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KEY DETERMINANTS OF NON-PERFORMING LOANS IN ROMANIAN BANKING SECTOR. A VAR APPROACH

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Abstract:
*The aim of this paper is to analyze the macroeconomic determinants of the percentage of non-performing loans (NPL) in Romanian banking sector. The vector autoregressive (VAR) model is estimated on quarterly data for period 2003-2015. Our empirical analysis confirms that economic growth is negatively related to NPL while unemployment and credit cycle positively influenced the evolution of nonperforming loans in Romania***.**

Key words: Nonperforming loans, credit risk, VAR model, financial stability, macro prudential framework

JEL classification: G21, C23

1. INTRODUCTION

This paper gives a introspection of key determinants and their impact on the percentage of non-performing loans (NPLs) in commercial banks of Romania. In the recent years, many EU countries encountered economic downturns and these effects were translated in the macroeconomic indicators. On the other hand, for the banks it was noticed an increase of the non-performing loans as the debtors were not able to meet their financial obligations. For the policy makers it is relevant to observe which of the macroeconomic variables do produce an effect on NPL ratio but also with which lag.

Different studies were engaged in order to obtain the relationship between NPL and macroeconomic factors. (Jakubik and Schmieder, 2008) using a Merton type one factor model find both in Czech Republic and Germany that default rate of corporate loans is affected by GDP growth rate and credit to GDP ratio. (Berge and Boye, 2007) on a research study for Norway, show that the effects of NPL for households is explained by the evolution of real house prices, real interest rates and unemployment while for corporate sector, real oil prices, real interest rates and corporate gross debt are the main determinants. (Vogiazas and Nikolaidou, 2011) using monthly data find that some macroeconomic variables such as construction and investment expenditure, inflation rate and unemployment together with external debt to GDP and M2 affect the credit risk in Romanian banking sector. Using dynamic panel data, Louzis et al (2010) find that the Greek banking sector is influenced by the following macroeconomic variables: GDP, unemployment rate, interest rates and public debt. (Nkusu, 2011) studies the relationship between non-performing loans and macroeconomic factors using panel vector autoregressive on a sample of 26 advanced countries. The author's conclusion is that asset price, unemployment rate and economic growth influences credit quality. (Baboučak and Jančar, 2005) investigate the same problem using an unrestricted VAR model for Czech economy. They evidence the results obtained for testing different hypothesis such as: an increase in unemployment rate/consumer price inflation causes NPL ratio to rise. (Salas and Saurina, 2002) using panel data investigate the determinants quality of loans for both Spanish commercial and savings banks and conclude that GDP growth rate explains credit risk. (Saurina and Jimenez, 2006) deploy an extended research on the non-performing loans determinants in Spain and show that acceleration of GDP and a decrease in real interest rates lead to a decrease of the problematic assets.

The paper contains the section of methodology while in the last section are presented the empirical results and conclusions.

2. METHODOLOGY

A vector autoregressive could be seen as a generalization of the AR (p) model for a multivariate case. Considering a vector of variables $y_t y_t$ as a first step we have to estimate the reduced form VAR model of order *p*, where A is an $(n \times n)(n \times n)$matrix of autoregressive coefficients for $j = 1,2, \dots ,p j = 1,2, \dots ,p$, $\alpha\alpha$ denotes an $(n \times 1)(n \times 1)$ vector of intercept terms and $e_t e_t$ is an $(n \times 1)(n \times 1)$ dimension vector of white noise and $\Sigma\Sigma$ is an $(n \times n)(n \times n)$ symmetric positive definite matrix.

$$y_t = \alpha + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t \tag{1}$$
$$E(e_t) = 0$$
$$E[e_t e_t'] = \Sigma$$

Considering

$$Y_t = [y_t', y_{t-1}', \dots, y_{t-p+1}'] \tag{2}$$

The VAR model could be written as an AR(1) process:

$$Y_t = \begin{bmatrix} \alpha \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{bmatrix} Y_{t-1} + \begin{bmatrix} e_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{3}$$

This is equal to:

$$Y_t = \Gamma_0 + \Gamma_1 Y_{t-1} + e_t \tag{4}$$

Using lag operator to Eq. (1):

$$(I_n - A_1 L + A_2 L^2 + \cdots + A_p L^p) y_t = \alpha + e_t \tag{5}$$
$$A(L) y_t = \alpha + e_t$$

Where $A(L)A(L)$ indicates a $(n \times n)$ $(n \times n)$ matrix polynomial in the lag operator.
$Y_t Y_t$ can be expressed as a convergent sum of the past values of $e_t e_t$:

$$y_t = \mu + e_t + \psi_1 e_{t-1} + \psi_2 e_{t-2} + \psi_p e_{t-3} + \cdots = \mu + \psi(L) e_t \tag{6}$$

The matrix $\psi_s \psi_s$ has the interpretation $\frac{\partial y_{t+s}}{\partial e_t} = \psi_s \frac{\partial y_{t+s}}{\partial e_t} = \psi_s$. Thus, the row *i*, column *j* element of ψ_s ψ_s identifies the consequences of one-unit increase in the *j*th variable's innovation at date *t* ($e_{jt} e_{jt}$) for the value of the *i*th variable at time *t*+*s* $(y_{i,t+s})(y_{i,t+s})$, maintaining all other innovations at all dates constant. The combined effects of the change of $e_{jt} e_{jt}$ innovation by $\delta_j \delta_j$ on the value of the $y_{t+s} y_{t+s}$ vector will given by:

$$\Delta y_{t+s} = \frac{\partial y_{t+s}}{\partial e_{1t}} \delta_1 + \frac{\partial y_{t+s}}{\partial e_{2t}} \delta_2 + \cdots + \frac{\partial y_{t+s}}{\partial e_{nt}} \delta_n = \psi_s \tag{7}$$

A plot of the row *i*, column *j* element of $\psi_s \psi_s$ as a function of *s* is named the impulse-response function. It presents the response of $y_{i,t+s} y_{i,t+s}$ to a one-time impulse in $y_{jt}, y_{jt},$ with all other variables dated *t* or earlier held constant.

3. EMPIRICAL RESULTS

In order to analyze the evolution of non-performing loans rate for companies we took into account a series of macroeconomic variables to study the behavioral in the period 2003-2015. Therefore taking the series of loans with days past due more than 90 days, the credit cycle, obtained from the series of loans granted to companies in 2003-2015, the unemployment rate and output gap, we evaluate a vector autoregressive (VAR) model. The source of time series of loans granted to companies is National Bank of Romania while the source of unemployment rate and GDP is Romanian National Institute of Statistics. The output gap was calculated by extracting the cycle using a Hodrick-Prescott filter. Before starting the estimation of the VAR model, we checked if the variables are stationary and this was confirmed by the results of Augmented Dickey Fuller (ADF) test. The first step in estimation of the VAR model was to evaluate the number of lags from the model and as it can be seen in (Table no. 1) most of criterions indicate that the optimal number of lags is one (it is selected the lag corresponding to tests results having *). The number of lags in a vector autoregressive model is important because it has to capture the system dynamics without consuming a high number of freedom degrees. The degrees of freedom are decreasing when we take into account too many lags. In addition, if we take to few lags, the model is not correctly specified. Therefore, the testing is realized by using the highest number of lags allowed by the data used and for plausibility.

Table no. 1. Selecting the number of lags

Vector Autoregressive Lag Order Selection Criteria					
Lag	LogL	LR	FPE	AIC	SC
0	3.84	NA	0.00	0.01	0.17
1	54.41	89.10*	2.29E-06*	-1.63*	-0.81*
2	62.41	12.57	0.00	-1.26	0.23
3	79.48	23.57	0.00	-1.31	0.84
4	97.90141	21.93496	3.44E-06	-1.42	1.38

Source: Own estimation

The stability of a vector autoregressive could be checked by calculating the roots of the characteristic polynomial. If the model is not stable the standard errors of the impulse response function are not valid. The necessary and sufficient condition for stability is that all characteristic roots lie outside the unit circle. When calculating the inverse roots, these should lie inside the unit circle as it is presented for our model in (Figure no. 1)

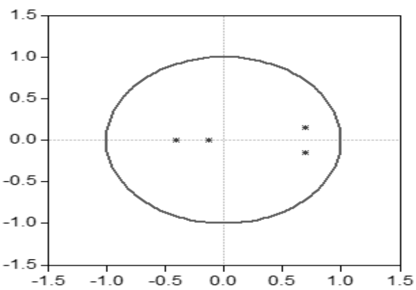

Figure no. 1. Inverse Roots of AR Characteristic Polynomial.
Source: Own estimation

As a next step, we have checked the residuals and if the model is correctly specified. In this respect, we employ the Residual Normality Tests by testing the null hypothesis that residuals are normally distributed by comparing the 3rd and 4th moments to those from a normal distribution. The results are provided in (Table no. 2) and the main conclusion is that the residuals are normally distributed as the p-value attached for both univariate and joint components are higher than 1%.

Table no. 2. Testing the hypotheses of VAR model

Vector Autoregressive Residual Normality Tests				
Component	Skewness	Chi-sq	df	Prob.
1	0.216142	0.350379	1	0.5539
2	0.338137	0.857526	1	0.3544
3	-0.524529	2.063484	1	0.1509
4	-0.068247	0.034932	1	0.8517
Joint		3.306321	4	0.5079
Component	Kurtosis	Chi-sq	df	Prob.
1	2.063263	1.645269	1	0.1996
2	2.067128	1.631720	1	0.2015
3	4.145752	2.461400	1	0.1167
4	3.152294	0.043488	1	0.8348
Joint		5.781877	4	0.2160
Component	Jarque-Bera	df	Prob.	
1	1.995648	2	0.3687	
2	2.489247	2	0.2880	
3	4.524884	2	0.1041	
4	0.078420	2	0.9615	
Joint	9.088198	8	0.3349	

Source: Own estimation

Portmanteau Autocorrelation Test (Box-Pierce-Ljung-Box Q statistics) was used for testing the residual correlation. The null hypothesis is that there is no serial correlation up to chosen lag and it has been accepted (p-value higher than 0.05) for all 10 tested lags. The results are shown below in (Table no. 3) and for each lag it is reported the Q-stat and adjusted Q-Stat to correct the small samples together with p-value attached.

Table no. 3. Portmanteau Test

VAR Residual Portmanteau Tests for Autocorrelations					
Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	4.001690	NA*	4.092637	NA*	NA*
2	14.72972	0.5445	15.31964	0.5014	16
3	28.82214	0.6282	30.41867	0.5467	32
4	50.51707	0.3743	54.23018	0.2490	48
5	67.06675	0.3724	72.84856	0.2098	64
6	81.49789	0.4324	89.49988	0.2190	80
7	94.09374	0.5360	104.4160	0.2616	96
8	114.1772	0.4250	128.8419	0.1319	112
9	121.9098	0.6350	138.5076	0.2479	128
10	133.2693	0.7288	153.1127	0.2860	144

Source: Own estimation

Once we have defined the VAR model, impulse response functions are analyzed, when we apply a shock to NPL. From the economic point of view, we expect a positive response for variables NPL, credit cycle and unemployment rate while for output gap, the answer would be negative.

An increase in unemployment, an increase in lending and an increase in NPL rate is positively correlated with the rate of NPL. When there is an increase in output gap instead, NPL rate should decline. In Figure no. 2 are presented the four responses of NPL to the shocks on the variables and as expected, the responses are positive for all variables analyzed except the output gap, where the answer is, although small, negative. The higher response of NPL to an NPL shock is explained by the fact that the ratio is persistent.

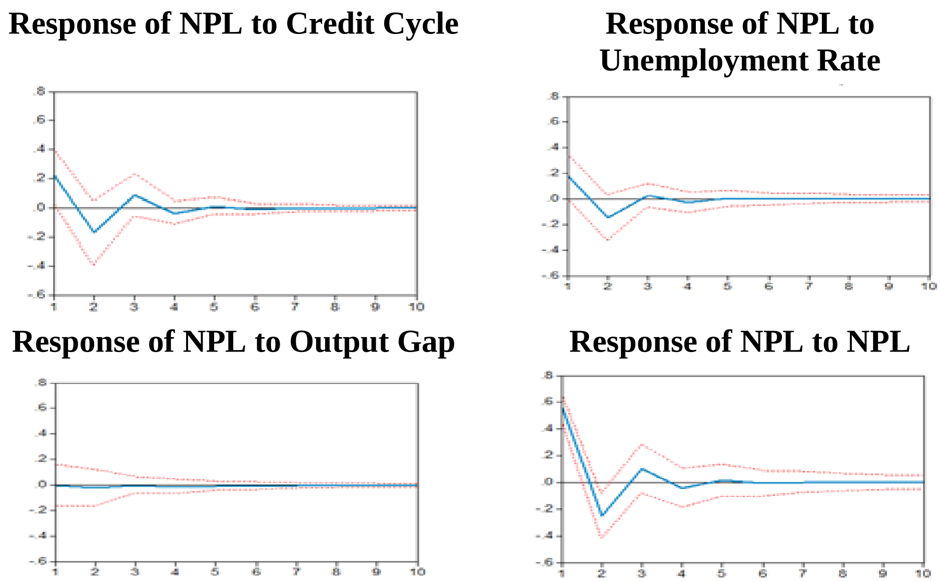

Figure no. 2. Impulse response functions.
Source: Own estimation

In the next step it was calculated the variance decomposition to see exactly how much of the variance of NPL is explained by the variance of those three variables. In the first quarter, 79.82% of the variance is explained by variance of NPL, followed by the credit cycle variance of 12.22% and 7.94% unemployment rate and the output gap below 1%. After the tenth quarter, the variance is given by 73% NPL, 16% credit cycle, 10% unemployment, while the output gap is still under 1%.

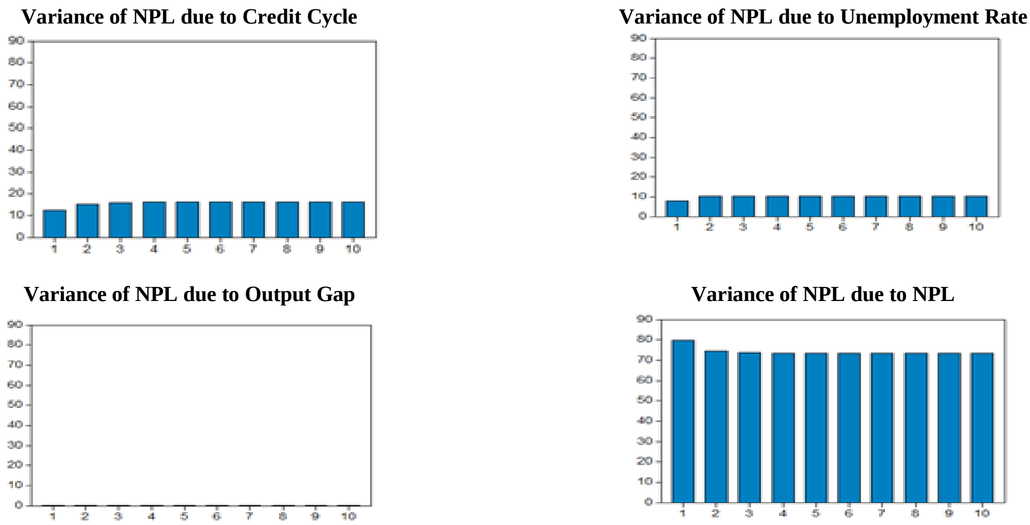

Figure no. 3. Variance Decomposition
Source: Own estimation

4. CONCLUSIONS

The main objective of this paper is to determine if the macroeconomic variables do influence the development of NPL ratio and with what lag. For this respect, we deployed a VAR model to capture the impulse response functions. When analyzing these functions one important feature is to observe that the shocks are vanished on long term. Secondly, the responses are intuitively with the economic expectations and the expected signs were positive only for GDP to be negative. The second objective was to decompose the variance of NPL and compare the results for each of the selected variables. The NPL ratio for Romanian corporate sector is an autoregressive process (almost 80% of the variance is due to NPL ratio one quarter before) since it is affected by the historical values and credit cycle's variation explains 16% of the NPL variation. Unemployment rate and output gap also explain the variance of NPL but in a smaller proportion, almost 10 % respectively less than 1%. Our results are in line with other similar studies: negative relationship between NPL and GDP growth (Nkusu, 2011; Klein, 2013), as in economic downturn the rise in unemployment causes an increase in debt and higher values for non-performing loans. The positive relationship between NPL ratio and unemployment rate, as suggested by our results was emphasized also in the research studies realized by (Nkusu, 2011; Klein, 2013). Another conclusion of our paper is that an increase in credit growth leads to an increase in NPL, the reason being higher credit growth is usually reflected in the literature in a lower underwriting standards framework (Klein, 2013).

As for the further research we would like to extend the list of the macroeconomic variables by including in our analysis foreign exchange, inflation, interest rate and house prices and also the bank specific individual variables.

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