Credit Risk and the Business Cycle:

What do we know?

Georgios Chortareas,[a,b] Georgios Magkonis[c] and Kalliopi-Maria Zekente[d]

Abstract

We perform a meta-regression analysis to characterize the relationship between ex post credit risk, measured through non-performing loans and real GDP growth. Although the prior empirical literature reveals a statistically significant inverse association, the precise effect of growth performance to credit quality diverges and remains subject to several qualifications. Using estimates from 56 studies and applying a Bayesian meta-regression analysis we explore the systematic patterns of the heterogeneity in the reported estimates. According to our evidence, the specification form as well as features related to the type of data, and the sample period are factors that systematically influence the estimated results.

Keywords. Non-performing loans; Credit risk; Macro-stress testing; Business cycles; Meta-analysis

JEL: G21, E44, C83

a Georgios Chortareas, Economics Group, King's Business School, *King's College London*, Bush House, 30 Aldwych, London, WC2B4BG, UK. Tel: +44(0)20 78484164. Email: georgios.chortareas@kcl.ac.uk

b Centre for Data Analytics for Finance and Macroeconomics, King's Business School, *King's College London,* Bush House, 30 Aldwych, WC2 B4BG, UK.

c ***(Corresponding Author)*** Economics & Finance Subject Group, Portsmouth Business School, *University of Portsmouth*, Portland Street, Richmond Building, Portsmouth, PO1 3DE, UK Email: georgios.magkonis@port.ac.uk

d Economic Research Division, Alpha Bank, 11 Sophocleous St., Athens, 10559, Greece, (Email: kalliopi-maria.zekente@alpha.gr)

1. Introduction

The need for designing regulatory and macroprudential policies in pursuit of financial stability gave rise to a massive and diverse empirical literature on the determinants of *ex post* credit risk. Part of these studies also emerged in the context of the traditional macro stress-testing framework. The macro stress tests were launched as an integral component of the Financial Sector Assessment Programs (FSAPs) jointly conducted by the IMF and the World Bank in the late 1990s (Blaschke *et al.*, 2001). These frameworks constitute part of policymakers' toolkit for monitoring and assessing potential vulnerabilities in the financial system, as well as for crisis management. In the aftermath of the crisis macro stress tests gained further prominence for both micro (individual institutions) and macro-prudential (system-wide) oversight.

The primary objective of the stress testing framework is to assess the resilience of individual financial institutions and/or the banking system as a whole to severe but plausible adverse events. Macro-stress test exercises can either be pursued in a "bottom-up" manner carried out by individual banking institutions or at a centralised level ("top-down" approach) without the individual banks being directly involved (Cihak, 2007; ECB, 2013). The credit risk stress-testing process usually involves the design of a macroeconomic stress scenario, the construction of a "satellite" credit risk model linking macroeconomic variables to asset quality variables and the assessment of the scenario's impact on banks' earnings and capital (see Foglia, 2009). The loan performance indicators typically featuring in a stress-testing framework include the probability of default and loss given default (or their product corresponding to the loss rate), as well as "*balance-sheet*"-type indicators such as non-performing loans (NPLs) and loan loss reserves.

The bulk of the prior empirical literature focusing on the link between the macroeconomic environment and asset quality suggests a statistically significant negative relationship between real GDP and NPLs. During economic upturns, the firms' and households' stream of income suffices to meet their debt obligations, while recessions reduce the borrowers' debt-servicing ability. Thus, NPLs tend to be low or to decline during economic upturns and to increase in recessions. While the majority of the voluminous empirical findings validates an inverse relationship between real GDP growth and NPLs, the evidence on the sensitivity of credit quality to growth performance diverges substantially and is subject to a number of qualifications. First, the various loan portfolio categories respond differently to macroeconomic conditions. For example, Louzis et al. (2012) show that the quantitative impact of GDP growth is more pronounced for business NPLs as compared to mortgage and consumer NPLs. Similarly, Vasquez et al. (2012) find that the effect of macroeconomic developments on loan quality differs across various credit types and sectors of economic activity.

Second, loan quality responds asymmetrically to the phases of the business cycle. Quagliariello (2007) provides evidence of a more severe NPLs' deterioration during the recessionary phase of the business cycle compared to their improvement during expansions. Third, the speed of transmission of macroeconomic shocks to credit quality, reflected in the lag structure of GDP growth, varies across studies. For example, Jimenez *et al.* (2013) and Salas and Saurina (2002) highlight the greater magnitude of contemporaneous GDP growth on NPLs compared to its lags, whereas Beck *et al*. (2013) report a positive correlation between lagged values of GDP growth and NPLs. Fourth, the empirical literature employs a highly diverse set of NPLs definitions and measurement. Finally, the empirical estimations emerge from widely different model specifications, estimation methods, time spans and country samples. The dissonance of the wide range of estimated coefficients reflects these distinct aspects of the empirical approaches.

In this paper, we pursue a meta-analysis as a means of navigating across the diverse evidence on the link between NPLs and the business cycle. Meta-regression analysis has become an increasingly popular tool in areas of banking and finance (e.g., Ewijk *et al*. 2012; Bialkowski and Perera, 2018). The objective of our analysis is to identify in a systematic manner the different factors that drive the heterogeneity in the estimated results reported in the prior literature, assessing also the potential existence of publication bias. To this end, we identify five broad categories of moderator variables, each pertaining to the different groups of study characteristics. We employ a Bayesian model averaging approach which allows to address model uncertainty. A comprehensive characterization of the impact of business cycle fluctuations on credit quality contributes to the prompt identification of potential vulnerabilities and sources of risks in the financial system. Moreover, the ECB (2017) highlights the importance in addressing asset quality issues taking into account that a high level of NLPs negatively affects credit growth and economic activity.

The remainder of this paper is structured as follows. *Section 2* reviews the main issues in the empirical literature on the nexus between the phase of the business cycle and NPLs. *Section 3* describes the data collection process and discusses the issues of heterogeneity and publication bias. *Section 4* presents the methodology employed in this paper. *Section 5* analyses the results from meta-regressions and *Section 6* provides additional robustness checks. *Section 7* concludes.

2. Review of main issues in the prior literature

On theoretical grounds, the life-cycle model underpins the analyses of the relationship between GDP and loan performance. Lawrence (1995) introduces explicitly the default option in the benchmark life cycle consumption model, drawing implications for individual consumption behavior. Rinaldi and Sanchis-Arellano (2006) extend this setup to allow borrowing not only for consumption but also for investment purposes. They show that the probability of default depends, *inter alia*, on current income and the unemployment rate associated, in turn, with bank lending rates and uncertain future income. The recently produced empirical evidence on loan performance dwarfs the related theoretical contributions.

Most empirical studies on the link between the business cycle and asset quality employ the NPL ratio as the dependent variable, which is commonly defined as NPLs over total loans or total assets corroborating a strong negative link between GDP and NPLs. NPLs are a key measure of *ex post* credit risk and constitute the most common indicator for the assessment of loan portfolio quality. According to the Basel Committee on Banking Supervision (2006, p. 100, § 452), a default of an obligor occurs when "(a) the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held), and/or (b) the obligor is past due more than 90 days on any material credit obligation to the banking group". The precise definition and measurement of NPLs, however, varies considerably both across national definitions and over time, rendering international and inter-temporal comparisons an arduous task. Barisitz (2013) provides an analytical comparison of NPLs national definitions in nine Western European counties, while Barisitz (2011) explores the corresponding definitions in ten Central, Eastern and South-eastern European countries. It emerges that in the majority of the above countries the NPLs' definitions embody common elements, with the most characteristic of them being the generic criterion of "over 90 days past due". More recently, the European Banking Authority, under the requirements of EU Regulation (575/2013, article 99 ¶4) has developed a common definition on non-performing exposures in order to produce a harmonized, comparable basis across definitions and classifications in the European Union (EBA, 2014).

On top of this general inverse relationship, however, NPLs seem to exhibit different sensitivity to GDP growth depending on the loan category (e.g., Louzis *et al*., 2012), the sector of economic activity (e.g., Vazquez *et al*., 2012) or the bank size (e.g., Gerlach *et al*., 2005). Furthermore, the responsiveness of NPLs to changes in aggregate economic activity varies significantly with respect to the type of financial institution (e.g., Salas and Saurina, 2002), the phase of the business cycle, (i.e., expansion or contraction) as well as the dynamic or static model specification (e.g., Quagliariello, 2007).

In addition to the general state of the economy, the empirical studies typically consider the effect of other macroeconomic variables on NPLs. Such variables include among others, the unemployment rate (e.g., Castro, 2013; Nkusu, 2011), the nominal and real exchange rate (e.g., De Bock and Demyanets, 2012), and the inflation rate (e.g., Shu, 2002; Fofack, 2005). Another strand in the literature goes beyond the macroeconomic environment, considering bank-specific factors. Such factors include, for instance, the return on assets (e.g., Quagliariello, 2007; Jimenez *et al*., 2013), the bank size (e.g., Jimenez and Saurina, 2006) and the solvency ratio (e.g., Louzis *et al.*, 2012). Some sporadic exceptions from the above systematic and idiosyncratic types of determinants take into account features of the institutional framework. Goel and Hasan (2011) consider corruption and central bank autonomy, while Babihuga (2007) focuses on the quality of banking supervision. Kauko (2014) explores the implications of the legal system and the political background.

Moreover, a substantial differentiation exists regarding the set of countries considered. Most studies cover groups of countries (e.g., Espinoza and Prasad, 2010; Beck *et al*., 2013) while others focus on individual banking systems (e.g., Shu, 2002; Gerlach *et al.*, 2005; Vazquez *et al.*, 2012). Finally, the existing literature is markedly diverse regarding the time span considered, covering both 'normal times' and crisis periods as well as the geographical allocation, covering various sets of countries and banking systems worldwide. The collected evidence used in our meta-analysis reflect this diversity.

3. Meta Dataset

3.1 Data collection process

To collect all the relevant papers on NPLs and the business cycle that exist in the literature we follow the procedure suggested by Stanley *et al*. (2013). We perform the main search through EconLit and Google Scholar using the words “non-performing loans” and “real GDP growth” as keywords. We then perform the same search adding the keywords “stress-test”, “estimation” and “business cycle”. We repeat this process twice to ensure that the pool includes all relevant papers that exist in the literature, resulting to a total of 105 papers. The majority of these papers provide empirical results, while a small portion of them is of either theoretical or descriptive nature and, therefore, do not qualify for the meta-analytic data set. Even after removing this class of papers from our sample, the remaining empirical studies are not directly comparable. As a first step, we exclude the studies classified as ‘first stage’ models (BIS, 2011). Such models typically estimate a battery of VAR specifications. Given that our focus is on the relationship between NPLs and real economy activity, the meta-analytic treatment of impulse responses is beyond the scope of this study. Some other studies rely on the methodological framework that falls within the focus of meta-analysis but fail to report a sufficient piece of information regarding the estimation. Therefore, we also exclude them from our sample. [1] The above process leads to a sample consisting of 56 papers and 574 estimates in total. We provide a list with all the papers covered by the meta-analysis in Table A in the Appendix.

These empirical studies provide several estimated versions of a benchmark econometric specification of the form:

$$NPLs\ Ratio_{it} = c + aGDP\ growth_{it} + bX_{it} + e_{it}, \quad (1)$$

where X is a vector of control variables and e is the error term.[2] Given that our interest lies in the relevance of real GDP in explaining loan quality, we focus on the estimated coefficient of the variable 'GDP Growth' (a). As discussed above, the variable used to capture credit quality can be quite dissimilar across studies. Given that the majority of the collected papers do not provide an analytical description or the exact definition of NPLs, the most appropriate way of handling the meta-data sample is through the use of partial correlations ρ_{ij},; $\rho_{ij} = t_{ij}/\sqrt{t_{ij}^2 + df_{ij}}$, where t and df are the t-statistics and the degrees of freedom, respectively, while i and j refer to the i^{th} observation from the j^{th} study (Doucouliagos *et al*., 2012; Stanley and Doucouliagos, 2012).[3] We use a box plot to provide a first depiction of our dataset in Figure 1. The box plot reveals a high degree of heterogeneity of estimated coefficients across and within studies. The average partial correlation is -0.118 with minimum and maximum being at -0.8 and 0.9, respectively, therefore suggesting a high degree of heterogeneity. Using the transformation of partial correlation allows us to

[1] For instance, some papers do not report either standard errors, t-statistics, or p-values. Instead, they signify statistical significance using only asterisks.

[2] While equation (1) serves as a benchmark, most studies adopt a dynamic version to account for the persistence of NPLs.

[3] The corresponding standard errors, SEρ, are equal to $\sqrt{(1-\rho_{ij}^2)/df_{ij}}$.

proceed with our analysis whose target is to discover the drivers of this variation.

Figure 1 here

3.2 Searching for publication bias

Before trying to explain this heterogeneity of the estimated coefficients, we examine the potential presence of publication bias in the literature and the meta-analytic dataset. First, we use funnel plots depicting the partial correlations against their inverse standard errors in Figure 2. The funnel plot appears to be asymmetric; relatively smaller negative values emerge more frequently. This provides a first indication that the editors/authors tend to prefer more negative estimates. In other words, positive estimates are more likely to be dismissed.

Figure 2 here

To supplement the graphical inspection for publication bias with a more formal analysis, we employ the funnel asymmetry test. Its specification after correcting for heteroscedasticity is:

$$\rho_i = \beta_0 + \beta_1 SE\rho_i + v_i \tag{2}$$

where *r* is the partial correlation (divided by its standard errors) and $SE\rho$ is the standard correlation of ρ. A statistically significant slope coefficient, β_0, suggests the presence of publication bias. Table 1 presents the regression results. Since all the collected papers report more than one estimate, the problem of dependence may affect our results and we use clustered standard errors to address it (Stanley and Doucouliagos, 2012). For robustness purposes, we report three different estimators, corresponding to WLS, fixed effects, and random effects. The results portray a clear picture; the estimated values of β_1

are statistically significant in all three models, indicating the existence of publication bias. That is, the funnel asymmetry regressions corroborate the indications emerging from the visual inspection of funnel plots. The results so far show that an estimated negative value is more probable to be reported and published than a positive one. However, the funnel plot does not show only this. It reveals the dispersion of values that we collected from the literature. In order to reach solid conclusions a more detailed analysis is needed. This topic is addressed in the next section.

Table 1 here

4. Explaining Heterogeneity

The existing empirical studies display a high degree of heterogeneity in the reported results. To understand what drives this heterogeneity, we consider the potential sources of systematic influence on the reported results. We assort the existing literature according to five categories. Each category considers different groups of study characteristics captured by the moderator variables used. The first group relates to the data characteristics and the type of analysis, considering three aspects: the type of data (cross-section, time-series, and panel), the frequency of observations (annual, quarterly, and monthly), and whether the study focuses on a single banking system or a set of countries. For each of the first two aspects, we create a dummy variable, treating the studies that use non-panel data and non-annual observations as the base category. Similarly, regarding the type of analysis we build a dummy variable, treating the studies that focus on a single banking system as the base.

The second category relates to the estimation technique, focusing on whether the different estimation methods can partially explain the observed heterogeneity of the literature results. Not taking into account the endogeneity between the examined variables may result to biased estimations. These concerns for endogeneity are the main reason driving researchers to shift from traditional estimation methods to instrumental variables approaches. We examine whether studies that consider the endogeneity issue tend to report different estimates from studies that do not deal with endogeneity. In other words, we test whether the estimates coming from techniques that capture the endogeneity (i.e., IV, GMM, 2SLS) differ systematically from the estimates that come from procedures that do not deal with this problem. For this purpose, we create the dummy 'endo' that takes the value 1 when the estimates from methods that take into account the endogeneity (GMM, IV, 2SLS) and 0 otherwise (OLS, pooled OLS).[4]

The third group of moderator variables refers to model specification. First, we examine whether the inclusion of bank-specific variables in our baseline specification (equation 1) plays a role in the reported estimates. A series of studies show that bank-specific features are important determinants of NPLs and thus, their inclusion in the set of control variables (***X***) is decisive. Second, we consider the dynamic nature of the credit risk indicator itself, focusing on the lags of the dependent variable. Given that a considerable number of studies adopt dynamic versions of equation (1), we use a dummy to account for time persistence of NPLs. In addition, we generate a dummy to account for the lag structure of real GDP growth, treating the inclusion of contemporaneous GDP growth as the base category. In most of the studies considered, the lag structure of GDP growth aims to capture the speed of transmission of macroeconomic shocks to credit quality and is conditional on the data frequency, as well as the overall sample size (e.g., Quagliariello, 2007). For instance, Jimenez *et al*. (2013) report that lagged values of GDP growth are less than half (in absolute terms) of contemporaneous values, indicating that

[4] We have also experimented with additional dummies in an attempt to capture the use of more sophisticated methods in detail. The resulting estimations, however, appear to suffer from high multicollinearity and, therefore, we use the broad endogeneity dummy as described above.

business cycle fluctuations affect relatively quickly credit portfolio quality. Beck *et al*. (2013), using annual data, report positive values for lagged GDP growth, suggesting that preceding expansions, which may be associated with lower credit standards, lead to a deterioration in credit quality. Thirdly, we investigate the exact type of variables used as controls, which may reveal useful information for the design of satellite models. Given that our meta-sample of papers includes a large variety of control variables, we focus on the macroeconomic variables which are most frequently employed. These include interest rates, inflation, unemployment, stock market indices, house prices, credit growth, trade variables (e.g., measures of openness), capital flows variables (including foreign direct investment), exchange rates, and debt. Finally, our list of moderator variables includes the total number of regressors that are used as control variables (set $\boldsymbol{X}$). It would be informative to include in the list of moderators the different types of NPLs. The reason of not doing it is because a significant percentage of our collected papers do not report this information.

The fourth category of moderator variables relates to publication characteristics. Apart from the inclusion of the standard error of partial correlation, SEρ, we include additional factors that may affect the estimated effect of GDP growth on NPLs. As a first publication feature, we use a dummy for studies that have been published in peer-reviewed journals versus unpublished research in the form of working papers, reports etc. We also consider the implications of authors' affiliation. In particular, we include a dummy for the studies in which at least one author is affiliated with a central bank or other policy institution (e.g., IMF, World Bank).

The last group of moderator variables takes into account the 'geographical/regional' aspect and the time period covered by the dataset used in each study. Credit risk indicators may exhibit different sensitivity to the diverse features of each financial system, as well as to the phase of the business cycle. In order to capture the 'geographical/regional' dimension and deal effectively with the large-scale data, we create seven regional dummies namely Euro-area, central and east Europe, middle East and North Africa, Asia, sub-Saharan Africa, Latin America and a mixed grouping. The advanced economies of the US, UK, Japan, Australia, and Switzerland correspond to our base category. Moreover, in order to control for the possible impact of the global financial crisis on the reported results, we add a dummy variable, treating the studies that do not include the 2007/2008 financial crisis in their sample as the base category. Table 2 below summarises the moderator variables.

Table 2 here

5. Meta-Regressions

To explore the existence of a systematic pattern of heterogeneity in the literature, we use the following meta-regression model;

$$\rho_{i,j} = c + \sum_{k=1}^{K} \beta_k X_{k,ij} + e_{ij} \qquad (3)$$

where ρ is the estimated partial correlations, X are the potential factors that affect the reported estimates, and i is an index for a regression estimate in the j^{th} study. We estimate the above specification using Bayesian Model Averaging (BMA), which can address model uncertainty (Havranek *et al.*, 2015). The large number of moderator variables makes the identification of the correct model difficult as the sequential 'general-to-specific' approach may lead to misspecifications. This problem becomes more pronounced given the increasing need of applied researchers for results that remain robust across a series of alternative specifications (Lu and White, 2014). The BMA approach overcomes the problem of model uncertainty by considering a fairly large number of potential regressions that arise from a given number of variables.

Based on the Bayes' rule, according to which

$$pr(\beta \mid \rho, \mathrm{X}) = \frac{pr(\rho, \mathrm{X} \mid \beta) pr(\beta)}{pr(\rho, \mathrm{X})} \tag{4}$$

(where $pr(\rho,\mathrm{X}|\beta)$ is the marginal likelihood, $pr(\beta)$ is the prior density and $pr(\rho,\mathrm{X})$ is the probability of the data), the main characteristic of the Bayesian model averaging approach is that it does not rely on individual regressions. Instead, it provides the weighted average of individual regressions. Assuming that N is the number of regressors, the maximum number of alternative models, M, is 2^N across which the researcher choose the best ones. This is equivalent to claim that there are $M_1,\ldots,M_m$ models where $m \in [1, 2^N]$. Assuming a prior density, we can write the posterior probability:

$$pr(\beta_m \mid M_m, \rho, \mathrm{X}) = \frac{pr(\rho \mid \beta_m, M_m, \mathrm{X}) pr(\beta_m \mid M_m)}{pr(\rho \mid M_m, \mathrm{X})}, \tag{5}$$

where each model M_m depends on the parameters β_m.

The posterior model probability (PMP) constitutes the criterion for choosing the best models. Specifically, the models with better fit are the ones that display higher posterior model probabilities. Utilizing Bayes' rule (4), the PMP of model M_m is equal to:

$$pr(M_m \mid \rho, \mathrm{X}) = \frac{pr(\rho \mid M_m, \mathrm{X}) pr(M_m)}{\sum_{m=1}^{2^{\mathrm{N}}} pr(\mathrm{X} \mid M_m) pr(M_m)}, \tag{6}$$

where $pr(\rho|M_m,\mathrm{X})$ is the likelihood function of model M_m, $pr(M_m)$ is the model prior, and the denominator is the integrated likelihood. Consequently, the emerging task is to identify the regressors that are consistently significant across the estimated models. The guide for answering this question is the posterior inclusion probability (PIP), which is defined as $PIP_n = \sum_{m=1}^{2^{\mathrm{N}}} p(M_m \mid \rho)$, where n $\in$ [1,...N] denotes each individual regressor. The PIP equation shows that each moderator variable has a specific PIP, which is the sum of posterior model probabilities of all models that include this variable. The higher the PIP of one variable is, the more its explanatory power.

Our analysis uses 28 moderators, implying that the total number of models exceeds 268 million. For computational reasons, we estimate a subset using a Monte Carlo Markov-chain Model Composition (MC^3)[5]. Using the Metropolis-Hastings algorithm (Zeugner, 2011), we begin our analysis with the unit information prior as parameters' prior, providing in this way the same of information as one observation in the dataset (Eicher *et al*. 2011). For the model prior, we use the uniform model prior, which assigns the same prior probability to each model.

Figure 3 summarises our results depicting the 5,000 models with the highest posterior inclusion probabilities. The horizontal axis measures the cumulative model probabilities with the best models shown on the left side. As we move to the right, each model's posterior probability diminishes. The vertical axis sorts the moderators by descending order according to their PIP. This means that the variables at the top of the vertical axis have more explanatory power than those in the bottom. The red colour (lighter grey in colourless version) suggests that the variable is included in the model and its estimated sign is negative, while the blue colour (darker grey) indicates a positive sign.

According to the estimated results presented in Table 3, a wide range of factors can explain the heterogeneity of the estimated coefficients. We follow Kass and Raftery's (1995) rule as a guide to the level of significance. Specifically, the effect of a variable is considered as weak, positive, strong and decisive if its PIP lies between *0.5-0.75*, *0.75-0.95*, *0.95-0.99* and *0.99-1*, respectively. Regarding the first group, which pertains to the characteristics of the data, our

[5] For a detailed discussion of MC, including the technical details see Moral-Benito (2015).

results suggest that the data frequency and the type of analysis influence the reported estimates. Gross and Población (2015) suggest that the usually short length of historical time series for credit risk indicators may constrain the model from encompassing all their potential determinants. This may lead to omitted variable bias, i.e., the effect of the variables included may be underestimated or overestimated. Studies using lower (i.e. annual) as compared to higher (i.e. monthly or quarterly) frequency of observations report less negatives coefficients. The type of analysis also emerges as a significant factor, since studies that focus on a set of countries tend to report more pronounced negative coefficients.

Turning our focus on the specification characteristics of equation (1) in the prior studies, our results suggest that including the lagged dependent variable or lagged values of real GDP growth are not significant factors in explaining the heterogeneity. Including several macroeconomic fundamentals in the model specification, however, plays an important role in explaining the diverse empirical estimates across literature. The negative estimates are more pronounced when the pool of regressors includes interest rates, capital flows, inflation, and stock market indices. Nevertheless, studies that include credit growth in the model, tend to report a less negative relationship between NPLs and economic activity. This finding is consistent with a spate of analyses that emphasizes the importance of these factors (e.g., Babihuga, 2007; De Bock and Demyanets, 2012).

As far as the publication characteristics are concerned, the affiliation of researchers as a major aspect of publication characteristics does not seem to play an important role. Also, there is no evidence that published papers tend to report different values on average from works that remain in a pre-publication stage. Finally, the standard error of partial correlation is not anymore statistically significant. This indicates that when we take into account all the potential factors that explain the variation of the reported estimates, then publication bias vanishes. Even though there is an evidence that more negative values are more frequently reported, this can be attributed to other factors.

Furthermore, both the regional/geographical aspect and the period of the dataset mater for the results obtained. Studies focusing on sub-Saharan countries tend to report more negative estimates. The diverse response of NPLs to real GDP across countries may be related to both the different level of real GDP, which can trigger a stronger impact on the quality of loans (Gasha and Morales, 2004) and the differential impact of real GDP growth on NPLs conditional on the stage of business cycle.

With reference to the last observation, several studies emphasize the asymmetric impact of real GDP on NPLs conditional on the phase of the cycle. NPLs tend to record a stronger deterioration during the recessionary phase of the cycle as compared to the improvement they register during periods of economic expansion (Quagliariello, 2007). Interestingly, our findings suggest that studies covering the 2007-2008 financial crisis in their sample tend to report less negative coefficients. This finding is in line with the analysis of ECB (2011), which suggests that during past systematic banking crises[6] the level of NPLs has been more heavily affected by economic recessions as compared to NPLs during 2008/2009. We should note, however, that this result does not directly challenge the non-linearities in the link between business cycles fluctuations and credit risk, if we take into account that the pre-2007 samples may also include systemic banking crises. Finally, the estimation method does not prove to be a significant factor. Even though neglecting endogeneity may lead to biased estimates, the differences in econometric techniques are not important in explaining the observed heterogeneity.

Table 3 here

[6] The comparison includes a common sample of 44 countries that experienced systemic crises during the period 1981-2003.

Figure 3 here

6. Robustness Checks

To attest the robustness of our findings we perform two additional exercises. First, we apply frequentist estimation techniques, instead of Bayesian inference. We show the results from clustered mixed effects in the right panel of Table 4 using all explanatory variables with a PIP value higher than 0.3 (Havranek *et al.*, 2015). Interestingly, both the estimated sign and the level of statistical significance reported suggest that the BMA results are quite robust. The second robustness check consists of assuming alternative priors, using Zellner's *g* and beta-binomial as parameters and model priors, respectively. Given that we do not really have any a priori knowledge regarding the parameters and the model's size, this choice appears even more suitable (Ley and Steel, 2009). We report the results in Figure 4 (graphical map) and in the left panel of Table 4. The results reveal that the factors which seem to have a significant influence remain the same irrespective of priors, thus, confirming the robustness of our initial results.

Table 4 here

Figure 4 here

7. Conclusions

This paper provides a quantitative assessment of the existing evidence on the relationship between *ex post* credit risk, measured through NPLs, and the business cycle, exploring the existence of systematic patterns of heterogeneity. Part of the evidence in the prior literature emerges in the context of the traditional macro stress-testing modelling techniques, establishing a link between aggregate credit risk parameters and macroeconomic fundamentals.

We estimate a meta-regression model through Bayesian Model Averaging (BMA) which, on top of traditional estimation techniques, addresses the issue of model uncertainty. In this way, we are able to assess the factors that drive the variability in the estimated coefficients throughout a large number of different models. Our findings suggest that the data characteristics, the model specification, the geographical distribution as well as the time span of the sample are significant determinants in explaining the observed heterogeneity of the reported estimates in the literature. Our results remain quite robust to standard meta-analysis estimation methodologies.

Acknowledgements

We would like to thank the editor and two anonymous referees for their useful comments and suggestions. Any remaining errors are the responsibility of the authors.

Disclaimer

The views and opinions expressed in this paper are those of the authors and do not reflect those of their respective institutions.

References

Basel Committee on Banking Supervision (2006) ' International Convergence of Capital Measurement and Capital Standards: A Revised Framework-Comprehensive version', *Bank for International Settlements,* June, 1-333.

Babihuga, R. (2007) 'Macroeconomic and Financial Soundness Indicators: An Empirical Investigation', *IMF Working Papers*, 1-30.

Barisitz, S. (2011) 'Nonperforming Loans in CESEE–What Do They Comprise', *Focus on European Economic Integration Q*4/11, OeNB, 46-68.

Barisitz, S. (2013) 'Nonperforming loans in Western Europe-A selective comparison of countries and national definitions', *Focus on European Economic Integration Q*1/13, OeNB, 28-47.

Blaschke, W., Jones, M., Majnoni, G. and S. M. Peria (2001) 'Stress Testing of Financial Systems: An Overview of Issues, Methodologies and FSAP Expereiences', *IMF Working Papers*, WP 01/88

Bank of International Settlements, (2011). *Research Task Force Working Group on the Transmission Channels between the Financial and Real Sectors of the Basel Committee on Banking Supervision*, Working Paper No.18. Basel, Switzerland.

Beck, R., Jakubik P., and Pilou A. (2013) 'Non-Performing Loans: What Matters in Addition to the Economic Cycle?' *ECB Working Paper* 1515.

Bialkowski, J. and D. Perera, (2018), 'Stock index futures arbitrage: Evidence from a meta-analysis', Forthcoming in *International Review of Financial Analysis*

Castro, V. (2013) 'Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI', *Economic Modelling,* 31, 672-83.

Cihak, M. (2007), 'Introduction to Applied Stress Testing', *IMF Working Papers* 07/59

De Bock, R. and Demyanets, M. A. (2012) 'Bank asset quality in emerging markets: Determinants and spillovers', *IMF Working Papers* 12/71.

Doucouliagos, H., Haman, J. and Stanley T.D. (2012) Pay for Performance and Corporate Governance Reform', *Industrial Relations*, 51, 670-03.

Eicher, T. S., Papageorgiou, C. and Raftery, A. E. (2011) 'Default Priors and Predictive Performance in Bayesian Model Averaging, with Application to Growth Determinants ', *Journal of Applied Econometrics*, 26, 30-55.

Espinoza, R. A. and Prasad, A. (2010) 'Nonperforming loans in the GCC banking system and their macroeconomic effects', *IMF Working Papers*, 1/24.

European Banking Authority (2014) 'Final draft Implementing Technical Standards on supervisory reporting on forbearance and non-performing exposures under article 99(4) of Regulation (EU) No 575/2013', 1-65.

European Central Bank (2011) 'Financial Stability Review', December, 132-139.

European Central Bank (2013) 'A Macro stress testing framework for assessing systemic risks in the banking sector', Occasional Paper Series, No 152.

European Central Bank (2017) 'Guidance to banks on non-performing loans', Banking Supervision Report.

Ewijk, C.v., de Groot, H.L.F, Santing, A.J. (2012) 'A Meta-analysis of the Equity Premium', *Journal of Empirical Finance*, 19, 819-830.

Fofack, H. (2005) 'Nonperforming loans in Sub-Saharan Africa: causal analysis and macroeconomic implications', *World Bank Policy Research Working Paper*.

Foglia, A. (2009) 'Stress Testing Credit Risk: A Survey of Authorities' Approaches', *International Journal of Central Banking*, 5, 9-45

Gasha, J.G. & Morales, R.A. (2004) 'Identifying Threshold Effects in Credit Risk Stress Testing' *IMF Working Papers*, 4/150

Gerlach, S., Peng, W. and Shu, C. (2005) 'Macroeconomic conditions and banking performance in Hong Kong SAR: a panel data study', *available on the BIS website (www. bis. org).*

Goel, R. K. and Hasan, I. (2011) 'Economy-wide corruption and bad loans in banking: international evidence', *Applied Financial Economics,* 21, 455-61.

Gross, M. and J. Población (2015) 'A false sense of security in applying handpicked equations for stress test purposes', *ECB Working Paper* 1845.

Havranek, T., Horvath, R., Irsova, Z. and Rusnak, M. (2015) 'Cross-Country Heterogeneity in Intertemporal Substitution', *Journal of International Economics*, 96, 100-118.

Jiménez, G., Lopez, J. A. and Saurina, J. (2013) 'How does competition affect bank risk-taking?', *Journal of Financial Stability,* 9, 2, 185-95.

Jiménez, G. and Saurina, J. (2006) 'Credit Cycles, Credit Risk, and Prudential Regulation', *International Journal of Central Banking*, 65-98.

Kass, R.E. & Raftery, A.E. (1995). 'Bayes Factors', *Journal of the American Statistical Association*, 90, 773-795.

Kauko, K. (2014) 'Do Bailouts Cause Moral Hazards or Franchise Value in Banking?', *Kyklos,* 67, 82-92.

Lawrence, E.C (1995) 'Consumer Default and the Life Cycle Model', *Journal of Money, Credit and Banking,* 27(4), pp. 939-954

Ley, E. and Steel, M. F. (2009) 'On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regression', *Journal of Applied Econometrics*, 24, 651-674.

Lu, X. & White, H. (2014). 'Robustness Checks and Robustness Tests in Applied Economics', *Journal of Econometrics*, 178, 194-206.

Louzis, D. P., Vouldis, A. T. and Metaxas, V. L. (2012) 'Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios', *Journal of Banking and Finance,* 36, 1012-27.

Moral-Benito, E. (2015) 'Model averaging in economics: An overview', *Journal of Economic Surveys*, 29, 46-75.

Nkusu, M. (2011) 'Nonperforming loans and macrofinancial vulnerabilities in advanced economies', *IMF Working Papers*, 1/27.

Quagliariello, M. (2007) 'Banks' riskiness over the business cycle: a panel analysis on Italian intermediaries', *Applied Financial Economics,* 17, 119-38.

Rinaldi, L. and A. Sanchis-Arellano (2006) 'Household debt sustainability. What explains household non-perfoming loans? An empirical Analysis', *ECB Working Paper* 570.

Salas, V. and J. Saurina (2002) 'Credit risk in two institutional regimes: Spanish commercial and savings banks', *Journal of Financial Services Research,* 22, 203-224.

Shu, C. (2002) 'The impact of macroeconomic environment on the asset quality of Hong Kong's banking sector', *Hong Kong Monetary Authority Research Memorandums*, 1-26.

Stanley, T., Doucouliagos, H., Giles, M., Heckemeyer, J. H., Johnston, R. J., Laroche, P., Nelson, J. P., Paldam, M., Poot, J. and Pugh, G. (2013) 'Meta-analysis of economics research reporting guidelines', *Journal of Economic Surveys,* 27, 390-94.

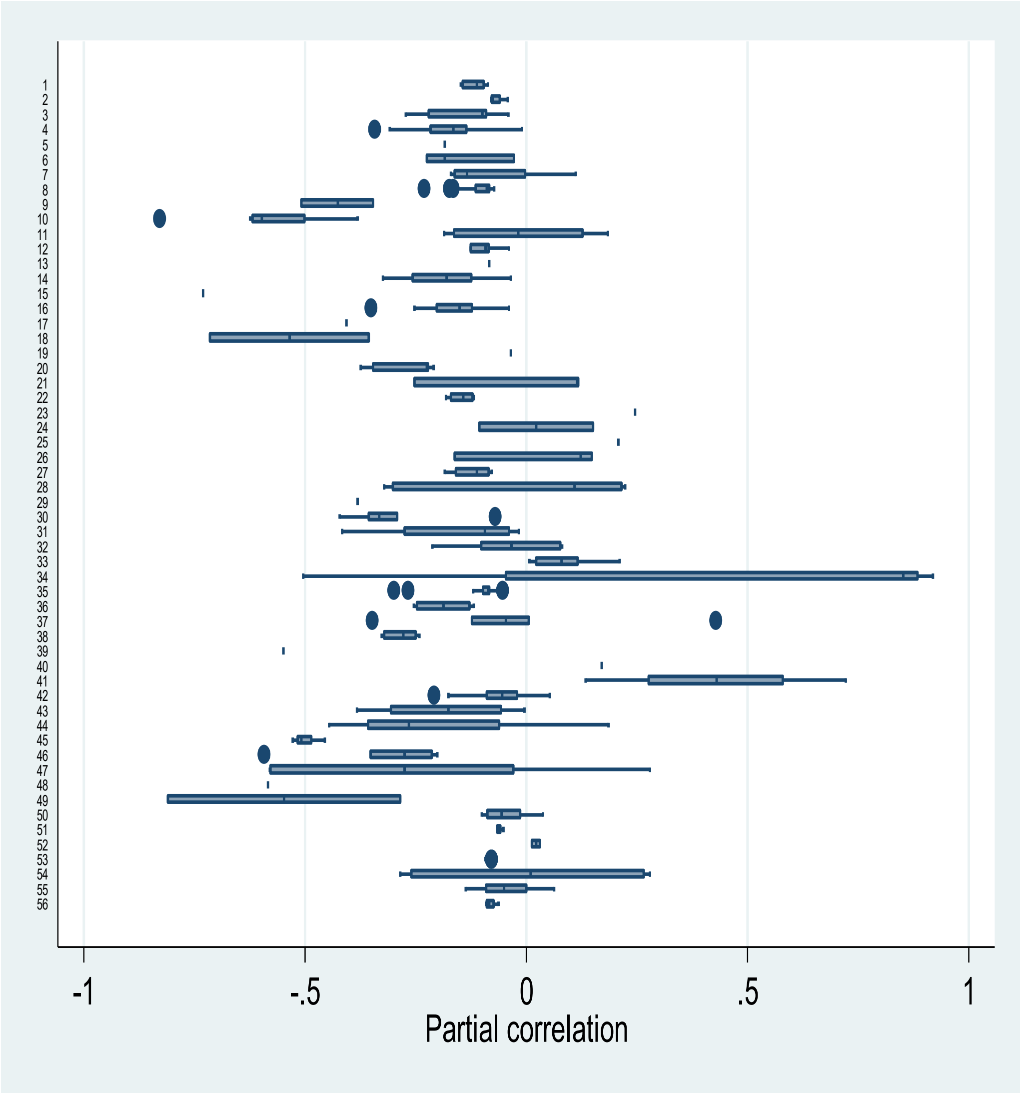
Stanley, T. D. and Doucouliagos, H. (2012) *Meta-regression analysis in economics and business*, Routledge.

Vazquez, F., Tabak, B. M. and Souto, M. (2012) 'A macro stress test model of credit risk for the Brazilian banking sector', *Journal of Financial Stability,* 8, 69-83.

Zeugner, S. (2011) 'Bayesian Model Averaging with BMS', Tutorial to the R-package.

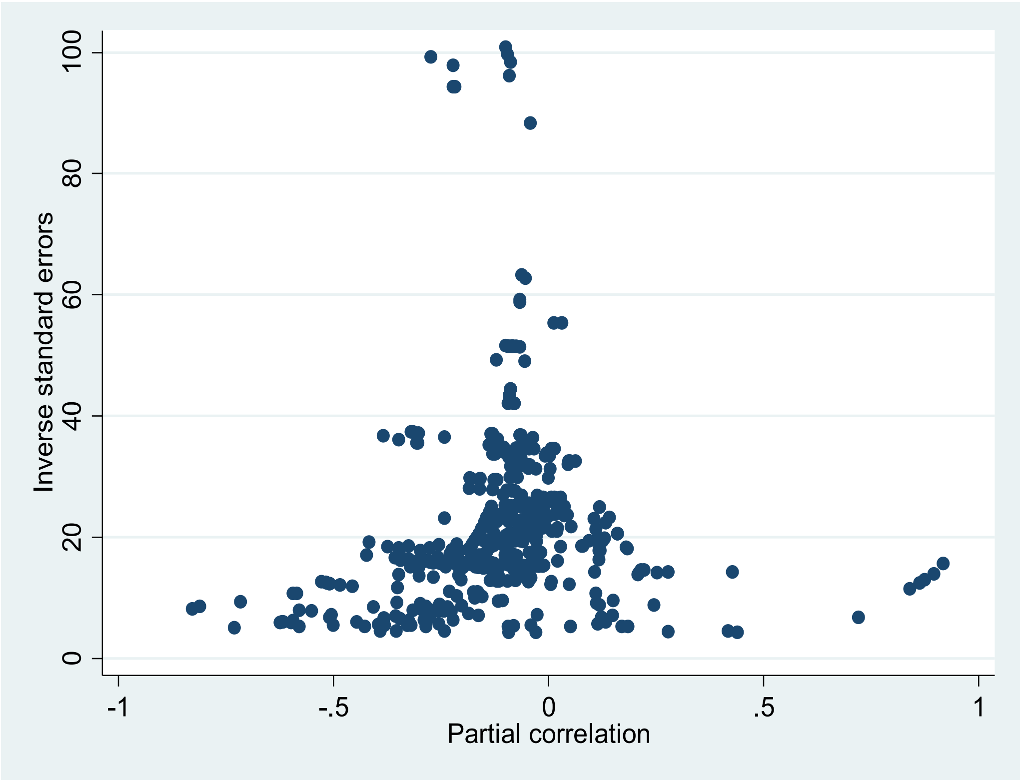
Figures

Figure 1. Box Plot



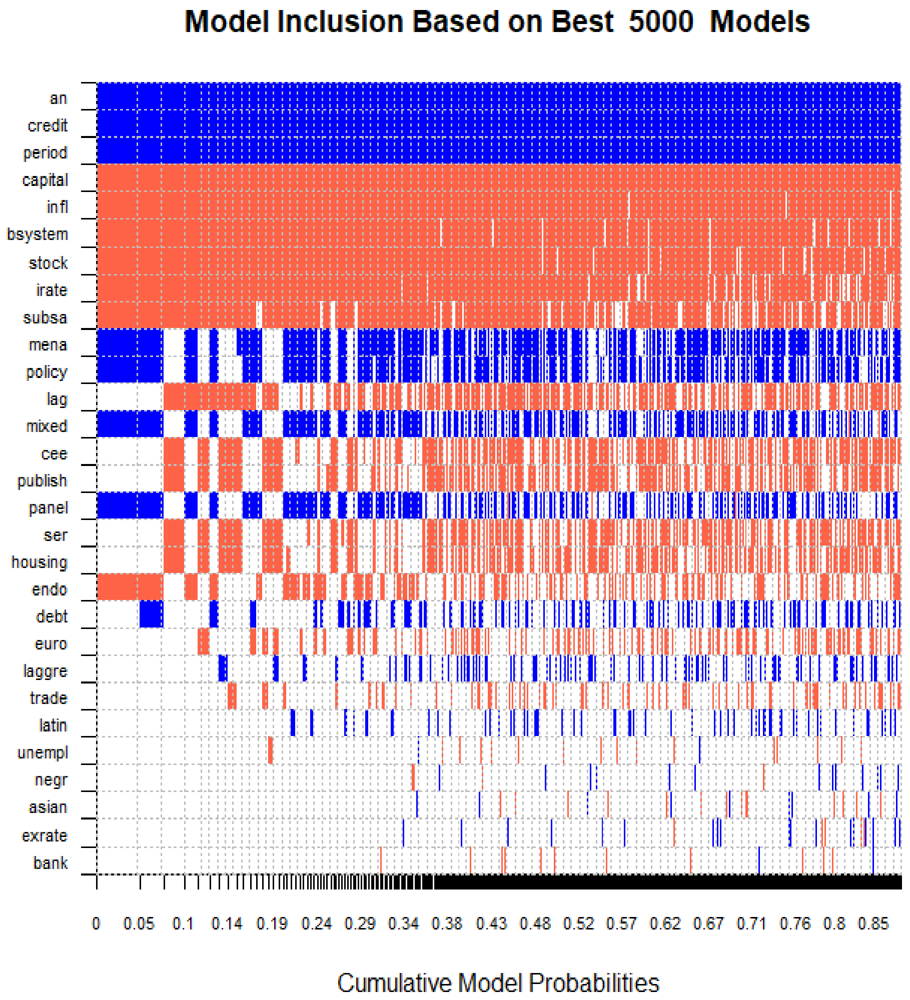
Notes: The figure depicts the boxplot of the collected estimates from the 56 empirical studies. For better exposition of the observed heterogeneity across studies, we have used partial correlation coefficients.

Figure 2. Funnel Plot



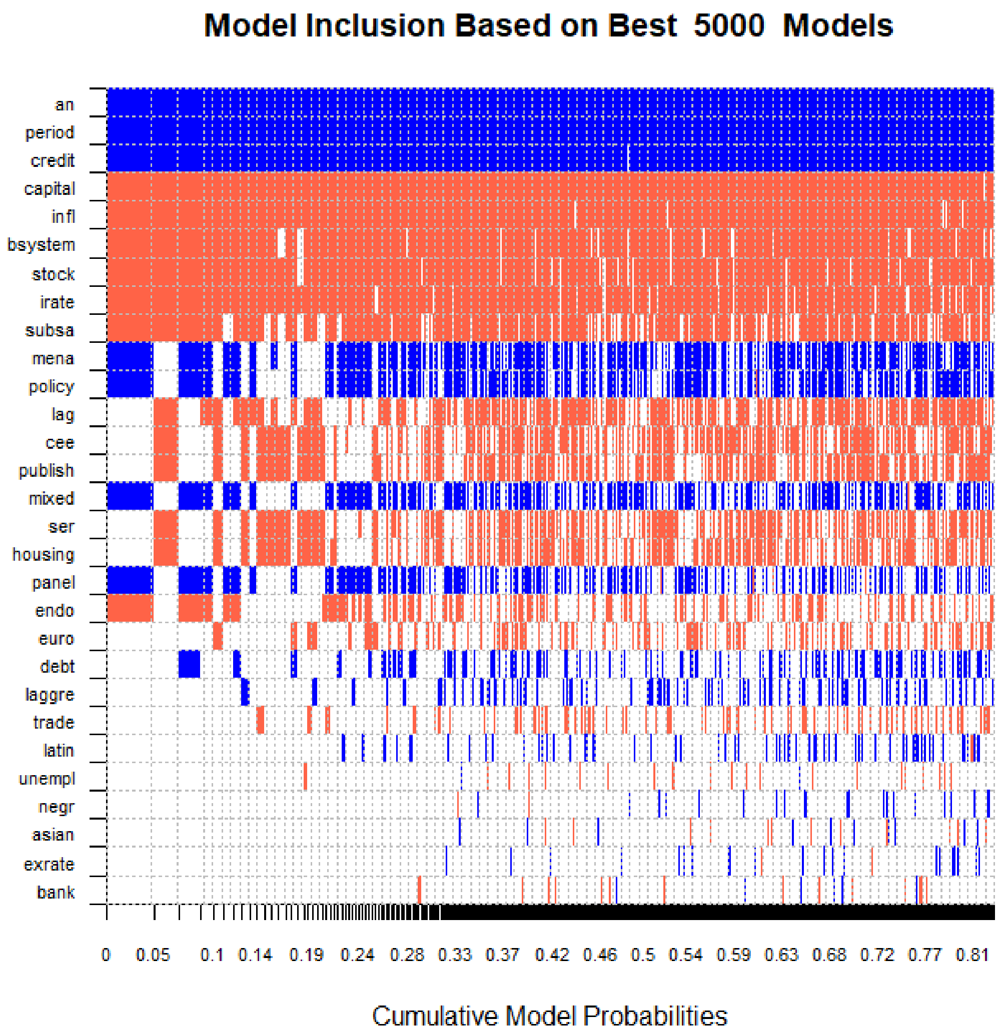
Notes: Presence of symmetry suggests the absence of publication bias and vice versa; an asymmetrical funnel plot indicates a possible publication bias.

Figure 3. Bayesian Map I



Notes: The vertical axis measures the cumulative posterior model probabilities, while the vertical one depicts the moderator variables that are explained in Table 2. Each column shows different model. Each variable in the left axis is sorted according to posterior inclusion probability in descending order meaning that variables on the top appear more frequently across different models than the ones in the bottom. Red color (light grey) shows negative sign, while blue color (dark grey) shows positive sign. Blank entries mean that the variable is not included in the model. 5000 models with the highest posterior probabilities are shown, while assuming unit information prior as parameters' prior and uniform model prior.

Figure 4-Bayesian Map II



Notes: The vertical axis measures the cumulative posterior model probabilities, while the vertical one depicts the moderator variables that are explained in Table 2. Each column shows different model. Each variable in the left axis is sorted according to posterior inclusion probability in descending order meaning that variables on the top appear more frequently across different models than the ones in the bottom. Red color (light grey) shows negative sign, while blue color (dark grey) shows positive sign. Blank entries mean that the variable is not included in the model. 5000 models with the highest posterior probabilities are shown, while assuming Zellner's *g* prior as parameters' prior and beta-binomial model prior.

Tables

Table 1. Selection Reporting Bias

	WLS	FE	RE
Slope coefficient β_0	-0.151***	-0.199***	-0.2***
	(0.038)	(0.053)	(0.038)
Intercept β_1	0.002	0.004	0.003**
	(0.001)	(0.002)	(0.002)
j	56	56	56
n	574	574	574

Notes: *j* refers to the number of studies and *n* stands for the number of total observations. Clustered standard errors reported in parenthesis.

Table 2. List of Moderator Variables

Variable Name	Abbreviation	Variable Description	Mean	SD
Partial Correlation	ρ		-0.118	0.188
Standard error of partial correlation	SEρ		0.065	0.042
		Data Characteristics		
Type of Data	Panel	D=1, when time-series or cross section data are used	0.911	0.285
Frequency of observations	An	D=1, when quarterly or monthly data are used	0.467	0.499
Type of Analysis (single banking system vs. set of countries)	Bsystem	D=1, when the analysis focuses on a set of countries	0.336	0.473
		Endogeneity-Econometric Method		
Endogeneity	Endo	D=1, when the econometric method takes into account the endogeneity	0.589	0.492
		Specification		

Bank-specific variables	Bank	D=1, when bank-specific variables are included as control variables	0.502	0.500
Lag endogenous Dummy	Lag	D=1, when lags of dependent variable are included	0.669	0.471
GDP lag structure	laggre	D=1, when lags of real GDP growth are included	0.594	0.491
Number of Regressors	Nreg	Number of regressors included	9.012	5.064
Trade	Trade	D=1, when measures of trade are included	0.033	0.179
Capital Flows	Capital	D=1, when measures of capital flows are included	0.016	0.124
Exchange Rate	exrate	D=1, when exchange rates are included	0.195	0.397
Inflation	Infl	D=1, when inflation is included	0.172	0.378
Interest Rate	Irate	D=1, when interest rates variables are included	0.432	0.496
Unemployment	Unempl	D=1, when unemployment is included	0.256	0.437
Stock Market Indices	Stock	D=1, when Stock Market Indices are included	0.054	0.226
Property Prices Indices	Housing	D=1, when indices od residential and commercial property prices are included	0.068	0.252
Credit Growth	Credit	D=1, when credit growth is included	0.077	0.266
Debt	Debt	D=1, when measures of debt are included	0.016	0.124
		Publication Characteristics		
Published/Working paper	Publish	D=1, when the study is published	0.735	0.442
Policy	Policy	D=1, when at least one author is affiliated with a central bank or a policy institution as the IMF or World Bank	0.718	0.450
		Geographical Characteristics and Period covered		
Central-Eastern Europe	Cee	D=1, when the observation comes from CEE	0.071	0.258

Euro Area	Euro	D=1, when the observation comes from Euro Area	0.298	0.458
Middle East North Africa	Mena	D=1, when the observation comes from MENA	0.057	0.233
Asia	asian	D=1, when the observation comes from Asia	0.092	0.290
Latin America	Latin	D=1, when the observation comes from Latin America	0.225	0.418
Sub-saharian	Subsa	D=1, when the observation comes from sub-Saharan Africa	0.016	0.124
Mixed	Mixed	D=1, when the observation comes from dataset that includes heterogeneous countries	0.190	0.393
Advanced		Base		
Time period covered	Period	D=1, when the 2008/2009 global financial crisis is included in the sample	0.700	0.459

Notes: The total number of observations is 574 collected from 56 studies.

Table 3. BMA Estimation

Variable Name	PIP	posterior mean	posterior SD
Panel	0.514	0.054	0.059
an	1.000[a]	0.153	0.031
bsystem	0.982[a]	-0.1340	0.055
endo	0.418	-0.024	0.032
bank	0.032	-0.001	0.004
lag	0.625	-0.036	0.032
laggre	0.194	0.006	0.015
negr	0.037	0.000	0.000

trade	0.172	-0.020	0.052
capital	0.999[a]	-0.429	0.082
exrate	0.034	0.004	0.006
infl	0.989[b]	-0.090	0.025
irate	0.947[b]	-0.065	0.024
unempl	0.051	-0.001	0.008
stock	0.977[b]	-0.127	0.040
housing	0.489	-0.066	0.075
credit	1.000[a]	0.248	0.046
debt	0.275	0.036	0.066
SEρ	0.506	-0.325	0.359
publish	0.515	-0.043	0.048
policy	0.647	0.057	0.048
cee	0.535	-0.084	0.088
euro	0.275	-0.015	0.027
mena	0.689	0.128	0.102
asian	0.037	0.000	0.008
latin	0.113	0.005	0.018
subsa	0.880[c]	-0.180	0.091
mixed	0.573	0.076	0.072
period	1.000[a]	0.110	0.021

Notes: We assume unit information prior as parameters' prior and uniform model prior. *PIP* stands for posterior inclusion probability; *post Mean* is the posterior mean and *post SD* is the posterior standard deviation. *a/b/c* denotes decisive/strong/positive evidence of a regressor having an effect respectively, according to Kass and Raftery (1995).

Table 4. BMA and Classical estimation results

	BMA results			Frequentist results	
Variable Name	PIP	post-mean	post SD	coefficient	SD
panel	0.476	0.050	0.059	0.061	0.042
an	1[a]	0.150	0.033	0.142	0.046***
bsystem	0.943[b]	-0.127	0.060	-0.139	0.065**
endo	0.388	-0.022	0.031	-0.046	0.036
bank	0.030	0.000	0.004		
lag	0.581	-0.034	0.033	-0.044	0.053
laggre	0.193	0.006	0.015		
negr	0.037	0.000	0.000		
trade	0.181	-0.022	0.054		
capital	0.997[a]	-0.422	0.086	-0.479	0.088***
exrate	0.036	0.000	0.007		
infl	0.988[b]	-0.0903	0.025	-0.081	0.036**
irate	0.937[b]	-0.064	0.025	-0.079	0.027***
unempl	0.046	-0.001	0.008		
stock	0.939[b]	-0.121	0.047	-0.142	0.073*
housing	0.523	-0.071	0.075	-0.084	0.059

credit	0.999[a]	0.242	0.053	0.268	0.077***
debt	0.266	0.035	0.065		
SEρ	0.535	-0.346	0.361	-0.448	0.284
publish	0.542	-0.045	0.047	-0.056	0.053
policy	0.617	0.054	0.048	0.069	0.039
cee	0.570	-0.090	0.087	-0.116	0.073
euro	0.281	-0.015	0.028		
mena	0.660	0.121	0.102	0.146	0.073
asian	0.037	0.000	0.009		
latin	0.107	0.005	0.018		
subsa	0.824[c]	-0.170	0.099	-0.212	0.116*
mixed	0.540	0.071	0.072	0.080	0.057
period	1[a]	0.109	0.022	0.120	0.037***

Notes: We assume Zellner's *g* prior as parameters' prior and beta-binomial model prior. *PIP* stands for posterior inclusion probability; *post Mean* is the posterior mean and *post SD* is the posterior standard deviation. *a/b/c* denotes decisive/strong/positive evidence of a regressor having an effect respectively, according to Kass and Raftery (1995). For the frequentist check, the variables with *PIP>0.3* are included. Statistical significance is indicated with stars: ***, ** and * denotes statistically significance at the 1%, 5% and 10% significance levels, respectively. Clustered standard errors are used based on study level.

APPENDIX

Table A-Papers used in the meta-study

1. Abid, L., Ouertani, M. N., & Zouari-Ghorbel, S. (2014). Macroeconomic and bank-specific determinants of household's non-performing loans in Tunisia: A dynamic panel data. *Procedia Economics and Finance*, *13*, 58-68.
2. Ahmad, F., & Bashir, T. (2013). Explanatory Power of Macroeconomic Variables as Determinants of Non-Performing Loans: Evidence from Pakistan. *World Applied Sciences Journal*, *22*(2), 243-255.
3. Alhassan, A. L., Kyereboah-Coleman, A., & Andoh, C. (2014). Asset quality in a crisis period: An empirical examination of Ghanaian banks. *Review of Development Finance*, *4*(1), 50-62.
4. Athanasoglou, P. P. (2011). Bank capital and risk in the South Eastern European region., Working Paper, Bank of Greece.
5. Babihuga, R. (2007). *Macroeconomic and financial soundness indicators: An empirical investigation* (No. 7-115). International Monetary Fund.
6. Bardhan, S & Mukherjee, V. (2016), Bank-specific determinants of nonperforming assets, *International Economic Policy*, 13, 483-498.
7. of Indian banksBeck, R., Jakubik, P., & Piloiu, A. (2013). Non-performing loans: What matters in addition to the economic cycle?, ECB Working Paper No. 1515
8. Bertay, A. C., Demirgüç-Kunt, A., & Huizinga, H. (2015). Bank ownership and credit over the business cycle: Is lending by state banks less procyclical? *Journal of Banking & Finance*, *50*, 326-339.
9. Bock de., Reinout & Demyanets, A. (2012). Bank Asset Quality in Emerging Markets: Determinants and Spillovers. *IMF Working Paper 71*.
10. Boudriga, A., Boulila Taktak, N., & Jellouli, S. (2009). Banking supervision and nonperforming loans: a cross-country analysis. *Journal of financial economic policy*, *1*(4), 286-318.
11. Boudriga, A., Taktak, N. B., & Jellouli, S. (2010, September). Bank specific, business and institutional environment determinants of banks nonperforming loans: evidence from mena countries. In *Economic Research Forum, Working Paper* (Vol. 547, pp. 1-28).
12. Breuer, J. B. (2006). Problem bank loans, conflicts of interest, and institutions. *Journal of Financial Stability*, *2*(3), 266-285.
13. Buncic, D., & Melecky, M. (2013). Macroprudential stress testing of credit risk: A practical approach for policy makers. *Journal of Financial Stability*, *9*(3), 347-370.

14. Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling*, *31*, 672-683.
15. Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research in international business and finance*, *33*, 1-16.
16. Das, A. and S. Ghosh (2007), "Determinants of Credit Risk in Indian State-owned Banks: An Empirical Investigation." *Economic Issues*, 12(Part 2).
17. Davis, E. P. and H. Zhu (2009), "Commercial property prices and bank performance." *The Quarterly Review of Economics and Finance*, 49(4) 1341-1359.
18. De Bock, R., & Demyanets, M. A. (2012). *Bank asset quality in emerging markets: Determinants and spillovers* (No. 12-71). International Monetary Fund.
19. Diaconaşu, D., M. Popescu and O.-R. Socoliuc (2014), "Macroeconomic Determinants of Non-Performing Loans in Emerging Markets: Evidence from Central and Eastern Europe". Working Paper, University of Iasi.
20. Espinoza, R. A. and A. Prasad (2010), "Nonperforming loans in the GCC banking system and their macroeconomic effects." IMF Working Papers, 1-24.
21. Festiæ, M., & Bekõ, J. (2008). The banking sector and macroeconomic performance in Central European economies. *Czech Journal of Economics and Finance (Finance a uver)*, *58*(03-04), 131-151.
22. Fofack, H. (2005), "Nonperforming loans in Sub-Saharan Africa: causal analysis and macroeconomic implications." World Bank Policy Research Working Paper,(3769).
23. Gerlach, S., W. Peng, et al. (2005), "Macroeconomic conditions and banking performance in Hong Kong SAR: a panel data study.", BIS Working paper 481.
24. Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, *20*, 93-104.
25. Gizycki, M. C., & Gizycki, M. (2001). *The effect of Macroeconomic conditions on banks' risk and profitability*. Reserve Bank of Australia.
26. Goel, R. K., & Hasan, I. (2011). Economy-wide corruption and bad loans in banking: international evidence. *Applied Financial Economics*, *21*(7), 455-461.

27. Greenidge, K., & Grosvenor, T. (2010). Forecasting non-performing loans in Barbados.. *Journal of Business, Finance & Economics in Emerging Economies*, *5*(1).
28. Guy, K., & Lowe, S. (2011). Non-performing loans and bank stability in Barbados. *Economic Review*, *37*(1), 77-82.
29. Jakubik, P. (2007). Macroeconomic environment and credit risk. *Czech Journal of Economics and Finance*, *57*(1-2), 60-78.
30. Jakubík, P., & Reininger, T. (2013). Determinants of nonperforming loans in Central, Eastern and Southeastern Europe. *Focus on European Economic Integration*, *3*, 48-66.
31. Janvisloo, A. and M. Junaina (2013), "Sensitivity of Non-Performing Loans to Macroeconomic Variables Malaysia Banking Sector: Panel Evidence." *World Applied Sciences Journal*, 28(12) 2128-2135.
32. Jiménez, G., J. A. Lopez, et al. (2013), "How does competition affect bank risk-taking?" *Journal of Financial Stability*, 9(2) 185-195.
33. Jiménez, G. and J. Saurina (2006), "Credit Cycles, Credit Risk, and Prudential Regulation." *International Journal of Central Banking*.
34. Kauko, K. (2012), "External deficits and non-performing loans in the recent financial crisis." Economics Letters, 115(2) 196-199.
35. Kauko, K. (2014), "Do Bailouts Cause Moral Hazards or Franchise Value in Banking?" *Kyklos*, 67(1) 82-92.
36. Khemraj, T., & Pasha, S. (2009). The determinants of non-performing loans: an econometric case study of Guyana. Working Paper.
37. Küçüközmen, C. C., & Yüksel, A. (2006). A macroeconometric model for stress testing credit portfolio. In *13th Annual Conference of the Multinational Finance Society*.
38. Louzis, D. P., A. T. Vouldis, et al. (2012), "Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios." *Journal of Banking & Finance*, 36(4) 1012-1027.
39. Makri, V., A. Tsagkanos, et al. (2014), "Determinants of non-performing loans: The case of Eurozone." *Panoeconomicus*, 61(2) 193-206.
40. Messai, A. S. and F. Jouini (2013), "Micro and Macro Determinants of Non-performing Loans." *International Journal of Economics and Financial Issues*, 3(4) 852-860.

41. Moinescu, B. G. (2012). Determinants of nonperforming loans in Central and Eastern European Countries: macroeconomic indicators and credit discipline. *Review of Economic and Business Studies*, (10), 47-58.
42. Morales, M. A. M., & Gasha, J. G. (2004). *Identifying threshold effects in credit risk stress testing* (No. 4-150). International Monetary Fund.
43. Nkusu, M. M. (2011). *Nonperforming Loans and Macrofinancial Vulnerabilities in Advanced Economies* (No. 11-161). International Monetary Fund.
44. Pestova, A., & Mamonov, M. (2013). *Macroeconomic and bank? specific determinants of credit risk: evidence from Russia* (No. 13/10e). EERC Research Network, Russia and CIS.
45. Quagliariello, M. (2007), "Banks' riskiness over the business cycle: a panel analysis on Italian intermediaries." *Applied Financial Economics*, 17(2) 119-138.
46. Rajan, R., & Dhal, S. C. (2003). Non-performing loans and terms of credit of public sector banks in India: An empirical assessment. *Occasional Papers*, *24*(3), 81-121.
47. Salas, V. and J. Saurina (2002), "Credit risk in two institutional regimes: Spanish commercial and savings banks." *Journal of Financial Services Research*, 22(3) 203-224.
48. Shijaku, H., & Ceca, K. (2011). *A Model for the Credit Risk in Albania Using Bank's Panel Data*. Bank of Albania.
49. Shu, C. (2002), "The impact of macroeconomic environment on the asset quality of Hong Kong's banking sector." Hong Kong Monetary Authority Research Memorandums, 1-26.
50. Škarica, B. (2014), "Determinants of non-performing loans in Central and Eastern European countries." Financial Theory and Practice, 38(1) 37-59.
51. Swamy, V. (2012). Impact of macroeconomic and endogenous factors on non-performing bank assets. *International Journal of Banking and Finance*, *9*(1), 2.
52. Thiagarajan, S. (2013). Determinants of Credit Risk in the Commercial Banking Sector of Belize. *Research Journal of Social Science and Management*, 3(4).
53. Vazquez, F., B. M. Tabak, et al. (2012), "A macro stress test model of credit risk for the Brazilian banking sector." *Journal of Financial Stability*, 8(2) 69-83.

54. Wu, W.-C., C.-O. Chang, et al. (2003), "Banking System, Real Estate Markets, and Nonperforming Loans." *International Real Estate Review*, 6(1) 43-62.
55. Yurdakul, F. (2014). Macroeconomic modelling of credit risk for banks. *Procedia-Social and behavioral sciences*, *109*, 784-793.
56. Zeman, J., & Jurca, P. (2008). Macro stress testing of the Slovak banking sector. *National bank of Slovakia working paper*, *1*.