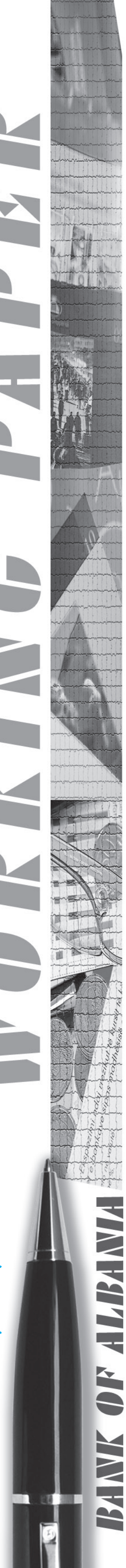
WORKING PAPER



A MODEL FOR THE CREDIT RISK IN ALBANIA USING BANKS' PANEL DATA

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1. INTRODUCTION

The recent financial crisis showed that the credit risk is an important source of risk of the financial system (Thoraval 2006, Moretti et al. (2008). Thoraval (2006) notes that credit risk associated to firms' failures and macroeconomic uncertainties amounts to 85% of bank's risks, and is considered as the key risk faced by banks. To defend against this risk, banks employ a large amount of capital and create provisions for which the opportunity cost is significant. According to Segoviano and Padilla (2006), to withstand the unexpected losses that its portfolio could experience, a bank holds economic capital. Basel Committee on Banking Supervision, 2001, defines unexpected losses as the 99.5 Value at Risk (VaR) of the probability loss distribution. The difference between the actual capital base of a financial institution and the economic capital calculated on the basis of the riskiness of its portfolio under different macroeconomic scenarios provides a measure of the solvency of the institution. In this context, stress tests are developed to assess the impact of the occurrence of a given scenario in the probability of default of the assets portfolio. Further refining the issues addressed by stress tests, the latter can be designed to identify potential vulnerabilities at the institution level or at the system level. In this paper we discuss the latter, and develop a framework for the banking system in Albania.

Moretti et al. (2008) summarise the mainstream approaches to stress testing and distinguish between sensitivity analysis, which addresses the impact of shocks to single risk factors, and scenario analysis, in which multiple risk factors are shocked in a way that provides internal consistency between them. Though historically prevailing among the macroprudential tools used by central banks, sensitivity analysis is nowadays seen as complementary to scenario analysis, for instance, as a means of obtaining some sense of the partial derivatives that may be associated with a broader, multi-factor scenario (Moretti et al., 2008). Sorge and Virolainen (2006) make a distinction between two classes of stress-testing models. In the "piecewise approach", a direct relationship between macroeconomic variables and indicators of financial soundness is estimated (balance sheet models). The estimated parameters of these models can be used later to simulate the impact of severe scenarios on the financial system. Balance sheet models can be either structural or reduced-form. The other class of models is the "integrated approach", in which multiple risk factors (credit, market risk etc.) are combined to estimate a probability distribution of aggregate losses that could arise in a stress scenario.

In this paper, we devise a macro stress test for Albania assessing the impact of the direct and indirect credit risk channels using aggregated banks data. We model the quality of the banks portfolio as a function of macroeconomic and financial variables to identify the systematic credit risk factors, which the central bank should consider in its function of preserving the financial stability. We extend the previous findings in this area in two directions. First, we test whether the relationship between loan quality and its determinants has been altered during the last two years of financial turmoil. Second, given the relatively high concentration in the Albanian banking system, we test if there are significant differences in credit quality responses to changes in financial and macroeconomic variables according bank specific characteristics. This stress test could be used as a satellite to the existing macroeconomic model in the Bank of Albania (BoA), to examine the macroeconomic implications of the scenarios derived by the latter or alternatively, the estimated parameters can be employed in sensitivity analysis.

The paper is structured as follows: In section 2, we conduct a review of the existing literature on macro stress tests in order to identify a suitable strategy for our investigation. In section 3, we discuss previous findings for Albania, identify areas for improvement and present our approach and research hypothesis. In section 4, we explain the empirical estimation and discuss the results. In the section 5, we present our conclusions, limitations of the research and future areas for possible improvement.

2. LITERATURE REVIEW ON CREDIT RISK MODELS

This section looks at the modelling strategies used for stress testing credit risk. By critically reviewing the various stages of the analysis, we identify the advantages and disadvantages of each of the choices made, in order to select a strategy for our own model and acknowledge the possible limitations. The section builds largely on Shijaku and Ceca (2010), in which a more extensive review of the literature is conducted; however, in order to make a direct link to the model and variable selection presented further in the paper, we summarise the main issues.

In a survey of stress tests practices, Cihak (2007) and Foglia (2009) distinguish the following steps in the process: (i) identification of main risk factors and channels in which shocks are transmitted; (ii) the construction of a scenario; (iii) identification of changes that the outputs of the scenarios cause on the institutions' balance sheets and income statements; (iv) performing the numerical analysis; (v) considering any second-round effects; and (vi) summarizing and interpreting the results.

Following the above discussion for the identification in the first stage, a stress event arising from exogenous factors is identified. The stress event can be thought as a shock which affects the domestic economy and which is very large, but still possible. The production of a scenario for the macroeconomic environment may be possible either by using historical information (Blavy, 2006), by using macroeconometric models, which is often the preferred approach of FSAPs or by using VARs and a set of AR equations which explain the joint evolution of macroeconomic and financial variables (Wong, 2006, Van den End et al., 2006 Castren et al., 2009) and/or (iii) pure statistical approaches (OENB).

In cases when macroeconometric models do not include financial sector variables, the stress testing framework is extended to include separate "satellite" models, which transmit the effects of macroeconomic variables to "key" financial intermediation responses (such as credit growth) and, in a third stage, link the latter together with macroeconomic variables to financial sector measures of asset quality and potential credit losses. The losses are then used to derive the buffers of profit and capital under various scenarios. Several studies have modelled default probabilities as non-linear functions of macro variables following Wilson (1997). The main advantage in using structural macroeconomic models lies in the fact that they impose consistency across the predicted values in the stress scenario. Moreover, they may allow for endogenous policy reactions to the initial shock. Scenarios cover a set of macro variables such as GDP, interest rates, and exchange rates, and range from less severe to crisis-type scenarios. In some cases, as reported by Moretti et al. (2008), variables accounting for cross-border lending, foreign currency lending, country exposure, or loan concentrations in general are also included. A major problem of these modelling strategies is that they are primarily devised for "normal business" times and the linearity embedded in them may fail to adequately represent the nonlinear behaviour characteristic of times of stress. Moreover, it is difficult to determine the likelihood of a specific scenario to implement in a stress test (Shijaku and Ceca 2010).

Vector Autoregressions (VARs) or Vector Error Correction models (VECMs) jointly combine the effects of exogenous shocks into various macroeconomic variables, which are then used in the scenario. These can also be extended to include some financial variables and allow for feedback effects (Babouček and Jančar 2005, Chan-Lau, 2006). Usually these models are used as an alternative to macroeconomic models; besides being substitutes for them, they are relatively flexible and produce a set of mutually consistent shocks, although they do not include the economic structure that is incorporated in the macroeconomic modelling approach. Allowing feedback effects between financial distress and the business cycle conforms the financial accelerator theory, which suggests that a decline in net worth in the corporate sector raises funding costs and leads to lower aggregate investment, and in turn, to lower future output. Agency theory also indicates that the incentive for corporations to invest in riskier projects increases as their credit quality deteriorates. In turn, this risk-shifting behaviour leads to higher output volatility (Chan-Lau, 2006). Once the VAR system is estimated, the sensitivity of default probabilities to shocks to the different economic variables can be quantified using impulse response analysis. Since IR analysis will depend on the restrictions used in the contemporaneous effects matrix, the ordering should reflect the speed of adjustment of the different variables to the shocks, which can be determined either from theory or empirical analysis (Hoggarth, Sorensen, and Zicchino, 2005).

A third approach is a purely statistical approach in which macroeconomic and financial variables are modelled through a multivariate t-copula to devise a scenario. This approach has the advantage of identifying the marginal distributions, which can be different from the multivariate distribution that characterizes the joint behaviour of the variables. In addition, the relationship between the macroeconomic variables and the financial variables displays tail dependence (i.e., "correlation" increases when the system is under stress). The main disadvantage lies in the fact that a purely statistical approach does not identify the key transmission channels that link the shock with its effect on the degree of credit risk.

In a second stage, macroeconomic scenarios are mapped into the financial variable proxing the credit quality or the probability of default. Typically this variable is the NPL ratio or the LLP, in absence of the former. These regression models include loan performance measures such as non-performing loans (NPL) or loan loss provisions (LLP) as dependent variables; explanatory variables typically include a set of macroeconomic indicators, sometimes bank/industry specific variables such as measures of indebtedness or market-based indicators of credit risk depending on the level of aggregation. Variables such as economic growth, unemployment, interest rates, equity prices and corporate bond spreads contribute to explaining default risk. Two points are worth stressing: first, the estimation regards different degrees of disaggregation such as by industry, type of borrower (sector), bank or individual borrower. Large concentration of the total portfolio hence calls for a careful selection of the determinants, favouring the group/industry specific ones over the usual broader macroeconomic aggregates. Second, to capture the credit crunch phenomena, or in more general terms the functioning of the credit channel, there should be some feedback effects, which link the credit quality with the supply of loans and as a final result endogenise economic/industry growth. Alternatively to historical NPL or LLP data, micro-level data related to the default risk of the household and/or the corporate sector can be used (Cihak, 2007).

Blaschke et al. (2001) models unexpected credit losses arising from external shocks by empirically estimating the determinants of observed default frequencies as captured by NPL ratios, which can be interpreted as a default frequency ratio. He proposes regressing NPL/total assets on a set of macroeconomic variables, including the nominal interest rate, inflation, GDP growth and percentage change in terms of trade. In addition, he proposes estimating this equation disaggregated NPL data across homogenous groups of borrowers. If we assume linearity in the risk exposures, the volatility of the ratio of NPLs to total assets can be expressed as a function of the variances of the regressors and the correlations between them; however, he recommends using Monte Carlo simulation techniques when this assumption is relaxed.

Hoggarth, Sorensen, and Zicchino (2005) use a VAR system to analyze the impact of macroeconomic factors on UK banks' loan write-offs, both at the aggregate and at the sectoral level. The economic variables included in their model are the output gap, the annual rate of retail price inflation, and the nominal bank short-term interest rate. They show that the write-off ratio to aggregate loans declines in response to positive output gaps or unexpected increases of the short-term interest rate. Positive inflation surprises, however, reduce the write-off ratio, as it is associated with positive economic growth surprises. The authors also report forecasting equations for write-off ratios for non-financial corporate and household loans. These equations include as additional variables the annual house price inflation and the real income of the household sector. In the case of the non-financial corporate sector, the debt-to-market value of equity is also included. In the case of the household sector, mortgage arrears are included as a financial distress indicator.

Castren et al. (2009) study the effects of macroeconomic shocks on VaR for different banks through two steps. First, they estimate a GVAR (Global Vector Autoregression) model to obtain impulse responses for real Gross Domestic Product (GDP), real stock prices, inflation, short-term and long-term interest rates and the EUR-USD exchange rate. In the second step, the results of these macroeconomic shocks are regressed on the sector-specific probability of default (PD) values.

Van den End et al. (2006) develop reduced-form balance sheet models to estimate the impact of macro variables on LLPs using data for the 5 largest Dutch banks. In modelling credit risk, they use two basic equations. First, they estimate the relationship between borrower defaults and real GDP growth, long-term interest rates, short-term interest rates and the term spread. In a second step, they develop a fixed effects regression model explaining LLPs using the default rate together with some macro variables. By using different constant terms, the structural differences in the level of provisions for each bank are taken into account. In the equations, nonlinear functions of the default rate and the ratio of LLPs to total credit – the logit – are used to extend the domain of the dependent variable to negative values and to take into account possible non-linear relationships between the macro variables and LLPs.

Gerlach et al. (2004) estimate a panel data model, which relates the NPLs for each bank with a number of macroeconomic and financial factors as well as the individual bank's characteristics. The set of macroeconomic variables includes growth and inflation, while that of the financial variables includes interest rates and changes in property prices, together with bank-specific variables, such as the asset size and sectoral concentration in lending. To test whether macroeconomic and financial variables have the same impact on all banks, they allow for interaction terms of macroeconomic and financial variables across small, medium and large banks.

For the simulations, Van den End et al. (2006) use the version in Sorge and Virolainen (2006), who simulate default rates over time by generating macroeconomic shocks to the system. The evolution of the related macroeconomic shocks is given by a set of univariate autoregressive equations of order 2 (AR(2)) or, alternatively, by a VAR model. The latter model takes into account the correlations between the macro variables. Van den End et al. (2006) use the vector of innovations, and a variance-covariance matrix of errors, in the equations governing the macroeconomic variables and in the default rate and LLP/credit equations. By using a Cholesky decomposition of the variance-covariance matrix, they are able to obtain correlated innovations in the macroeconomic factors, default rate and LLP/CRED and obtain future paths of the macroeconomic variables, default rate and LLP/CRED by simulation with a Monte Carlo method. With these outcomes and the information on outstanding exposures of the banking sector, the distributions of credit losses are determined. The simulated distributions of losses are skewed to the right, due to the correlation structure of the innovations.

Wong (2006) studies the effects of macro variables on total credit risk and mortgage credit risk in Hong Kong. The model involves the construction of two macroeconomic credit risk models, each consisting of a multiple regression model and a set of autoregressive models, which include feedback effects from the default rate on bank loans to different macroeconomic values estimated by the method of seemingly unrelated regression. The stress testing framework uses Wilson (1997a, 1997b), Boss (2002) and Virolainen (2004) and allows for a more realistic dynamic process, in which the macroeconomic variables are mutually dependent and, most importantly, explicitly captures the feedback effects of bank performances on the economy by letting the macroeconomic variables depend on past values of the financial variables. The set of equations define a system of equations governing the joint evolution of macroeconomic performance, associated default rates and their error terms. By taking non-zero error terms in the default rate equation and allowing for randomness in the behaviour of the macroeconomic variables with the various stochastic components being correlated, he takes into account the probabilistic elements and uses Monte-Carlo simulation to obtain frequency distributions for the default ratios in various scenarios. The default rate is hypothesised to depend on the real GDP growth of Hong Kong, the real GDP growth of mainland China, real interest rates in Hong Kong and real property prices in Hong Kong. Nonlinearities are taken into account by using a logit transformation of the NPL ratio and first differences are used to avoid spurious regression in the presence of nonstationarity in the variables.

Though there is an extensive use of loan performance data to measure credit quality in the literature, several considerations apply (Foglia, 2009). Loan performance as measured by NPLs or LLPs is a "retrospective" indicator of asset quality, in that it reflects past defaults. Provisioning rules, in addition to varying across countries, may also pose a problem for "within country" estimation as they may vary with changes in credit risk in time, bank-specific factors or the use of income-smoothing policies.

One caveat in applying macroeconomic-based models is the necessity for the data series span to contain at least one business cycle, otherwise the model would not capture completely the impact of the business cycle on default probabilities (Chan Lau, 2006). There is empirical evidence of 2 business cycles in Albania between 2004-2009 in Kota (2007).

Another frequent problem in interpreting macroeconomic models of credit risk concerns the use of linear statistical models: in the majority of cases, this is taken into account by using nonlinear specifications, such as the logit and probit transformation to model the default rate. These transformations extend the domain of the dependent variable to negative values and take into account possible nonlinear relationships between macroeconomic variables and the default rate that are likely in stress situations. Several other studies on stress-testing models take nonlinearities into account by including squares and cubes of the macroeconomic variables (Drehmann et al. 2005).

Finally, aggregate economic data are usually reported at substantial lags and subject to revision rendering macroeconomic-based models unsuitable for tracking rapidly deteriorating conditions of a firm or sector.

3. THE MODEL AND DATA SELECTION

A previous study for the macroeconomic determinants of the probability of default of a loan for Albania was done by Shijaku and Ceca (2010). By using the Wilson (1997) framework, they find that the nonperforming loans rate, proxing the probability of default, is determined by the real growth rate, the foreign interest rates, and the exchange rate versus the euro. The reason that the nonperforming loan rate is influenced by the "foreign" variables is the large foreign currency share of loans in the Albanian banking system.

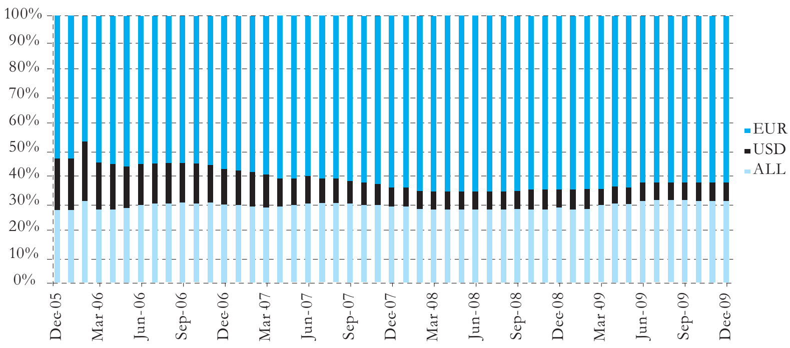
We extend the model in Shijaku and Ceca (2010) to consider the following issues:

First, different factors may be relevant for different currency denominated loan portfolios, hence they should be investigated separately. The introduction of the new regulation for the credit risk management by the Bank of Albania increases the opportunity cost for a bank which invests in foreign currency loans; hence, a gradual shift towards the ALL denominated portfolio is to be expected. In terms of transmission channels, this would reinforce the central bank's policy shocks transmission, and on the other hand influence the credit quality more significantly. In this context, it would be interesting to test if the domestic interest rate shocks affect the credit quality. Figure 1 below shows that a large percentage of credit is in fact in Euro, while ALL and USD constitute a smaller part.

Second, in the last two years, there has been an apparent break in the relationship between the foreign money market rates and the interest rates that banks charge on foreign currency loans. Thus, differently from Shijaku and Ceca (2010), we test if the relevant interest rate is the rate charged on loans rather than the reference rate.

Third, banks are likely to react differently to extreme developments in the scenarios, dependent on a number of individual characteristics such as size, risk aversion, type of business etc. To account for these differences and following Van den End (2006), we use a fixed effects model, which captures the bank specific factors in the constant term.

Figure 1: Currency composition of the loan portfolio



Fourth, the last two years of financial turmoil have seen both a quite large increase in the nonperforming loans rate, as well as an increased role of the financial intermediation. We test if the framework proposed in Shijaku and Ceca (2010) still captures nonlinearities in the relationships between variables and provide a consistency check on the parameters. In particular we are interested in the exchange rate behaviour, which for the period examined by Shijaku and Ceca (2010) has been quite stable. Cihak (2007) argues that in an extreme case when considering a scenario that involves de-pegging in a country with a currency board regime, models estimated on past data cannot capture the impact of the exchange rate change on credit risk, hence other approaches, such as calibration may be more appropriate. Though this is not exactly the case for Albania, large devaluations have not yet been experienced.

3.1 THE DATA

The period considered in this study is 2005Q1-2009Q4, which is 6 years shorter than in Shijaku and Ceca (2010). The reason for that is that the major bank of the banking system was allowed to give loans only in 2004, action which changed the behaviour of other banks as well. We include a balanced panel of 10 banks excluding the small banks which are not active in the credit market. Moretti et al., (2008) argue that including all banks rather than a subsample has the obvious advantage of being more comprehensive, hence, the approach is more adapted to supervisors, who aim the supervision of all institutions. However, when the interest is in macroprudential issues it may be sufficient to include only the systemically important institutions. In our case, the exclusion of the other institutions is also practical for reasons of computational complexity, since the smaller banks have a limited lending activity.

The model follows Shijaku and Ceca (2010) and considers the relationship between the NPL ratio, proxing the probability of default, as the dependent variable, and the real growth, the exchange rates of ALL versus the USD and the EUR, and interest rates as explanatory variables. Explanatory variables are entered with a lag structure selected by the data. We consider the logit transformation of the NPLR separately for ALL and FC portfolios as the dependent variable. This is done in order to extend the range of the dependent variable from [0,1] to R and also to capture nonlinearities in the relationship between NPL ratio and the explanatory variables. The exchange rates considered are both the USD and EUR exchange rates versus the ALL. Interest rates are the banks' weighted average new loan rates for each quarter in ALL, USD and EUR respectively. Money market rates such as the Treasury Bills rate, Euribor and Libor are also considered. Dummy variables for the first years for some of the banks are included to capture the high fluctuations in the NPL rate as a result of an initial small number of borrowers.

3.2 METHOD OF ESTIMATION AND SOME TECHNICAL ISSUES

Following Van den end (2006) and Gerlach et al. (2004) for our estimation, we have selected a fixed effects model in the form of

$$dy_{it} = \alpha_i + \beta x_{it} + \gamma D + \varepsilon_{it}$$

where dy is the first difference of the logit transformation of the NPL ratio (separately for the ALLand FC credit portfolio), and X is the set of the explanatory variables, all of them in first difference with the exception of real growth, and D includes dummy variables. For the exchange rates, we take the first difference of the logarithm. Previous studies for Albania have concluded that the variables transformed as such are I(0). Formal unit root tests are not carried out because of the short estimation sample.

This formulation allows heterogeneity over cross section units via the intercepts while treating slopes as identical over all units. The term ε_{it} it captures general ignorance of determinates of dyit,, while the α_i i captures specific ignorance about bank i. Differently from Shijaku and Ceca (2010) is this first specification: we do not include a lagged dependent variable as it would make the fixed effects estimators biased. We prefer to choose a FE model over a RE model since our results apply only to the units in the study and we do not want to generalise outside the sample. Thus, since N is fixed, FE is more suitable.

Differencing the data minimises autocorrelation and heteroskedasticity, thus improving the chances of correct statistical inference, but it also reduces the absolute size of inter-group variability causing fixed effects to disappear. Thus, we also estimate the model in levels. Richard and Sollis (2003) argue that the unit root problems can be less severe in panel data and recommend the use of a FE in the levels subject to a time trend or a lagged dependent variable to alleviate autocorrelation. Wooldrige (2009) argues that when T is large, when dealing with unit root processes with first differencing, we can apply the central limit theorem. Normality in the idiosyncratic shocks is not needed, and heteroskedasticity and serial correlation can be dealt with by adjusting standard errors for serial correlation and heteroskedasticity. Inference with the fixed effects estimator is potentially more sensitive to nonnormality, heteroskedasticity and serial correlation in the idiosyncratic errors. On the possibility that one of the explanatory variables is not strictly exogenous, for example when a lagged dependent variable is included, the FE estimator likely has substantially less bias than the first difference estimator. The resulting bias in the first difference estimator does not depend on T while the bias in the FE estimator tends to zero at the rate 1/T. In conclusion, Wooldrige (2009) advises to report both results and, when they differ substantially, to try to determine why they differ. In our case, the time series dimension is not very small relative to the cross sectional dimension (N=10 T =20). The bias arising from the inclusion of a lagged dependent variable could be sizeable as argued by Judson and Owen (1999). Various methods have been developed to address this issue, including the use of instrumental variables leading to consistent estimates (Anderson and Hsiao, 1981), a GMM procedure that is more efficient than that of Anderson and Hsiao (1981) proposed by Arellano and Bond (1991) and Arellano and Bover (1995). In future work, we intend to explore whether these techniques improve our estimation.

4. ESTIMATED RESULTS

Our estimations did not find evidence of a satisfactory economic and statistical model for the portfolio in ALL neither in the first differenced model nor in the levels model. We think that a possible explanation for that is its limited use (only 30% of the total portfolio in 2008-2010), as well as the high concentration of it in some of the banks. The investigation of this issue perhaps requires a further disaggregation according to the use of loan, i.e. industry or economic sector, and a further reduction in the number of banks included in the study.

The results for the first differenced model are presented in Box 1. We have excluded insignificant variables from our specification[1]. The coefficients have the correct (expected) sign and we note that the real growth coefficient, although small, is much more important than in previous findings of Shijaku and Ceca (2010). This can be considered as in line with our expectations: the data included in Shijaku and Ceca (2010) displayed very little variation as regards real growth. Other statistically significant variables are the interest rate for loans in USD and the exchange rate versus the USD both current and lagged once. The Euro-denominated loans related variables surprisingly were not significant though this was a finding in Shijaku and Ceca (2010) and is somehow suggested by the last developments in the credit quality. We suspect that perhaps the variability in this explanatory variable is reduced by overdifferencing. Data inspection shows that after the transformations the USD exchange rate displayed much more variability than the Euro exchange rate. However, the NPLs in USD accounted only for about 5% of the total NPLs in 2009, while the NPL in Euro amounted to nearly 60%. Another point worth stressing is that the αi i do not vary significantly, hence evidence of banks reacting differently to economic shocks as a result of their specific characteristics could not be found.

[1] Plots of residuals indicated nonnormality in the residuals, however OLS-based estimators are still unbiased and relatively the most efficient. White corrected standard errors were used to overcome the problem of heteroskedasticity.

BOX 1 First differenced model

In Box 2 we report the estimates using levels. A lagged dependent variable is also included.

Dependent Variable: DYVAL
Sample: 2005Q2-2009Q4 *Periods included: 19*
Cross-sections included: 10 *Total panel (balanced) observations: 190*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.506	0.138	-3.667	0.000
RGDP(-2)	0.057	0.020	2.880	0.005
DUM	-7.564	0.499	-15.158	0.000
DUMRB	5.071	0.497	10.199	0.000
DLNUSD	-2.201	0.918	-2.399	0.018
DLNUSD(-1)	-2.221	0.917	-2.422	0.017
DKRUSD	-0.029	0.013	-2.144	0.033
Effects Specification				
Cross-section fixed (dummy variables)				
R-squared	0.696	Mean dependent var	-0.128	
Adjusted R-squared	0.670	S.D. dependent var	0.839	
S.E. of regression	0.482	Akaike info criterion	1.459	
Sum squared resid	40.444	Schwarz criterion	1.733	
Log likelihood	-122.624	F-statistic	26.547	
Durbin-Watson stat	2.273	Prob(F-statistic)	0.000	

DYVAL is the first difference of the logit transformed NPL ratio, RGDP is the real growth rate, DUM and DUMRB are two dummies capturing the starting period for two of the banks, DLNUSD is the first differenced logarithm of the exchange rate versus the USD. And DKRUSD is the first differenced loan interest rate for USD loans for each bank.

bank	1	2	3	4	5	6	7	8	9	10
αi	0.09	0.142	0.012	-0.242	-0.027	0.021	-0.108	0.045	0.117	-0.051

The αi are bank-specific constant terms.

BOX 2 Levels model

The estimation in levels yielded significant response of the dependent variable to Euro-related variables, namely the exchange rate and the 12-month Euribor rate. The real growth, however, was not significant.

Dependent Variable: YVAL
Sample: 2005Q3-2009Q4 *Periods included: 18*
Cross-sections included: 10 *Total panel (balanced) observations: 180*

Variable	Coefficient		Std. Error	t-Statistic	Prob.
C	51.310	12.035	4.263	0.000	51.310
YVAL(-1)	0.532	0.038	13.943	0.000	0.532
LNEUR(-1)	-10.266	2.464	-4.166	0.000	-10.266
EURIB(-2)	-0.102	0.051	-2.024	0.045	-0.102
Effects Specification					
Cross-section fixed (dummy variables)					
R-squared		0.728	Mean dependent var		3.363
Adjusted R-squared		0.708	S.D. dependent var		1.041
S.E. of regression		0.562	Akaike info criterion		1.756
Sum squared resid		52.794	Schwarz criterion		1.986
Log likelihood		-145.019	F-statistic		37.235
			Prob(F-statistic)		0.000

YVAL is the logit transformed NPL ratio, RGDP is the real growth rate, LNEUR is the logarithm of the exchange rate versus the EUR, and EURIB is the 12-month EURIBOR interest rate.

bank	1	2	3	4	5	6	7	8	9	10
αi_i	-0.122	0.5	0.214	-0.01	-0.103	0.219	-0.298	-0.426	0.07	-0.044

The αi are bank specific constant terms.

5. CONCLUSIONS AND POSSIBLE FURTHER AREAS OF RESEARCH

The analysis so far has concentrated on detecting a model of the response of credit quality to macroeconomic shocks, using banks panel data. Though acknowledging the shortcomings related to lack of robustness in the results, some important findings emerge, which can be further investigated using more sophisticated estimation techniques and longer data series.

First, there is evidence of a stronger response of the credit quality to GDP shocks. Second, no evidence could be found on the response of the ALL portfolio, suggesting that the credit channel may still be weak for transmitting monetary policy if no effects on the exchange rate are assumed. Third, the exchange rates and reference rates in foreign currency lending were found to be important determinants of credit quality. Fourth, no significant differences were found among banks responses; hence, the assumption of a similar response of the credit portfolio to macroeconomic shocks assumed until present by the stress testing practices could be grounded.

Further issues still remain to be considered. One of them is the disaggregation of the credit portfolio by industry or economic sector rather than by banks. A second one is the use of more sophisticated techniques which could avoid the bias and improve the efficiency of the parameter estimates.

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