Credit Risk in European Banks:

Does Effective Risk Management Matter?

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Abstract

This paper investigates the empirical relevance of macroeconomic variables, bank-specific features and institutional variables on bank loan portfolio deterioration. In particular, we establish the empirical relevance of two novel bank-specific characteristics, i.e. the effectiveness of bank risk management and the bank's risk profile. We employ a novel panel data set of 177 Western European banks over a decade period spanning from 2006 to 2015. Our dynamic panel estimates show that during the recent financial and economic crisis, banks with a lower risk appetite and relying on more sophisticated risk-management practices faced a lower deterioration of their loan portfolios and offered more credit than other banks without increasing their credit risk. Our analysis acknowledges also the importance of the juridical and institutional context as drivers of loan quality deterioration.

Keywords: credit risk; non-performing loans; internal rating based model, GMM.

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1. Introduction

During the last decade, following the burst of the international financial crisis, credit risk levels of European banks have dramatically increased, turning into one of the main concerns of regulators and banks. It is well know that a high burden of non-performing loans (henceforth NPLs) is considered as a major obstacle to bank credit offer and to the European economy recovery (IMF, 2015). There is a wide consensus among academics that a high level of NPLs negatively affects banks' lending capacity (Jimenez and Saurina, 2006; Hou and Dikinson, 2007; Tomak, 2013; Zhang et al., 2016; Cucinelli, 2016), reduces banks' profitability and the ability to raise new capital and, ultimately, threatens both their stability and the macroeconomic stability (Espinoza and Prasad, 2010; Zeng, 2012; Klein, 2013). It thus appears of great importance for regulators and banks to identify the main factors driving loan portfolios deterioration during negative economic cycles to set up effective policy measures and management practices.

It is a common view that NPLs proliferation is a consequence of persistent adverse macroeconomic conditions. A number of studies investigates the relationship between the economic cycle and banks' credit risk (Laeven and Majnoni, 2003; Farhan et al., 2012; Castro, 2013; Beck et al., 2015) and find empirical evidences of a negative relationship. A decreasing GDP growth rate, together with an increasing unemployment rate and other economic slowdown indicators, raise the probability of default of bank borrowers and the severity of losses in case of default. However, the increase of credit risk occurring during an economic downturn appears to differ significantly across banks facing the same macroeconomic conditions, suggesting that credit risk is driven also by bank-specific factors (Berger and De Young, 1997; Salas and Saurina, 2002; Marcucci and Quagliariello, 2009; Louzis et al., 2011; Ghosh, 2015; Zhang et al., 2015; Dimitrios et al., 2016; Chaibi, 2016). Indeed according to bank management principles, the increase in credit risk occurring during an economic downturn depends on two crucial bank specific features: i) its ability to manage credit risk, i.e. capacity to screen and monitor borrowers effectively, and ii) its risk profile and risk appetite, since loans to more risky customers have a higher probability of becoming non-performing as the macroeconomic conditions worsen. These two aspects are of paramount importance in the current prudential regulatory framework (Basel II) and, as a matter of fact, may eventually affect the level of capital requirements banks should comply with.

In this paper we aim to assess the empirical relevance of two bank-specific characteristics in determining the deterioration of bank loan portfolios in a time of crisis. More specifically, we assess whether banks that are ‘better’ managed and may rely on more sophisticated risk management procedures, and that are more risk averse and implement less aggressive lending policies, may successfully contain the increase in credit risk determined by adverse macroeconomic conditions

Our analysis contributes to the existing literature in several ways. First, among the determinants of NPLs we introduce a new variable, the Risk Weighted Assets to total assets ratio,as a proxy of the bank risk profile assets ratio, also referred to as ‘RWA density’. Despite some lack of homogeneity across countries and banks and the possible manipulation by banks, this ratio is still considered a valuable proxy of the level of risk borne by each bank (Le Leslé and Avramova, 2012; Cannata et al.,2012; Beltratti and Paladino, 2016). Moreover it represents a valid complement to the leverage ratio variable traditionally used in empirical analysis as a proxy of the bank risk appetite (Berger and De Young, 1997; Makri et al., 2014; Chaibi and Ftiti, 2015; Cahibi, 2016). We then assess the relevance of risk management practices. The ability of a bank to evaluate credit risk effectively depends on several aspects, such as the availability of a wide array of data with a forward-looking informative content, sound risk management practices, an effective scoring/rating system. Unfortunately, this type of information is not publicly available. However, since the enforcement of Basel II, when bank internal procedures to measure credit risk are deemed to be accurate and robust, they can be validated by supervisory authorities and used for the computation of the minimum capital requirement. For this reason we choose to proxy banks credit risk management expertise with a dummy variable that takes value1 if the bank/banking group uses the internal rating based (IRB) to compute the regulatory capital minim requirement, and 0 otherwise. Thus, we verify also if banks that use IRB models for regulatory purpose are better able i) to counterbalance the negative effects of the economic cycle on their loans portfolios and ii) to offer more credit than their competitors/peers without taking on excessive risk. Finally, in addition to macroeconomic and bank-specific determinants of credit risk, we consider a novel type of potential drivers, that includes two proxies of the juridical and institutional context of each country. The first variable is a proxy of the effectiveness of the insolvency procedures on which depends the recovery rate in case of insolvency, hence the rate of the loss given default. The second is a measure of the support (state aid) that banks – individually or at the country bank-system level - have received, to enhance the sale/write-off of NPLs. Our analysis spans the period from the onset of the international financial crisis until the recent real economic crisis, thus covering the whole economic downturn that has hit the European economy, while most other studies that are based on bank-level data cover a shorter period.

We employ a novel panel of 177 banks from 14 European countries and covers the period from 2006 to 2015. Our econometric analysis is conducted via system GMM estimation , its robustness is verified by implementing a two-step GMM estimation with Roodman (2009) standard errors correction.

We consider two alternative proxies for credit risk: the ratios of NPLs over gross loans and loan-loss provisions (LLPs) over gross loans. In both cases results confirm that the deterioration of loans portfolio is lower for banks with a lower risk attitude relying on validated IRB models, suggesting that IRB model based procedures allow for a more accurate and effective credit risk management. Our findings confirm that the increase in credit risk is lower for banks that in the previous years have adopted a less expansive lending policy; however, quite interestingly, we find that higher loan growth rate do not determine an increase in credit risk for banks using IRB models. This supports the view that during an economic downturn banks that rely on a more effective risk management may continue to offer credit despite the adverse economic conditions without taking on excessive risk. Finally, we find that juridical and institutional framework affect the bank ability to manage NPLs. More specifically, the presence of more effective insolvency procedures and a stronger creditor protection reduces credit risk burden as well as the provision of public support in the form of a public bad bank or capital injections by the state.

The remainder of the paper is organized as follows: Section 2 surveys the relevant literature and proposes our hypotheses; Section 3 describes the sample and the econometric methodology. In Section 4, we comment on our results and in the last section, we draw some conclusions.

2. The determinants of credit risk: a review of the literature and our hypotheses

Many studies analyse the determinants of NPLs and of credit risk. A first strand of literature focuses mostly on macroeconomic variables such as the growth rate of real GDP, the unemployment rate, the level of house prices and the interest rate (Laeven and Majnoni, 2003; Bikker e Metzemakers, 2005; Bofondi and Ropele, 2011; Glen and Mondragon-Velèz, 2011; Farhan et al., 2012; Beck et al., 2015). Findings confirm that changes in the level of bank loan quality are largely due to simultaneous or previous changes in macroeconomic conditions and that credit risk is a countercyclical phenomenon. However, the cyclical effects are not symmetric and during bad times the increase of risk is stronger than its reduction during the expansionary phase (Marcucci and Quagliariello, 2009).

Another strand of the literature considers as NPLs' determinants bank-specific features (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., 2015; Dimitrios et al., 2016; Chaibi, 2016) together with macroeconomic variables. These studies are quite diverse in terms of hypotheses tested and empirical analysis design: i.e. a few studies use aggregate data at the country level, while others use bank-level data; some studies focus on one or very few countries, while others consider a much higher number of countries; significant differences can be found as well in the panel time span used and the econometric methodology employed. In the overall these studies suggest that credit risk and NPLs are determined, in addition to the macroeconomic variables, by three different drivers at the bank-level: i) the stance of the bank lending policy ; ii) the quality of management; iii) the bank capitalization and moral hazard incentives.

With regard to the bank lending policy, several studies (Radlet and Sachs, 1998, Keeton, 1999, Ranjan and Dhal, 2003 and Foos et al.2010) find evidence that faster loan growth leads to higher loan losses during the subsequent years (up to four years). A faster loan growth occurs typically during a positive business cycle, when banks are more willing to lend and may use laxer credit standards and accept a lower quality of borrower: this ultimately leads to an increase in credit risk when macroeconomic conditions worsen. Alternatively, a fast loan growth may be the consequence of an aggressive lending policy, resulting in new market shares; in this case the bank can incur in adverse selection problems and embark more risk (Salas and Saurina, 2002; Jimenez and Saurina, 2006).

With regard to the quality of management, the literature considers two opposite hypotheses. According, to the so called “bad management hypothesis” - originally proposed by Berger and De Young (1997) - the level of NPLs is affected by the quality of the banks’ management, which is usually proxied by the previous or simultaneous ROE and/or by the cost-income ratio. As shown by Podpiera and Weill (2008); Louzis et al., (2011), Klein (2013) and Chaibi (2016), a poor management quality implies a scant ability in underwriting and monitoring loans, that to a large extent eventually become NPLs. Alternatively, a high cost efficiency may hide the deployment of scarce resources to manage risk (skimping hypothesis) and may cause a subsequent deterioration of loan quality (Berger and De Young, 1997).

Finally, the level of capitalization is at the core of the “moral hazard hypothesis”, that posits that banks with a low level of capital have an incentive to voluntarily engage in more risky activities, in view of their limited liability and deposit insurance and bailout expectations. Keeton and Morris (1987), Berger and DeYoung (1997), Salas and Saurina (2002), Jimenez and Saurina (2006), Klein (2013), Makri et al. (2014) and Chaibi (2016) find evidence of a negative significant relationship between bank’s capitalization and the subsequent level of NPLs. However, the current prudential regulation try to curb moral hazard incentives by imposing risk-sensitive capital requirement, hence we would expect that only well capitalized banks have a higher risk appetite and profile. At the same time these banks need higher return to compensate their shareholder for the higher riskiness of their investment and this can explain the positive significant relationship between the banks' capitalization and the NPLs found by Macit (2012) and Ghosh (2015).

The effectiveness of the current prudential regulatory framework in curbing bank moral hazard and credit risk has been somehow questioned and, as far as our study is concerned, two points has been highlighted. The first one concerns the comparability of the validated IRB models. It is well known that one of the most important innovation of the Basel II framework is the introduction of the Internal Rating-Based approach (IRB) that allows banks to employ their internal rating systems for estimating the parameters to calculate the minimum capital requirement under Pillar I. The use of IRB models is conditional on the supervisory authorities' validation, i.e. can occur after supervisors have assessed the soundness and appropriateness of internal credit risk measurement and management systems, and doubts have been raised on possible inconsistencies and variability across countries and banks (EBA, 2013 and 2015). As a matter of fact, the extreme flexibility of validated IRB models may have compromised comparability across banks to some extent, thus urging the need for a revision and harmonization of technical aspects (EBA, 2016). However, the IRB framework has proven its validity as a risk-sensitive way of measuring capital requirements and EBA has confirmed a general agreement on the validity of this approach and the intention to continue to use the IRB models (EBA, 2015). In a recent paper (Erdinc and Gurov, 2016), the use by banks of validated IRB models is used to proxy the degree of sophistication of the risk management techniques of a sample of European banking systems and results show a negative and significant impact of the IRB on the NPLs.

The second point that may affect our analysis concerns the computation of RWA and may be linked to the use of validated IRB. Mariathasan and Merrouche (2014) suggest that the use of the IRB leads to a risk-weight decline, that is particularly pronounced among weakly capitalized banks and in countries where supervisors are overseeing many IRB banks. Similarly, Le Leslé and Avramova (2012) suggest that banks adopting IRB under Basel II as a lower RWA density than banks under Basel I. Conversely, Barakova and Palvia (2014) find a positive correlation between RWA defined using the IRB models and the loan performance as a measure of portfolio risk, and underline that capital requirements under the IRB approach are higher than those under Basel I. Despite this possible flaw affecting this complex measure, the RWA density has often been used as a proxy of the risk profile of banks' assets (Shim, 2013, Ayadi and De Groen, 2014) and, assuming that the risk weights assigned to each asset category represent its contribution to the overall risk borne by a bank, the higher the RWA to total assets ratio, the higher the risk attitude (Cannata et al., 2012; Beltratti and Paladino, 2016).

In this paper we delve into the bank-specific determinants of credit risk, examining the significance of two new variables that capture the bank risk profile and its risk management effectiveness. Moreover, we try to disentangle the effects on credit risk of the following types of factors: economic cycle, lending behaviour, credit-risk management quality, and other bank-specific variables. We argue that banks that have a lower risk appetite and engage in less risky activities are less negatively affected by an economic downturn and that an important factor that can offset the deterioration of loan portfolios during a negative economic cycle is a bank's ability to evaluate and manage credit risk effectively. Hence, banks that are more efficient in allocating credit may continue to offer credit without taking on excessive risk and putting their stability at risk, even when macroeconomic conditions worsen. Finally, we deem that the juridical and institutional context may affect the intensity of the risk increase.

In the rest of the paper we test the following hypotheses:

Hp_1: During an economic downturn banks with a lower risk appetite and with a more conservative lending policy face a lower deterioration of loan portfolio;

Hp_2: During an economic downturn banks relying on validated internal-based models show a lower increase in credit risk and may afford a higher loan growth rate without excessively increasing their credit risk;

Hp_3: More effective insolvency procedures and the possibility for banks to resort to state aid, either for the disposal of NPLs or for re-capitalization, decrease their credit risk.

3. Data and Methodology

3.1 The sample

Our empirical analysis is based on a sample of 177 banks from 14 Western European countries[1], accounting for about 63% of the countries banking system total assets. The initial sample consisted of 341 banks and has been selected according to the availability of the information concerning the type of approach used for regulatory purposes under Basel II, i.e. the standardized approach versus the validated IRB approach, for the whole period under analysis. This information has been obtained by the SNL Unlimited data-base. We restricted our analysis to commercial banks, cooperative banks, savings banks, real estate banks and bank holdings, i.e. the types of banks that are most exposed to credit risk. Banks with total assets of less than 10 billion euros at 2015 were

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

excluded and, in line with De Haas and Van Lelyveld (2014) we also excluded banks with annual growth of total earning assets greater than 75%, to control for the effects of mergers and acquisitions.

Our analysis covers the period 2006-2015[2]; thus accounting forthe whole economic downturn that hit the European economy. Our data set was built using different sources: the macroeconomic data were collected from the IMF, the World Bank and the Eurostat databases; the bank-specific data were drawn from Bankscope, with the exception of the data relating to the use of validated IRB models or standardized approach, which was collected by SNL. We used consolidated balance-sheet data at the country level[3], on the view that credit risk and the ensuing capital policies are usually envisaged and managed mainly at the group level. For banks that are independent (no shareholder recorded with more than 50% of direct ownership) we used unconsolidated data. As for the juridical context we drew data from the Doing Business data base provided by the World Bank. Finally, data concerning the state intervention in support of individual banks or member state bank systems were taken from the State Aid Scoreboard of the European Commission. All data are available on an annual basis.

< Table 1 approximately here >

3.2 Econometric Methodology

Empirical evidences suggest that NPL displays strong persistence across time implying that fixed and random effects methods will yield biased and inconsistent estimates. To account for the significant serial autocorrelation in the dependent variable, we adopt a dynamic panel specification with a two way error component:

$$y_{it} = \alpha y_{it-1} + \beta X_{it-1} + \varepsilon_{it} \quad i = 1, \dots, N, t = 1, \dots, T \qquad (1)$$
$$\varepsilon_{it} = v_i + \lambda_t + u_{it}$$

where the subscripts i and t denote respectively the cross sectional and time series dimension of the data. The dependent variable y_{it} is the variation in the level of credit risk of bank portfolio, X_{it} is a vector of explanatory k variables that include macroeconomic variables, bank-specific features

[2] Basel II was enacted in 2004 and in the following years supervisory authorities started to validate the IRB models. This is why we restricted our analysis to the period starting from 2006. Besides, since 2005 all public companies have been required to prepare their consolidated accounts using the new standards (IAS/IFRS). Thus, balance-sheet data from 2005 onwards incorporate IAS/IFRS requirements (Guggiola, 2010).

[3] For banking groups that operate in more than one country, we use the consolidated balance-sheet of the holding company, for each country included in our sample. Thus we can control for the macroeconomic context at the country level.

and observable environment indicators. Consistent estimation of Eq. (1) can be achieved via the Generalized Method of Moments (GMM) of Arellano and Bond (1991) and Blundell and Bond (1998). GMM estimation relies on the first difference trasformation of Eq (1) to eliminate the correlation between the individual unobserved heterogeneity v_i and the explanatory variables:

$$\Delta y_{it} = \alpha \Delta y_{it-1} + \beta \Delta X_{it} + \Delta \varepsilon_{it} \quad i = 1, \dots, N, t = 1, \dots, T \qquad (2)$$

The differenced model of Eq.2 no longer displays fixed effect bias, but by construction it is affected by the endogeneity arising from the correlation between the lagged dependent variable y_{it-1} and the differenced error term $\Delta\varepsilon_{it}$,thus requiring instrumental variables estimation methods. A good instrument should be as correlated as possible with the variable it is instrumenting for and uncorrelated with the error term. Under the assumption of serially uncorrelated errors (which need not to be independent across time), lags of order two and more of the dependent variable satisfy the following (T-2) (T-1)/2 population moment conditions for t≥3:

$$E\left[y_{it-j} \Delta\varepsilon_{it}\right] = 0 \quad t = 3, \dots, T \; and \; j = 2, \dots, t-1 \quad (3)$$

Moreover under the assumption of weak exogeneity of the explanatory variables, any inconsistency arising from a correlation between the regressors and the disturbances can be taken care of by using as instruments in the differenced equation for period s the set of X_{i1}, X_{i2},..., X_{is-1} that satisfy the following population moment conditions for t≥3:

$$E\left[X_{it-j} \Delta\varepsilon_{it}\right] = 0 \quad t = 3, \dots, T \; and \; j = 2, \dots, t-1 \qquad (4)$$

In this context the optimal instrument matrix at time s is the (T-2)(T-2)[k(T+1)+(T-1)]/2 matrix $Z_i = diag(y_{i1}, \dots, y_{is}, X_{i1}, \dots, X_{it+s})$

for s=1,...,T-2. Because sample averages are consistent estimators of their population equivalent, the GMM estimator of the coefficients vector δ= (α,β)′ is found by minimization of the following quadratic for:

$$\hat{\delta} = (XZA_nZ'X)^{-1}(XZA_nZ'\Delta y_{it})$$

where X is the matrix of observations on Δx_{it} and A_n is the weight matrix. According to the choice of A_n, the GMM estimation might result into a one or a two steps procedure. In particular the two step GMM method uses the residuals of the first step estimation to derive the optimal weight matrix A_n. .

In the empirical literature on NPLs' determinants both one and two steps GMM estimation methods have been used to investigate the determinants of non-performing loans in balanced dynamic panel with a small time dimension, see for example Louzis et al (2011) and Beck et al. (2015). A drawback of this estimation method is that persistent explanatory variables, that display little variation across time, are poorly instrumented by their lagged levels, leading to inefficient standard errors of the estimated parameters and this inconclusive inference. In order to avoid this drawback, Arellano and Bover (1995) propose a system GMM estimator that combines the regression in difference with the regression in levels, imposing additional moment conditions for the equation in levels. The system GMM estimation appears more appropriate in our analysis since some of the explanatory variables such as IRB and recovery rate display cross-section variations only in the panel. A possible shortfall of this estimation method is the risk of proliferation of internal instruments that can easily grow large with respect to the sample size making specification tests misleading. To avoid such a problem we follow Arellano (2003) estimate the model with the system GMM estimator of Arellano and Bover setting a cap to the number of instruments for each period, so that the instrument count is linear in T. We test for stationarity of all the variables included in the model using the panel unit root test of Levin and Lin and we are able to reject the null hypothesis of a unit root for all the variables included. Our dynamic panel model is specified as:

$$\Delta CR_{it} = \beta_1 + \sum_{j=1}^{2} \beta_2 \, \Delta CR_{it-j} + \beta_3 \Delta GDP_{t-1} + \beta_4 UN_{t-1} + \beta_5 \Delta HPI_{t-1} + \beta_6 IRB_{t-2} + \sum_{j=1}^{2} \beta_{7j} \, \Delta RWA\_TA_{t-j} + \sum_{j=1}^{2} \beta_{8j} \, \Delta ROAE_{t-j} + \sum_{j=1}^{2} \beta_{9j} \, \Delta ROAE_{t-j} + \sum_{j=1}^{2} \beta_{10j} \, \Delta C\_I_{t-j} + \sum_{j=1}^{2} \beta_{11j} \, \Delta E\_TA_{t-j} + \sum_{j=1}^{2} \beta_{12j} \, \Delta GLGR_{t-j} + \beta_{13} (IRB_{t-2} * GLGR_{t-2}) + \beta_{14} SIZE_t + \beta_{15} BADB1 + \beta_{16} RRATE + \varepsilon_{it} \quad (5)$$

We proxy the dependent variables with two measures of credit risk in bank loan portfolio: the ratio of gross NPLs to gross loans at time t (NPL_GL and the ratio of LLPs to gross loans at time t (LLP_GL). The next section contains a detailed discussion on the choice and definition of our variables. For empirical purposes we estimate two separate specification of Eq5, respecvely :

$$\Delta NPL\_GL_{it} = \beta_1 + \sum_{j=1}^{2} \beta_2 \, NPL\_GL_{it-j} + \beta_3 \Delta GDP_{t-1} + \beta_4 UN_{t-1} + \beta_5 \Delta HPI_{t-1} + \beta_6 IRB_{t-2} + \sum_{j=1}^{2} \beta_{7j} \, \Delta RWA\_TA_{t-j} + \sum_{j=1}^{2} \beta_{8j} \, \Delta ROAE_{t-j} + \sum_{j=1}^{2} \beta_{9j} \, \Delta ROAE_{t-j} (2)$$

$$+ \sum_{j=1}^{2} \beta_{10j} \, \Delta C\_I_{t-j} + \sum_{j=1}^{2} \beta_{11j} \, \Delta E\_TA_{t-j} + \sum_{j=1}^{2} \beta_{12j} \, \Delta GLGR_{t-j} + \beta_{13} (IRB_{t-2} * GLGR_{t-2})$$

$$+ \beta_{14} SIZE_t + \beta_{15} BADB1 + \beta_{16} RRATE + \varepsilon_{it}$$

and

$$\Delta LLP\_GL_{it} = \beta_1 + \sum_{j=1}^{2} \beta_2\, LLP\_GL_{it-j} + \beta_3 \Delta GDP_{t-1} + \beta_4 UN_{t-1} + \beta_5 \Delta HPI_{t-1} + \beta_6 IRB_{t-2} + \sum_{j=1}^{2} \beta_{7j}\, \Delta RWA\_TA_{t-j} + \sum_{j=1}^{2} \beta_{8j}\, \Delta ROAE_{t-j} + \sum_{j=1}^{2} \beta_{9j}\, \Delta ROAE_{t-j} + \sum_{j=1}^{2} \beta_{10j}\, \Delta C\_I_{t-j} + \sum_{j=1}^{2} \beta_{11j}\, \Delta E\_TA_{t-j} + \sum_{j=1}^{2} \beta_{12j}\, \Delta GLGR_{t-j} + \beta_{13}(IRB_{t-2} * GLGR_{t-2}) + \beta_{14} SIZE_t + \beta_{15} BADB1 + \beta_{16} RRATE + \varepsilon_{it}$$

In both specification we assume that macroeconomic, bank specific and environmental variables are weakly exogenous. To verify the validity of the GMM enlarged set of moment conditions we rely on the Sargan specification test and assess the overall validity of the instruments. Then we verify the assumption of serially uncorrelated disturbances using the Baltagi-Wu test (1999) for panel serial correlation and we are able to reject the null hypothesis of second order correlation. For robustness we report the result of the two step GMM estimation.

3.3 Our variables

Our dependent variable CR is measured by two different ratios: the ratio of gross NPLs to gross loans at time t (NPL_GL) and by the ratio of LLPs to gross loans at time t (LLP_GL). The NPL ratio 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, 2005; Hess et al., 2009; Boudriga et al., 2009; Louzis et al., 2011; Beck et al., 2015), although it may be affected by differences in the accounting policies adopted across Europe[4]. As an alternative proxy of the quality of bank loans we have used the LLP ratio; in comparison to the NPL ratio this variable reacts more quickly to the deterioration of loan portfolio, thus it might be more volatile.

Our explanatory variables have been divided in three different categories: macroeconomic, bank-specific variables and indicators of the juridical and institutional context. The first group includes three measures of the economic cycle, i.e. the growth of GDP (GDP), the unemployment rate (UN), and the house price index (HPI). A reduction in the economic growth of a country, and the subsequent rise in the unemployment rate and fall of house prices, are among the primary

[4] 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.

determinants of the deterioration of bank asset quality which tends to occurs 3-4 quarters later (Bofondi and Ropele, 2011); to account for this evidence, we applied a 1-year lag to these variables.

The second group consists of bank-specific variables and includes a measure of the bank's profitability (ROAE) and a proxy of the bank's efficiency (Cost_Income). These measures have been used in previous studies to test the so called 'bad management hypothesis' (Berger and De Young, 1997; Louzis et al. 2011) and are meant to proxy the quality of the bank management. However, these proxies do not specifically capture the bank ability in screening and monitoring credit risk, which is one of the main driver of the level of credit risk. Under the current regulatory framework, the use of IRB models to calculate the minimum capital requirement is conditional on the supervisory authorities' validation, i.e. can occur after supervisors have assessed the soundness and appropriateness of internal credit risk measurement and management systems. We therefore assume that banks with validated IRB models have demonstrated the accuracy and effectiveness of their risk management models. For this reason we introduced a dummy variable (IRB) that equals 1 if the bank/banking group uses the IRB approach to calculate the regulatory minim capital requirement, and 0 otherwise[5].

As a proxy of the bank risk attitude/appetite we use a measure of the capitalisation of the bank – i.e. equity/total assets (E_A) - which have been already used in previous empirical studies. The relation between the bank capitalisation and its risk exposure is not completely clear. On the one hand, a week capitalisation may create moral-hazard incentives to take more risk. On the other hand, given the current prudential regulation only banks with a strong capital base may engage in riskier businesses. Hence we add a new variable that captures more explicitly the risk profile of the bank, i.e. the ratio of RWA to total assets[6] (RWA_TA). The higher the RWA, the higher the risk borne by a bank[7]. To proxy for the risk appetite of a bank we have included in our model also the rate of growth of gross loans (GLGR). As suggested by the economic theory and confirmed by empirical evidence (Jimenez and Saurina, 2005, Foos et al., 2010), the expansion of bank loan

[5] As for the method used to calculate the regulatory minimum capital requirement, the SNL Unlimited data base reports one of 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; 'Mixed' when, referring to different segments of the loan portfolio, both the standardized and the IRB approach are used; 'Foundation IRB' and 'Advanced IRB' when the respective approach is used for the whole bank loan portfolio. 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.

[6] The level of RWAs depends on the entire range of risks born by a bank – i.e. credit risk, market risk and operational risk - therefore banks with the same (total) RWAs may have a different level of credit risk due to a different business model. Besides, each component of the loan portfolio, i.e. sovereign/corporates/retail loans, may be associated to different weights depending on the prudential approach (standardized or IRB) used by the bank. We control for the business model by including in our sample only banks whose core business is typically represented by credit intermediation; we could not control for the loan portfolio mix because of lack of data.

[7] The inclusion of RWA and IRB in the model might pose a problem of imperfect multicollinearity thus making estimates inefficient, however as the sample correlation turs out to be around 0,38 we do not need to correct for this.

portfolios may be the result of laxer credit standards or of adverse selection, which may cause a subsequent deterioration of credit quality. We therefore expect a positive relation between past credit growth and the level of credit risk. However, in time of crisis the growth rate of loans tend to be very low if not negative, and this is due partly to an increase in counterparty risk, and partly to the tightening of credit standards that may lead banks to refuse loan applications whose net present value is positive (Berger and Udell, 2004). Therefore, we could argue that banks that rely on sophisticated and effective screening tools may correctly measure the risk of their counterparts, thus offering more credit than other banks without taking on excessive risk. To test for this hypothesis, we create a new variable that interacts the IRB dummy with the rate of growth of gross loans (IRB*GLGR).

Considering that NPLs and the need for LLPs usually do not arise in the same year as the loan has been granted, for all the bank-specific determinants we have used a 1-year and 2-years lag, but for the IRB dummy variable and the interaction term IRB*GLGR that are measured at lag t-2.

Finally, to account for possible portfolio diversification and to control for size effects we included the natural logarithm of the total assets, at time t.

The third group of explanatory variables includes two proxies of the juridical and institutional context of each country. The first variable is a proxy of the effectiveness of the insolvency procedures on which depends the recovery rate in case of insolvency, hence the rate of the loss given default. More specifically, we use data taken from the Doing Business of the World Bank that computes the amount recovered by a secured creditor in case of insolvency as a percentage of the loan value (RRATE). This recovery rate measure takes into account both compensation time and compensation costs - i.e. court fees and government levies; fees of insolvency administrators, auctioneers, assessors and lawyers, and the outcome of insolvency proceedings involving domestic entities. This variable may be used as a proxy of the effectiveness and efficiency of insolvency procedures of each country and the higher this rate, the lower the level of NPLs and of LLPs in the bank balance-sheet. The second variable (BadB) is a measure of the support (state aid) that banks – individually or at the country bank-system level - have received, either to enhance the sale/write-off of NPLs or to increase their capital. This is a dummy variable that takes the value 1 in the following cases: i)) the bank is located in a country where a bad bank has been created or the state has supported the disposal of NPLs by local banks; ii) the bank has directly received a capital injection by the state; iii) the bank has had the possibility to apply to a national support scheme aimed at the recapitalization of banks of a specific country. The value 1 applies both in the year when the event occurred – or for the entire length of the scheme - and in the following year, to account for the time necessary to a bank to sell its NPLs on the secondary market.

Table 2 provides further details on the calculation of variables, sources of information and the expected sign and Table 3 reports descriptive statistics.

< Table 2 and 3 approximately here >

4. Results

Our results are reported in Table 4 which shows for the two model specifications the system GMM coefficient estimation. At the bottom of the table we report the value of the Sargan test for over identification that rule out the problem of overfitting. To check the robustness of the system GMM estimates we estimate the model with the 2 step GMM estimator. Comparing Table 4 and Table 5 suggests that our estimated coefficient maintain their significance and order of magnitude with both estimation methods, even if the GMM fails to instrument for the time persistent system and bank specific features as previously explained.

< Table 4 and 5 approximately here >

In line with the current literature, we find a negative and significant explanatory power of all the macroeconomic variables – i.e. the GDP growth rate, the unemployment rate (UN) and the house price index (HPI). Overall, our findings confirm that adverse macroeconomic conditions are among the main drivers of credit risk.

As for the bank-specific determinants of credit risk, the most innovative result is the negative coefficient of the dummy variable IRB. This evidence confirms that banks relying on risk-management tools and procedures which have been judged accurate and effective by the supervisory authorities, have weathered the economic downturn and curbed the deterioration of their loan portfolios better than other banks. This finding is consistent with the negative relation between the level of risk and bank profitability (ROAE) and the positive sign of the efficiency measure (C_I), supporting the hypothesis that banks that are better managed are more efficient in managing risk.

We also find significant evidence that the increase of credit risk is higher the higher the bank risk profile (RWA_TA), suggesting that loan quality deterioration is greater for those banks that have a greater risk appetite and, thanks to a stronger capitalisation (E_A), have (voluntarily) invested in riskier assets. We can therefore discard the hypothesis of moral hazard. Moreover, the sign of the proxy of the lending policy (GLGR) is positive, confirming that aggressive loan growth may raise adverse selection effects, as shown in most previous studies. On the contrary, the opportunity to diversify portfolio risk, thanks to a larger size of the bank, contributes to reduce the risk borne by the bank.

A noteworthy result is the negative sign of the interaction term between IRB and GLGR, which support the view that during an economic downturn banks with validated IRB, and allegedly more sophisticated risk management practices, are better able to evaluate risk in time of a crisis and may continue to offer credit despite the adverse economic conditions without taking on excessive risk. This result is in line with Mascia et al. (2016), who find that banks using the IRB approach have moved towards safer borrowers without decreasing their lending activity.

Finally juridical and institutional framework appear to affect the bank ability to manage and contain NPLs at a very high confidence level. More specifically, the presence of more effective insolvency procedures and a stronger creditor protection reduce the burden of credit risk as well as the provision of public support in the form of a public bad bank or capital injections by the state.

5. Conclusions

In this paper we investigated whether banks that rely on more sophisticated risk management procedures and that are more risk averse may limit the increase in credit risk determined by adverse macroeconomic conditions during an economic downturn. It is well understood that a high burden of NPLs threatens the profitability and even the stability of banks, and is also a major obstacle to bank credit supply. However, better credit allocation skills might allow some banks to afford a less conservative lending policy despite the ongoing recession, without taking on excessive credit risk.

We employed a panel177 Western European banks for the 2006-2015 period and implemented both two-steps and system GMM estimation methods to test the empirical relevance of three types of variables determining the level of risk in bank loan portfolios. As far as the bank-specific drivers, we also test the significance of two novel variables, i.e. a dummy variable that equals 1 when the bank uses IRB models for regulatory purposes - that should proxy effectiveness of the bank's risk management practices- and the RWA density as a proxy of the bank's risk appetite. We also assess the relevance of the environmental context by testing the relevance of two proxies of the juridical ad institutional context.

Our results show that banks with a lower risk appetite and that rely on more sophisticated risk-management tools and procedures can to some extent offset adverse macroeconomic effects on their loan portfolios. We also demonstrate that during the recent financial and economic crisis, these banks have weathered the economic downturn and curbed the deterioration of their loan portfolios better than other banks, without trimming their loan portfolios. Our analysis acknowledges the relevance of macroeconomic conditions as shown in previous study, and adds the importance of the juridical and institutional context as drivers of loan quality deterioration. More effective insolvency procedures contributes to reducing the level of NPLs in bank balance sheet, as well as the opportunity for banks to resort to state aid in order to enhance the reduction of NPLs.

Overall, our results contribute to advance our knowledge of the implications of bank management policies, as they confirm i) the importance of risk management as a way to counterbalance and control the adverse effects of the economic cycle on credit risk, and ii) that a stronger risk appetite, though backed by a higher capitalization, may threaten bank profitability and stability as the macroeconomic conditions worsen. Moreover, these findings contribute to the ongoing debate on the effectiveness of prudential regulation and more specifically of risk-sensitive capital requirements. In our empirical analysis the increase of credit risk is lower for banks whose internal rating model have been validated, thus supporting the view that, all else being equal, these banks are more effective in managing risk. On the other hand, an increase in RWA density determines an increase in the burden of NPLs. This evidence hints that during the recent economic crisis the regulatory framework of Basel II and the use of IRB approach have proven to be effective in preventing an excessive credit-risk taking by banks, despite their complexity and the drawbacks in terms of comparability and transparency.

These results represent a first step towards a more rigorous understanding of the role of risk management in determining the level of credit risk and of the effectiveness of IRB models. Our analysis may be improved by introducing more detailed information concerning risk management practices, such as the percentage of loan portfolio that is weighted using different IRB models, i.e. foundation or advanced, and risk management organizational features. Further analysis may also include a measure of the interest rates applied to loans as to assess whether risk is correctly priced. Unfortunately, data needed for these purposes are either not included in the available databases or not public.

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Table 1 - Sample description

Country	N. banks	Sample total assets/ Total Asset of banking system (% at 31/12/2015)
AT	10	72,61
BE	8	96,78
DE	22	63,57
DK	10	72,87
ES	6	41,49
FI	4	41,37
FR	41	86,46
GB	17	45,69
IE	5	83,36
IT	27	74,98
NL	7	37,54
NO	9	83,48
PT	5	51,04
SE	6	91,87
TOT SAMPLE	**177**	**62,62**

Table 2 Variables and expected sign

Variable	Description	Source	Expected sign
Dependent variables			
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	/
Macroeconomic variables			
GDP_{t-1}	Growth of GDP at time t-1 at the bank's country-level	Eurostat	Negative
HPI_{t-1}	House price index at time t-1 at the bank's country-level	Eurostat	Negative
$UNEMP_{t-1}$	Growth of unemployment rate at time t-1 at the banks' country level		Positive
Bank-specific variables			
IRB_{t-2}	Dummy variable that equals 1 if at time t-2 the bank uses IRB model to calculate the regulatory minimum capital requirement, and 0 otherwise.	SNL Unlimited	Negative
RWA_TA_{t-2}	Risk weighted assets to total assets at time t-2 as measure of bank's risk appetite	Bankscope	Positive
$ROAE_{t-2}$	Return on average equity at time at time t-2		Negative
C_I_{t-2}	Total operating costs on total operating income at time t-2	Bankscope	Positive
E_TA_{t-2}	Equity over total assets.	Bankscope	Positive/negative
$GLGR_{t-2}$	Growth rate of Gross Loans at time t-2	Bankscope	Negative
IRBGLGR	Product between the IRB dummy variable and the growth rate of gross loans at time t-2		Negative
$SIZE_t$	Logarithm of bank's total assets	Bankscope	Negative
Juridical and Institutional variables			
RRATE	Percentage of loans recovered by a secured creditor in case of insolvency of the counterpart, accounting for time and cost of insolvency proceedings in each country.	'Doing Business' Database World Bank	Negative
BadB	Dummy variable equal to 1 if the single bank receives state aid or if in the country there is a recapitalization scheme or if a public bad bank is created; 0 otherwise. The value 1 applies both in the year when the event occurred – or for the entire length of the scheme - and in the following year.	European Commission	Negative

Table 3. Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Skweness	Kurtosis	J.Bera
LLP_GL	0.629	0.343	1.568	21.705	684.356	3.34449e+007 (0.000)
NPL_GL	4.656	2.792	5.589	3.099	12.788	13,801.2 (0.000)
GDP	1.723	1.700	3.130	-0.433	9.385	5241.6 (0.000)
UNEMP	5.077	5.000	2.104	2.577	10.784	10,537.2 (0.000)
HPI	101.627	100.190	10.6739	0.782	2.873	700.238 (8.81547e-153)
IRB	0.601	1.000	0.489	-0.412	-1.830	283.859 (2.29517e-062)
RWA_TA	46.263	45.300	18.586	0.149	-0.611	30.337 (2.58472e-007)
SIZE	17.813	17.455	1.605	0.255	0.175	20.9755 (2.78759e-005)
GRGL	5.854	4.021	16.732	4.326	45.512	151,133 (0.000)
E_TA	6.429	5.913	3.397	3.253	33.081	81224.9 (0.000)
ROAE	3.953	5.972	18.356	-9.124	138.868	1.40591e+006 (0.000)
BadB	0.205	0.000	0.403	1.460	0.134	630.863 (1.02275e-137)
RRATE	73.114	77.500	15.646	-0.663	-0.984	161.129 (1.02622e-035)

Table 4: System GMM estimation results

Variables	**Model 1**	**Model 2**
ΔNPL_GL_{t-1}	0.570*** (0.006)	-
ΔNPL_GL_{t-2}	0.213*** (0.017)	-
ΔLLP_GL_{t-1}	-	0.416*** (0.001)
ΔLLP_GL_{t-2}	-	0.152*** (0.031)
ΔGDP_{t-1}	-0.731*** (0.002)	-0.411*** (0.001)
ΔUN_{t-1}	0.187*** (0.008)	0.362*** (0.007)
ΔHPI_{t-1}	-0.073* (1.093)	-0.043* (1.075)
$\Delta RRATE_{t}$	-0.0512*** (0.005)	-0.0473*** (0.002)
$BadB_{t}$	-0.095** (0.903)	-0.063** (0.789)
ΔRWA_TA_{t-1}	0.603** (0.490)	0.91** (0.217)
ΔRWA_TA_{t-2}	0.210*** (0.005)	0.225*** (0.010)
$\Delta ROAE_{t-1}$	-0.64*** (0.007)	-0.406*** (0.009)
$\Delta ROAE_{t-2}$	-0.052*** (0.006)	-0.031*** (0.008)
$\Delta\ C\_I_{t-2}$	0.0048** (0.032)	0.0051* (1.002)
ΔC_I_{t-1}	0.037* (1.001)	0.051* (0.198)
ΔE_TA_{t-1}	0.052* (1.784)	0.053* (1.016)
ΔE_TA_{t-2}	0.091** (0.141)	0.091** (0.141)
$\Delta GLGR_{t-1}$	0.007*** (0.420)	0.0064*** (0.290)
$\Delta GLGR_{t-2}$	0.050*** (0.097)	0.061*** (0.061)
IRB_{t-2}	-0.061*** (0.003)	-0.082*** (0.005)
$IRB*GLGR_{t-2}$	-0.0012** (0.094)	-0.0011** (0.057)
$SIZE_{t}$	-0.0013** (0.062)	-0.0005** (0.072)
Sargan test	271.16	-
Sargan test	-	267.01
Serial correlation test	p-value 0.8732	p-value0.7821

Note: The dependent variable in the Model 1 is the NPL ratio, in the Model 2 is the LLP ratio. N° Observations 1320. *** Denote significance at 1% respectively. ** Denote significance at 5% respectively. * Denote significance at 10% respectively.

Table 5. Robustness check two stage GMM estimation

Variables	**Model 1**	**Model 2**
ΔNPL_GL_{t-1}	0.541*** (0.006)	
ΔNPL_GL_{t-2}	0.341 (0.017)	-
ΔLLP_GL_{t-1}	-	0.418*** (0.001)
ΔLLP_GL_{t-2}	-	0.142*** (0.031)
ΔGDP_{t-1}	-0.321*** (0.03)	-0.610*** (0.011)
ΔUN_{t-1}	0.069** (0.103)	0.093** (0.110)
Δ HPI_{t-1}	-0.071* (1.537)	-0.086* (1.926)
ΔRWA_TA_{t-1}	0.063** (0.071)	0.082** (0.071)
ΔRWA_TA_{t-2}	0.220*** (0.005)	0.158*** (0.018)
$\Delta ROAE_{t-1}$	-0.531** (0.051)	-0.482** (0.914)
$\Delta ROAE_{t-2}$	-0.015*** (0.005)	-0.024*** (0.003)
Δ C_I_{t-2}	0.048** (0.032)	0.051** (0.008)
Δ C_I_{t-1}	0.008* (1.001)	0.007* (0.176)
ΔE_TA_{t-1}	0.024* (1.859)	0.021* (1.106)
ΔE_TA_{t-2}	0.091** (0.141)	0.091** (0.141)
$\Delta GLGR_{t-1}$	-0.018*** (0.420)	-0.024*** (0.990)
$\Delta GLGR_{t-2}$	-0.050*** (0.097)	-0.078*** (0.071)
Sargan TEST	186.5	
Sargan TEST		165.3
Serial correlation test	p-value 0.666	p-value 0.752

Note: The dependent variable in the Model 1 is the NPL ratio, in the Model 2 is the LLP ratio. N° Observations 1320. *** Denote significance at 1% respectively. ** Denote significance at 5% respectively. * Denote significance at 10% respectively.