Bridging the banking sector with the real economy: a financial stability perspective[1]

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Abstract

The paper builds a macroprudential tool to assess whether a banking sector is adequately prepared to orderly withstand losses resulting from normal or stressed macro and microeconomic scenarios. The link between the banking sector and the real sector is performed through the corporate sector channel. The macroprudential tool consists in a two-step approach. The first one is building a probability of default model for the corporate sector to quantify the 1-year ahead developments in the banks' corporate loans quality. The framework is constructed using micro data and following a bottom-up approach. The second step is to bridge the PD model with a macroeconomic module, in order to capture the feedback effects from the macro stance into the banking sector, through the corporate sector channel. The usage of the macroprudential tool is exemplified on the Romanian economy.

Keywords: probability of default, financial stability, macroprudential analysis

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1. Introduction and literature review

There are at least two important lessons the crisis has taught about evaluating systemic credit risk. The first one is that the current instruments used to assess the overall banking sector level of risk witnessed important flaws in times of high distress. Probability of default is one of these key instruments. It is used by both banks and the micro and macroprudential authorities (to compute expected and unexpected losses, for stress testing exercises, etc.), but it proved to be procyclical and not very responding to material shocks that occur quite frequently in the real life[4]. The second lesson is that financial stability analysis should look into a deeper macro-prudential perspective, 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 banking sector credit risk assessments.

The paper builds a macroprudential tool to assess whether a banking sector is adequately prepared to orderly withstand losses[5] resulting from normal or stressed macro and microeconomic scenario. The tool is developed into two steps. In the first step, we build a probability of default (PD) model for the corporate sector. Such models help financial stability evaluation in three avenues: (i) show the main micro factors that best explain companies' behavior in servicing their bank debts, (ii) indicate the level and direction of credit risk that lay in the banks' portfolio within a specific time horizon (1-year ahead PD is the most common tenor) and (iii) point out if the expected loss from the credit portfolio is adequately covered by provisions. The framework is constructed using micro data, following a bottom-up approach and highlighting the main factors that deter firms from servicing their bank loans. We use Basel definition for default (90-days past due default) and firm-level data for all non-financial companies with bank loans. 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 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 macro stance into the banking sector, through the corporate sector channel. We compute how the main macroeconomic variables (annual GDP growth, real effective exchange rate, inflation rate, etc.) may impact corporate PD outcomes. The tool also allows us to use different macro scenarios for both normal or stress times in order to evaluate the ability of the corporate sector to withstand shocks and the degree these shocks are translated to the banking sector.

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[4] 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, while they take place every 5 to 10 years.

[5] This tool primarily focuses on loan losses from 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 remain insensitive in the macroeconomic scenario (e.g. 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 macro stress-testing approach with results on profitability or solvability.

Forecasting aggregate default rates for the corporate sector based on macroeconomic conditions has gained steam in the literature on financial stability. Viroleinen (2004) shows that, in case of Finland, the evolution of the default rate can be explained by the GDP growth and the level of indebtedness of the corporate sector. Fong and Wong (2008) use a vector autoregressive model to link the default rates with macroeconomic environment for stress-testing purposes. Simmons and Rolwes (2008) embark on finding the determinants of default for Holland, 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 default barrier depending on the macroeconomic environment.

Finally, we estimate the risks to financial stability via the direct channel. We take into consideration the probability of default (both at individual and 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 banks have already built to cover the expected losses.

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

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

2. Non-linear models (logit and probit) assume 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). *Banco de España*, *Banque Nationale de Belgique* or *Banca Naţională a României* are amongst the central banks using such methodology to quantify the credit risk stemming from the corporate sector (WGRA, 2007; Vivet, 2011);

3. Non-parametric, non-linear models (such as neural networks or support vector machines - SVM) carry the advantage of not being restricted to a certain functional form and are able to better uncover 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. *Deutsche Bundesbank* is using an SVM model for assessing credit risk for non-financial companies (WGRA, 2007).

In this paper we use a logistic regression since this type of models deliver better results compared to linear models. Furthermore, Bunn and Redwood (2003), and Chi and Tang (2006) point out to 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 neighbor) and find the latter have superior in-sample performance, but lower out-of-sample performance, compared to the logit regression.

Logit models require a large proportion of defaulters in order to produce accurate results. This is an important drawback of such models. In practice, researchers use artificial samples built up with all 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 a low default sample. Hence, the level of PDs will 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 remaining of the paper is organized as follows. Section 2 describes the methodology and the input data for the probability of default model and the macroeconomic module, section 3 applies the macroprudential tool to the Romanian economy, while the last section concludes the main ideas of the paper.

2. Methodology

2.1. Probability of default model: development and calibration

The corporate PD model development is the first step in building our macroprudential tool. We use a logit approach:

$$PD = \frac{1}{1+e^{\alpha+\beta X}} \qquad (1)$$

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

We winsorize[6] the explanatory variables in the training sample in order to exclude extreme values. From empirical simulations, we find a threshold of 15% being appropriate for a large amount of variables. However, for the variables qualified in the final model, we take an in-depth study of the relationship between the natural logarithm of the odds of default and the variable values, modifying the winsorize thresholds according to this function’s linearity.

The variables in the forecast sample are winsorized using the same values as in the training sample. When applying the model, we use this technique rather than the same quantiles, because we notice large shifts in the tails of the distributions of some variables over the past few years, resulting in unrealistic shifts in calculated PD due to extreme values. The logic behind winsorizing at the same values as the training sample is that the coefficients are estimated on the same interval of the variable’s values.

In order to derive the final default model, additional filters and discriminatory power tests are employed on a pool of candidate explanatory variables and intermediary default models[7].

[6] 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 made tail-analysis for each distribution of the balance-sheet variables.

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

In the first step, the Kolmogorov-Smirnov (KS) test is applied. The purpose of this filter is to exclude ratios that are independent from default events. 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 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 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, to check their in and out-of-the-sample discriminatory power. We exclude variables with a univariate ROC less than 55%[8]. The univariate analysis is an important step due to the following reasons: (i) robustness checks of the coefficients and (ii) individual discriminatory power (in 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 at the previous step. Variables are dropped if the correlation coefficient is higher than 0.7[9].

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

The process of estimation of the multivariate model of default is split 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 companies. For this purpose, we use all defaulted firms and we draw a random sample out of the non-defaulted firms of same size as the defaulted ones. In this way, 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 where we compute the coefficients by using only the variables of the model with the highest occurrence.

This un-calibrated model bears a number of drawbacks which may result in an underestimation of the PD in times of high stress. These drawbacks mainly relate to: (i) a certain pro-cyclicality degree of the PD outcome, (ii) low frequency of companies' financial data (semiannual) and (iii) the considerable delay between the end of reporting date of the financial statements and the date when these figures are effectively available

[8] 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.
[9] The idea is to set the threshold high enough in order to exclude high correlated variables.

for analysis. In such conditions, the latest explanatory variables might not incorporate the most recent economic developments, which might lead to an over/under estimation of the true PD. In order to alleviate these drawbacks, we use King and Zeng (2001) methodology for recalibrating the model to reflect the true default rate by adjusting the intercept in the logit formula with a coefficient dependent on the two rates:

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

where 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 building the macroprudential tool is to adjust the PDs with the forecasted default rate, based on the methodology proposed by Jakubík (2007) consisting in an one-factor Merton type model with default barrier depending on macroeconomic environment.

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

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

where:

- R_{it} denotes the logarithmic asset return for economic agent *i* in 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 might 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 modeled by taking 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 given 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} :

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

The default probability conditional on the realization F_t (noted as f_t) of a random unobservable factor representing the state of the economy at time t corresponding to the default probability (4) is given by formula (5).

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

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:

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

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 conditional probability given by equation (5) and the number of economic agents n_t. Then the macroeconomic model is calibrated by maximizing 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 macro variables (GDP, exchange rate, interest rate, etc.). The link with the PD model is made through the calibration method (King correction formula), which shifts the distribution of the PDs in order to reflect the developments in the macroeconomic context (represented by the annually forecasted default rate – π_d in equation [2]). This methodology also helps to avoid cases where 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 point-in-time, based on past/non-crisis information.

2.3. Measuring the risk to financial stability

The main aim of this macroprudential tool is to assess whether a banking sector holds 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 the 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 macroprudential approach with a micro perspective, in order to compute the portfolio at risk of those banks that might put pressure on the financial stability (e.g. systemically important institutions).

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

$$EL = \sum_i PD_i \cdot E_i \cdot LGD \tag{7}$$

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 lack of information, LGD is assumed to be constant across all obligors, at 45%, as stipulated in the 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 9 additional dummy variables (8 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 reported by companies to the authorities (e.g. Ministry of Public Finance, Trade Register, etc.). The database used in 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 booked in the credit registers. In the case of Romania, this register is a database where all banks report exposures exceeding around EUR 5,000, at the obligor level. This credit register consists of around 220,000 credits and 90,000 individual debtors. The intersection of the above-mentioned databases delivers more than 90% of all credit to non-financial companies sector.

An out-of time analysis of the PD model is employed on a sample consisting of the 2010 financial statements and the observed defaults during January 2010 – December 2011. After validating the model, the PDs for 2012 are forecasted based on the 2011 semiannual financial statements.

Table 1: Logit model for 1-year default horizon using 2009-2010 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 (2010-2011): 85,5%
-Neutral cost policy function:

- Optimal cut-off (2010): 9.5% implying a Hit rate: 72% and False alarm rate: 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

n.a. – not applicable

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 consists of all companies having bank loans and not being in default at the beginning of the period (i.e. no overdue payment of more than 90 days past due in the last 12 months prior to the compilation of the sample). The performance of the model and other results are presented in the Appendix.

We find that the main factors explaining firms' ability to service the bank debts in our empirical case are: (i) debt to equity, (ii) debt to value added, (iii) interest cover ratio, (iv) receivables cash conversion days and (v) sales growth. A higher leverage indicates that the company might bear debt higher than its capacity to service the obligations pertaining to commercial clients and financial creditors. Debt to value added measures the ability of the 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 defaults 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 be ultimately transmitted into a delay of debt service payment, which may cause a firm to default. Sales growth has also an important impact on credit risk assessment indicating the evolution of the firm's activity.

In order to assess the model robustness, we perform an out-of-time analysis to check the discriminatory power and the calibration performance of the model. The model calibrated to the registered annual default rate of year 2010 (using equation [1]) has the same discriminatory power as the model calibrated using the actual default rate. For both these models, in- and out-of-sample ROCs show a very good discriminatory power (84.2% and 85.5% respectively, Chart 1, Appendix). Furthermore, the optimal cut-off point that can be used to make binary predictions in 2010 is 9.5% (Chart 2, Appendix), implying a 72% hit rate and a false alarm rate of 17% in 2011. The only important difference between the models is given by the levels of PDs, which are overestimated in the first case (Charts 3 and 4, Appendix). We calibrate the PDs aiming at converging to the "true" annual default rate. The results in Table 1 represent the calibrated model with the actual default rate of 2011. The binomial test reveals that, in some cases, the model underestimates the PDs for the construction and the trading sectors (Table 5, 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 1-year ahead PDs starting with the date the analysis is performed, we run a calibration using the default rate registered in 2011. Since the actual default information for the period is unknown, we use a forecasted default rate stemming from the macroeconomic credit risk module described in part 2.2. The results are presented in the next 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 2003 Q1 and 2011 Q4). All the figures are collected from the central bank macroeconomic forecasting model in order to have consistency between the last-mentioned instrument used for price stability purposes and the tool we present in the paper, used for financial stability purposes. The dependent variable is the quarterly registered default rate.

The macro variables that proved to be representative for 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 real interest rate for lending and 3M 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 characterized by the smallest root mean square error (RMSE). The errors have been tested for both autocorrelation and heteroskedasticity.

We re-write the equation (5) in the following form:

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

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 (yoy)	0	-0.0215	0.0061
REER (qoq)	1	0.0921	0.0151
CORE1 (yoy)	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[10], we use the forecasted values from the central bank macroeconomic baseline scenario, which had the following key assumptions for the 2012 euro area[11] developments: (i) annual growth of 0.5%, (ii) annual inflation rate of 1.7% and (iii) 3M 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 expected losses for the banking sector for year 2012, using the methodology described in section 2.3 and the baseline scenario described in section 3.2. Companies that defaulted during July 2011-December 2011 are excluded from the updated sample and are considered to be in default. We use a constant LGD of 45%[12] across all companies' exposures, in line with the Basel II requirements for internal rating based approach modeling. The macroprudential tool highlights three main conclusions. The monitored banking sector is in a relatively good shape to withstand developments that would manifest in the corporate sector portfolio and in the considered macroeconomic scenario. This is the first conclusion. The gap of provisions is less than 0.11% of the total assets of the banking sector (in December 2011). Such an amount should be covered relatively easy and in an orderly manner. *In extremis*, the level of core Tier 1 capital ratio is sufficient to shelter expected losses stemming from the corporate sector, if the additional costs with provisions would finally translate in capital damages for some particular banks.

[10] Lagged macroeconomic variables can be explained by the fact that a company must have at least 90 days past due payments in order to be in default.
[11] National Bank of Romania – Inflation Report, Inflation Outlook Section, November 2011.
[12] It is true that theory suggests that LGD should fluctuate across an economic cycle. In reality, at least for the emerging European economies, such a behavior is difficult to capture, due to (i) low history with LGD databases and (ii) the credit institutions' policies of not running material collateral liquidations due to actual improper market conditions (price, liquidity, etc.).

The second conclusion is that the gap between the expected losses stemming from the macro scenario and the already uploaded provisions does not display a risk pattern for the financial stability. Moreover, large banks (most likely systemically important entities) 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 is that the annual default rates remain below their peak (Chart 5, Appendix). Such trend would reflect a decrease in the non-performing loans ratio pace of increase, if new lending gets more steam and the macroeconomic picture does not deteriorate compared with the considered scenario.

4. Conclusions

We build a macroprudential tool to assess whether a banking sector is prepared to orderly withstand losses from the corporate sector developments, in a given macroeconomic scenario. The tool is constructed in two steps. First, we model a logit 1-year ahead probability of default model for the corporate sector using micro data, with Basel II definition of default and following a bottom-up approach. Second, we bridge the PD model with a macroeconomic module, in order to capture the feedback effects from the macro stance into 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 in the banks' non-performing loan ratio and (iii) complement the macroprudential approach with a micro perspective, in order to compute the portfolio at risk of those entities that might put pressure on the financial stability (e.g. systemically important institutions).

We test the tool for the Romanian economy. The conclusions highlight the investigated banking sector is in a relatively good shape to withstand developments that would manifest in the corporate sector portfolio and in the macroeconomic explored scenario. The up-trending level of provisioning is rather easy to be accommodated in an orderly fashion. The main micro factors identified to impair companies from servicing their bank debt are: 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, change in the real effective exchange rate, CORE1 annual inflation rate and the FX interest rate spread.

The tool proposed in the paper helps the macroprudential policy makers mainly in the following directions: (i) to signal whether the level of some macroprudential instruments (such as solvency ratio or provisions for credit risk) might reach critical benchmarks in the near future, (ii) to give a flavor of the trend and the speed of the corporate sector non-performing loans, or (iii) to flag the need for adjustments in some macroprudential measures (change in the LTV ratio, better credit risk management to avoid unsustainable credit growth, etc.).

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Appendix

Table 1: Financial ratios and filter results

Ratio name/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 utilization 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:

	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			
	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	104.56	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	1.0000
	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 – p-value greater than 0.05
yellow – p-value between 0.01 and 0.05
red – p-value less than 0.01

Chart 1: Discriminatory power

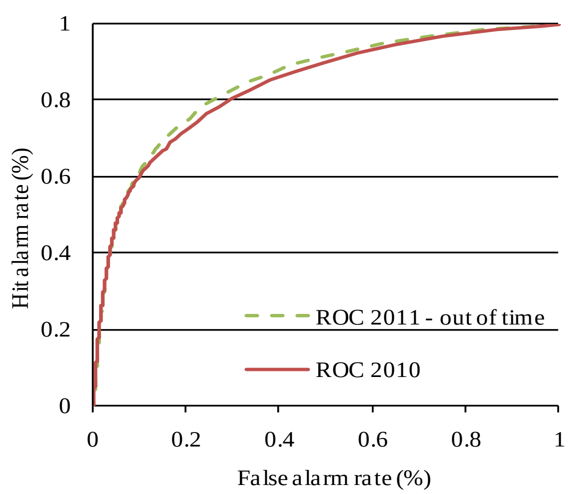

Chart 2: Out of time – performance measure

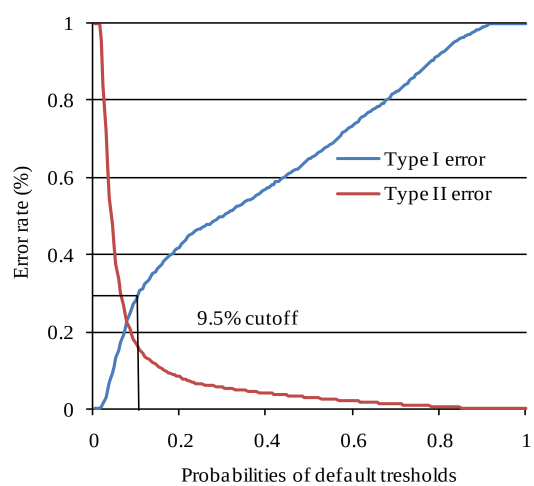

Chart 3:Calibration comparison - economy

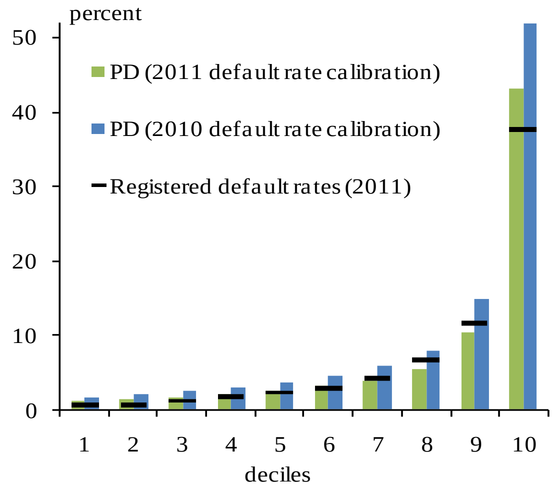

Chart 4:Calibration comparison – sector level

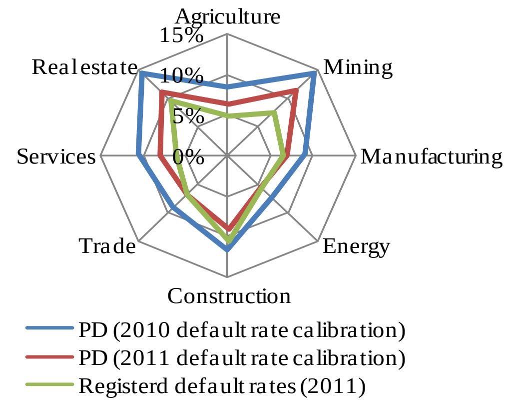

Chart 5: Annual default rates