# The Effect of Regulatory and Risk Management Advancement on Non-Performing Loans in European Banking, 2000-2011

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**Abstract**

We study whether the implementation of advanced risk management techniques in compliance with the Basel Core Principles improved the NPL dynamics and hence, had a significant impact in controlling credit risk in emerging and advanced European banks during 2000-2011. The analysis reveals that there exists a wide variation in terms of the adoption of such advanced techniques (internal rating-based, IRB) across European banks, and that emerging Europe which suffered the most from the surge in NPLs in the post-crisis period lags significantly behind the Eurozone economies in terms of the intensity of IRB adoption rates. We employ dynamic GMM estimation methods in our panel regressions to investigate the effect of such regimes on the level of NPLs at a country level. Our findings confirm that intensity of IRB usage within the banking system leads to a statistically significant decrease in the aggregate amount of non-performing loans, especially in the post-crisis period, after controlling for macroeconomic and bank-specific characteristics of the individual economies. This result is consistent with the view that the efficiency of credit risk management may turn out to be critical for avoiding widespread distress and for improving the profitability and solvency of banking systems as a whole, which in turn leads to better allocation of resources and faster economic growth.

*Keywords:* banking efficiency, risk management, non-performing loans, panel data, GMM

*JEL classification: G21, G28, G32*

## 1. Introduction

The last two decades have marked one of the most dynamic development periods of the banking industry, which has greatly influenced the way banks do their core business of assuming credit risk. These developments have been initiated on one hand by some break-through research in the area of credit risk valuation and management. Among other things, implementing powerful rating methodologies and sophisticated portfolio models for expected loss and economic capital estimation, respectively, has become a must for best-practice banks. This new orientation has been stimulated by significant developments in the international regulatory framework. Most importantly, the capital rules, which came to be known as Basel II called for a more risk-sensitive calculation of the amount of capital a bank should hold against risks in its portfolio. This in turn required that banks employ quantitative systems for the measurement of such risks. These more advanced methodologies, which needed to meet rigorous supervisory requirements among other things, were intended to provide regulatory capital relief, leading banks in some European economies to invest significantly in their development and implementation.

Looking at the recent data for the year 2012 from the European Banking Authority, one can observe a wide dispersion of implementation intensity. At the high end, countries such as the Netherlands and Sweden show more than 75 percent of total reported capital requirements due to credit risk based on the advanced internal ratings-based (IRB) approaches for measurement. While most emerging European economies show a degree of IRB-based reported capital requirements between 10 and 40 per cent, there are also countries where these advanced approaches for measurement and reporting of credit risk are not yet implemented at all (e.g. Serbia, Macedonia, Ukraine, Albania).

The onset of the global financial crisis in late 2008 followed by the sovereign debt strains in the European Union had a major influence on the workings of financial institutions, especially in emerging Europe. On the one hand, the quality of loan portfolios deteriorated significantly due to the severe contraction in economic activity and caused an increase in loan-loss provisions. On the other hand, weak lending activity and higher funding costs due to the limited access of these institutions to wholesale borrowing markets led to sizeable reduction in their profitability. At the same time, financial institutions showed varying performance both in terms of profitability and credit quality deterioration, in particular, in terms of the non-performing loans (NPLs) during the 2009-2011 period. The emerging Europe, which experienced a credit boom prior to the 2008 global financial crisis has been hardest hit by the surge in the NPLs and consequently a significant deterioration in profitability as measured by both ROE and ROA (See Table 3 on the descriptive statistics and the usage of IRB systems).

Could more advanced risk management techniques have reduced the extent of NPLs in the banking sectors during and in the aftermath of the global financial crisis? Given that there are sizable differences among banks in Europe, in terms of their NPL performance, it is natural to ask whether the intensity of IRB usage in the banking sectors of European countries had a significant favorable role in terms of controlling credit risks effectively. The main objective of this paper is to theoretically motivate how IRB implementation could lead to lower NPLs (and by extension to higher ROEs, and even economic growth) and to test empirically if the data support our theory.

In this paper, we use a panel of European banking sector data and test for the effect of a newly introduced IRB-variable on non-performing loans (NPLs), while controlling for the macroeconomic, and bank-specific determinants determinants as discussed in the existing literature. Our empirical results confirm that European banking sectors with a higher level of IRB penetration exhibit significantly lower NPLs across different countries, even after controlling for the global financial crisis.

The paper proceeds as follows: The next section discusses the related literature. Section 3 establishes why IRB as a more advanced system of risk management should lead to lower NPLs and hence, better bank performance and optimal allocation of savings for lending. Section 4 discuss the data, the variables and the econometric methodology. Section 5 justify the regression specifications and present the results of the GMM estimation. Section 6 concludes with policy implications.

## 2. The Literature Review

The relationship between measures of banking efficiency and regulatory sophistication has been studied by several papers extensively both on the individual bank and aggregate sectoral levels. This reflects partly its importance for the policy makers. There exist several articles, which look at the determinants of NPLs such as Barsitz (2011 and 2013), Sundararajan et. al. (2001), Beck et.al. (2013), Nkusu (2011), Babihuga (2007) and Demirgüç-Kunt et. al. (2009) among others.

One strand of this literature uses direct compliance with regulations in tests for the determinants of NPLs (e.g. Babihuga (2007) or cite others). Compliance is measured with the use of the so-called Basel Core Principles (BCPs) with the data compiled on a country level within the Financial Stability Assessment Program (FSAP) as a joint undertaking of the International Monetary Fund and the World Bank. These papers find mixed evidence of the effect of regulatory compliance on NPLs.

Based on aggregate data of a sample of 25 countries, Sundararajan et. al. (2001) find that an overall index of BCP compliance is not a significant determinant of measures of bank soundness, namely nonperforming loans (NPLs) and loan spreads. Podpiera (2004) employs an extended panel data set of 65 countries for the period 1998-2002 and finds a significant effect of BCP compliance on NPLs, controlling for different levels of financial and economic development and other macroeconomic and structural factors.

Similarly, Babihuga (2007) uses a panel dataset of selected macroeconomic and financial soundness indicators (FSIs) for 96 countries covering the period 1998-2005. More generally than Podpiera (2004), this paper analyzes the relationship between key macroeconomic indicators and FSIs of capital adequacy, asset quality and profitability. She finds that FSIs fluctuate strongly with a number of variables, such as the phase of the business cycle, the inflation rate, short-term interest rates, and the real exchange rate, and hence, revealing a high level of heterogeneity in the relationship between macroeconomic indicators and FSIs across the sample of countries. Along with country and industry specific characteristics including income level, financial depth, market concentration, Babihuga (2007) also finds that the quality of regulatory supervision is significant in explaining the cross-country variation in FSIs.

Using data for more than 3000 individual banks from 86 different countries, Demirgüç-Kunt et. al. (2009) test for the dependence between compliance with the Basel Core Principles for effective banking supervision and the level of bank risk as measured by Z-scores. They find that neither the overall index of compliance with the Basel Core Principles nor the individual components of the index are significant determinants of bank soundness.

Another strand of related literature have been motivated by the introduction of the capital rules known as Basel II (see Basel 2004) and studied empirically the effects of their implementation (on what? Be specific here). The majority of these contributions focus on the regulatory capital savings in the application of the Internal Ratings-Based (IRB) approach (Basel (2003) and Schwaiger (2003)).

The effects of the IRB implementation on the overall stability and competitiveness of banking sectors, however, has received much less attention in the literature. The scarcity of empirical research in this area follows directly from the lack of available data for use in estimations. One of the few examples is Stein et. al. (2003) which use an extensive databank on default in order to quantify the competitive advantages that can be gained by a credit institution from applying more advanced rating systems. Stein et. al. (2003) employ a Monte Carlo simulation in order to estimate the effects of different rating sophistication models on bank profitability. They find that, on average, using a more advanced model can lead to significant improvements in a bank's profitability.

Jankowitsch et. al. (2007) use a similar approach to assess the economic value of rating systems for a portfolio calibrated to Austrian mid-market data. Gurov (2014) confirms their results for an arbitrary portfolio and shows additionally how the analysis can be related to popular measures of rating accuracy (accuracy ratio and area under curve) and vice versa.

To our knowledge, no empirical research has been conducted in the literature so far to analyze quantitatively the effectiveness of IRB implementation in reducing country-wide NPLs. In this paper, we seek to fill this gap in the literature and investigate empirically, in a panel framework, the importance of employing advanced risk management (IRB compatible) methodologies in reducing the aggregate level of NPLs. We look at a number of emerging and advanced European economies using aggregate banking data for the period of 2000-2011 (see Appendix, Table 2 for a list of countries). After controlling for both macroeconomic and bank-specific determinants of NPLs, we include a newly designed variable, IRB, in our regression specifications to isolate the independent effect of IRB on NPLs. We obtained data for IRB from the European Banking Authority and it stands for the relative amount of risk-weighted assets reported under the IRB approach as a percentage of the total risk-weighted assets in a given country in a given year.

## 3. Motivation

In this section, we consider banking institutions from the point of view of their main purpose of existence, which is to grow value for their shareholders. The fact that in doing so they perform an important economic role in channeling funds from savers to investors is an issue that we address in the conclusion. Moreover, we assume that banks' specialness as economic entities is manifested mainly in their business model, which is to assume risk in exchange for a compensating return. Without loss of generality, we focus our argument on the topic of credit risk, whereas the results and implications could be easily extended to cover all types of risks carried by financial institutions.

In essence, credit risk encompasses all risks resulting from the lending activities of commercial banks - the core activity of traditional banking. There are a number of different approaches to quantifying credit risk, which banks could potentially implement with implications for both internal capital and risk management as well as for regulatory compliance with minimum capital requirements. In the following we will always consider internal and regulatory risk management to be part of the same methodological process, which has become a convention for best-practice banks, and will treat them interchangeably.

Broadly speaking, one can identify two main categories of risk assessment methods: the Standardized approach and the Internal Ratings-based approach (IRB). The Standardized and IRB approaches represent two levels of risk management sophistication with the former being cheaper to implement, whilst the latter leads to regulatory capital savings and additional positive effects as explained below.[1]

The Standardized Approach is intended for smaller, less sophisticated banks which would calculate the MCR based on broad regulatory risk weights. The risk weights depend on the type of the credit, the type of the borrower, and the type of the collateral. Additionally, the risk weights depend on the external rating of the borrowers, so that higher rated customers receive lower risk weights. Unsecured exposures to (unrated) corporates receive a risk weighting of 100% irrespective of the creditworthiness of the borrower.

The use of the Standardized approach in this sense could be preferable to banks due to the much lower level of involved costs. These refer to the cost of development or acquisition of vendor IRB models, but also to changing the bank's internal processes and procedures as well as data storage and management systems. Additionally, personnel would need to be trained or new experts hired, which possess the necessary education and experience to deal with the more sophisticated processes. Especially in countries where the level of competition in the banking is not very high and/or banks rely on a strong house-bank relationship to their customers, paying the high cost for IRB implementation might not be justified.

[1] For a more detailed discussion of this issue, see Gurov (2014)

On the other hand, under the IRB approach, banks with more developed risk measuring tools are allowed to employ own systems for estimating the required Expected and Unexpected Loss risk parameters. The probability of default (PD) reflects the probability that a certain customer will not fulfill its obligation in the observed time horizon. Loss given default (LGD) refers to the relative amount that will be lost in the case that the credit will not perform as contractually agreed and is equal to one minus the recovery rate (from the sale of collateral for example). Finally, the exposure at default (EAD) measures the possible outstanding amount in the case that the credit goes to default.

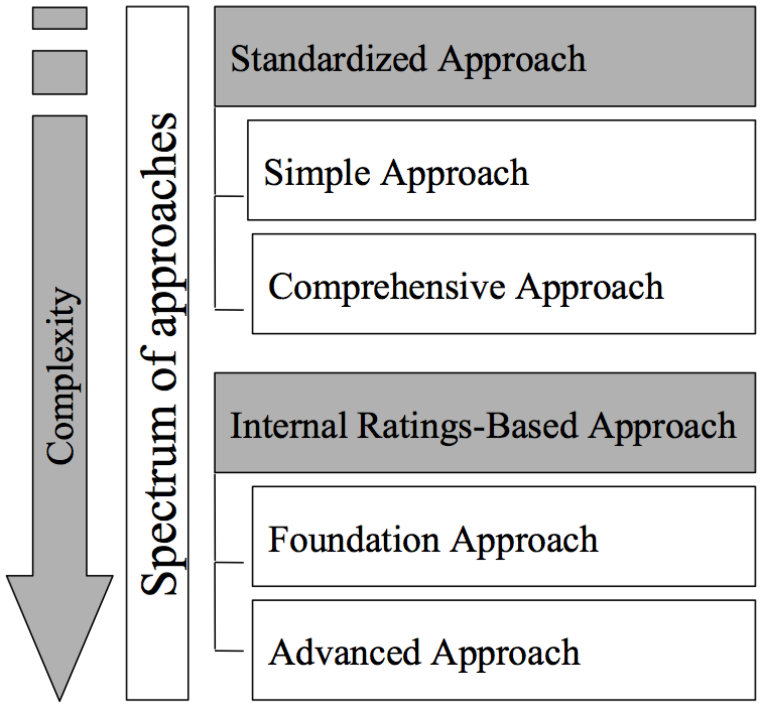
The Foundation IRB approach calls for banks to provide internal estimates of the first parameter, i.e. the PD, while for the other two the regulator provides supervisory estimates. Furthermore, the Advanced IRB approach allows banks with state of the art risk management systems to provide own estimates also for the LGD and EAD components. As part of the overall supervisory process, banks that aim to adopt the IRB approach for credit risk measurement must demonstrate to the regulators that that risks are being correctly and consistently estimated. [2]

Obviously, the implementation of the IRB approaches is far more complex and expensive. This is due to the need of developing internal rating systems for estimating the risk parameters and the far from trivial requirements that these should satisfy. Such efforts on the side of the banks, however, are stimulated by the regulators in that the use of the IRB approaches results (ceteris paribus) in lower capital requirements. This follows from the fact that in the Standardized approach all calculations are based on one-size-fits-all capital requirements, which in turn results in generic and thus more conservative risk weights, or on external ratings, which have failed repeatedly and most notoriously in the recent sub-prime crisis in the US. Moreover, the IRB approaches allow for a more thorough recognition of collateral.

In addition to the stand-alone effects discussed above, it turns out that gains from the implementation of advanced risk management systems provide a significant competitive advantage to financial institutions. One reason for that is the change in the way advanced banks do their credit business. The use of sophisticated portfolio models has allowed institutions to move from traditional buy-and-hold strategies to an active portfolio management of their banking books. This has been made possible also through the development of structured products, credit derivatives and other instruments, which aim at the transfer and provide for a more liquid secondary market of credit

[2] Before they could adopt this advanced method, banks need to pass a thorough investigation by the responsible regulatory bodies (national and supranational (e.g. EBA)) and to fulfill a set of strict requirements before they could implement the IRB approach including: a) All employed models should be well based in general economic theory, b) Under validation-backtesting, banks need to prove that these models work well in a variety of markets and different economic environments and they also need to identify under what circumstances the models do not perform effectively, c) banks need to demonstrate that they use the models/ratings in a meaningful way in the overall business model - from customer acquisition, through measurement and management to strategic planning and capital allocation (so called “use test”).

Figure 1: Spectrum of Approaches for Credit Risk Measurement




risk. A prerequisite for the introduction of an active portfolio and regulatory/economic capital management, however, is the implementation of advanced credit risk measurement methodologies.

Another competitive advantage for individual institutions stemming from the IRB approach is that it allows banks to use more risk-sensitive pricing when competing for borrowers. This has the positive effect of allowing advanced institutions to grow their portfolios by attracting good customers through more attractive tailor-made pricing. On the other hand, such institutions could also cherry-pick their portfolios by extending credit only to borrowers which provide an attractive risk-adjusted return on an individual basis (Gurov, 2014).

To summarize, the improvement in a bank's risk assessment systems is expected to lead to better management of its risks and therefore to better financial results. Even though the advantages of the IRB approach are well established for individual institutions, it is not clear how this would lead to a higher efficiency of the banking sector of a particular country as a whole, e.g. in reducing the level of NPLs. To establish this we argue here, that the increased level of well-priced loans would naturally increase the level of a given market's competitiveness, which would naturally lead to lower lending rates across the board. This would have the effect, on the one hand, that banks would look for high quality borrowers, so that they could maintain their profitability due to lower risk costs. On the other hand, the lower rates would render many of the high-risk high-return projects unprofitable, so that they will fail to find financing on the market.

## 4. Data and Analysis

### *4.1. Data*

Our data consists macroeconomic and banking data taken from the IMF, World Bank, and a country-level measure of IRB from the European Banking Authority (EBA) to construct a panel of Eurozone and emerging European countries (both EU and Non-EU members) for the 2000-2011 period. Our data covers the timing of the global financial crisis (in addition, the partially overlapping eurozone crisis of 2009-11) and hence, gives us an opportunity to split the sample into pre- (pre-2009) and post-crisis (post-2009) periods to analyze how the crisis affected the NPLs and the IRB usage rates in these two groups of countries.

We conduct our econometric analysis to assess whether the intensity of IRB usage in the banking sectors in Europe reduces the NPLs, after controlling for various macroeconomic and banks-specific variables. We also intend to identify a pattern of differential effect of IRB on NPLs in the pre- and post-crisis periods with a stronger impact of IRB usage rates on NPLs in the post-crisis period. This latter effect will be tested with an interactive term, $IRBCRIS$, created as the product of the IRB and the post-crisis dummy, $DPOSTCR$.

Table 1 summarizes the main variables used in this study and their expected effects on the dependent variable, $NPL$. At the macro-level, we include real GDP growth ($RGRWTH$) as a proxy for credit demand as well as business cycle shocks. In several studies on NPLs, there is a strong relation between macroeconomic vulnerabilities and non-performing loans and that recessions are key determinants of bad loans (Nkusu, 2011; Quagliarello, 2007; Salas and Saurina, 2002; Pesola, 2007; Dash and Kabra, 2010).[3]Hence, we expect a negative link between $RGRWTH$and $NPL$ as credit risk is countercyclical and banks tend to better control their credit risk when the real economy is growing. We also include the change in CPI for inflation, $INF$, in our regression specifications. We expect a negative impact of inflation on $NPL$ to the extent that rapid price increases worsen market frictions, forcing banks to ration credit (Boyd et. al., 2001). On the other hand, inflation may also reduce the real value of loan portfolios there may also be an additional negative impact of inflation on credit default, enhancing the effect of the negative sign on $NPL$. Yet, $INF$ can also worsen the level of $NPL$ when it captures deterioration in macroeconomic fundamentals and growing economic uncertainty. In this latter case, it might have a positive effect on $NPL$.[4] As in Salas and Saurina (2002), we also include a variable, $CRGRWTH$ in our regressions in lagged

[3]In a recession, real GDP growth slows down or turns negative, generating an increase in credit default rates. By contrast, a positive growth in real GDP leads to higher income which in turn contributes to higher debt servicing capacity of the borrowers and thus lowering the ratio of non-performing loans.

[4]Babouček and Jančar (2005) find evidence of positive correlation between non-performing loans and inflation in the Czech banking sector

form. This is because rapid credit growth may lead to adverse selection, and may be associated with reduced credit quality as risk taking intensifies during such periods, adversely affecting the level of non-performing loans. Consequently, more reserves need to be provisioned for rising level of bad loans. Additionally, bank-credit to the private sector as percent of GDP, $BPRIVCRGDP$, is a measure of financial depth and is expected to have a negative effect on $NPL$.

Several bank-specific controls also are included in the panel regressions as in the literature (Quagliariello, 2007; Salas and Saurina, 2002; Espinoza and Prasad, 2010). Since the charter value of banks increase with more profitability, higher return on equity, $ROE,$ is likely to curb incentives for risk-taking and may improve performance in monitoring loan quality. We include $ROE$ or return on assets, $ROA$ in our regressions as we expect higher profitability to lead to lower levels of $NPL$. Loan to deposit ratio, $LOANDEP$ is used as a measure of banks' relative access to external funding, and availability of wholesale funding which may also stand for the degree of financial deepening in the banking system. This effect is likely to reduce $NPL$ if it signals the quality of bank management as well. Yet, it may also serve as an indicator of risk-taking on the part of bank managers, as higher loans to deposits ratio may reflect the choices of bank managers for riskier loans as opposed to holding safer government securities. Larger the proportion of bank assets allocated to loans, greater the credit risk exposure, leading to a higher level of $NPL$. Hence, we expect either positive or negative sign for this variable, depending on which of the two effect dominates. Additionally, bank equity to assets, $CAP$, stands for the degree of bank solvency and may curb incentives for risk-taking for bank managers so we anticipate its sign to be negative. We also add several other bank-specific variables such as $LOANLOSS$ (loan loss reserves to gross loans) as a proxy for expected loan quality(+ sign), 5-bank concentration ratio, $CONCEN$ (- sign) and interest spread between lending and deposit rates, $ISPREAD$ (+ sign) to different regression specifications. In line with the literature, we believe that management quality as well as cost efficiency of banks do matter for loan quality as in Louzis et al., (2011), Berger and DeYoung (1997) and Podpiera and Weill (2008). These authors attribute problem loans to bank-specific factors such as a worsening in banks' cost efficiency. We include two measures of efficiency in our regressions specifications: $ISPREAD$, and $OVERHEAD$ where the latter measures the operating costs including overhead expenses as percent of total assets and these variables are expected to have a positive effect on the $NPL$ variable. We also include lending rate, $LENDR$, the bank rate on loans. Banks charging the highest interest rates are those that later have higher levels of problem loans (Salas and Saurian, 2002). Higher lending rates may induce adverse selection in the pool of potential borrowers and raise the risks of default on loans. In addition, in the face of adverse income shocks, the borrower has greater probability to default when interest payments on borrowed funds are larger. Hence, higher lending rates are expected to enhance loan defaults.

Table 1: Variables and Thier Expected Effect on the Dependent Variable

| | Variable | Notation | Exp. Effect |
|---|---|---|---|
| Dependent | Non-Perf. Loans/Total Loans | NPL | |
| | Risk-Weighted (RW) Assets reported under IRB/ Total RWAssets | IRB | (-) |
| | IRB*DPOSTCR | IRBCRIS | (-) |
| Bank-Specific | | | |
| | Overhead Costs/Total Assets | OVERHEAD | (+) |
| | Bank Equity (capital) / Assets | CAP | (-) |
| | Lending-Deposit Rate Spread | I_Spread | (+) |
| | Gross Profits/ Assets or Equity | ROA, ROE | (-) |
| | Bank Loans/Deposits | LOANDEP | (-,+) |
| | Lending Rtae | LENDR | (+) |
| Macroeconomic | | | |
| | Post_Crisis dummy: post-2009 | DPOSTCR | (+) |
| | Real GDP growth | RGRWTH | (-) |
| | Inflation | INF | (-) |
| | Credit Growth Rate | CRGRWTH | (+) |
| | Bank Credit to Priv. Sector to GDP | BPRIVCRGDP | (-) |

### *4.2. Descriptive Statistics*

The results in Table 3 in the Appendix indicate that the Eurozone banks are, on average, less profitable, yet still more cost-efficient as measured by overhead expenses, $OVERHEAD$. More importantly, they have better control over their credit risk as they register significantly less NPLs as compared to emerging European banks in both periods. On the other hand, the Eurozone banks are less capitalized as measured by $CAP$- despite some improvement in this variable in the post-crisis period- as compared to the emerging European countries. Strikingly, there exists a wide variation in terms of the adoption of such advanced techniques (internal rating-based, IRB) across European banks, and that emerging Europe which suffered the most from the surge in NPLs in the post-crisis period lags significantly behind the Eurozone economies in terms of the intensity of $IRB$ adoption rates. Most notably, the banks in the Eurozone have dramatically increased their IRB usage from 3.5 percent in the pre-crisis period to 39.1 percent in the post-crisis period in their attempt to control their credit risk while saving on expensive capital. By contrast, the emerging Europe has much lower rates with 1.4 percent and 15.9 percent respectively despite a noticeable increase in their adoption of IRB techniques in the post-crisis period.

The trend in loan loss provisions to total loans, $LOANLOSS$, suggests that the Eurozone countries provisioned significantly less reserves for their credit risk exposures in the post- crisis period than the emerging European banks, possibly due to more intense employment of enhanced risk management systems like IRB and consequent improvement in credit quality.

*4.3. Correlation Analysis with IRB*

In the full sample, we observe that the *NPL* displays a negative association with the $IRB$ usage rates and this correlation gets stronger in the post-crisis period, especially for the Eurozone economies. Table 4 shows the pairwise correlations of $IRB$ variable with selected bank-specific variables for both Eurozone and emerging European countries in both sub-periods. A striking observation is that the negative correlation of $IRB$ with $NPL$ gets stronger in absolute value for Eurozone countries in the post-crisis period, increasing from -0.0731 to - 0.4148 while it gets weaker for the emerging European economies. This may suggest, among other plausible reasons, that bad loan problem in emerging Europe has become more sensitive to the (deterioration) in macroeconomic conditions as compared to bank-specific factors such as credit risk management.

In line with our expectations, $IRB$ is negatively related to overhead costs, i.e. management quality. The more efficient bank management gets, more likely that they adopt the $IRB$ regimes in their attempt to curb their credit risk exposures. As expected, $IRB$ usage is negatively related to $CAP$, potentially capturing the effect of capital savings banks generate by adopting such risk management techniques.

## 5. Panel Estimation and Results

We report a set of panel regressions for the period 2001-2011 to disentangle the independent impact of $IRB$ variable on $NPL$. In all of our regressions, we include a post-crisis dummy for the period 2009 and on–$DPOSTCR$– to distinguish between pre- and post-crisis behavior of NPLs in European banking. We interact this crisis dummy with IRB, and use $IRBCRIS$ to analyze whether banks with greater IRB usage, all else equal, had a better control over their credit risk in the post-crisis period. All panel regressions contain macroeconomic variables and bank-specific, time-varying control variables that measure the financial characteristics of the banks.

We first estimate equation (1) in a static context as a simple pooled OLS model, run F-test on poolability, and confirm the presence of significant degree of cross-country heterogeneity in the form of fixed effects in NPL dynamics. Then we continue with random effects estimation and run Hausman test to see whether the individual effects are significantly correlated with the explanatory variables. The results are reported in Table 5.[5]Our test results favor fixed effects estimation over random effects based on the Hausman test. After a series of serial correlation tests, we find that our dependent variable, $NPL$, exhibits a significant degree of serial correlation which requires a dynamic modelling in a panel context. Our estimations show that NPLs are very persistent, suggesting that the response of credit losses to the macroeconomic shocks could take time to materialize and possibly

[5]The fixed effect model assumes that intercepts vary across the countries and can thus account for possible unobserved time invariant heterogeneity across countries. A random effects model, on the other hand, assumes that the individual country intercepts are random variables drawn from a common distribution.

captures the feedback effect from loan losses back to the real economy. As a result, our baseline panel specification includes a lagged dependent variable, $NPL_{it-1}$ and becomes:

$NPL_{it} = \alpha NPL_{it-1} + \delta_1 IRB_{it-1} + \sum \beta_j MacroVar_{jt-1} + \sum \gamma_k BankVar_{it-1} + \delta_2 dPostCr_{it} + \delta_3 IRBCris_{it-1} + \varepsilon_{it}$

$$\varepsilon_{it} = \gamma_i + \mu_t + u_{it} \tag{1}$$

where $\gamma_i$ captures unobserved country-specific fixed effects, $\mu_t$ is the unobservable time effect, and $u_{it}$ is the random error term. $NPL_{it}$ is the logarithmic transformation of the aggregate ratio of non-performing loans to total loans whereas regressor $NPL_{it-1}$captures persistence in loan quality over time.[6] $MacroVar_{jt-1}$ is a vector of $j$ macroeconomic variables including the real GDP growth ($RGRWTH$), bank credit to the private sector to GDP ratio ($BPRIVCGDP$), domestic credit growth rate ($CRGRWTH$) and inflation ($INF$). All of the macro variables enter Equation (1) with a lag to account for plausible delay with which macroeconomic shocks affect banks' credit portfolio. The macroeconomic variables are taken as strictly exogenous,[7] while bank-level variables are all one-period lagged as they are modeled here as predetermined.[8]

We address concerns about the presence of unit roots in the series by conducting panel unit root tests for unbalanced panels. Fisher Augmented Dickey-Fuller (ADF) and Im-Pesaran-Shin (IPS) unit root tests, which are suitable for unbalanced panels-were conducted for all the variables used in the data set with time trends, lags and demeaning of cross-sectional means. Both tests consistently reject the presence of unit roots for all variables included in regression specifications, indicating that they are stationary.[9]Hence, we consider all our variables as stationary based on these test results and include them in equation (1) in levels without differencing. Based on the LM test for the joint significance of time effects, we find them to be jointly significant at 5 percent level, and hence, we consider including year-specific dummy variables. We employ a post-crisis dummy, $DPOSTCR$ instead as time effects are significant as a subset in the post-crisis period.

Although we report regressions with lagged $NPL$ in Table 5, fixed and random effects estimation with lagged dependent variable can cause bias in estimation. Hence, we apply the System and Difference-GMM estimation (two-step, robust and non-robust) where we use forward orthogonal

[6] The ratio of reserves for impaired loans to total loans is bound by zero and one; we use its logarithmic transformation so that it spans a wider interval over $[-\infty; +\infty]$. (see Salas and Saurina, 2002; Espinoza and Prasad, 2010)

[7] They can be instrumented by themselves as "IV-style" instruments in system GMM estimations. See Roodman (2006).

[8] Hence, they are instrumented in the GMM-style in the same way as the lagged dependent variable.

[9] The null hypothesis is that all series are non-stationary and the alternative hypothesis is that at least one of the series in the panel is stationary.

deviations instead of first differencing (Arellano and Bover, 1995) and report the results in the first two columns of Table 6.[10] This transformation removes panel fixed effects and has the added benefit of better preserving sample size in our unbalanced panel than its alternative, the difference GMM (Arellano and Bond, 1991). We use also system-GMM (Arellano and Bond, 1991) as system GMM which exploits the additional moment conditions in the levels equations may provides an improvement in the accuracy of the estimates when the dependent variable is persistent (Blundell and Bond, 2000). The system GMM specification is estimated using the xtabond2 command in Stata (Roodman, 2005). We control the number of instruments by limiting our analysis to 2 lags as this helps avoid bias due to too many instruments in a relatively small sample.

Our econometric results show that lagged dependent variable, NPL(-1) is significant for all specifications, confirming a considerable amount of persistence in NPL dynamics in the region. As expected, NPLs increased significantly in the post-crisis period as evidenced by the significant positive sign of the $DPOSTCR$ variable and this result is robust in different specifications and when controlling for a battery of bank-specific and macroeconomic variables. In all specifications, $RGRWTH$, $INF$, $ROA$, $LENDR$ appear significant with the correct signs. Most notably, $RGRWTH$ and $INF$ as proxies for macroeconomic shocks are significant in all models, confirming that as in other countries, the European banks are quite vulnerable to macroeconomic risks and high volatility in the GDP. In addition, inflation, $INF$ is very significant with a negative impact on the NPLs, suggesting that inflation reduces the real debt obligations of borrowers and hence, lowers the level of credit defaults. As expected, lending interest rate, $LENDR$ has a significant positive effect on the level of credit risk, raising the cost of loans and borrowers' ability to service their loans. Most importantly, $IRB$ has a significant negative effect on loan losses in the post-crisis period as seen from the negative sign of the $IRBCRIS$ variable.

We report the outcomes of our specification tests and Hansen's test for exogeneity of regressors and confirm exogeneity of $IRB$ as well as other regressors in our models. We apply several GMM specification tests and the Arellano and Bond test for autocorrelation of order 1 and 2 with p-values greater than the significance level show that the null hypothesis of no second-order autocorrelation (first-order autocorrelation does not imply inconsistent estimates, but we also find no evidence for it) should not be rejected, confirming the validity of our instruments. Hence, our GMM regressions are well-specified.

Despite their different approaches, system GMM and diff GMM as well as RE and FE and POLS all arrive mostly at similar results as to sign, statistical signicance, and the coeficient magnitude.

In columns 3-4, we report estimates with difference GMM as a benchmark for comparing them with the system GMM estimation. Our results continue to hold in difference GMM (two-step,

[10]We report the results from the two-step estimations since the two-step GMM estimation is more efficient. See Cameron and Trivedi (2005, 746) for details.

non-robust) specifications in terms of the sign and significance of the IRB variable. Finally, we estimate the basic specification with several other bank-specific variables but they turn out to be insignificant.

We also seek to quantify the relative importance of omitted variable bias by adding several controls into the regression specifications. Hence, in our regressions we control for a rich set of observable bank-level, and macroeconomic covariates that, if omitted, could confound our estimates of the impact of the $IRB$ on the $NPL$ variable. Intuitively, this is to see how the coefficients of interest change when we include a richer set of independent variables. If the coefficients and their significance change substantially in different specifications, then it is more likely that results are biased and the estimated impacts are smaller. Our results show that the estimated effects are relatively insensitive to adding additional covariates, mitigating concerns about possible omitted variables bias and misspecification. Our results do not change materially in terms of the significance and sign of the $IRB$ and $IRBCRIS$ variables which is a strong indication that our regression model is robust.

## 6. Conclusions

It is well-known that excessive credit growth fueled by lax lending standards was one of the critical factors behind the global financial crisis, and subsequently, the widespread distress in the banking systems across Europe. In this context, the emerging Europe was hardest hit as compared to other emerging economies as well as Eurozone economies, registering a dramatic surge in NPLs accompanied by a significant decline in bank profitability and solvency. In this paper, we find that the IRB regime in the banking sectors of European countries had a significant favorable impact in terms of controlling credit risks and displayed a strong negative effect on NPLs, especially in the Eurozone countries where the degree of IRB adoption has been sizably larger than the case in emerging European economies. This latter group showed a wide-variation in terms of IRB adoption rates with some countries displaying no implementation of advanced risk management regimes at all. Hence, it should come as no surprise that this group suffered the most from the excessive amount of loan defaults in the aftermath of the crisis. On the other hand, notwithstanding a deep recession and a steep decline in bank profitability in the Eurozone in the post-crisis period, the former group thwarted a much more serious potential banking distress compounded by a surge in NPLs, at least in part, due to their greater reliance on the IRB method for assessing and monitoring their credit risks. The empirical results in this paper confirm the benefits of such advanced risk management techniques in reducing NPLs and hence, their contribution to bank stability and solvency with the added benefit of better allocation of resources and higher economic growth. In this regard, regulators and policy makers in emerging Europe are well-advised if they facillitate the usage of such modern risk management regimes- with a direct control over credit lending criteria and greater transparency and visibility of loan quality- to avoid future distress in their banking sectors.

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## Appendix

Table 2: List of Countries In Data Set

| EuroZone Countries | Non-EuroZone, EU Countries | Non-EU Countries |
|---|---|---|
| Austria | Bulgaria | Albania |
| Belgium | Poland | Belarus |
| Italy | Lithuania | Bosnia and Herzegovina |
| Netherlands | Sweden | Macedonia, FYR |
| Cyprus | Romania | Moldova |
| Estonia | Czech Republic | Serbia |
| Ireland | Croatia | Ukraine |
| France | Hungary | Russia |
| Germany | | Turkey |
| Greece | | Norway |
| Luxembourg | | |
| Spain | | |
| Latvia | | |
| Malta | | |
| Slovakia | | |
| Slovenia | | |
| Portugal | | |

Table 3: Descriptive Statistics for Selected Variables

| BANKS IN EUROZONE COUNTRIES* | *pre-crisis* | | *post-crisis* | |
|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. |
| NPL | 3.897 | 8.434 | 4.938 | 3.948 |
| IRB | 0.035 | 0.123 | 0.391 | 0.213 |
| ROA | 0.628 | 0.632 | -0.316 | 1.827 |
| OVERHEAD | 5.458 | 1.403 | 5.863 | 1.306 |
| CAP | 1.536 | 1.141 | 1.1311 | 0.386 |
| LOANDEP | 130.24 | 45.56 | 125.77 | 36.674 |
| LOANLOSS | 77.26 | 48.68 | 50.78 | 12.185 |
| No. of Obs. | 124 | 124 | 42 | 42 |

| BANKS IN EMERGING EUROPE** | *pre-crisis* | | *post-crisis* | |
|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. |
| NPL | 8.207 | 10.038 | 10.426 | 5.155 |
| IRB | 0.014 | 0.065 | 0.159 | 0.225 |
| ROA | 1.542 | 1.180 | 0.417 | 1.819 |
| OVERHEAD | 11.127 | 4.523 | 10.880 | 3.275 |
| CAP | 4.331 | 2.337 | 3.583 | 3.395 |
| LOANDEP | 104.572 | 60.698 | 118.757 | 35.843 |
| LOANLOSS | 69.76 | 39.29 | 65.021 | 29.743 |
| No. of Obs. | 171 | 171 | 57 | 57 |

Note: (*) To this group, Sweden and Norway have been added. (**) To this group, Estonia, Latvia, Slovenia, Slovakia have been added as emerging European economies.

Table 4: Correlations of Bank Specific Variables with IRB

| *Correlations with IRB* | E-Zone Banks* | E-Zone Banks | Non-E-Zone Banks** | Non-E-Zone Banks |
|---|---|---|---|---|
| | *pre-crisis* | *post-crisis* | *pre-crisis* | *post-crisis* |
| NPL | -0.0731 | -0.4148 | -0.1214 | -0.0827 |
| ROA | -0.3808 | 0.2216 | -0.1652 | 0.0417 |
| OVERHEAD | -0.1821 | -0.6443 | -0.2635 | -0.3646 |
| CAP | -0.1918 | -0.5760 | -0.2104 | -0.3442 |
| LOANDEP | 0.0512 | 0.0036 | 0.1000 | 0.1321 |
| CONCEN | 0.0445 | 0.1608 | 0.1120 | 0.4822 |
| No. of Obs. | 88 | 88 | 114 | 114 |

Note: (*) To this group, Sweden and Norway have been added. (**) To this group, Estonia, Latvia, Slovenia, Slovakia have been added as emerging European economies.

Table 5: Pooled OLS, Fixed and Random Effects Estimation (Robust St. Errors)

Dependent Variable: Non-Performing Loans to Total Loans (NPL)

| | Pooled OLS | Fixed Effects | Random Effects |
|---|---|---|---|
| NPL (-1) | 0.6530*** | 0.5530*** | 0.652943 *** |
| IRB | 0.8857 | 0.8888* | 0.8857 |
| RGRWTH | -0.0221*** | -0.0311*** | -0.0221*** |
| INF | -0.0362*** | -0.0402*** | -0.0362*** |
| ROA | -0.0741*** | -0.0322 | -0.0741*** |
| LENDR | 0.0374*** | 0.0304*** | 0.0374*** |
| CRGR(-1) | -0.2420 | -0.5422** | -0.2420 |
| IRBCRIS | -1.0016 | -0.4189898 | -1.0016 |
| DPOSTCRIS | 0.3737*** | 0.2975*** | 0.3737*** |
| No. of obs. | 124 | 124 | 124 |
| R-sq (overall) | 0.8439 | 0.8220 | 0.8439 |

Note: This table shows panel regressions to estimate the impact of IRB usage rates on NPL before and during the crisis based on the full sample that include all countries listed in Table 2. The dependent variable is the log of the non-perfoming loans to total loans at the country level and all independent variables are defined in Table 1. The DPOSTCRIS variables takes on values of "1" in the years 2009 , 2010 and 2011 and "0" otherwise. Standard errors are clustered at the country level and p-values appear as ***, **, * corresponding to the 1, 5 and 10 percent level of significance next to the estimated coefficients, respectively. Source: authors' calculations based on the data from the IMF, World Bank, and the EBA.

Table 5: Difference and System GMM Estimation

Dependent Variable: Non-Performing Loans to Total Loans (NPL)

| | System GMM (1) Two-step | System GMM (2) Two-step | Diff- GMM (3) Two-step | Diff- GMM (4) Two-step |
|---|---|---|---|---|
| NPL (-1) | 0.6248 *** | 0.7055 *** | 0..4915*** | 0.5284*** |
| IRB | 2.18503 ** | 3.1476** | 2.2573*** | -0.6601 |
| RGRWTH | -0.0373*** | -.0525*** | -0.0192** | -0.0723*** |
| INF | -0.0513*** | -0.0520*** | -0.2321*** | -0.1883*** |
| ROA | 0.0429618*** | 0.0366191*** | -0.0973*** | -0.0285*** |
| LENDR | 0.0379*** | | 0.0480*** | -0.0944*** |
| CAP | | .0235057*** | | |
| IRBCRIS | -2.7756* | -3.5777** | -2.1121*** | -3.5120** |
| DPOSTCRIS | 0.5081929*** | 0.4907314 *** | 1.8622*** | 1.8771*** |
| No. of obs. | 124 | 130 | 73 | 161 |
| Wald Chi_sq Statistic | 7483.24 | 2376.94 | 763.19 | 300219.64 |
| No. of Instruments | 27 | 27 | 17 | 25 |
| Hansen Test (p-value) | 0.716 | 0.898 | — | — |
| Diff-Hansen Test (p-value) | 0.907 | 0.743 | — | — |
| $AR(1)$ Test (p-value) | 0.112 | 0.069 | — | 0.140 |
| $AR(2)$ Test (p-value) | 0.219 | 0.495 | — | 0.216 |
| Sargan Test (p-value) | — | — | 0.1191 | 0.192 |