EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 1592 / SEPTEMBER 2013

BRIDGING THE BANKING SECTOR WITH THE REAL ECONOMY

A FINANCIAL STABILITY PERSPECTIVE

Adrian Costeiu and Florian Neagu

In 2013 all ECB publications feature a motif taken from the €5 banknote.

MACROPRUDENTIAL RESEARCH NETWORK

Macroprudential Research Network

This paper presents research conducted within the Macroprudential Research Network (MaRs). The network is composed of economists from the European System of Central Banks (ESCB), i.e. the national central banks of the 27 European Union (EU) Member States and the European Central Bank. The objective of MaRs is to develop core conceptual frameworks, models and/or tools supporting macro-prudential supervision in the EU.

The research is carried out in three work streams: 1) Macro-financial models linking financial stability and the performance of the economy; 2) Early warning systems and systemic risk indicators; 3) Assessing contagion risks.

MaRs is chaired by Philipp Hartmann (ECB). Paolo Angelini (Banca d'Italia), Laurent Clerc (Banque de France), Carsten Detken (ECB), Simone Manganelli (ECB) and Katerina Šmídková (Czech National Bank) are workstream coordinators. Javier Suarez (Center for Monetary and Financial Studies) and Hans Degryse (Katholieke Universiteit Leuven and Tilburg University) act as external consultants. Fiorella De Fiore (ECB) and Kalin Nikolov (ECB) share responsibility for the MaRs Secretariat.

The refereeing process of this paper has been coordinated by a team composed of Gerhard Rünstler, Kalin Nikolov and Bernd Schwaab (all ECB).

The paper is released in order to make the research of MaRs generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the ones of the author(s) and do not necessarily reflect those of the ECB or of the ESCB.

Acknowledgements

The authors wish to express their gratitude to Romulus Mircea and Vlad Teodorescu for their important contributions to the methodology of the corporate PD model. The authors are also indebted to Gerhard Winkler and the team from the Working Group on Risk Assessment within the European Committee of Central Balance-Sheet Data Offices (ECCBSO) for their very useful comments, to the participants of the ECB Macro-prudential Research Network 2012 meeting, to the participants of the 2011 NBR-IMF Regional Seminar on Financial Stability in Sinaia, and 2013 EFMA Conference in Reading.

Adrian Costeiu

National Bank of Romania; e-mail: adrian.costeiu@bnro.ro

Florian Neagu

National Bank of Romania; e-mail: florian.neagu@bnro.ro

Address	Kaiserstrasse 29, 60311 Frankfurt am Main, Germany
Postal address	Postfach 16 03 19, 60066 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Internet	http://www.ecb.europa.eu
Fax	+49 69 1344 6000

ISSN	1725-2806 (online)
EU Catalogue No	QB-AR-13-089-EN-N (online)

Abstract

This paper builds a macro-prudential tool designed to assess whether the banking sector is adequately prepared to orderly withstand losses resulting from normal or stressed macroeconomic and microeconomic scenarios. The link between the banking sector and the real sector is established via the corporate sector channel. The macro-prudential tool consists of a two-step approach. In the first step, we build a model for the probability of default (PD) in the corporate sector, so as to quantify one-year ahead developments in the quality of banks' corporate loans. The framework is established using micro data, with a bottom-up approach. The second step consists of bridging the PD model with a macroeconomic module in order to capture the feedback effects from the macroeconomic stance into the banking sector, via the corporate sector channel. The macro-prudential tool is tested on the Romanian economy.

Keywords: probability of default, financial stability, macro-prudential analysis, ROC

JEL Classification: G32;G21;E17

Contents

Non-technical summary

This paper examines the usefulness of a macro-prudential tool designed to assess whether the banking sector is adequately prepared to orderly withstand losses resulting from normal or stressed macroeconomic and microeconomic scenarios. The link between the banking sector and the real economy is established through the corporate sector channel. There are three additional uses for this tool for financial stability purposes: (i) to evaluate the overall and sectorial distribution of credit risk in the real economy; (ii) to gauge the trend of the overall default rate for the corporate sector, highlighting the most likely direction it will take in the banks' non-performing loan ratio; and (iii) to complement the macro-prudential approach with a micro-prudential perspective in order to compute the portfolio at risk of those entities that could put pressure on financial stability (e.g. systemically important institutions).

The tool has been developed in two steps. In the first step, a probability of default (PD) model for the corporate sector is built. The framework is established using micro data, with a bottom-up approach and is based on the Basel II definition of default (90-days past due date). The purpose of this experiment is to outline the main microeconomic factors that best explain companies' behaviour in servicing their banks' debts.

The second step is to bridge the PD corporate model with a macroeconomic module in order to capture the feedback effects of the macroeconomic stance on the banking sector. We examine the ways in which the main macroeconomic variables (annual GDP growth, real effective exchange rate, inflation rate, etc.) could impact corporate PD results. The module allows us to evaluate the ability of the companies in the banks' portfolio to withstand normal or stressed macroeconomic scenarios.

The new PD, adjusted in line with the macroeconomic stance, is used to estimate the expected losses that a banking sector would face as a result of its corporate sector portfolio. The gap between the expected losses and the prudential buffers already in place to shield such losses is thereby determined. We then assess whether this gap could be dealt with in an orderly manner, so as to avoid putting undue pressure on financial stability.

This tool is tested on the Romanian economy. The main microeconomic factors identified as hindering the corporate sector from servicing its debt are a deterioration in the receivables turnover ratio, sales-to-total assets ratio, short-term bank debt-to-total assets and debt–to-equity, while the macroeconomic factors affecting the corporate default rate are annual GDP growth, a change in the real effective exchange rate, CORE1 annual inflation rate and the FX interest rate spread. It is revealed that the banking sector under review is in relatively good shape in order to withstand developments stemming from the explored scenario, the up-trending level of provisioning being rather easy to accommodate in an orderly manner.

1 Introduction and literature review

There are at least two important lessons that the crisis has taught us about evaluating systemic credit risk. The first one is that the current instruments used to assess the overall level of risk in the banking sector are subject to significant flaws in times of high distress. The probability of default (PD) is one of these key instruments. It is used by both banks and the micro and macro-prudential authorities (to compute expected and unexpected losses, for stress-testing exercises, etc.), but it has proved to be pro-cyclical and does not respond very well to material shocks that occur quite frequently, as in real life[1]. The second lesson is that financial stability analyses should examine the macro-prudential aspects more closely, with more emphasis on the link between the real economy and the financial system. Corporate and household sectors, as well as macroeconomic developments, should be more closely integrated into the credit risk assessments of the banking sector.

This paper builds a macro-prudential tool designed to assess whether the banking sector is adequately prepared to orderly withstand losses[2] resulting from normal or stressed macroeconomic and microeconomic scenarios. The tool has been developed in two steps. In the first step, we construct a PD model for the corporate sector. Such models help to assess financial stability by means of a three-pronged approach: (i) by showing the main microeconomic factors that best explain companies' behaviour in servicing their bank debts; (ii) by indicating the level and direction of credit risk that currently exists in the bank's portfolio for a specific time-horizon (a one-year ahead PD is the most common time-frame); and (iii) by assessing whether the expected loss arising from the credit portfolio is adequately covered by provisions. The framework is constructed using micro data, with a bottom-up approach, and outlines the main factors that prevent firms from servicing their bank loans. We have used the Basel II definition of default (90-days past due date) and firm-level data for all non-financial companies with bank loans. By using financial data reported by all companies, we overcome some of the limitations of other models that are biased towards large firms or small samples. This approach also enables us to draw conclusions for the entire corporate portfolio of a given banking sector.

The second step is to bridge the PD corporate model with a macroeconomic module in order to capture the feedback effects from the macroeconomic stance in the banking sector, through the corporate sector channel. We compute the ways in which the main macroeconomic variables (annual GDP growth, real effective exchange rate, inflation rate, etc.) could impact corporate PD outcomes. The tool also allows us to use different macroeconomic scenarios for both normal and stressed times in order to assess the ability of the corporate sector to withstand shocks and the degree to which these shocks are transmitted to the banking sector.

[1] Kindleberger and Aliber (2005) show that large shocks (as panics or crashes) are quite usual. Standard models for assessing risk consider such material shocks as once-in-a-lifetime events, however, they tend to occur every five to ten years.

[2] This tool primarily focuses on loan losses arising in the corporate sector and thus it provides a partial analysis of the ability of the banking system to withstand shocks (for instance, the banks' exposures to the household sector are not taken into account). Another caveat is that some elements are insensitive in the macroeconomic scenario (e.g. the impact of interest rate changes in banks' profitability), because the main purpose of this tool is to assess whether the banking sector has adequate buffers to withstand expected losses stemming from credit risk. The methodology proposed here might provide a starting-point for a broader macroeconomic stress-testing approach with results on profitability or solvability.

Forecasting aggregate default rates for the corporate sector based on macroeconomic conditions has gained ground in the literature on financial stability. Viroleinen (2004) shows that, in the case of Finland, developments in the default rate can be explained by the GDP growth rate and the level of indebtedness of the corporate sector. Fong and Wong (2008) use a vector autoregressive model to link the default rates with the macroeconomic environment for stress-testing purposes. Simmons and Rolwes (2008) embark on finding the determinants of default for the Netherlands, showing that GDP growth and the oil price are representative determinants of default, while the exchange rate and the interest rate seem to weigh less. Band et al. (2008) model the impact of macroeconomic factors on the equilibrium in the corporate debt market and reveal that, on the supply side, this equilibrium depends on the change in the default rate. Jakubík (2007, 2011) applies, to the Czech corporate and household sectors, a one-factor Merton type model with a default barrier depending on the macroeconomic environment.

Finally, we estimate the risks to financial stability via the direct channel. We take into account the PD (both at the individual and the aggregate levels) and the exposures to which firms could potentially default. We quantify the risks to financial stability by using the expected loss measure. This figure is compared with the outstanding buffers that banks have already built to cover the expected losses.

The literature discloses three main types of methodologies employed in modelling credit risk for non-financial companies.

i) Linear models divided the firms into two groups (defaulters and non-defaulters), using a linear function of the financial ratios. The aim is to maximise the distance between the two groups. These models were first used in credit risk assessment by Beaver (1966) and Altman (1968). The Banque de France uses a multivariate discriminant analysis technique to estimate a scoring model (WGRA, 2007);

ii) Non-linear models (logit and probit) assume that the probability of default follows a logistic or normal cumulative distribution function. One of the main developers of the logit model in credit risk assessment is Ohlson (1980). The Banco de España, the Bank of Belgium or the Banca Naţională a României are amongst the central banks that use this methodology to quantify the credit risk stemming from the corporate sector (WGRA, 2007; Vivet, 2011);

iii) Non-parametric, non-linear models (such as neural networks or support vector machines - SVM) have the advantage of not being restricted to a certain functional form and are better able to illustrate the relationship between the dependent and independent variables. Their main disadvantages are the opaqueness (because is hard to describe the link between each variable and default) and the high number of regressors reflected in a lower precision of the estimated coefficients. The Deutsche Bundesbank uses an SVM model for assessing credit risk for non-financial companies (WGRA, 2007).

For the purpose of this paper, we use a logistic regression model, as this type of model delivers better results compared with linear models. Furthermore, Bunn and Redwood (2003) and Chi and Tang (2006) underline the non-linearity relationship between default and explanatory variables. Malhotra et al. (1999) test the performance of non-parametric models (neural networks and k-nearest neighbour) and find that the latter are superior in terms of an in-sample performance, but are inferior when it comes to an out-of-sample performance, compared with the logit regression model.

Logit models require a large proportion of defaulters in order to produce accurate results. This is a significant drawback for such models. In practice, researchers use artificial samples consisting of mainly defaulters and a number of randomly chosen non-defaulters (most often, the sample composition is 50:50) in order to better capture the characteristics of rare events than that captured with a low default sample. Hence, the level of PDs will only reflect the estimation sample composition and not the true population. King and Zeng (2001) propose a methodology for recalibrating the model to reflect the true default rate by adjusting the intercept in the logit formula and shifting the distribution of the PDs.

The rest of the paper is structured as follows. Section 2 describes the methodology and the input data for the PD model and the macroeconomic module, Section 3 applies the macro-prudential tool to the Romanian economy, while the final section draws some conclusions ensuing from the main hypotheses of the paper.

2 Methodology

2.1 Probability of default model: development and calibration

The development of the corporate PD model is the first step towards building our macro-prudential tool. We use a logit approach:

$$PD = \frac{1}{1+e^{\alpha+\beta X}} \tag{1}$$

whereby the PD is the calculated probability of default and X are the explanatory variables.

We winsorise[3] the explanatory variables in the training sample in order to exclude extreme values. From the empirical simulations, we find that a threshold of 15% is appropriate for a large amount of variables. However, for the variables qualified in the final model, we conduct an in-depth study of the relationship between the natural logarithm of the odds of default and the variable values, modifying the winsorise thresholds according to this function's linearity.

The variables in the forecast sample are winsorised using the same values as in the training sample. When applying the model, we use this technique rather than the same quantiles, as we have noticed large shifts in the tails of the distributions of some variables over the past few years, resulting in unrealistic shifts in the calculated PDs owing to extreme values. The logic behind winsorising at the same values as the training sample is that the coefficients are thus estimated on the basis of the same intervals of the variables' values.

[3] A transformation process that limits extreme data values in order to remove outliers. This step is necessary in order to obtain unbiased estimates, especially when the initial values of the variables have very wide distributions. In order to exclude extreme values, we conduct a tail-analysis for each distribution of the balance-sheet variables.

In order to derive the final default model, additional filters and discriminatory power tests are used on a pool of candidate explanatory variables and intermediary default models[4].

As part of the first step, the Kolmogorov-Smirnov (KS) test is applied. The purpose of this filter is to exclude ratios that are independent of default scenarios. A one-tail hypothesis test is carried out in order to compare the distributions of the values of defaulters and non-defaulters for each candidate variable. The null hypothesis for this test is that the two groups are drawn from the same continuous distribution. In the next step, we test the presence of a monotone, linear relationship between the logarithm of the odds of default and the candidate variables. First, we divide the estimation sample into several sub-groups that contain the same number of observations. For each group, the historical default rate (the empirical logarithm of the odds of default) is established. We run a linear regression between the historical default rate and the mean value of the variables and exclude those variables for which the linear regression assumptions are not accepted.

We run univariate logit models for the remaining candidate variables in order to check their in and out-of-the-sample discriminatory power. We exclude variables with a univariate ROC of less than 55%[5]. The univariate analysis is an important step for the following reasons: (i) robustness checks of the coefficients and; (ii) individual discriminatory power (at this stage we are not interested in the univariate PD estimate, but only in the capacity of the variable to select "good" from "bad" companies).

We test the lasting variables for multicolinearity. We compute their correlation matrix. The selection is based on the ROC levels achieved in the previous step. Variables are excluded if the correlation coefficient is higher than 0.7[6].

After filtering the candidate variables, we proceed to derive a multivariate model of default. We use a backward selection method for which we initially estimate the full model – including all the variables which passed the selection filters – and then eliminate the worst covariates based on their significance (calculated using a likelihood ratio test).

The process of estimation of the multivariate model of default is divided into two steps. First, we run a bootstrapping exercise by conducting 100 simulations. In each simulation, we derive a multivariate model using the backward selection method and a proportion of 50:50 of defaulted to non-defaulted firms. For this purpose, we use all of the defaulted firms and we draw upon a random sample from the non-defaulted firms of the same size as the defaulted firms. In this respect, we ensure that the model is able to better capture the characteristics of defaulting entities. Finally, we count how often a certain model specification is obtained, as well as how often each explanatory variable is observed during the simulations. In order to avoid sample biases, we use another similar bootstrapping procedure, whereby we compute the coefficients by using only those variables of the model with the highest occurrence.

[4] A comprehensive approach for the methodology used to run these tests is provided by Mircea (2007).

[5] The main purpose of this threshold is to indicate that a candidate variable shows evidence of discriminatory power. Our findings indicate that a higher threshold would not have a major impact on the number of variables to be considered for the multicolinearity test.

[6] The idea is to set the threshold high enough in order to exclude high correlated variables.

This uncalibrated model reveals a number of drawbacks, which could result in an underestimation of the PD during times of high stress. These drawbacks mainly relate to: (i) a certain degree of pro-cyclicality in the PD result; (ii) low frequency of companies' financial data (semi-annual); and (iii) the considerable delay between the end of the reporting date of the financial statements and the date on which these figures are effectively available for analysis. Under such conditions, the latest explanatory variables may not incorporate the most recent economic developments, which could cause the PD to be either over or underestimated. In order to overcome these drawbacks, we use the King and Zeng (2001) methodology for recalibrating the model in order to reflect the true default rate by adjusting the intercept in the logit formula with a coefficient that is dependent on the two rates:

$$log\left(\frac{PD}{1-PD}\right) = \alpha + X\beta + log\left(\frac{\pi_d}{1-\pi_d}/\frac{p}{1-p}\right) + \varepsilon \tag{2}$$

where the PD is the calculated probability of default, π_d is the default rate at which we calibrate the PD, p is the average unadjusted computed probability of default for the forecast sample and X is the explanatory variables vector. The advantage of using this correction method is that it changes only the intercept of the logit formula without affecting the discriminatory power of the model (basically it shifts the PD distribution so that the mean of the distribution of the PDs converges to π_d).

2.2 Macroeconomic credit risk module

The second step in designing the macro-prudential tool is to adjust the PDs with the forecasted default rate, based on the methodology proposed by Jakubík (2007), consisting of a one-factor Merton type model with a default barrier depending on the macroeconomic environment.

This type of model assumes a random variable with a standard normal distribution for the standardised logarithmic asset returns of economic agent i at time t:

$$R_{it} = \sqrt{\rho}F_t + \sqrt{1-\rho}U_{i,t} \tag{3}$$

where:

— R_{it} denotes the logarithmic asset return for economic agent i in the economy at time t;

— F_t stands for the logarithmic asset return of the economy at time t, which is assumed to be a random variable with a standard normal distribution;

— U_{it} represents the economic agent-specific asset return, which is assumed to be random with a standard normal distribution;

— ρ_i is the correlation of the economic agent's asset return with the systematic factor F_t.

The variable F_t represents the part of the asset return which is not specific to the economic agent and could be attributed to the general macroeconomic conditions. F_t and U_{it} are assumed to be uncorrelated.

In order to model aggregate credit risk by incorporating different macroeconomic indicators, we assume that the value of the default threshold T depends on the state of the economy. This is modelled by using a linear combination of macroeconomic variables (x_{it}) to represent the value of the default threshold T.

The final representation of the macroeconomic, one-factor credit risk model used in this model is shown in equation (4), where Ψ denotes the cumulative distribution function of the standard normal distribution that represents the impact of a change in the macroeconomic indicators, β_0 is a constant and β_j are the coefficients of the macroeconomic variables x_{jt}:

$$p_{it} = P(R_{it} < T) = P(\sqrt{\rho}F_t + \sqrt{1-\rho}U_{it} < \beta_0 + \sum_{j=1}^{N}\beta_j x_{jt}) = \Psi(\beta_0 + \sum_{j=1}^{N}\beta_j x_{jt}) \quad (4)$$

The default probability conditional on the realisation F_t (noted as f_t) of a random unobservable factor representing the state of the economy at time t, which corresponds to the default probability (4), is given in formula (5).

$$p_i(f_t) = P\left(U_{it} < \frac{\beta_0 + \sum_{j=1}^{N}\beta_j x_{jt} - \sqrt{\rho}f_t}{\sqrt{1-\rho}}\right) = \Psi\left(\frac{\beta_0 + \sum_{j=1}^{N}\beta_j x_{jt} - \sqrt{\rho}f_t}{\sqrt{1-\rho}}\right) \quad (5)$$

If we assume a homogeneous portfolio of non-financial companies in the economy whose asset returns follow process (3), the default rate in the economy will converge – based on the law of large numbers – to the companies' default probabilities. The specification of the model obtained from equation (4) is:

$$p_t = \Psi\left(\beta_0 + \sum_{j=1}^{N}\beta_j x_{jt}\right) \quad (6)$$

where p_t represents the default rate of the corporate sector, β_0 is a constant, x_{jt} is the vector of macroeconomic variables and β is the coefficient vector.

In order to estimate model (4) we assume that, at each point in time, the conditional number of defaults d_t is a binomial distribution with a conditional probability given by equation (5) and the number of economic agents n_t. Subsequently, the macroeconomic model is calibrated by maximising the following likelihood function:

$$l(\beta_0, ..., \beta_N, \rho) = \sum_{t=1}^{T} ln\left\{\int_{-\infty}^{\infty}\binom{n_t}{d_t}\Psi\left(\frac{\beta_0 + \sum_{j=1}^{N}\beta_j x_{jt} - \sqrt{\rho}f_t}{\sqrt{1-\rho}}\right)^{d_t}\left[1 - \left(\frac{\beta_0 + \sum_{j=1}^{N}\beta_j x_{jt} - \sqrt{\rho}f_t}{\sqrt{1-\rho}}\right)\right]^{n_t - d_t}\phi(f_t)\,df_t\right\}$$

where $\phi(f_t)$ is the density function of the standard normal distribution.

The role of the macroeconomic module is to estimate the future default rate, based on the developments in the macroeconomic variables (GDP, exchange rate, interest rate, etc.). The link with the PD model is achieved by means of the calibration method (King correction formula), which shifts the distribution of the PDs in order to reflect developments in the macroeconomic context (represented by the annually forecasted default rate – π_d in equation (2)). This methodology also helps to avoid cases in which GDP growth, exchange rate, etc., prove to be statistically insignificant or display a wrong sign in the logit formula, since their coefficients have been estimated at a point-in-time, based on past/non-crisis information.

2.3 Measuring the risk to financial stability

The main aim of this macro-prudential tool is to assess whether the banking sector holds an adequate volume of prudential buffers in order to withstand expected losses from normal or adverse developments in the macroeconomic stance. There are three additional uses of this tool for financial stability purposes: (i) to evaluate the overall and sectorial distribution of risk in the real economy; (ii) to gauge the trend of the overall default rate for the corporate sector, highlighting the most likely direction in the banks' non-performing loan ratio; and (iii) to complement the macro-prudential approach with a microeconomic perspective in order to compute the portfolio at risk of those banks that could exert pressure on financial stability (e.g. systemically important institutions).

Total expected loss (EL) is computed using the following equation:

$$EL = \sum_{i} PD_i E_i LGD \tag{7}$$

where PD_i is the probability of default for obligor i, E_i is the total loans of obligor i and LGD is loss given default (due to a lack of information, LGD is assumed to be constant across all obligors, at 45%, as stipulated under Basel II).

3 Empirical results

3.1 Results from the probability of default model

We compute the PD model (Table 1) for the corporate sector of the Romanian economy using the methodology presented in Section 2.1. The explanatory variables consist of 47 financial ratios and nine additional dummy variables (eight for the sectors in the economy and one size dummy). The data used for building the PD model was obtained from:

a) the financial statements provided by companies to the authorities (e.g. Ministry of Public Finance, Trade Register, etc.). The database used for the model development stage consists of approximately 610,000 companies (December 2009). We exclude companies with invalid financial statements (such as negative turnover or total assets);

b) the defaults recorded in the credit registers. For Romania, this register is a database for which all banks report exposures in excess of around €5,000, at the obligor level. This credit register consists of around 220,000 individual loans and

90,000 individual debtors. The intersection of the above-mentioned databases delivers more than 90% of all credit to the non-financial companies sector.

An out-of time analysis of the PD model is conducted on a sample of the 2010 financial statements and the defaults observed between January 2010 and December 2011. After validating the model, the PDs for 2012 are forecast based on the 2011 semi-annual financial statements.

Table 1: Logit model for one-year default horizon using 2009-10 data

-Number of observations in the dataset used for building the model: **68,463** out of which **6,903** defaults
-Number of observations in the bootstrapping exercise: **13,806** out of which **6,903** defaults
-In sample ROC: 84.2%
-Out-of-time ROC (2010-11): 85.5%
-Neutral cost policy function:
o Optimal cut-off (2010): 9.5% implying a hit rate of: 72% and a false alarm rate of: 17% in 2011

Variables	**Coefficient**	**Standard error**
Adjusted intercept	-1.2395	n.a.
Debt-to-equity	0.0496	0.0045
Debt-to-value added	0.0630	0.0101
Interest cover ratio	-0.0424	0.0083
Receivables cash conversion days	0.0045	0.0003
Sales growth	-0.6223	0.0622
<15 days past due dummy	1.6419	0.0728
15-30 days past due dummy	2.2398	0.1064
30-60 days past due dummy	2.8703	0.0944
60-90 days past due dummy	3.6170	0.1341

The variables used in the model, their individual performance and the descriptive statistics on the data structure are detailed in the Appendix (Tables 1, 2, 3 and 4). The samples consist of all companies with bank loans that are not in default at the beginning of the period (i.e. no overdue payment of more than 90 days past due over the past 12 months prior to the compilation of the sample). The performance of the model and other results are presented in the Appendix.

On the basis of our empirical study, we find that the main factors behind a firm's ability to service its bank debts are: (i) debt-to-equity ratio; (ii) debt-to-value added ratio; (iii) interest cover ratio; (iv) receivables cash conversion days; and (v) sales growth. A higher leverage indicates that the company could have difficulties in servicing its financial obligations vis-à-vis its commercial clients and financial creditors. Debt-to-value added measures the ability of a firm to efficiently use its debt resources to generate profit: lower values for this variable are associated with smaller chances of default. Interest burden is a measure of the cost of indebtedness relative to the volume of activity: as the variable goes up, higher probabilities of default emerge. The period of time for the account receivables to be converted into cash has a direct implication on default: a delay of cash-inflows from customers will ultimately be translated into a delay of debt service payment, which may cause a firm to default. Sales growth also has a significant impact on credit risk assessment, indicating the development of a firm's activity.

In order to assess the model's robustness, we conduct an out-of-time analysis to verify the discriminatory power and the calibration performance of the model. The model that was calibrated to the registered annual default rate in 2010 (using equation (1)) possesses the same discriminatory power as the model calibrated to the actual default rate. For both of these models, in and out-of-sample ROCs exhibit a very good discriminatory power (84.2% and 85.5% respectively, Chart 1 of the Appendix). Furthermore, the optimal cut-off point that can be used to make binary predictions in 2010 is 9.5% (Chart 2 of the Appendix), implying a 72% hit rate and a false alarm rate of 17% in 2011. The only important difference between the two models is the levels of the PDs, which are overestimated in the first case (Charts 3 and 4 of the Appendix). We calibrate the PDs with a view to converging towards the "true" annual default rate. The results in Table 1 are those of the calibrated model, with the actual default rate in 2011. The binomial test reveals that, in some cases, the model underestimates the PDs for the construction and the trading sectors (Table 5 of the Appendix). This can be explained by the use of the same default rate for calibration purposes, instead of multiple default rates (e.g. default rate for each economic sector, for rating classes, etc.).

Finally, in order to extract the estimated one-year ahead PDs, starting with the date the analysis is conducted, we run a calibration process, using the default rate registered in 2011. Since the actual level of default is unknown for that period, we use a forecasted default rate based on the macroeconomic credit risk module described in Section 2.2. The results are presented in the following section.

3.2 Results from the macroeconomic credit risk module

The data used for building the macroeconomic credit risk module are selected from 36 quarterly macroeconomic time series (between the first quarter of 2003 and the fourth quarter of 2011). All the figures are taken from the central bank's macroeconomic forecasting model, in order to have consistency between this instrument used for price stability purposes, and the financial stability tool we present in this paper. The dependent variable is the registered quarterly default rate.

The macroeconomic variables that proved to be significant in explaining the corporate default rate are: (i) annual GDP growth (GDP growth); (ii) change in the real effective exchange rate (REER); (iii) CORE1 annual inflation rate (CORE1) and; (iv) the FX interest rate spread (spread), computed as the difference between the real interest rate for lending and the three-month EURIBOR in real terms. The coefficients for these variables comply with the sign restrictions and are statistically significant. The model specification that includes these variables is characterised by the smallest root mean square error (RMSE). The errors have been tested for both autocorrelation and heteroskedasticity.

We reformulate the equation (5) in the following form:

$$p_t = \Psi\left(\beta_0 + \beta_1 gdpgrowth_t + \beta_2 reer_{t-1} + \beta_3 CORE1_{t-2} + \beta_4 spread_{t-2}\right) \qquad (8)$$

where the values for the coefficients are presented in Table 2.

Table 2: Macroeconomic credit risk module

Methodology		**Jakubík (2007)**	
Time interval		March 2003 - December 2011	
Number of observations		34	
Number of variables		6	
Variables	**Lag**	**Coefficient**	**Standard error**
Constant	-	2.0450	0.0790
GDP growth (year-on-year)	0	-0.0215	0.0061
REER (quarter-on-quarter)	1	0.0921	0.0151
CORE1 (year-on-year)	2	-0.0295	0.0089
spread	2	0.0222	0.0088
ρ	-	0.0001	0.0055
R-squared	83.95		
LR - test	94.98		
RMSE	0.020		

Since almost all of the time series are lagged[7] , we use the forecasted values from the central bank's macroeconomic baseline scenario, which made the following key assumptions for euro area developments in 2012[8] : (i) annual growth of 0.5%; (ii) annual inflation rate of 1.7%; and (iii) three-month EURIBOR interest rate of 1.06%. Based on the 2012 forecasted quarterly default rates, we obtain an annual forecasted default rate of 10.98%, which is used to calibrate the level of the corporate PDs, using equation (2).

3.3 The ability of the banking sector to withstand losses

We compute the expected losses for the banking sector for 2012, using the methodology described in Section 2.3 and the baseline scenario described in Section 3.2. Companies that defaulted between July 2011 and December 2011 are excluded from the updated sample and are considered to be in default. We use a constant LGD of 45%[9] across all companies' exposures, in line with the Basel II requirements for an internal rating-based approach for modelling. The macro-prudential tool leads us to draw three main conclusions. The monitored banking sector is in relatively good shape to withstand developments that could manifest in the corporate sector portfolio and in the macroeconomic scenario under consideration. This is the first conclusion. The gap of provisions is less than 0.11% of the total assets in the banking sector (in December 2011). Such an amount could be covered relatively easily and in an orderly manner. *In extremis*, the level of core Tier 1 capital ratio is sufficient to withstand expected losses stemming from the corporate sector, if the additional costs with provisions were to ultimately translate into capital damages for certain banks.

The second conclusion to be drawn is that the gap between the expected losses stem-

[7]Lagged macroeconomic variables can be explained by the fact that a company must be at least 90 days past due payments in order to be considered to be in default.

[8]National Bank of Romania – *Inflation Report, Inflation Outlook Section,* November 2011.

[9]It is true that theory suggests that the LGD should fluctuate across an economic cycle. In reality, at least for the emerging European economies, such behaviour is difficult to capture owing to: (i) little history of LGD databases; and (ii) credit institutions' policies of not enforcing material collateral liquidation owing to actual improper market conditions (price, liquidity, legal, etc.).

ming from the macroeconomic scenario and the provisions already uploaded does not display any particular risk pattern for financial stability. Moreover, large banks (most likely systemically important institutions) do not exhibit material gaps in provisioning. Also, banks that should increase their coverage with provisions are not the drivers in the corporate lending market.

The third conclusion to be drawn is that the annual default rates remain below their peak level (Chart 5 of the Appendix). Such a trend could reflect a decrease in the pace of increase of the non-performing loans ratio, if new lending were to gain more ground and the macroeconomic picture were to remain stable compared with the scenario under consideration.

4 Conclusions

We build a macro-prudential tool in order to assess whether the banking sector is adequately prepared to orderly withstand losses from corporate sector developments, under certain macroeconomic scenarios. The tool is designed in two steps. First, we model a logit one-year ahead probability of default (PD) model for the corporate sector using micro data, in line with the Basel II definition of default, with a bottom-up approach. Second, we bridge the PD model with a macroeconomic module in order to capture the feedback effects of the macroeconomic stance on the banking sector, through the corporate sector channel. The tool is also able to: (i) evaluate corporate risk at the sectorial and aggregate economy levels; (ii) gauge the trend of the overall default rate for the corporate sector, highlighting the most likely direction it would take in the banks' non-performing loan ratio; and (iii) complement the macro-prudential approach with a microeconomic perspective in order to compute the portfolio at risk of those entities that could put pressure on financial stability (e.g. systemically important institutions).

We tested the tool on the Romanian economy. The conclusions indicate that the banking sector under review is in relatively good shape to withstand developments that could manifest in the corporate sector portfolio and in the macroeconomic scenario under consideration. The up-trending level of provisioning can be rather easily accommodated in an orderly manner. The main microeconomic factors identified as hindering companies from servicing their bank debt are: a deterioration in the receivables turnover ratio, sales-to-total assets ratio, short-term bank debt-to-total assets and debt-to-equity, while the macroeconomic factors affecting the corporate default rate are annual GDP growth, a change in the real effective exchange rate, the CORE1 annual inflation rate and the FX interest rate spread.

The tool under review in this paper helps macro-prudential policy-makers in the following main areas: (i) to signal whether the level of some macro-prudential instruments (such as the solvency ratio or provisions for credit risk) could reach critical benchmarks in the near future; (ii) to give a flavour of the trend and the pace of the corporate sector non-performing loans; and (iii) to flag the need for adjustments to some macro-prudential measures (change in the LTV ratio, better credit risk management to avoid unsustainable credit growth, etc.).

References

[1] Altman, E., (1968), "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy", The Journal of Finance, 23, pp. 589-609.

[2] Band, de O., Bruneau, C., El Amri, W., (2008), "Stress testing and corporate finance", Journal of Financial Stability, 4(3), pp. 258–274.

[3] Beaver, W., (1966), "Financial ratios as predictors of failure", Journal of Accounting Research, 4, pp. 71-111.

[4] Bunn, P., Redwood, V., (2003), "Company accounts based modeling of business failures and the implications for financial stability", Bank of England, Working paper No 210.

[5] Chi, L., Tang, T., (2006), "Bankruptcy Prediction: Application of Logit Analysis in Export Credit Risks", Australian Journal of Management.

[6] Engelmann, B., Hayden, E., Tasche, D., (2003), "Measuring the discriminatory power of rating systems", the Deutsche Bundesbank, Discussion paper 1.

[7] Fong, T. P. and C. Wong., (2008), "Stress testing banks' credit risk using mixture vector autoregressive models," Hong Kong Monetary Authority, Working Paper, 13/2008.

[8] Jakubík, P., (2007), "Macroeconomic Environment and Credit Risk", Czech Journal of Economics and Finance, 57(2), pp. 60-78.

[9] Jakubík, P., (2011), "Households Balance Sheets and Economic Crises", IES Working Paper, No 20.

[10] Kindleberger, C., Aliber, R., (2005), "Manias, panics and crashes", 5th edition, Basingstoke: Palgrave Macmillan.

[11] King, G., Zeng, L., (2001), "Logistic Regression in Rare Events Data", Harvard University, Center for Basic Research in the Social Sciences.

[12] Lennox, C., (1999), "Identifying failing companies: A reevaluation of the logit, probit and DA approaches", Journal of Economics and Business, 51, pp. 347-364.

[13] Malhotra, M., Sharmab, S., Nairc, S., (1999), "Decision making using multiple models", European Journal of Operational Research, Vol. 114, Issue 1, pp. 1-14.

[14] Mircea, R., (2007), "Credit risk of non-financial companies in the context of financial stability", DOFIN Dissertation paper.

[15] Morris, R., (1997), "Early Warning Indicators of Corporate Failure", Ashgate Publishing.

[16] Ohlson, J., (1980), "Financial ratios and the probabilistic prediction of bankruptcy", Journal of Accounting Research, 18, pp. 109-131.

[17] Simons, D. and Rolwes, F. (2009), "Macroeconomic Default Modeling and Stress Testing", International Journal of Central Banking, 5(3),pp. 177-204.

[18] Virolainen, K., (2004), "Macro Stress Testing with a Macroeconomic Credit Risk model for Finland", Bank of Finland, Discussion Paper 18.

[19] Vivet, D., (2011), "Development of a financial health indicator based on companies' annual accounts", National Bank of Belgium, Working Paper, No 213.

[20] Working Group on Risk Assessment (WGRA), (2007), "Credit Risk Assessment Revisited – Methodological Issues and Practical Implications", European Committee of Central Balance-Sheet Data Offices.

Appendix

Table 1: Financial ratios and filter results

Ratio/description	Monotony and linearity test	Univariate logit
	R^2	ROC
Debt-to-equity	81%	75%
Short-term bank debt-to-total assets	38%	50%
Receivables turnover ratio	84%	64%
Sales-to-total assets	88%	63%
Gross profit-to-sales	12%	50%
Operational profit margin	56%	63%
Net profit margin	79%	67%
Return on equity	55%	68%
Return on assets	9%	50%
Sales to equity	26%	50%
Sales-to-receivables	44%	50%
Cost of goods sold to inventories	0%	50%
Debt-to-value added	84%	67%
Debt-to-total assets	89%	70%
Debt-to-equity (one year prior)	11%	50%
Long-term debt-to-equity	46%	50%
Short-term debt-to-equity	50%	70%
Credit line utilisation ratio	0%	50%
Inventories to cost-of-goods sold	42%	50%
Inventories to cost-of-goods sold (one year prior)	27%	50%
Payables turnover ratio (estimation) = (short-term non-bank debt/cost of goods sold) * 360	52%	62%
Short-term bank debt-to-total bank debt	0%	50%
Short-term bank debt-to-equity	0%	50%
Financing mismatch = (short-term debt - current assets)/total assets	65%	60%
Financing mismatch cover ratio = sales/(short-term debt - current assets)	0%	50%
Bank debt growth ratio	0%	50%
Foreign exposure (internal foreign exchange-denominated debt + long and medium-term external debt)/equity	0%	50%
Operational leverage = (Sales - cost of goods sold)/operating profit	50%	50%
Operational leverage (one-year prior)	11%	50%
Sales growth rate	56%	64%
Total assets growth rate	43%	50%
Fixed assets growth rate	38%	50%
Investment in fixed assets = (fixed assets at t + depreciation)/fixed assets at *t-1*	0%	50%
Short-term assets growth rate	34%	50%
Net profit growth rate	42%	50%
Operational leverage change ratio	46%	50%
Inventories change ratio	23%	50%
Liquidity	68%	58%
Acid test	41%	50%
Cash ratio	35%	50%
Operational cash flow-to-net profit	11%	50%
Operational cash flow-to-equity	31%	50%
Interest coverage ratio	75%	67%
Interest-to-total assets	0%	50%
Inventories-to-total assets	17%	50%
Cash-to-total assets	22%	50%
Fixed assets-to-total assets	23%	50%

Table 2: Population statistics: number of companies with bank loans

	December 2009	**December 2010**	**June 2011**
Number of observations	68,463	59,311	48,783
Defaulters (in year t+1)	6,903	4,110	
Default rate	10.08%	6.92%	

Table 3: Population statistics: structure of companies with bank loans by sector of activity

Sector	**December 2009**		**December 2010**		**June 2011**	
	Obs.	Defaults	Obs.	Defaults	Obs.	Defaults
Agriculture	5.1%	4.4%	5.7%	4.0%	6.3%	-
Mining	0.3%	0.5%	0.3%	0.3%	0.3%	-
Manufacturing	16.2%	15.6%	16.3%	15.1%	17.7%	-
Energy	0.8%	0.6%	0.8%	0.7%	1.0%	-
Construction	9.4%	14.5%	8.9%	13.6%	9.2%	-
Trade	39.6%	36.4%	39.5%	39.5%	40.6%	-
Services	25.7%	25.3%	25.5%	22.8%	22.7%	-
Real estate	2.9%	2.7%	3.0%	4.1%	2.2%	-

Table 4: Descriptive statistics for the variables included in the final model for 2009 and 2010 validation sample

	December 2009				**December 2010**			
Variables	Defaulters		Non-defaulters		Defaulters		Non-defaulters	
	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Debt-to-equity	10.28	5.71	7.31	6.08	10.25	5.77	7.16	6.12
Debt-to-value added	3.99	2.35	2.86	2.14	4.31	2.42	3.03	2.25
Interest cover ratio	0.36	2.87	1.87	3.30	0.18	2.91	2.09	3.45
Receivables cash conversion days	104.57	73.95	74.04	66.48	107.53	76.54	77.91	68.07
Sales growth	0.72	0.39	0.88	0.33	0.75	0.40	0.95	0.32

Table 5: Binomial test*

	Deciles		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Sectors of activity	Agriculture	PD	1%	1%	1%	2%	2%	3%	4%	5%	8%	37%
		Default rate	0%	0%	1%	1%	2%	2%	3%	5%	7%	28%
		p-value	N/A	N/A	0.7117	0.9319	0.7287	0.8102	0.7479	0.4541	0.8310	0.9997
	Mining	PD	1%	2%	2%	3%	3%	5%	7%	10%	21%	57%
		Default rate	0%	0%	0%	0%	11%	0%	0%	11%	22%	28%
		p-value	N/A	N/A	N/A	N/A	0.1351	N/A	N/A	0.5607	0.5286	0.9971
	Manufacturing	PD	1%	1%	2%	2%	2%	3%	3%	5%	9%	41%
		Default rate	1%	0.2%	1%	1%	1%	2%	4%	5%	10%	39%
		p-value	0.9657	0.9999	0.9964	0.9545	0.9839	0.8276	0.3364	0.2344	0.2297	0.8640
	Energy	PD	1%	1%	1%	1%	2%	2%	3%	4%	9%	30%
		Default rate	0%	0%	0%	2%	2%	4%	0%	6%	8%	33%
		p-value	N/A	N/A	N/A	0.5009	0.5722	0.2855	N/A	0.3600	0.5914	0.3809
	Construction	PD	1%	1%	2%	2%	3%	4%	5%	7%	15%	52%
		Default rate	1%	2%	2%	4%	4%	6%	9%	12%	19%	46%
		p-value	0.5063	0.0967	0.1800	0.0188	0.0433	***0.0017***	***0.0001***	***0.0001***	***0.0027***	0.9971
	Trade	PD	1%	1%	2%	2%	2%	3%	4%	5%	9%	40%
		Default rate	1%	1%	1%	2%	2%	3%	4%	7%	11%	39%
		p-value	0.9910	0.9994	0.9956	0.7789	0.9323	0.7003	0.5647	***0.0000***	***0.0004***	0.8708
	Services	PD	1%	1%	2%	2%	3%	3%	4%	6%	12%	46%
		Default rate	0%	1%	1%	2%	3%	2%	3%	6%	11%	32%
		p-value	0.9945	0.9662	0.9496	0.7693	0.5279	0.9974	0.9751	0.6795	0.8597	0.9999
	Real estate	PD	1%	2%	2%	3%	4%	5%	8%	11%	17%	57%
		Default rate	1%	1%	2%	3%	2%	5%	10%	7%	23%	40%
		p-value	0.5905	0.7936	0.7793	0.4372	0.9216	0.5949	0.1091	0.9605	0.0218	0.9998
	Economy	PD	1%	1%	2%	2%	2%	3%	4%	5%	10%	43%
		Default rate	1%	1%	1%	2%	2%	3%	4%	7%	11%	38%
		p-value	0.9998	0.9999	0.9986	0.9379	0.8218	0.7520	0.1928	***0.0001***	***0.0052***	0.9999

*Null hypothesis *H0*: the PD of a category is correct.
Alternative hypothesis *H1*: the PD of a category is underestimated
Green result- *p-value* greater than 0.05
Yellow result - *p-value* between 0.01 and 0.05
Red result - *p-value* less than 0.01

Chart 1: Discriminatory power

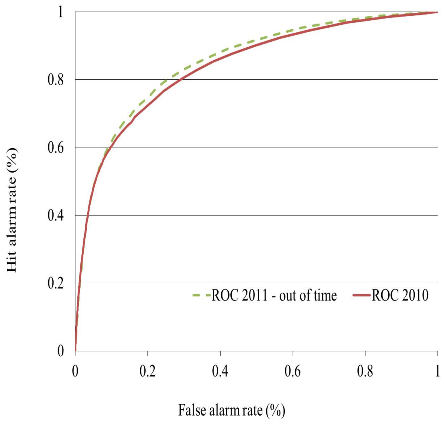

Chart 2: Out-of-time - performance measures

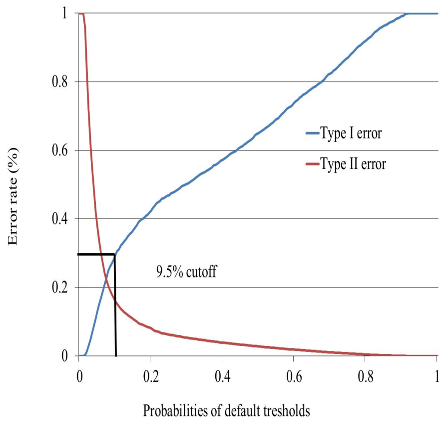

Chart 3: Calibration comparison - economy

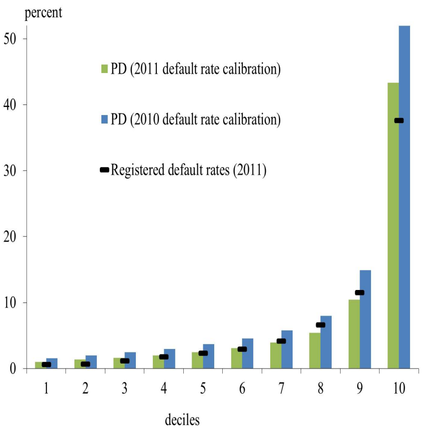

Chart 4: Calibration comparison - sector level

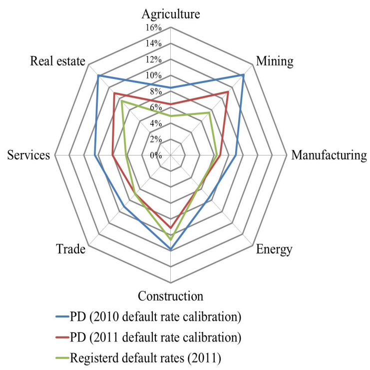

Chart 5: Annual default rates