)*	*(0.001)*	*(0.008)*	*(0.005)*
UN_{t-1}	0.135***	0.138**	0.133***	0.135***	0.130***	0.136***	0.133***	0.134**
	(0.005)	*(0.011)*	*(0.002)*	*(0.008)*	*(0.000)*	*(0.004)*	*(0.000)*	*(0.015)*
HPI_{t-1}	-0.055**	-0.050**	-0.044**	-0.051**	-0.048**	-0.047**	-0.050**	-0.051**
	(0.037)	*(0.019)*	*(0.042)*	*(0.038)*	*(0.028)*	*(0.038)*	*(0.041)*	*(0.033)*
$DREC_t$	-	-	-	*0.002** *(0.053)*	-	-	-	*0.003** *(0.076)*
Country Dummies	Yes	-	Yes	Yes	-	Yes	-	Yes
N. Obs.	1239							
Hansen Test	0.765	0.782	0.767	0.803	0.777	0.793	0.756	0.779
Sargan Test	0.331	0.323	0.432	0.411	0.388	0.411	0.336	0.376
AR(1)	0.271	0.235	0.268	0.249	0.238	0.267	0.291	0.265
AR(2)	0.554	0.543	0.544	0.578	0.532	0.567	0.576	0.561
Wald chi-sq test	1236	1335	1765	1198	1245	1126	1250	1178

Panel A reports the results of the dynamic selection equation and reports the Quasi Maximum Likelihood estimates of the dynamic Probit selection equation. Convergence is achieved at the 11th iteration. The covariance matrix used is Sandwich and the Quadrature method is the Gaussian Quadrature with 26 points. The reported Log-Likelihood values suggest that this first stage equation is highly significant as a predictive equation. The dependent variable is the IRB dummy equals to 1 if bank adopts IRB approach, 0 otherwise.

Panel B reports the results of the System GMM estimates for the main equation for different baseline model specifications. The reported number of observations refers to the level equation.

The dependent variable is the ratio of non-performing loans on gross loans as measure of bank's asset quality (NPL/GL). The IMR is the Inverse Mills ratio at time t-1. Explanatory variables are: the dummy variable IRB at time t-1 that equals 1 if bank adopts the internal rating based approach; the return on average equity ratio at time t-1 (ROAE); the cost to income ratio at time t-1 (C_I); the equity over total assets at time t-1 (E_TA); the growth rate of gross loans at time t-1 (GLGR); the loan premium at time t-1 (LP) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; the gross loans over total assets ratio at time t-1 (GL_TA) and the interest income divided by gross revenues at time t-1 (II_GR); the GDP growth rate at country level at time t-1. In addition, in Panel A: the Natural Logarithm of total assets at time t-1 (SIZE), RWA density, i.e. RWAs divided by Total Assets at time t-1 (RWA) and Total Capital Ratio at time t-1 (TCR). In Panel B: Unemployment rate (UN), House Price Index (HPI) and the dummy variable for the recovery period that takes value 1 only in 2013, 2014 and 2015 (DREC) and Country dummies.

***, ** and * indicate that coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

Table 5
Determinants of LLP ratio

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
LLP_GL$_{t-1}$	0.332**	0.335***	0.328**	0.337***	0.331**	0.233**	0.334**	0.230***
	(0.022)	*(0.000)*	*(0.026)*	*(0.008)*	*(0.028)*	*(0.030)*	*(0.033)*	*(0.005)*
IMR$_{t-1}$	-0.021***	-0.020***	-0.019***	-0.017**	-0.021***	-0.018**	-0.021**	-0.019***
	(0.000)	*(0.000)*	*(0.000)*	*(0.027)*	*(0.005)*	*(0.031)*	*(0.022)*	*(0.006)*
IRB$_{t-1}$	-0.118***	-0.116***	-0.120***	-0.119***	-0.121***	-0.122**	-0.120**	-0.118***
	(0.000)	*(0.007)*	*(0.005)*	*(0.009)*	*(0.000)*	*(0.030)*	*(0.005)*	*(0.000)*
ROAE$_{t-1}$	-0.040**	-0.042**	-0.041**	-0.042**	-0.041*	-0.040**	-0.042*	-0.038*
	(0.048)	*(0.025)*	*(0.036)*	*(0.027)*	*(0.046)*	*(0.038)*	*(0.057)*	*(0.058)*
C_I$_{t-1}$	0.342***	0.336***	0.340**	0.335**	0.331***	-	0.338***	-
	(0.000)	*(0.000)*	*(0.016)*	*(0.018)*	*(0.000)*		*(0.000)*	
E_TA$_{t-1}$	0.252***	0.255**	0.258**	0.541***	0.554***	0.548***	0.562***	0.555***
	(0.000)	*(0.01)*	*(0.012)*	*(0.006)*	*(0.003)*	*(0.004)*	*(0.005)*	*(0.000)*
GLGR$_{t-1}$	-	0.060**	0.061**	-	0.063**	0.061**	-	0.062**
		(0.035)	*(0.040)*		*(0.031)*	*(0.038)*		*(0.026)*
LP $_{t-1}$	-	-	-	0.125*	0.127*	-	-	-
				(0.072)	*(0.081)*			
GL_TA $_{t-1}$	0.048***	0.050**	0.047**	0.044**	0.050**	-	0.047**	-
	(0.007)	*(0.029)*	*(0.026)*	*(0.033)*	*(0.026)*		*(0.047)*	
II_GR$_{t-1}$	-	-	-	-	-	0.052*	-	0.050*
						(0.068)		*(0.071)*
GDP$_{t-1}$	-0.384***	-0.385***	-0.383**	-0.385***	-0.387***	-0.381***	-0.380***	-0.383***
	(0.000)	*(0.004)*	*(0.10)*	*(0.006)*	*(0.000)*	*(0.003)*	*(0.000)*	*(0.000)*
UN$_{t-1}$	0.134**	0.128**	0.133**	0.129**	0.132***	0.133**	0.135**	0.128**
	(0.035)	*(0.032)*	*(0.036)*	*(0.028)*	*(0.009)*	*(0.024)*	*(0.027)*	*(0.014)*
HPI$_{t-1}$	-0.045**	-0.047**	-0.048**	-0.043**	-0.049**	-0.043*	-0.050*	-0.051**
	(0.08)	*(0.033)*	*(0.028)*	*(0.041)*	*(0.042)*	*(0.057)*	*(0.061)*	*(0.048)*
DREC$_{t}$	-	-	*-0.006** *(0.057)*	-	-	-	-	*-0.007** *(0.083)*
Coutry dummy	Yes	-	Yes	Yes	-	Yes	-	Yes
N. Obs.	1239							
Hansen test	0.567	0.558	0.632	0.687	0.654	0.765	0.669	0.554
AR(1)	0.266	0.257	0.227	0.238	0.259	0.234	0.287	0.220
AR(2)	0.555	0.632	0.671	0.521	0.647	0.283	0.776	0.631
Wald chi-sq t	1345.6	1453.4	1444.5	1387.5	1458.2	1378.8	1229.0	1765.3
Sargan	0.387	0.371	0.445	0.492	0.466	0.365	0.334	0.357

This Table reports the results of the System GMM estimates for the main equation for different specifications of our baseline model. We report the number of observations for the equation in levels.

The dependent variable is the ratio of loan loss provisions on gross loans as measure of bank's asset quality (LLP/GL). The IMR is the Inverse Mills ratio at time t-1. Explanatory variables are: the instrumenting variable LLP_GL at time t-1; the dummy variable IRB at time t-1 that equals 1 if bank adopts the internal rating based approach; the return on average equity ratio at time t-1 (ROAE) and the cost to income ratio at time t-1 (C_I); the equity over total assets at time t-1 (E_TA), the growth rate of gross loans at time t-1 (GLGR); the loan premium at time t-1 (LP) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; the gross loans over total assets ratio at time t-1 (GL_TA) and the interest income divided by gross revenues at time t-1 (II_GR); the GDP growth rate at country level at time t-1, the unemployment rate at time t-1 (UN) and the house price index at time t-1 (HPI). A dummy variable for the recovery period that takes value 1 only in 2013, 2014 and 2015 (DREC) and Country dummies.

***, ** and * indicate that coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

Table 6

Determinants of NPL ratio for the subsample of 'Larger Banks'

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NPL_GL_{t-1}	0.221**	0.225***	0.227***	0.220**	0.226**	0.230**	0.228**	0.227***
	(0.035)	*(0.011)*	*(0.008)*	*(0.030)*	*(0.047)*	*(0.034)*	*(0.011)*	*(0.012)*
IMR_t	-0.018**	-.015***	-0.016**	-0.017***	-0.016**	-.0021**	-.016**	-.015**
	(0.033)	*(0.008)*	*(0.015)*	*(0.006)*	*(0.042)*	*(0.040)*	*(0.387)*	*(0.033)*
IRB_t	-0.0913***	-0.0891**	-0.0884***	-0.0901***	-0.0902***	-0.0868**	-0.0875**	-0.0874**
	(0.000)	*(0.006)*	(0.000)	*(0.005)*	(0.000)	*(0.018)*	*(0.026)*	*(0.034)*
$ROAE_{t-1}$	-0.042**	-0.043 *	-0.046*	-0.040**	-0.042**	-0.044**	-0.040*	-0.041**
	(0.036)	*(0.075)*	*(0.083)*	*(0.040)*	*(0.037)*	*(0.029)*	*(0.055)*	*(0.036)*
C_I_{t-1}	0.311***	0.308**	0.315***	0.322**	0.308***	-	0.319***	-
	(0.003)	*(0.035)*	*(0.007)*	*(0.027)*	*(0.0077)*		*(0.008)*	
E_TA_{t-1}	0.183*	0.193**	0.180**	0.191**	0.187**	0.188**	0.185*	0.194**
	(0.072)	*(0.036)*	*(0.011)*	*(0.028)*	*(0.018)*	*(0.041)*	*(0.057)*	*(0.043)*
$GLGR_{t-1}$	-	0.060**	0.062**	-	0.058***	0.061*	-	0.058**
		(0.037)	*(0.036)*		*(0.003)*	*(0.071)*		*(0.040)*
LP_{t-1}	-	-	-	0.127**	0.125*	-	-	-
				(0.028)	*(0.055)*			
GL_TA_{t-1}	0.023**	0.024**	0.025*	0.021**	0.026**	-	0.022**	-
	(0.043)	*(0.476)*	*(0.057)*	*(0.043)*	*(0.037)*		*(0.047)*	
II_GR_{t-1}	-	-	-	-	-	0.050*	-	0.056*
						(0.065)		*(0.068)*
GDP_{t-1}	-0.346***	-0.332***	-0.341**	-0.352***	-0.343***	-0.353***	-0.338**	-0.271***
	(0.007)	*(0.008)*	*(0.031)*	*(0.007)*	*(0.009)*	*(0.007)*	*(0.011)*	*(0.009)*
UN_{t-1}	0.131***	0.151***	0.127***	0.158**	0.115***	0.148**	0.147***	0.152**
	(0.008)	*(0.007)*	*(0.008)*	*(0.028)*	*(0.007)*	*(0.048)*	*(0.009)*	*(0.017)*
HPI_{t-1}	-0.031***	-0.033**	-0.032**	-0.037*	-0.039***	-0.029**	-0.035*	-0.034**
	(0.009)	*(0.015)*	*(0.007)*	*(0.057)*	*(0.009)*	*(0.047)*	*(0.088)*	*(0.049)*
$DREC_t$	-	-	-	-0.003 (0.114)	-	-	-	-.002** (0.085)
Country Effect	Yes	-	Yes	Yes	-	Yes	-	Yes
N. Obs.	1239							
Hansen test	0.652	0.732	0.777	0.681	0.716	0.683	0.711	0.723
AR(1)	0.327	321	0.386	0.365	0.352	0.289	0.365	0.338
AR(2)	0.668	0.562	0.611	0.543	0.558	0.534	0.550	0.558
Wald chi_sq	1567	1665	1347	1579	1632	1363	1329	1324
Sargan	0.331	0.354	0.332	0.361	0.358	0.401	0.337	0.396

This Table reports the results of the System GMM estimates for the main equation for different specifications of our baseline model on a subsample made of the 'large banks', i.e. those banks that display a value of their total asset over the sample median. The dependent variable is the ratio of non-performing loans on gross loans as measure of bank's asset quality (NPL/GL). The IMR is the Inverse Mills ratio at time t-1. Explanatory variables are: the instrumenting variable NPL_GL at time t-1; the dummy variable IRB at time t-1 that equals 1 if bank adopts the internal rating based approach; the return on average equity ratio at time t-1 (ROAE) and the cost to income ratio at time t-1 (C_I); the equity over total assets at time t-1 (E_TA) , the growth rate of gross loans at time t-1 (GLGR); the loan premium at time t-1 (LP) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; the gross loans over total assets ratio at time t-1 (GL_TA) and the interest income divided by gross revenues at time t-1 (II_GR); the GDP growth rate at country level at time t-1, the unemployment rate at time t-1 (UN) and the house price index at time t-

1 (HPI). A dummy variable for the recovery period that takes value 1 only in 2013, 2014 and 2015 (DREC) and Country dummies.

***, ** and * indicate that coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

Table 7

Determinants of NPL ratio for the subsample of 'Less risky banks'

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NPL_GL_{t-1}	0.225**	0.228***	0.222**	0.227**	0.224***	0.225***	0.228***	0.219***
	(0.042)	*(0.009)*	*(0.021)*	*(0.036)*	*(0.008)*	*(0.000)*	*(0.002)*	*(0.004)*
IMR_{t-1}	-0.017***	-0.018**	-0.019**	-0.016**	-0.020**	-0.018**	-0.019**	-0.018**
	(0.008)	*(0.032)*	*(0.036)*	*(0.044)*	*(0.035)*	*(0.050)*	*(0.046)*	*(0.028)*
IRB_{t-1}	-0.116**	-0.114***	-0.115**	-0.109***	-0.116***	-0.113**	-0.111**	-0.103***
	(0.033)	*(0.008)*	*(0.031)*	*(0.003)*	*(0.032)*	*(0.037)*	*(0.042)*	*(0.005)*
$ROAE_{t-1}$	-0.048*	-0.047*	-0.043*	-0.045*	-0.040*	-0.042*	-0.043**	-0.044*
	(0.066)	*(0.075)*	*(0.083)*	*(0.062)*	*(0.075)*	*(0.061)*	*(0.048)*	*(0.064)*
C_I_{t-1}	0.312***	0.308***	0.315**	0.317**	0.314***	-	0.316***	-
	(0.005)	*(0.000)*	*(0.015)*	*(0.028)*	*(0.008)*		*(0.007)*	
E_TA_{t-1}	0.151***	0.148**	0.154***	0.152***	0.156**	0.148**	0.149***	0.151*
	(0.000)	*(0.032)*	*(0.002)*	*(0.007)*	*(0.044)*	*(0.035)*	*(0.009)*	*(0.053)*
$GLGR_{t-1}$	-	0.071*	-	-	0.072*	0.070**	-	0.073**
		(0.076)			*(0.064)*	*(0.332)*		*(0.032)*
LP_{t-1}	-	-	-	0.128*	0.133**	-	-	-
				(0.055)	*(0.048)*			
GL_TA_{t-1}	0.028**	0.023*	0.027*	0.028***	0.026**	-	0.024**	-
	(0.033)	*(0.055)*	*(0.057)*	*(0.008)*	*(0.029)*		*(0.033)*	
II_GR_{t-1}	-	-	-	-	-	0.060**	-	0.062*
						(0.058)		*(0.072)*
GDP_{t-1}	-0.348***	-0.352***	-0.354***	-0.350***	-0.356***	-0.351***	-0.355**	-0.356***
	(0.000)	*(0.000)*	*(0.003)*	*(0.000)*	*(0.000)*	*(0.009)*	*(0.027)*	*(0.000)*
UN_{t-1}	0.095**	0.009**	0.103***	0.093**	0.095***	0.097*	0.104***	0.112**
	(0.046)	*(0.032)*	*(0.007)*	*(0.038)*	*(0.008)*	*(0.058)*	*(0.000)*	*(0.044)*
HPI_{t-1}	-0.067***	-0.063***	-0.070***	-0.060**	-0.068**	-0.063***	-0.065***	-0.070***
	(0.000)	*(0.006)*	*(0.085)*	*(0.032)*	*(0.027)*	*(0.038)*	*(0.042)*	*(0.000)*
$DREC_t$	-	-	-.	*-0.003** *(0.098)*	-	-	-	*-0.004* *(0.145)*
Country effect	Yes	-	Yes	Yes	-	Yes	Yes	-
N. Obs.	1239							
Hansen	0.663	0.674	0.772	0.685	0.752	0.775	0.665	0.753
AR(1)	0.228	0.237	0.303	0.267	0.285	0.233	0.276	0.301
AR(2)	0.555	0.542	0.512	0.533	0.534	0.542	0.568	0.559
Wald chi_sq	1224	1347	1567	1339	1470	1225	1324	1203
Sargan	0.335	0.456	0.432	0.339	0.453	0.381 0.453		0.337

Table reports results of the System GMM estimates on a subsample made of the 'less risky banks', i.e. those banks that at the end of 2007 display a value of their NPL ratio under the sample median.

The dependent variable is the ratio of non-performing loans on gross loans as measure of bank's asset quality (NPL/GL). The IMR is the Inverse Mills ratio at time t-1. Explanatory variables are: the instrumenting variable NPL_GL at time t-1; the dummy variable IRB at time t-1 that equals 1 if bank adopts the internal rating based approach; the return on average equity ratio at time t-1 (ROAE) and the cost to income ratio at time t-1 (C_I); the equity over total assets at time t-1 (E_TA), the growth rate of gross loans at time t-1 (GLGR); the loan premium at time t-1 (LP) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; the gross loans over total assets ratio at time t-1 (GL_TA) and the interest income divided by gross revenues at time t-1

(II_GR); the GDP growth rate at country level at time t-1, the unemployment rate at time t-1 (UN) and the house price index at time t-1 (HPI); A dummy variable for the recovery period that takes value 1 only in 2013, 2014 and 2015 (DREC) and Country dummies.

***, ** and * indicate that coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

Table 8
Determinants of NPL ratio for the subperiod 2008-2013

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NPL_GL_{t-1}	0.334***	0.327**	0.331**	0.351***	0.320**	0.341***	0.346**	0.337***
	(0.000)	*(0.018)*	*(0.029)*	*(0.009)*	*(0.023)*	*(0.006)*	*(0.012)*	*(0.000)*
IMR_{t-1}	-0.021**	-0.024**	-0.019***	-0.025***	-0.022**	-0.018**	-0.023**	-0.026**
	(0.033)	*(0.027)*	*(0.000)*	*(0.006)*	*(0.041)*	*(0.032)*	*(0.015)*	*(0.019)*
IRB_{t-1}	-0.118***	-0.115**	-0.113***	-0.121**	-0.120***	-0.110***	-0.117**	-0.112***
	(0.000)	*(0.016)*	*(0.000)*	*(0.0021)*	*(0.000)*	*(0.000)*	*(0.015)*	*(0.000)*
$ROAE_{t-1}$	-0.040*	-0.033*	-0.037*	-0.041*	-0.039*	-0.042*	-0.038*	-0.035*
	(0.058)	*(0.064)*	*(0.058)*	*(0.063)*	*(0.0755)*	*(0.052)*	*(0.063)*	*(0.066)*
C_I_{t-1}	0.321**	0.337**	0.318**	0.329**	0.331***	-	0.338**	-
	(0.040)	*(0.022)*	*(0.037)*	*(0.044)*	*(0.008)*		*(0.029)*	
E_TA_{t-1}	0.114***	0.126***	0.123***	0.118**	0.115**	0.125**	0.120***	0.157**
	(0.000)	*(0.003)*	*(0.000)*	*(0.032)*	*(0.043)*	*(0.078)*	*(0.000)*	*(0.042)*
$GLGR_{t-1}$	-	0.098***	0.101**	-	0.095**	0.102**	-	0.096**
		(0.007)	*(0.032)*		*(0.037)*	*(0.026)*		*(0.032)*
LP_{t-1}	-	-	-	0.073	0.076*	-	-	-
				(0.109)	*(0.063)*			
GL_TA_{t-1}	0.047**	0.040*	0.042**	0.051**	0.043*	-	0.042*	-
	(0.036)	*(0.062)*	*(0.041)*	*(0.022)*	*(0.065)*		*(0.076)*	
II_GR_{t-1}	-	-	-	-	-	0.059*	-	0.061*
						(0.083)		*(0.079)*
GDP_{t-1}	-0.387***	-0.394***	-0.382***	-0.395***	-0.384***	-0.392***	-0.398***	-0.397***
	(0.000)	*(0.008)*	*(0.000)*	*(0.006)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
UN_{t-1}	0.097**	0.102*	0.095*	0.093**	0.096**	0.102**	0.091*	0.229*
	(0.040)	*(0.076)*	*(0.065)*	*(0.043)*	*(0.039)*	*(0.048)*	*(0.068)*	*(0.067)*
HPI_{t-1}	-0.116**	-0.118***	-0.109***	-0.112**	-0.107***	-0.114**	-0.104**	-0.108***
	(0.034)	*(0.000)*	*(0.000)*	*(0.025)*	*(0.000)*	*(0.024)*	*(0.028)*	*(0.000)*
DREC	-	-	-	*0.004**	-	-	-	*0.006**
				(0.095)				*(0.087)*
Country Dummies	Yes	-	Yes	Yes	-	Yes	-	Yes
N. Obs.	885							
Hansen test	0.768	0.681	0.658	0.666	0.782	0.754	0.765	0.758
Sargan test	0.576	0.632	0.643	0.555	0.532	0.524	0.531	0.567
AR(1)	0.341	0.373	0.341	0.279	0.336	0.387	0.348	0.339
AR(2)	0.661	0.634	0.643	0.658	0.601	0.589	0.596	0.578
Wald chi-sq test	1267	1281	1254	1264	1238	1255	1256	1233

Table reports results of the System GMM estimates on a subperiod 2008-2013.

The dependent variable is the ratio of non-performing loans on gross loans as measure of bank's asset quality (NPL/GL). The IMR is the Inverse Mills ratio at time t-1. Explanatory variables are: the instrumenting variable NPL_GL at time t-1;

the dummy variable IRB at time t-1 that equals 1 if bank adopts the internal rating based approach; the return on average equity ratio at time t-1 (ROAE) and the cost to income ratio at time t-1 (C_I); the equity over total assets at time t-1 (E_TA), the growth rate of gross loans at time t-1 (GLGR); the loan premium at time t-1 (LP) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; the gross loans over total assets ratio at time t-1 (GL_TA) and the interest income divided by gross revenues at time t-1 (II_GR) as measures of bank's business model; the GDP growth rate at country level at time t-1, the unemployment rate at time t-1 (UN) and the house price index at time t-1 (HPI); a dummy variable for the recovery period that takes value 1 only in 2013, 2014 and 2015 (DREC) and country dummies.

***, ** and * indicate that coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

Table 9
Panel A - Determinants of NPL ratio for the subsample of 'More conservative banks' over the period 2008-2013

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NPL_GL_{t-1}	0.276**	0.282**	0.291**	0.273**	0.295*	0.291**	0.292**	0.235*
	(0.040)	*(0.041)*	*(0.045)*	*(0.043)*	*(0.086)*	*(0.048)*	*(0.040)*	*(0.076)*
IMR_{t-1}	-0.016**	-0.015**	-0.017*	-0.022*	-0.024**	-0.019**	-0.018*	-0.026*
	(0.047)	*(0.038)*	*(0.082)*	*(0.076)*	*(0.043)*	*(0.046)*	*(0.095)*	*(0.080)*
IRB_{t-1}	-.102**	-.109*	-.118**	-.113*	-0.111**	-.102**	-.104*	-.114**
	(0.039)	*(0.070)*	*(0.049)*	*(0.096)*	*(0.047)*	*(0.043)*	*(0.092)*	*(0.040)*
$ROAE_{t-1}$	-0.046	-0.032*	-0.044*	-0.041*	-0.038*	-0.041*	-0.038*	-0.041*
	(0.134)	*(0.079)*	*(0.083)*	*(0.072)*	*(0.091)*	*(0.072)*	*(0.086)*	*(0.076)*
C_I_{t-1}	0.296*	0.305*	0.299*	0.283*	0.298**	-	0.301**	-
	(0.072)	*(0.070)*	*(0.082)*	*(0.072)*	*(0.042)*		*(0.045)*	
E_TA_{t-1}	0.219*	0.221*	0.224**	0.218**	0.217*	0.226*	0.219*	0.225*
	(0.083)	*(0.081)*	*(0.037)*	*(0.042)*	*(0.071)*	*(0.083)*	*(0.072)*	*(0.075)*
$GLGR_{t-1}$	-	0.062*	0.063*	-	0.064*	0.061	-	0.065*
		(0.073)	*(0.081)*		*(0.085)*	*(0.109)*		*(0.067)*
LP_{t-1}	-	-	-	0.131	0.135*	-	-	-
				(0.113)	*(0.076)*			
GL_TA_{t-1}	0.047*	0.042*	0.046*	0.038	0.041*	-	0.035*	-
	(0.072)	*(0.081)*	*(0.057)*	*(0.101)*	*(0.063)*		*(0.072)*	
II_GR_{t-1}	-	-	-	-	-	0.068*	-	0.072*
						(0.059)		*(0.068)*
GDP_{t-1}	-0.324*	-0.389*	-0.337**	-0.342**	-0.334*	-0.324*	-0.385*	-0.333**
	(0.061)	*(0.065)*	*(0.042)*	*(0.046)*	*(0.069)*	*(0.067)*	*(0.051)*	*(0.045)*
UN_{t-1}	0.135*	0.138*	0.133*	0.135*	0.130*	0.136*	0.133*	0.134
	(0.072)	*(0.071)*	*(0.062)*	*(0.059)*	*(0.053)*	*(0.064)*	*(0.068)*	*(0.103)*
HPI_{t-1}	-0.051*	-0.048	-0.064*	-0.043*	-0.049	-0.049*	-0.043*	-0.051*
	(0.061)	*(0.119)*	*(0.066)*	*(0.062)*	*(0.105)*	*(0.060)*	*(0.041)*	*(0.073)*
$DREC_t$	-	-	-	*0.003* *(0.133)*	-	-	-	*0.002* *(0.135)*
County Dummies	Yes		Yes	Yes		Yes		Yes
N. Obs.	567							
Hansen Test	0.553	0.521	0.528	0.551	0.537	0.534	0.572	0.503
Sargan Test	0.323	0.311	0.308	0.364	0.313	0.335	0.311	0.329
AR(1)	0.268	0.211	0.223	0.217	0.209	0.237	0.217	0.222
AR(2)	0.283	0.236	0.264	0.259	0.267	0.211	0.244	0.254
Wald chi-sq test	1196	11172	1168	1110	1201	1004	1123	1006

Panel B - Determinants of NPL ratio for the subsample of 'Less conservative banks' over the period 2008-2013

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NPL_GL_{t-1}	0.271*	0.269**	0.284**	0.266*	0.283**	0.288*	0.263*	0.269**
	(0.054)	*(0.048)*	*(0.043)*	*(0.055)*	*(0.040)*	*(0.065)*	*(0.071)*	*(0.043)*
IMR_{t-1}	-0.014*	-0.017**	-0.011*	-0.012**	-0.018*	-0.015**	-0.011*	-0.019*
	(0.106)	*(0.043)*	*(0.078)*	*(0.046)*	*(0.075)*	*(0.041)*	*(0.082)*	*(0.070)*
IRB_{t-1}	-.108**	-.111*	-.117**	-.105*	-0.107**	-.102**	-.114*	-.107**
	(0.042)	*(0.077)*	*(0.043)*	*(0.084)*	*(0.050)*	*(0.045)*	*(0.071)*	*(0.043)*
$ROAE_{t-1}$	-0.046*	-0.032	-0.044*	-0.041	-0.038*	-0.041*	-0.038*	-0.041*
	(0.068)	*(0.109)*	*(0.074)*	*(0.126)*	*(0.080)*	*(0.068)*	*(0.071)*	*(0.066)*
C_I_{t-1}	0.288*	0.284*	0.291*	0.296**	0.291**	-	0.288**	-
	(0.063)	*(0.068)*	*(0.057)*	*(0.043)*	*(0.040)*		*(0.041)*	
E_TA_{t-1}	0.218*	0.217**	0.219*	0.222**	0.211*	0.220*	0.223*	0.218*
	(0.079)	*(0.046)*	*(0.056)*	*(0.044)*	*(0.073)*	*(0.068)*	*(0.078)*	*(0.067)*
$GLGR_{t-1}$	-	0.066*	0.068*	-	0.061	0.060	-	0.069*
		(0.073)	*(0.071)*		*(0.108)*	*(0.113)*		*(0.067)*
LP_{t-1}	-	-	-	0.126*	0.128*	-	-	-
				(0.068)	*(0.062)*			
GL_TA_{t-1}	0.047*	0.042*	0.046*	0.038	0.041*	-	0.043*	-
	(0.068)	*(0.072)*	*(0.057)*	*(0.101)*	*(0.063)*		*(0.072)*	
II_GR_{t-1}	-	-	-	-	-	0.071*	-	0.075*
						(0.068)		*(0.075)*
GDP_{t-1}	-0.324*	-0.389*	-0.337**	-0.342**	-0.334*	-0.324*	-0.385*	-0.333**
	(0.061)	*(0.065)*	*(0.042)*	*(0.046)*	*(0.069)*	*(0.067)*	*(0.051)*	*(0.045)*
UN_{t-1}	0.127*	0.129*	0.125*	0.116*	0.118*	0.123*	0.114*	0.115
	(0.078)	*(0.073)*	*(0.075)*	*(0.065)*	*(0.064)*	*(0.068)*	*(0.075)*	*(0.112)*
HPI_{t-1}	-0.047	-0.048*	-0.045	-0.043	-0.045*	-0.046*	-0.041	-0.046*
	(0.104)	*(0.091)*	*(0.103)*	*(0.102)*	*(0.097)*	*(0.068)*	*(0.103)*	*(0.063)*
$DREC_t$	-	-	-	*0.005* *(0.128)*	-	-	-	*0.004* *(0.121)*
County Dummies	Yes		Yes	Yes		Yes		Yes
N. Obs.	672							
Hansen Test	0.532	0.527	0.533	0.511	0.521	0.524	0.526	0.518
Sargan Test	0.327	0.343	0.314	0.324	0.336	0.329	0.318	0.314
AR(1)	0.251	0.233	0.247	0.241	0.256	0.219	0.269	0.234
AR(2)	0.213	0.229	0.225	0.217	0.213	0.227	0.215	0.211
Wald chi-sq test	1202	1201	1224	1326	1276	1297	1233	1211

Panel A reports results of the System GMM estimates on a subsample of more conservative banks. More conservative banks are defined as banks that, over the 2008-2013 period, show an average value of the growth of gross loans below the median of the growth of gross loans of the total sample.

Panel B reports results of the System GMM estimates on a subsample of less conservative banks. Less conservative banks are defined as banks that, over the 2008-2013 period, show an average value of the growth of gross loans above the median of the growth of gross loans of the total sample.

The dependent variable is the ratio of non-performing loans on gross loans as measure of bank's asset quality (NPL/GL). The IMR is the Inverse Mills ratio at time t-1. Explanatory variables are: the instrumenting variable NPL_GL at time t-1; the dummy variable IRB at time t-1 that equals 1 if bank adopts the internal rating based approach; the return on average equity ratio at time t-1 (ROAE) and the cost to income ratio at time t-1 (C_I); the equity over total assets at time t-1 (E_TA), the growth rate of gross loans at time t-1 (GLGR); the loan premium at time t-1 (LP) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; the gross loans over total assets ratio at time t-1 (GL_TA) and the interest income divided by gross revenues at time t-1 (II_GR); the GDP growth rate at country level at time t-1, the unemployment rate at time t-1 (UN) and the house price index at time t-1 (HPI); a dummy variable for the recovery period that takes value 1 only in 2013, 2014 and 2015 (DREC) and country dummies.

***, ** and * indicate that coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

Table 10
Determinants of NPL ratio for the subsample of 'no-switching banks'

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NPL_GL_{t-1}	0.281**	0.275**	0.291**	0.288***	0.302***	0.305**	0.311**	0.296***
	(0.013)	*(0.047)*	*(0.035)*	*(0.009)*	*(0.008)*	*(0.032)*	*(0.064)*	*(0.000)*
IMR_{t-1}	-0.020***	-0.018***	-0.024**	-0.025***	-0.017**	-0.026***	-0.018**	-0.021***
	(0.006)	*(0.000)*	*(0.018)*	*(0.000)*	*(0.012)*	*(0.000)*	*(0.038)*	*(0.000)*
IRB_{t-1}	-.101***	-.103***	-.107**	-.108**	-0.103***	-.100**	-.109***	-.111***
	(0.000)	*(0.000)*	*(0.014)*	*(0.026)*	*(0.000)*	*(0.016)*	*(0.000)*	*(0.000)*
$ROAE_{t-1}$	-0.040*	-0.042*	-0.041*	-0.042*	-0.045*	-0.041*	-0.043*	-0.046*
	(0.068)	*(0.066)*	*(0.057)*	*(0.068)*	*(0.089)*	*(0.075)*	*(0.092)*	*(0.061)*
C_I_{t-1}	0.321***	0.323**	0.322***	0.317**	0.318**	-	0.319***	-
	(0.008)	*(0.027)*	*(0.004)*	*(0.021)*	*(0.012)*		*(0.006)*	
E_TA_{t-1}	0.218**	0.227**	0.232***	0.236**	0.222**	0.219***	0.224***	0.228**
	(0.017)	*(0.032)*	*(0.003)*	*(0.015)*	*(0.011)*	*(0.006)*	*(0.005)*	*(0.046)*
$GLGR_{t-1}$	-	0.068**	0.061**	-	0.075**	0.070**	-	0.068**
		(0.038)	*(0.029)*		*(0.044)*	*(0.042)*		*(0.015)*
LP_{t-1}	-	-	-	0.135**	0.133**	-	-	-
				(0.033)	*(0.038)*			
GL_TA_{t-1}	0.038**	0.044**	0.041**	0.040**	0.040*	-	0.042*	-
	(0.045)	*(0.044)*	*(0.047)*	*(0.048)*	*(0.052)*		*(0.051)*	
II_GR_{t-1}	-	-	-	-	-	0.061**	-	0.063**
						(0.041)		*(0.047)*
GDP_{t-1}	-0.345***	-0.356***	-0.341**	-0.352***	-0.339***	-0.335***	-0.364***	-0.351***
	(0.001)	*(0.006)*	*(0.012)*	*(0.000)*	*(0.008)*	*(0.000)*	*(0.005)*	*(0.000)*
UN_{t-1}	0.135**	0.133***	0.132***	0.138**	0.137***	0.131***	0.137**	0.132**
	(0.015)	*(0.005)*	*(0.006)*	*(0.011)*	*(0.005)*	*(0.009)*	*(0.016)*	*(0.008)*
HPI_{t-1}	-0.043**	-0.048***	-0.051*	-0.053**	-0.050**	-0.049*	-0.052**	-0.047*
	(0.022)	*(0.009)*	*(0.052)*	*(0.046)*	*(0.011)*	*(0.058)*	*(0.048)*	*(0.067)*
$DREC_t$	-	-	-	*0.005* *(0.116)*	-	-	-	*0.008** *(0.085)*
County Dummies	Yes	-	Yes	Yes	-	Yes		Yes
N. Obs.	1078							
Hansen Test	0.665	0.643	0.672	0.649	0.658	0.663	0.691	0.666
Sargan Test	0.318	0.289	0.311	0.322	0.328	0.307	0.316	0.322
AR(1)	0.211	0.228	0.229	0.259	0.202	0.218	0.211	0.233
AR(2)	0.623	0.639	0.611	0.628	0.615	0.607	0.615	0.622
Wald chi-sq test	1342	1348	1356	1349	1355	1358	1362	1331

Table reports results of the System GMM estimates on a subsample of banks that do not change their credit risk measurement approach during the period observed (154 banks).

The dependent variable is the ratio of non-performing loans on gross loans as measure of bank's asset quality (NPL/GL). The IMR is the Inverse Mills ratio at time t-1. Explanatory variables are: the instrumenting variable NPL_GL at time t-1; the dummy variable IRB at time t-1 that equals 1 if bank adopts the internal rating based approach; the return on average equity ratio at time t-1 (ROAE) and the cost to income ratio at time t-1 (C_I); the equity over total assets at time t-1 (E_TA) , the growth rate of gross loans at time t-1 (GLGR); the loan premium at time t-1 (LP) calculated as the difference between the bank average interest rate applied on bank loans (measured as the interest income on gross loans divided by the average of gross loans at time t-1 and t) and the interest rate on 10-years Government Bond of the respective country; the gross loans over total assets ratio at time t-1 (GL_TA) and the interest income divided by gross revenues at time t-1 (II_GR); the GDP growth rate at country level at time t-1, the unemployment rate at time t-1 (UN) and the house price index at time t-1 (HPI); a dummy variable for the recovery period that takes value 1 only in 2013, 2014 and 2015 (DREC) and country dummies.

***, ** and * indicate that coefficients are statistically significant at the 1%, 5% and 10% levels respectively.