ANALYSIS MODEL ON THE RELATION BETWEEN MACROECONOMICAL VARIABLE TENDENCIES AND COMERCIAL BANK'S CREDIT RISK

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The main goal of this study is to apply a macroeconomic credit risk model which links a set of macroeconomic factors and industry-specific corporate sector default rates using Romanian data over the time period from 2002:2 to 2008:2. Using the modeled and estimated industry specific default rates we will simulate with Monte Carlo method a loss distribution of a hypothetical corporate credit portfolio and we will analyze the impact of the different macroeconomic variables on the credit portfolio loss distribution.

Keywords: credit risk, industry-specific default rate, credit portfolio loss distribution.

JEL Classification: C15, G21, G28.

Introduction

The macroeconomic environment has a major impact on the credit risk. In the credit risk models this exposure to the macroeconomic environment can be captured in different ways: in several studies the relation between credit losses and macroeconomic environment[363] is modeled, in other studies the relation between the individual data of debtors and the macroeconomic environment[364] is modeled. In this study we follow the methodology developed by Wilson, T. C. (1997). The studies based on Wilson's methodology modeled the relation between corporate default rate and macroeconomic variables. This model was applied by Boss, M. (2002) in Austria on corporate aggregate data. His results indicate that the industrial production, the inflation rate, the stock exchange index, the nominal short-term interest rate and the oil price are the most important determinants of the corporate default rates. Virolainen, K. (2004) applied the Wilson's model in order to analyze the sector-specific default rate of the nonfinancial companies in Finland. Virolainen used the following macroeconomic variables to determine the default rates: GDP, interest rate and the level of corporate sector indebtedness. Misina, M. et al. (2006) analyzed the effect of the modification of GDP and interest rate on the Canada's bank credit portfolio losses. Valentinyi-Endrész, M. & Vásáry, Z. (2008) applied the model in Hungary. The results suggest that the most significant factors of the credit risk are: the business cycles, the interest rate and the leverage.
Following the methodology developed by Wilson, in this study we will apply a macroeconomic credit risk model[365] which links a set of macroeconomic factors (GDP growth rate, consumer price index, exchange rate on forex market RON/EUR, industry-specific indebtedness rate) and

[363] For example, in the study of Kaliari, H. & Scheicher, M. (2002), Bikker, J. A. & Metzemakers, P. A. J. (2002), Laeven, L. & Majnoni, G. (2002), Pain, D. (2003), Delgado, J. & Saurina, J. (2004), Marcucci, J. & Qualiariello, M. (2006).
[364] For example, in the study of Hamerle, A. et al. (2004), Chava, S. & Jarrow, R. A. (2004), Jacobson, T. et al. (2005), Carling, K. et al. (2007).
[365] The results of previous research were published in the following studies: Benyovszki, A. & Petru, T. P. (2008), Benyovszki, A. & Trenca, I. (2008).

industry-specific corporate sector default rates (industry, services, construction, agriculture) using Romanian data during the 2002:2 to 2008:2 time period.

1. Methodology

As a *first step* we start with the modeling of the average default rate for industry i by the logistic functional form[366] as:

$$p_{i,t} = \frac{1}{1+e^{y_{i,t}}}, \qquad (1)$$

where $p_{i,t}$ is the default rate in industry i at time t, $y_{i,t}$ is the industry-specific macroeconomic index, whose parameters will be estimated, i, $i=\overline{1,m}$ indicates the number of industries.

We adopt Wilson's original formula and model the macroeconomic index in such a way that a higher value for $y_{i,t}$ implies a better state of the economy with a lower default rate $p_{i,t}$. Thus we obtain that:

$$y_{i,t} = \ln\left(\frac{1-p_{i,t}}{p_{i,t}}\right). \qquad (2)$$

The logit transformed default rate is assumed to be determined by a number of exogenous macroeconomic factors, i.e.:

$$y_{i,t} = a_{i,0} + a_{i,1}x_{1,t} + \dots + a_{i,n}x_{n,t} + \mu_{i,t}, \qquad (3)$$

where a_i is a set of regression coefficients to be estimated for the i^{th} industry, $x_{j,t}$ is a set of explanatory macroeconomic factors in t period, $\left(j=\overline{1,n}\right)$ and $\mu_{i,t}$ is a random error assumed to be independent and identically normally distributed, $\mu_{i,t} \sim N(0,\sigma_j)$ and $\mu_t \sim N(0,\Sigma_\mu)$, where μ_t indicates the array of error terms $\mu_{i,t}$ and Σ_μ is its variance-covariance matrix.

The equations (1) and (3) can be seen as a multifactor model for determining industry-specific average default rates. The systemic component is captured by the macroeconomic variables $x_{j,t}$, with an industry-specific surprise captured by the error term $\mu_{i,t}$.

Follows the *second step*, where we model and estimate the development of the individual macroeconomic time series. We use a set of univariate autoregressive equations of order n[367]:

$$x_{j,t} = b_{j,0} + b_{j,1}x_{j,t-1} + b_{j,2}x_{j,t-2} + \dots + b_{j,n}x_{j,t-n} + \varepsilon_{j,t}, \qquad (4)$$

where b_j is a set of regression coefficients to be estimated for the j^{th} macroeconomic factor $x_{j,t}$ indicates the value of macroeconomic factor j in the period t, and $\varepsilon_{j,t}$ is a random error assumed to be independent and identically normally distributed in t period, $\varepsilon_{j,t} \sim N(0,\sigma_j)$ and $\varepsilon_t \sim N(0,\Sigma_\varepsilon)$, where ε_t indicates the array of error terms $\varepsilon_{j,t}$ and Σ_ε is its variance-covariance matrix

Equations (2)-(4) together define a system of equations governing the joint evolution of the industry-specific default rates and associated macroeconomic factors with a $(i+j)\times 1$ vector of error terms, E, and a $(i+j)\times(i+j)$ variance-covariance matrix of errors, Σ, defined by:

$$E = \begin{pmatrix}\mu_t \\ \varepsilon_t\end{pmatrix} \sim N(0,\Sigma), \quad \Sigma = \begin{bmatrix}\Sigma_\mu & \Sigma_{\mu,\varepsilon} \\ \Sigma_{\varepsilon,\mu} & \Sigma_\varepsilon\end{bmatrix}$$

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366 Which is widely used in modeling bankruptcies to ensure that default rate estimates fall in the range (0,1).

367 In the initial model the macroeconomic variables was modeled by univariate autoregressive process of order 2.

The *final step* is to utilize the parameter estimates and the error terms together with the system of equations to simulate future paths of joint default rates across all industries over some desired time horizon. By assuming that defaults are independent is possible to determine credit loss distribution for portfolios with Monte Carlo method. The simulation over one year time horizon will have the following steps:

- *First*, the Cholesky decomposition of the variance-covariance matrix of the error terms Σ is defined as *A*, so that $\Sigma = A \cdot A'$.
- *Second*, for each step of the simulation an *(i+j)x1* vector of standard normal random variables $Z_{t+s} \sim N(0,1)$ is drawn. This is transformed into a vector of correlated error terms in the macroeconomic factors and the industry-specific default rates by $E_{t+s} = AZ_{t+s}$. Using the simulated realizations of the error terms and some initial values for the macroeconomic factors, the corresponding simulated values for $x_{j,t+s}$, $y_{i,t+s}$ and $p_{i,t+s}$ can then be derived using the system of equations (2)-(4). The procedure is iterated until the desired time horizon and the desired number of simulated path of default probabilities is reached.

The simulated path of future default rates can be used to determine loss distributions for hypothetical corporate credit portfolio. The defaults of individual debtors can be considered independent events and assuming further that the recovery rate is fixed, loss distributions can be determined under the assumption of binomially distributed defaults. The loss given default (*LGD*) parameter is assumed to be equal with 0.45 throughout the simulation.

2. Data used

In this study we used the quarter-yearly data of the nonfinancial corporate sector defaults by main industries and on macroeconomic factors over the 2002:2 to 2008:2 period. We can obtain default rates for a time period by dividing the number of bankruptcy proceedings instituted by the number of active companies. We analyzed the default data for the following *four main industries* according to the methodology used by the National Institute of Statistics: industry, construction, services[368] and agriculture[369].

We analyzed the explanatory power of the following *macroeconomic variables*: annual GDP growth rate, the deviation of GDP from trend, the GDP index[370], consumer price index, the interest rate of credit institutions on loans (real and nominal), the interest rate of credit institutions on time deposits, ROBOR, reference rate, average exchange rate on forex market (RON/EUR), average exchange rate on forex market (RON/USD), annual percentage changes of the industrial output, annual percentage changes of the domestic trade, real sales, current account, employment in economy, registered unemployment total, registered unemployment rate, medium and long term foreign debt, consolidated general government deficit.

In order to quantify the corporate sector indebtedness (*L/GVA*), industry-specific variables have been used, being measured by the volume of loans for an industry divided by the seasonally adjusted gross value added of that industry, all in current prices.

We obtained the quarterly input data from the following sources:

- number of bankruptcy proceedings instituted, the number of active companies – *The National Trade Register Office*

368 Comprise activity of trade, transports, post and telecommunications, tourism, hotels and restaurants, general government and defense, education, health and social assistance and other services for economic units and for the population.

369 Comprise activity of agriculture, silviculture and pisciculture.

370 Volum index.

- the interest rate of credit institutions on loans (real and nominal), the interest rate of credit institutions on time deposits, ROBOR, reference rate, average exchange rate on forex market (RON/EUR), average exchange rate on forex market (RON/USD), annual percentage changes of the industrial output, annual percentage changes of the domestic trade, real sales, current account, employment in economy, registered unemployment total, registered unemployment rate, medium and long term foreign debt, consolidated general government deficit, volume of loans by industries – *National Bank of Romania*, Monthly Bulletins, 2002-2008
- GDP index, GVA by industry, consumer price index – *National Institute of Statistics*, Monthly Statistical Bulletin, 2001-2008.

3. The estimation results

The results of univariate test indicate that the most significant explanatory variables are the GDP growth rate, the consumer price index (*CPI*), the average exchange rate on forex market (RON/EUR) (*RON/EUR*) and the industry-specific corporate indebtedness (*L/GVA_Ind, L/GVA _Serv, L/GVA _Constr, L/GVA _Agr*). *Table 1.* presents the results of the univariate autoregressive estimation of order *n*. The results indicate that the GDP index and the average exchange rate on forex market RON/EUR follow univariate autoregressive process of order 2. The consumer price index, the sector-specific corporate indebtedness rate in industry, services and constructions follow univariate autoregressive process of order 1, but in the case of agriculture only the 4th term was statistically significant.

Table 1. Estimates for AR macro factor models

	GDP	**CPI**	**RON/EUR**	**L/GVA _Ind**	**L/GVA _Serv**	**L/GVA _Constr**	**L/GVA _Agr**
Const	0.572***	—	0.723*	—	—	—	—
AR(1)	1.091***	0.860***	1.259***	1.022***	1.102***	0.997***	—
AR(2)	-0.628**	—	-0.457**	—	—	—	—
AR(3)	—	—	—	—	—	—	
AR(4)	—	—	—	—	—	—	1.410***
Adj. R^2	0.825	0.952	0.875	0.918	0.985	0.976	0.923
DW	2.190	2.139	2.029	2.210	2.252	2.431	1.520

Note: ***, ** and * indicate significance level 1%, 5% and 10%
Source: Own calculations in STATA

The adjusted R^2 indicates a good determination of the dependent variable by independent variables in all of the equations. The Durbin-Watson (DW) statistics indicate no significant autocorrelation in the data, with values near 2.

According to empirical studies, the GDP index is positively related with the industry-specific macroeconomic index, meanwhile the consumer price index, exchange rate and the corporate indebtedness is negatively related with it, since a higher value for the macroeconomic index implies a better state of the economy with lower corporate default rates. We estimated the macroeconomic index equations for the four industries as static model with the seemingly unrelated regression (SUR) method in STATA. Our results are presented in *Table 2.*

Table 2. SUR estimates for the static model (sample period 2002:2-2008:2)

	y_{IND}	y_{SERV}	y_{CONSTR}	y_{AGR}
GDP(-1)	4.980***	7.326***	6.634***	4.700***
CPI	-7.083***	-2.949**	-3.848*	-4.837***
RON/EUR (-1)	-0.405***			
L/GVA_i	-1.415***	-1.536***	-1.232**	-0.093**
R^2	0.9968	0.9980	0.9957	0.9968
χ^2	7632.17	12160.41	5595.14	7574.00
P	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan test of independence: χ^2 (6)=109.521 with p-value p=0.0000				

*Note: ***, ** and * indicate significance level 1%, 5% and 10%*
Source: Own calculations in STATA

The factors which influence the macroeconomic index in case of industry are: the GDP index, the consumer price index, the average exchange rate on forex market (RON/EUR) and the corporate indebtedness. In case of other sectors (services, construction and agriculture) the influencing factors are: the GDP index, the consumer price index and the corporate indebtedness. The variables are statistically significant; the signs are in correlation with the economic theory. The values of adjusted R^2 show that the models have good predictive power.

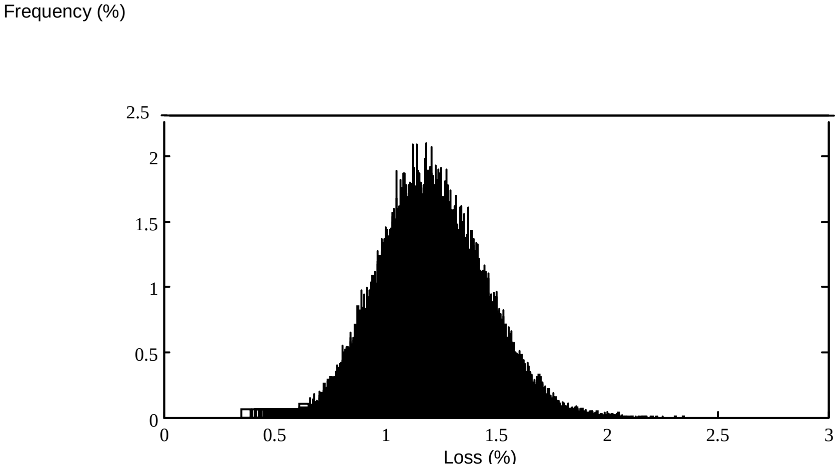
3.1. The results of the simulations on the credit portfolio loss distribution

Our analysis is based on a hypothetical credit portfolio consisting of 3,000 corporate loans. Constructing the credit portfolio we took in consideration the loan value distribution by sectors (industry 31.01%, services 53.54%, construction 11.86%, agriculture 3.92%) and the distribution of those companies which had credit applications, by sectors (industry 26.92%, services 62.57%, construction 6.82%, agriculture 3.68%), based on data from National Bank of Romania. The total credit portfolio value is 100 million RON.

The simulation of the credit loss distribution was made in Matlab using the Monte Carlo method. One hundred thousand simulations have been made in similar conditions to determine the credit portfolio loss distribution and its probability. *Figure 1.* presents the simulated loss distribution for the defined credit portfolio over an one-year time horizon.

The quarterly expected loss of the credit portfolio (conditioned to the macroeconomic environment) is 1.23% of total credit exposure on 1 year time horizon. The expected loss is the expected value of the individual losses. The unexpected losses are defined as the differences between the losses pertaining to the 99th and 99.9th percentile and the expected losses. The value of the unexpected loss is 2.15%, respectively 2.30% of total credit exposure.

Figure 1. Simulated loss distribution of the hypothetical corporate credit portfolio in 1 year horizon



Source: Simulations in Matlab (100,000 simulations)

3.2. The results of the stress test analysis

Stress test is an important tool in financial institutions' risk management, are used to complement financial institutions' internal model, such value-at-risk (VaR) models. Standard VaR models have been found to be of limited use in measuring financial institutions' exposure to extreme market events, i.e. events that occur too rarely to be captured by statistical models, which are normally based on relatively short periods of historical data (Isaic-Maniu, I., 2006:92).

An artificial shock can be introduced in the vector of error terms for stress testing purposes. The corresponding element in the vector $Z_{t+s} \sim N(0,1)$ of random numbers is replaced by the assumed shock. This shock is introduced in the first step of each simulation round and it has its impact to the other macro factors through the variance-covariance matrix.

In stress analysis we assume the following hypothesis:

- the default rate are equal for each loan for each sector
- the credit portfolio is representative of the corporate sector, thus the default rate can be approximated by the generated bankruptcy rate
- in the lack of individual data, the concentration risk of the portfolio is ignored
- the loss given default is set to 45%
- the composition of the loan portfolio does not change over de investigated period.

We analyze the impact of the following stress scenarios on the credit portfolio loss distribution:

1. GDP shock scenarios: the decrease/increase of the GDP index by 2% for four consecutive quarters;
2. consumer price index shock scenarios: the decrease/increase of the consumer price index by 0,5% for four consecutive quarters.

3.1.1.The impact of the GDP shocks

We assumed that for some exogenous reason the consumer price index increases by two percent for four consecutive quarter years. As result of this shock the default rates and the expected and unexpected losses will increase.

Similarly to the above generated simulation we made 100,000 simulations to determine the credit portfolio loss distribution and its probability. Comparing the outcome with the initial results we

can observe some decrease in the expected loss and in the unexpected losses, because the relation between the GDP index and probability of default is indirect. The expected loss of the portfolio decreased from 1.23% to 1.01% of total credit exposure. The unexpected loss (for the 99^{th} percentiles) decreased from 2.15% to 1.85% of total credit exposure, meanwhile the unexpected loss for the 99.9^{th} percentiles increased from 2.30% to 2.04% of the total credit exposure.
The expected losses, due to bad macroeconomic environment, increase to 1.44%, the unexpected losses (for the 99.9^{th} percentiles) increased to 2.60%.

3.1.2.The impact of consumer price index shocks

The results of the consumer price index shock scenarios indicate that the expected and the unexpected loss decreases as result of the consumer price index decrease, to 1.06%, respective to 2.22% (for the 99^{th} percentiles).
On the other hand, the increase of the consumer price index by 0,5% for four consecutive quarters causes the increase of the expected loss (to 1.43%) and of the unexpected loss (for 99.9^{th} percentiles, to 2.52%).

Conclusions

We have modeled and estimated a macroeconomic credit risk model for the Romanian corporate sector. The modeled and estimated industry-specific default rates let us obtain more accurate credit loss estimations than those obtained with more aggregated models.
The empirical results suggest a significant relationship between industry-specific default rates and macroeconomic factors including GDP growth rate, consumer price index, average exchange rate on forex market (RON/EUR) and industry-specific indebtedness. These results are in line with previous studies. We use the model to analyze the impact of stress scenario on the credit risk of a hypothetical corporate credit portfolio.

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