



BANK OF GREECE
EUROSYSTEM

Special Conference Paper

A credit risk model for Albania

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FEBRUARY 2011

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ISSN 1792-6564

Editorial

On 19-21 November 2009, the Bank of Greece co-organised with the Bank of Albania the 3rd Annual South Eastern European Economic Research Workshop held at its premises in Athens. The 1st and 2nd workshops were organised by the Bank of Albania and took place in Tirana in 2007 and 2008, respectively. The main objectives of these workshops are to further economic research in South Eastern Europe (SEE) and extend knowledge of the country-specific features of the economies in the region. Moreover, the workshops enhance regional cooperation through the sharing of scientific knowledge and the provision of opportunities for cooperative research.

The 2009 workshop placed a special emphasis on three important topics for central banking in transition and small open SEE economies: financial and economic stability; banking and finance; internal and external vulnerabilities. Researchers from central banks participated, presenting and discussing their work.

The 4th Annual SEE Economic Research Workshop was organised by the Bank of Albania and took place on 18-19 November 2010 in Tirana. An emphasis was placed upon the lessons drawn from the global crisis and its effects on the SEE macroeconomic and financial sectors; adjustment of internal and external imbalances; and the new anchors for economic policy.

The papers presented, with their discussions, at the 2009 SEE Workshop are being made available to a wider audience through the Special Conference Paper Series of the Bank of Greece.

Here we present the paper by Hilda Shijaku (Bank of Albania) and Kliti Ceca (Bank of Albania) with its discussion by Faidon Kalfaoglou (Bank of Greece).

February, 2011

Altin Tanku (Bank of Albania)
Sophia Lazaretou (Bank of Greece)
(on behalf of the organisers)

A CREDIT RISK MODEL FOR ALBANIA

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Bank of Albania

Kliti Ceca
Bank of Albania

ABSTRACT

Our methodology takes into account existing methods of stress testing for credit risk for the system as a whole, and adapts them to the Albanian financial intermediation features and data. The model starts by testing the presence of a system of equations (stationary VAR) capturing the joint behaviour of financial and real variables. The equation is modelled to contain some dynamics allowing for the persistence of shocks over more than one period given the backward looking nature of the chosen proxy for the default rate. In the second step, by using Monte Carlo simulations we propose generating the distribution of losses of the default rates. We relax the assumption of zero error terms in the reduced form estimates in step one and simulate univariate/multivariate normally distributed vectors of error terms *via* Monte Carlo methods, where the information on the variance/covariance matrix is obtained from the reduced form equations in step one. Next, we introduce a shock to the nonfinancial variable (growth rate, interest rates, exchange rates etc.) and similarly compute a range of values for the default rate in the stressed scenario.

JEL classification: C51, E58.

Keywords: stress testing, credit risk

Acknowledgments: We would like to thank the participants of the 3rd SEE Workshop for a useful exchange discussion. Special thanks are due to our discussant Faidon Kalfaoglou for his valuable comments and suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Albania and the Bank of Greece. We alone are responsible for the remaining errors and omissions.

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1. Introduction

Stress tests are a very important tool for assessing the ability of economic agents to offset the impact of large shocks on their wealth. In the aftermath of the world's biggest financial crisis since the Great Depression, there is an ever increasing interest in stress testing financial intermediaries to assess their capital needs in the event of large but plausible shocks. The extensive debate about stress tests has covered issues of aggregation/disaggregation of stress tests, top-down *versus* bottom-up approaches and modelling strategies. The various approaches are considered as complementary rather than substitutes as they serve different needs. However, central banks have an important role in all cases by either setting basic standards and coordinating stress tests at the micro level, or tailoring them to assess the financial stability implications of macroeconomic developments and systematic risk.

In this paper, we devise a macro stress test for Albania assessing the impact of the direct and indirect credit risk channels using aggregate data. This stress test could be used as a satellite to the existing macroeconomic model in the Bank of Albania (BoA) that may help in examining the macroeconomic implications of the scenarios derived by the latter. The paper builds on an existing methodology of the top-down approach at the BoA (Financial Sector Assessment Program, FSAP) and proposes a different modelling strategy to identify the channels. The main contribution is the parameterisation of the impact of macroeconomic factors on credit quality for the Albanian banking system. We also propose a method for the assessment of a range of measures of portfolio deterioration under various scenarios integrating a measure of uncertainty in the above assessment.

The paper proceeds 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 outline the existing FSAP methodology, identify areas for improvement and present our approach and research hypotheses. In Section 3, we explain the empirical estimation and discuss the results. In Section 4, we conduct an exercise using the data for September 2008. Finally, Section 5 presents the main conclusion of the analysis and the

limitations of the research followed, and mentions possible areas for further improvement.

2. A review of the literature

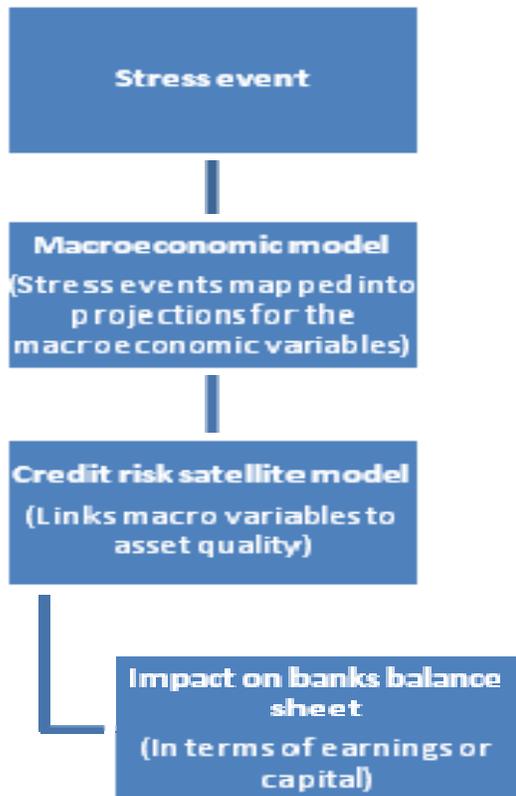
This section looks at the modelling strategies used for stress testing credit risk. By critically reviewing the various stages of the analysis, we identify the advantages and the disadvantages of each of the choices made, in order to select a strategy for our own model and acknowledge the possible limitations.

Stress testing is an increasingly popular method of analysing the resilience of financial systems to adverse events. According to Cihak (2007), stress testing as a process includes: (i) the identification of specific vulnerabilities or areas of concern; (ii) the construction of a scenario; (iii) the mapping of the output of the chosen scenario into a form that is usable for an analysis of the balance sheet and the income statement of the financial institutions; (iv) the performance of the numerical analysis; (v) the consideration of any second round effects; and (vi) the summary and the interpretation of the results. In particular, stress tests for credit risk focus on the risk that a borrower may be unable to repay its debt under specific conditions. Quantifying this risk has advanced markedly since the late 1990s with the development and dissemination of models for measuring credit risk on a portfolio basis.

Sorge and Virolainen (2006) make a distinction between two classes of stress testing models. The first refers to the ‘piecewise approach’, in which a direct relationship between the macroeconomic variables and the 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 ones. The other class of models concerns the ‘integrated approach’, in which multiple risk factors (credit, market risk etc.) are combined to estimate the probability distribution of aggregate losses that could arise in a stress scenario. Several studies have modelled default probabilities as non-linear functions of macro variables (Wilson 1997) or have incorporated them into a value-at-risk (VaR) measure (Sorge and Virolainen 2006).

In a review of the stress testing techniques for credit risk, Foglia (2009) and Cihak (2007) summarize the stages in a macro stress test as shown in Figure 1.

Figure 1. Summary of the stages in a macro stress test



Source: The figure is adapted from Foglia (2009).

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. Then, these shocks are used to produce a scenario for the macroeconomic environment. A common way to execute this stage is to use a macroeconometric model. Given that macroeconometric models do not typically 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.

The effects of the stress scenario on macroeconomic conditions are typically measured using (i) a structural econometric model; (ii) vector autoregressive methods; and/or (iii) pure statistical approaches (Foglia 2009).

Existing structural macroeconomic models (such as those used by the central bank for forecasts and policy analysis) are used to project the levels of key macroeconomic indicators under various scenarios including a set of initial exogenous inputs over a given scenario horizon. Typically all FSAPs use macroeconomic models used for monetary policy purposes and in some cases are extended to incorporate international effects (Foglia 2009). 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. 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 in times of stress. Further, it is difficult to determine the likelihood of a specific scenario to implement in stress testing.

A second approach used in various central bank studies makes use of Vector Autoregressions (VARs) or Vector Error Correction models (VECMs) to jointly combine the effects of exogenous shocks into various macroeconomic variables which are then used in the scenario chosen (Foglia 2009). These models are often 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.

A third approach is used by the Oesterreichische Nationalbank (OeNB) in its Systemic Risk Monitor (SRM), in which a purely statistical approach is used to design a scenario. Macroeconomic and financial variables are modelled through a multivariate t-copula. 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). For policy analysis purposes, however, being a purely statistical approach, it does not identify the key transmission channels that link the shock with its effect on the degree of credit risk.

The second stage of stress testing regards the modelling of auxiliary models that link credit risk to the macroeconomic variables derived in stage one. These models are estimated either for the whole system or for different levels of disaggregation such as by industry, type of borrower (sector), bank or individual borrower. 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 approaches are common (Cihak 2007). One is based on data on loan performance, such as the NPLs, the LLPs or the historical default rates; and the other is based on micro-level data related to the default risk of the household and/or the corporate sector. We concentrate on the former as a full discussion of all approaches is beyond the scope of this section. In models based on loan performance, the key dependent variables are the NPL ratio, the LLP ratio and the historical default frequencies.

Blaschke *et al* (2001) model 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. They propose regressing NPL-to-total assets ratio on a set of macroeconomic variables, including the nominal interest rate, inflation, GDP growth and the percentage change in terms of trade. In addition, they propose estimating this equation by using disaggregated NPL data across homogenous groups of borrowers. If we assume linearity in the risk exposures, the volatility of the ratio of the NPLs to total assets can be expressed as a function of the variances of the regressors and the correlations between them. However, they recommend the use of the Monte Carlo simulation techniques when this assumption is relaxed.

More recently, 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 euro-dollar 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 the macro variables on the 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 effect regression model explaining the 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, non-linear 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 take into account possible non-linear relationships between the macro variables and the LLPs.

For the simulations, van den End *et al* (2006) use the version developed by 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, i.e. 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, the 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 *et al* (2006) study the effects of macro variables on total credit risk and mortgage credit risk in Hong Kong. Their 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 the seemingly unrelated regression. The stress testing framework uses the models developed by Wilson (1997a, 1997b), Boss (2002) and Virolainen (2004), and allows for a more realistic dynamic process in which the macroeconomic variables are mutually dependent. Most importantly, it explicitly captures the feedback effects of bank performance 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, the 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, Wong *et al* take into account the probabilistic elements and use 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 and real property prices in Hong Kong. Non-linearities 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 non-stationarity in the variables.

Though there is an extensive use of loan performance data to measure credit quality in the literature, several considerations are applied (Foglia 2009). Loan performance as measured by the NPLs or the LLPs is a ‘retrospective’ indicator of asset quality because it reflects past defaults. Provision 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.

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

3. The methodology of stress testing in Albania

The methodology of stress testing for credit risk in the BoA is based on directly stressing the growth in non-performing loans of the banking system and measures the effect on the capital adequacy of the banking system. It also stresses GDP growth and estimates its effect on the change in the NPLs of the banking system. The relation between real GDP growth and the growth of the NPLs is assumed to be linear as shown in equation (1)

$$\Delta NPLR_t / NPLR_{t-1} = 2 - 5\Delta GDP_t / GDP_{t-1} \quad (1)$$

which implies that a shock to the nominal growth rate at a given time causes, other things being equal, a corresponding growth of 5 times the shock in the NPL ratio (NPLR). Under the assumption of zero growth in total loans, the relative change in NPLR equals the relative change in NPLs.

In a second step, by assuming a zero value for e , and by shocking the GDP growth rate of the given year, a point estimate of the growth of the NPLs is obtained. These predicted values are (point) estimates of the expected values of the NPLs conditional on the occurrence of the scenario.

Another scenario includes the effect on the NPLR of a currency depreciation capturing the credit risk arising from foreign currency lending and the effects of indirect credit risk from an increase in credit interest rates. For the former, assuming the increase in total debt after a given currency depreciation by $\Delta^r FX$, denoted as $D \cdot \Delta^r FX$, is

incurred all within a year and not amortized throughout the lifetime of the debt, borrowers will face a yearly income loss proportional to the debt in foreign currency to income ratio D/I .

Hence, the relative income change will be:
$$\Delta^r I = \frac{D}{I} \Delta^r FX \quad (2)$$

Following (1) and assuming $\Delta^r I = \Delta^r GDP$

we get equation (3), i.e.

$$\Delta^r NPLR_b = B * \Delta^r I = -B \frac{D}{I} \Delta^r FX \quad (3)$$

where $B=-5$ from equation (1) and the leverage D/I is assumed 2 for all currencies.

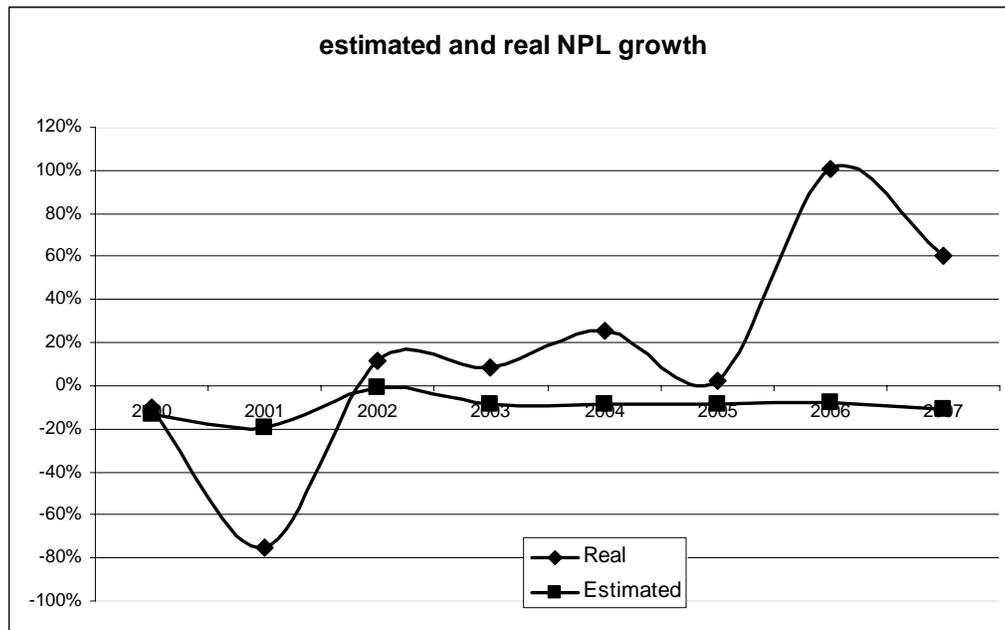
For the indirect credit risk arising from an increase in interest rates and the total increase in debt is faced by the borrowers, the same assumption holds, i.e. all income loss through the increase in debt is incurred within a year. By calculating the debt increase for different remaining maturity re-pricing buckets, the corresponding NPLR equals:

$$\Delta^r NPLR_b = B * \Delta^r I = -B \frac{D}{I} \Delta^r D \quad (4)$$

A number of weaknesses can be identified in the above approach. First, the values of the parameters linking GDP growth to the change in non-performing loans seem unrealistic if we compare the fitted values with the observed values of the change in non-performing loan growth. Hence, the conclusion drawn by stress testing is erratic and biased downward (see Figure 2).

Second, the effect of a shock to GDP on the NPLs may not peak in the same period and will last over some quarters, because of the interactions between industries and various groups of agents. The present model does not include information about this.

Figure 2. Observed and estimated NPL growth



Note: The estimated NPL is according to equation (1).

Third, the present model only provides a point estimate of the probable losses and does not allow us to obtain the range of losses the shock may bring at a desired level of significance. Thus, even if the predicted value of the soundness indicator is not significantly affected by the realization of the adverse scenario, it is hard to conclude that the risk is low because a large deviation from the average may occur with a ‘tangible’ probability. Fourth, once a scenario is chosen, how likely it is to occur is no longer an issue in stress testing (Wong *et al* 2006). Finally, only one economic indicator is modelled, yet the shock may be directly generated through a range of indicators that influence the level of the NPLs and interact with economic growth. By inserting dynamics in the model, we would be able to estimate which effect is bigger and the period in which we expect it to appear.

In the next section, we construct our model by addressing the above mentioned issues.

4. Methodology

Our methodology is based on Wong *et al* (2006). We first construct a model of either a system of equations or single equations linking our variables of interest. In other words, we model non-performing loans as a function of some macroeconomic variables. Second, a Monte Carlo simulation is used to generate the distribution of losses of the default rates under the unstressed and stressed scenarios.

The equations are modelled to contain some dynamics allowing for the persistence of shocks over more than one period given the backward-looking nature of the chosen proxy for the default rate and the effect's persistence caused by the interrelations between different industries and sectors. Empirically, the equations are estimated by means of a stationary VAR, where exogeneity restrictions are imposed on the foreign variables only. Otherwise, domestic macroeconomic variables are allowed to be affected by past values of the default rate. Specifically, we test the following hypotheses:

- a. The default rate both is affected by and affects the economic growth. In the first step, we allow the effect to run from the default rate to economic growth as there might be incentives for commercial banks to restrict credit growth which by construction affects the default rate and negatively impacts economically new investment and thus the growth rate.
- b. The default rate is affected by changes in foreign interest rates (Euribor or Libor rates). In this way, we model indirect foreign interest rate risk which alters payments, and the cash flow of households and firms on loans extended in foreign currency and linked to these interest rates.
- c. The default rate is affected and affects the domestic interest rate. As in point b, we model the indirect domestic interest rate risk.
- d. The default rate is affected by the exchange rates of the Euro and USD *vis-à-vis* the Albanian Lek (ALL). These variables capture deteriorations in the credit portfolio as a result of unhedged borrowing in foreign currency.
- e. The default rate is negatively affected by inflation.

We relax the assumption of zero error terms in the reduced form estimates and simulate univariate/multivariate normally distributed vectors of error terms *via* Monte Carlo methods, where the information on the variance-covariance matrix is obtained from the reduced form equations. Based on the parameters estimated in the VARs and the most updated information on the nonfinancial variables (growth rate, interest rates, exchange rates etc), we compute a range of values for the default rate and obtain confidence levels for the unstressed scenario. Next, we introduce a shock to one of the nonfinancial variables (growth rate, interest rates, exchange rates etc) and similarly compute a range of values for the default rate in the stressed scenario. Although we do not compute the related VaR statistics as in Wong *et al* (2006), they can easily be derived from the model.

5. Empirical estimates

We model the interactions between the financial variables and the set of macroeconomic indicators in the form of a stationary VAR process as in equation (5)

$$Y_t = \varphi_0 + \sum_{i=1}^n \Phi_i L^i (Y_t) + \sum_{j=0}^m \Psi_j L^j (X_t) + e_t \quad (5)$$

where Y_t is a vector of endogenous (domestic) variables, φ_0 is the matrix of deterministic components containing a trend or a constant, dummy variables and seasonal dummies, L is the lag operator, X_t is a vector of exogenous (external) variables and e_t is a sequence of serially uncorrelated random vectors normally distributed with mean zero and positive definite covariance matrix Σ .

Summarizing the hypotheses in Section 2, we define the real growth rate and the default rate as being the endogenous variables while foreign interest rates (Euribor, Libor), exchange rates (ALL/USD and ALL/Euro) and inflation as being the exogenous variables. Given the rate of non-performing loans to total loans taking values in the range $[0, 1]$, we use its logit transformation as in equation (6)

$$y_t = \ln \left(\frac{1 - NPLR_t}{NPLR_t} \right) \quad (6)$$

where $NPLR_t$ denotes the non-performing loans ratio in period t .

A dummy variable is included to account for the write-off of non-performing loans in 2001Q3. Seasonal dummies are also included to alleviate potential problems with diagnostic tests.

Before proceeding, unit root tests are conducted to ensure that the individual series are $I(0)$ processes. To this end, we employ ADF tests, unit root tests with a structural break and DF-GLS tests. Given the low power of the ADF test in small samples, the lag length is chosen as the minimum lag length for which statistical tests do not indicate serial correlation in the residuals of the ADF specification. Saikkonen and Lütkepohl (2002) and Lanne *et al* (2002) propose unit root tests for the model including unknown/known break points, which are based on estimating the deterministic term first by a generalized least squares (GLS) procedure under the unit root null hypothesis and subtracting it from the original series. Then, an ADF type test is performed on the adjusted series which also includes terms to correct for estimation errors in the parameters of the deterministic part. The asymptotic null distribution is nonstandard and critical values are tabulated in Lanne *et al* (2002). We employ this test acknowledging that stationarity is a statistical approximation of the long-run properties of the series; if the time span is very short, a near unit root is most likely to appear as a non-stationary process. Similarly, we can argue that the likelihood of observing ‘structural’ changes in the series or large shocks increases in small samples.

From the results of the unit root tests¹ we may conclude that changes in nominal interest rates and the logarithms of ALL/USD and EUR/USD exchange rates are all $I(0)$. Hence, a stationary VAR can be specified with these variables while avoiding spurious relationships and the persistence of shocks in the system. In the next section, we will present these VARs which are satisfactory both statistically and economically.

The next step in our analysis includes the generation of 20.000 numbers from a normal distribution with mean 0 and variance obtained in step 1 using Monte Carlo procedures for the simulation of a normal distribution. Because a large amount of random

¹ Results of the tests are available on request.

(or pseudorandom) numbers is thus generated, we consider procedures of reduction of the statistical errors by selecting special algorithms.

Although the theory of Monte Carlo simulation gives many formulae for the simulation of random numbers of different distributions, serious statistical errors may happen during the actual simulation using some algorithms. Although theoretically these algorithms are deterministically supposed to generate random numbers from a given distribution, their practical application may produce ‘biased’ numbers because of the approximation given by computers. The computers work based on a limited ‘word length’ and hence obtain limited precision for numerical values of any variable. Truncation and round-off errors may in some cases lead to serious problems of statistical quality. In addition, there are statistical errors which arise as an inherent feature of the simulation algorithm due to the finite number of members in the generated ‘statistical sample’. Some of the errors may be systematic.

In the case of the VAR estimation in which residual autocorrelation is present, the Cholesky decomposition of the variance-covariance matrix of the residuals obtained in step 1 can be used to transform the Monte Carlo $N(0,1)$ generated random vector into mutually correlated shocks for our equations. Alternatively, by obtaining the error terms from the estimation in the macroeconomic model and those for our default rate, we can obtain the variance-covariance matrix and perform a similar exercise.

Based on the parameter estimates obtained in the VAR model and the residuals taken using the Monte Carlo simulation, we obtain values for dy under two scenarios:

- (i) the evolution of the nonfinancial variables is consistent with ‘normal business’, i.e. no change in them or evolution according to a pattern known *ex ante*.
- (ii) the evolution of the nonfinancial series is shocked, according to an extreme but possible scenario.

For both scenarios we can obtain the distribution of the NPLs (after transforming the variable dy) for a given probability.

Acknowledging the problems of inference associated with a VAR on a short data series, the VAR order is chosen as the smallest order which satisfies VAR specification

tests (all using 4 lags): namely, the residuals are serially uncorrelated (on the basis of the LM and Portmanteau tests) and are normally distributed (on the basis on the Jarque-Bera test on skewnesses and kurtosis of the residuals, see Doornik & Hansen 1994 and Lütkepohl 1993) with a homoscedastic variance (on the basis of the ARCH-LM test and multivariate ARCH-LM test). Given that the VAR models are generally suitable for estimation over a relatively homogenous period, we also present VAR stability tests, i.e. the CUSUM and CUSUM squared tests of VAR stability.

Using different VAR orders in an iterative process, we cannot obtain meaningful estimates (i.e. correct sign and significant parameters) of the effects of the abovementioned variables on non-performing loan ratios. Taking into account the effect of multicollinearity on the significance of the parameters, we proceed by estimating the VAR models on dy and the macroeconomic variables separately in order to investigate whether the latter can be specified as exogenous (i.e. there is no significant effect of the lagged dy on the current macroeconomic indicators). Finally, using a parsimonious model which excludes insignificant variables and redundant equations, the following set of equations is obtained (see Table 1-6).

Table 1. Deterioration in GDP

<i>Variable</i>	dy_t	dy_{t-1}	rg_{t-2}	<i>dum Bart</i>	<i>SI</i>
Coefficient	1	0.255	0.009	1.148	-0.137
p-Value		(0.004)	(0.004)	(0.000)	(0.008)

Table 2. Diagnostic tests

	<i>statistic</i>	<i>p-value</i>	<i>df</i>
Autocorrelation			
<i>Portmaneau test (4 lag)</i>	NA		
	NA		
<i>LM-type test</i>	LM 3.1251	0.5371	4
Nonnormality			
<i>Doornik & Hansen (1994)</i>			
joint	0.3886	0.8234	2
skewness only	0.0095	0.9224	2
kurtosis only	0.3791	0.5381	2
<i>Lütkepohl (1993)</i>			
joint	0.3886	0.8234	2
skewness only	0.0095	0.9224	2
kurtosis only	0.3791	0.5381	2
<i>Jarque-Bera test</i>			
joint	0.3886	0.8234	
Heteroscedasticity			
<i>ARCH-LM test</i>			
	4.6927	0.3203	
<i>VARCHLM test</i>			
	4.6927	0.3203	4

Table 3. Foreign interest rate risk

<i>Variable</i>	dy_t	dy_{t-1}	$dnreu_t$	<i>dum Bart</i>	<i>SI</i>	<i>S2</i>
Coefficient	1	0.337	-0.126	1.143	-0.079	0.135
p-Value		(0.000)	(0.071)	(0.000)	(0.108)	(0.004)

Note: sample range: [2000 Q1, 2007 Q4], T = 32

Table 4. Diagnostic tests

	<i>statistic</i>	<i>p-value</i>	<i>df</i>
Autocorelation			
<i>Portmaneau test (4 lag)</i>	NA		
<i>LM-type test</i>	LM 1.8708	0.7595	4
Nonnormality			
<i>Doornik & Hansen (1994)</i>			
joint	0.2087	0.9009	2
skewness only	0.0001	0.9934	2
kurtosis only	0.2086	0.6478	2
<i>Lütkepohl (1993)</i>			
joint	0.2087	0.9009	2
skewness only	0.0001	0.9934	2
kurtosis only	0.2086	0.6478	2
<i>Jarque-Bera test</i>	0.2087	0.9009	
Heteroscedasticity			
<i>ARCH-LM test</i>	4.3519	0.3605	
<i>VARCHLM test</i>	4.3519	0.3605	4

Table 5. Euro/ALL exchange rate

<i>Variable</i>	dy_t	dy_{t-1}	$dlneu_{t-1}$	<i>dum Bart</i>	<i>S1</i>	<i>S2</i>
Coefficient	1	0.0356	-2.536	1.284	-0.092	0.104
p-Value		(0.000)	(0.004)	(0.000)	(0.054)	(0.025)

As is evident from these estimates, all macroeconomic variables appear exogenous to developments in dy , though they may be related to each other. However, this can be taken into account by constructing a scenario outside this model which accounts for the relationship between the macroeconomic indicators (such as a macroeconomic model or previous historical information), and then using this scenario to investigate the effect on dy .

Table 6. Diagnostic tests

	<i>statistic</i>	<i>p-value</i>	<i>df</i>
Autocorrelation			
<i>Portmaneau test (4 lag)</i>	NA		
<i>LM-type test</i>	LM 0.6371	0.9588	4
Nonnormality			
<i>Doornik & Hansen (1994)</i>			
joint	0.1942	0.9075	2
skewness only	0.1039	0.7472	2
kurtosis only	0.0904	0.7637	2
<i>Lütkepohl (1993)</i>			
joint	0.1942	0.9075	2
skewness only	0.1039	0.7472	2
kurtosis only	0.0904	0.7637	2
<i>Jarque-Bera test</i>	0.1942	0.9075	
Heteroscedasticity			
<i>ARCH-LM test</i>	7.9663	0.0928	
<i>VARCHLM test</i>	7.9663	0.0928	4

Using the information taken from estimations in Tables 1, 3 and 5, we next construct a nested model by specifying dy as the only endogenous variable (see Tables 7 and 8).

Table 7

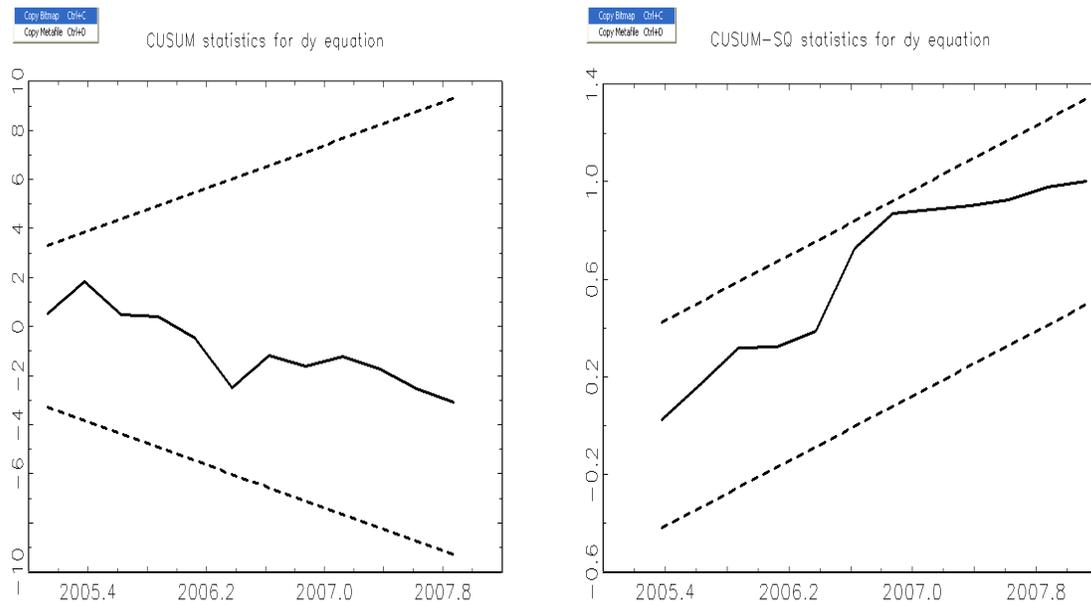
<i>Variable</i>	dy_t	dy_{t-1}	$dnreu_{t-1}$	$dlneu_{t-1}$	rg_{t-2}	<i>dum Bart</i>	<i>SI</i>
Coefficient	1	0.1.88	-0.137	2.411	0.013	1.211	-0.127
p-Value		(0.064)	(0.090)	(0.005)	(0.005)	(0.00)	(0.02)

Note: Residual variance: 1.321055e-02 ; Sample range: [2001 Q2, 2007 Q4], T = 27

Table 8. Diagnostic tests

	<i>statistic</i>	<i>p-value</i>	<i>df</i>
Autocorrelation			
<i>Portmaneau test (4 lag)</i>	NA		
<i>LM-type test</i>	LM 1.9527	0.7445	4
Nonnormality			
<i>Doornik & Hansen (1994)</i>			
joint	1.0941	0.5787	2
skewness only	1.0926	0.2959	2
kurtosis only	0.0014	0.9699	2
<i>Lütkepohl (1993)</i>			
joint	1.0941	0.5787	2
skewness only	1.0926	0.2959	2
kurtosis only	0.0014	0.9699	2
<i>Jarque-Bera test</i>	1.0941	0.5787	
Heteroscedasticity			
<i>ARCH-LM test</i>	6.6670	0.1546	
<i>VARCHLM test</i>	6.6670	0.1546	4

Figure 3. Stability tests



We conclude that the model is correctly specified with respect to the diagnostic tests and the process is stable at 5 per cent significance level. We also notice that all variables have the correct sign and are statistically significant at 5 and 10 per cent significance levels. Credit growth appears to be importantly affected by changes in the exchange rate and the euro interest rate while the effect of GDP deterioration seems trivial. A possible reason for this may be the small variation in the GDP data used in the estimation. Given that the quarterly data entries are obtained by filtering annual data, some of the variation may have been lost, thus resulting in the true effect of GDP on dy captured by the parameters on other coefficients.

6. Illustration

As a final step in this analysis we proceed by extracting 20.000 numbers from the $N \sim (0; \sqrt{1.321055e-02})$ distribution and use the parameters in Table 7 to compute the probability distribution of dy under the stressed and unstressed scenarios.

For illustrative purposes, we present the following analysis using the data for September 2008 and relying on the respective assumptions. We do not make use of the stochastic components of the macroeconomic model for this illustration and allow for a stochastic component just in the default rate. A simulation allowing for randomness in the macroeconomic variables and using the variance-covariance between the stochastic components in the latter and the estimated ε from this equation is subject to further investigation.

Table 9. Scenarios

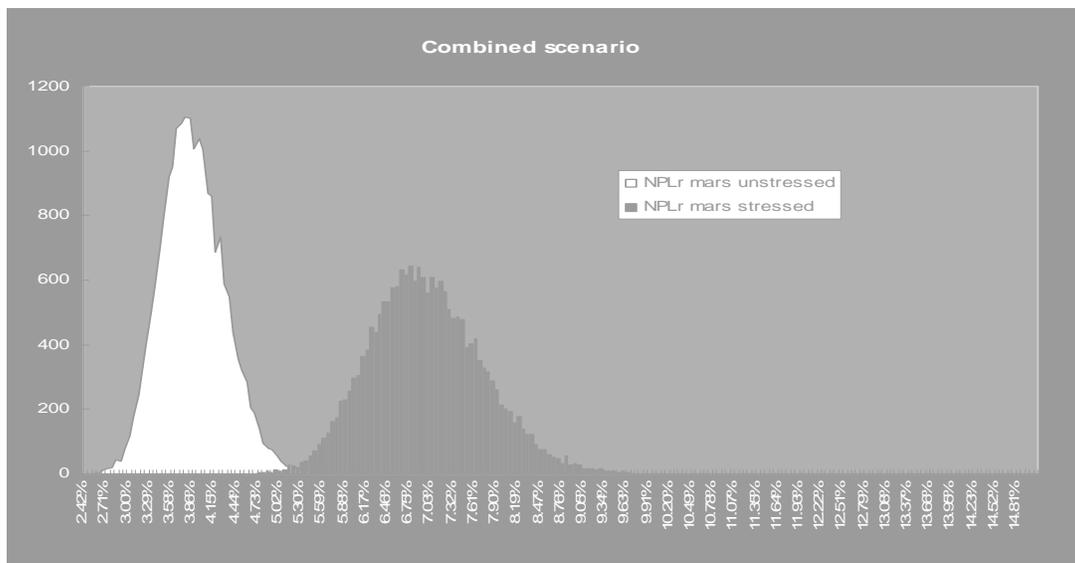
<i>Given</i>	y September	3.147244	unstressed	stressed
<i>Given</i>	dy September	0.047068		
<i>Given</i>	rg June	6		
<i>Given</i>	dnreu September	0.063		
<i>Given</i>	dlneu September	-0.01496		
<i>Computed</i>	dy December	0.114294		
<i>Assumptions</i>	rg September		6	2
<i>Assumptions</i>	dlneu December		0	0.182322
<i>Assumptions</i>	dnreu December		0	1
	Change in the exchange rate			0.2
	Euro/ALL September	122.05		

In the unstressed scenario, we assume an annual GDP growth of 6% in September, consistent with that of the end of the year. We assume no changes in the Euribor and no change in the exchange rate *vis-a-vis* the ALL. In the stressed scenario, we assume a 20 per cent depreciation of the ALL, a 100 basis points change in the Euribor and GDP growth of 2 per cent. The estimates show that, under these assumptions, the expected value of the NPLR of March 2009 increases from 3.82 to 6.93 per cent. From Table 10 where we present descriptive statistics of the computed NPLR under the two scenarios, we can obtain also interval estimates of the NPLR. As an example, the 90 per cent interval estimates change from [3.29; 4.38] to [6.00; 7.90]. Another important finding is also the probability of encountering ‘tail’ values of the NPLR increases as shown by the increase in the standard deviation of the stressed scenario from 0.004 to 0.007. Figure 4 presents the graphical illustration of the probability distribution.

Table 10. Statistics of the NPLR for the stressed and unstressed scenarios

	Nplr mars09 unstress	Nplr mars09 stressed
Mean	3.82%	6.93%
St dev	0.004270794	0.007485153
5th Q	3.16%	5.77%
95th Q	4.55%	8.21%
10th Q	3.29%	6.00%
90th Q	4.38%	7.90%
15th Q	3.39%	6.17%
85th Q	4.26%	7.70%
20th Q	3.46%	6.29%
80th Q	4.17%	7.55%

Figure 4. Probability distribution under the stressed and the unstressed scenarios



7. Summary and conclusions

The paper presents several improvements in the methodology of stress testing of indirect credit risk in Albania. We find a significant effect of the changes in the euro exchange rates and the Euribor interest rates on the non-performing loan ratio while the effect of GDP growth, *albeit* small, is found to be significant too. Most importantly, our methodology provides a measure of uncertainty of the estimates through the computation

of the probability distribution of the variables of interest both under the stressed and the unstressed scenarios.

While at this stage the model seems to be satisfactory both from a theoretical and statistical perspective, there are various ways in which this part of research could be extended in the future. First, given our data length and the asymptotic properties of the VAR analysis, a re-estimation of the model is necessary once a new/revised data set comes available. Second, a VaR statistic would be obtained using several assumptions about the evolution of total loans. However, this is beyond the main objective of this paper. Third, estimation at a more disaggregated level would also be of great interest, as different portfolio performances might prevail among different groups of banks, or separately for households, businesses, mortgages, different industries, etc. Finally, the model can also use scenarios derived from the macroeconomic model accounting for the impact of a shock to one macroeconomic indicator may have on other macroeconomic indicator and evaluating the effects of macroeconomic policies on the banking system.

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Discussion

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A stress test is commonly described as the evaluation of the financial position of a bank under an extreme but plausible scenario in order to facilitate decision making within the bank. Similarly, macro stress testing refers to a range of techniques used to assess the vulnerability of a financial system to ‘exceptional but plausible’ macroeconomic shocks. Both approaches gained significant momentum during the current financial crisis since the importance of complementing the micro-prudential analysis with a macro-prudential perspective has become evident. Increasingly, macro stress testing plays an important role in the macro-prudential analysis of public authorities. The main objective is to identify structural vulnerability and overall risk exposures in a financial system that could lead to systemic problems. In addition, macro stress testing forms the main part of system-wide analysis, which measures the risk exposure of the financial system to a specific stress scenario. However, several research papers have indicated that stress test exercises conducted before the crisis have significant vulnerabilities related to their informativeness, scenario severity and model robustness (see, for example, Rodrigo and Drehmann 2009). In the de Larosier (2009) report (p8)³ it is clearly mentioned that ‘...model-based risk assessments underestimated the exposure to common shocks and tail risks and thereby the overall risk exposure. Stress-testing too often was based on mild or even wrong assumptions’. These conclusions, among others, initiated an increase in research interest in macro stress testing, and the topic is rapidly evolving. The paper by Shijaku and Ceca is a contribution to this strand of literature, particularly the applied part which refers to the Albanian banking sector.

The model presented in the paper was initiated during an FSAP mission from the IMF, has gone through substantial improvement and follows the traditional approach. A

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³ High level group on financial supervision in EU, chaired by J. de Larosier, February 2009.

traditional macro stress test is illustrated in Figure 1 whereas a more modern approach is illustrated in Figure 2.

Figure 1

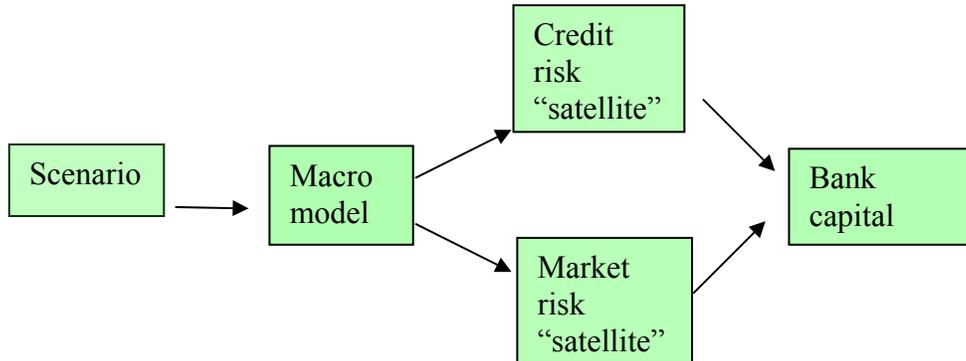
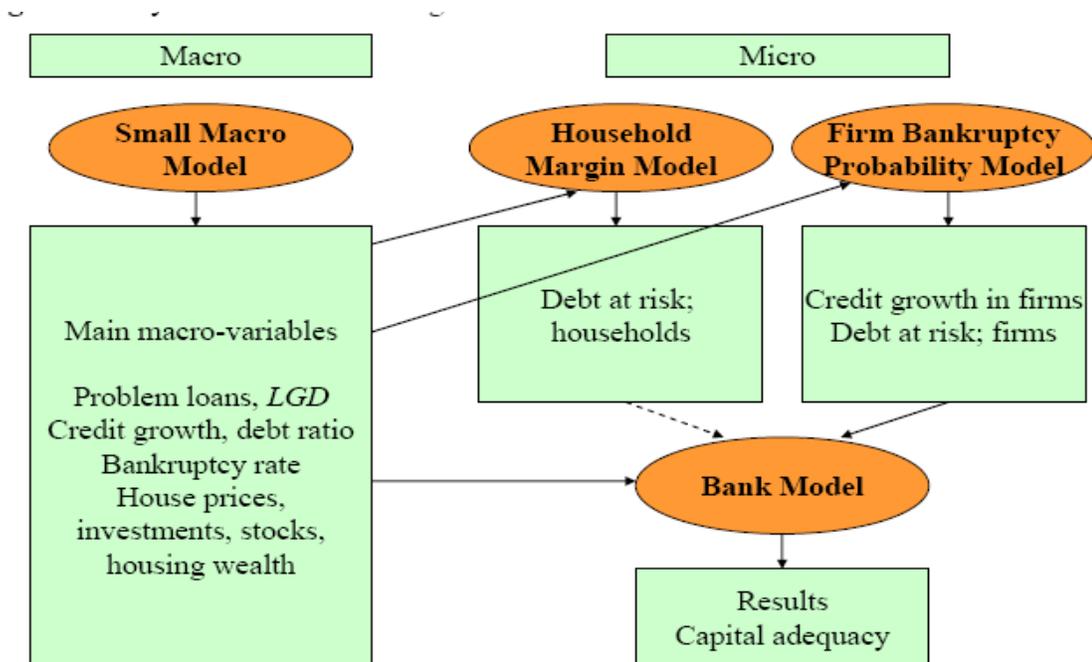


Figure 2



Source : Andersen *et al.* (2008).

The paper uses the traditional approach shown in Figure 1 and some traces of the modern approach can be found in the effort to model the indirect credit risk effect. However, direct interaction and feedback from the real economy (household and firms) are ignored. Further, the model developed in the paper uses VAR (Vector Autoregressive)⁴ techniques to create macroeconomic forecasts and focuses on the upper leg of the figure, namely, on the credit ‘satellite’ model. Thus, the model can be considered as part of a larger and more comprehensive macro stress testing framework.

However, the paper does not specify the purpose of the model. Macro stress testing model can be used either for risk management purposes or financial stability purposes. The former tries to investigate vulnerabilities of systemically important financial institutions to adverse macroeconomic events and the latter common vulnerabilities across institutions that could undermine the overall stability of the financial system.

The second issue is the specification of the credit model. There are several alternative specifications and the literature review of the paper analyses some important contributions to the subject, namely the paper by Foglia (2009). The macroeconomic variables to be considered in a macro stress test include: domestic variables (short-term and long-term interest rates, inflation, GDP and unemployment) and external variables (external demand, foreign interest rates, exchange rate fluctuations, etc.). The model by Shijaku and Ceca uses three variables: GDP, interest rates, exchange rates and some dummy variables.

Focusing on credit risk, the key parameters are basically the probability of default (PD), the loss given default (LGD) and the exposure at default (EAD). Most models focus on PD by increasing it by a predetermined amount, implying the credit quality of all borrowers is worsened by some risk categories (downgrading). The customary procedure for LGD and EAD is to assume an *ad hoc* increase by a given percentage or to define some kind of range of variation and use it to calculate the change in credit risk. The model here uses a proxy for the PD (non-performing loans) due to lack of data for

⁴ More sophisticated approaches use DSGE (Dynamic Stochastic General Equilibrium) modelling. See, Jokivuolle E., J. Kilponen and T. Kuusi (2007).

the PD and it is silent on LGD and EAD. The final version of the paper uses a model similar to that used by the Bank of Greece and presented to the banking community in a special conference on November 2009.

The functional form of the model is:

$$NPL_{it} = \beta_1 NPL_{it-1} + \beta_2 RGDP_t + \beta_3 RLR_{it-1} + \beta_4 U_{t-1} + u_{it}$$

whereas the model by Shijaku and Ceca is :

$$NPL_{it} = \beta_1 NPL_{it-1} + \beta_2 RGDP_{t-2} + \beta_3 RLR_{it-1} + \beta_4 FX_{t-1} + u_{it}$$

However, the estimated elasticities deviate substantially and the paper reaches the unconventional conclusion that the change in GDP does not affect significantly the NPLs whereas indirect credit risk from interest rates and exchange rates is significant.

The paper is an attempt to develop a framework for applying macro stress testing in Albania. All supervisory authorities consider it desirable to carry out stress tests, since they can be a key prudential tool for analysing the risk profile of individual banks and assessing the stability of the financial system as a whole. In that sense, the paper is a major contribution to that effort.

As for the modelling approach, it should correspond to the sophistication of the banking sector, and consequently the model can be considered appropriate. However, the modelling effort in all countries with less mature banking systems, like Albania, is hindered by the availability of data and data cleanliness. The size of the shock chosen sometimes cannot be calibrated appropriately due to the lack of depth in the available databases. The model should be recalibrated each year with new data and the methodology should be appropriately enhanced until the researchers feel confident enough to use it for policy recommendation.

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1. Hardouvelis, Gikas, Keynote address: “The World after the Crisis: S.E.E. Challenges & Prospects”, February 2011.
2. Tanku, Altin “Another View of Money Demand and Black Market Premium Relationship: What Can They Say About Credibility?”, February 2011.
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