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Macroeconomic Determinants of Loan Portfolio Credit Risk in Banks

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The credit risk is one of the main risks in commercial banks and the ability to manage it meaningly affects banks' stability. This risk arises due to the particular reasons related to the possibility to lose loans if the debtors are not able to meet their financial obligations. When making the decisions of financing the loan applicants, banks use the credit risk assessment models that allow estimating the probability of the potential borrowers to default on their loan commitments. The main goal of managing the credit risk in banks is to compound the loan portfolio of the acceptable risk level. According to Derelioglu and Gurgen (2011) the credit risk analysis aims to decrease future losses by estimating the potential risk and eliminating the new credit proposal if the risk is higher than a defined tolerance value. In this respect, it is essential to identify the main factors causing this risk in order to manage it. When assessing the credit risk of every company, banks usually analyze the financial data and some qualitative factors as the independent variables in the statistical credit risk assessment models. But in changing the credit policy in banks and pricing the credits, it is very important to predict the quality of loan portfolio in future. The problem can be summarized as finding the statistical methods that relates the proportion of doubtful and non-performing credits in the loan portfolio (dependent variable) with the set of explanatory variables (macroeconomic information of a country). The aim of this research is to find the macroeconomic determinants that significantly influence the changes of loan portfolio credit risk in banks and to develop the statistical model for prediction of the proportion of doubtful and non-performing loans. The scientific literature analysis results confirmed the influence of macroeconomic conditions on credit risk of debtors in banks and presented that the changes in quality of loan portfolio in banks depend on GDP, inflation, interest rates, money supply, industrial production index, current account balance and other. In empirical research 22 EU countries were grouped into 3 clusters according to their similarity in changes of the doubtful and non-performing loans percentage in banks. The set of 20 independent variables as factors determining the changes in amount of doubtful and non-performing loans was created. These variables were calculated from 9 macroeconomic indicators of 3 years. The model was developed to classify the countries into clusters applying the logistic regression, factor analysis and probit methods. The classification accuracy is 100 %. The predictions of doubtful and non-performing loans indexes are based on the analysis of the scores of extracted 5 factors as new independent variables. The multiple regression and polynomial regression methods were applied for the index predictions in clusters. The developed model in this research enables to predict the percentage of doubtful and non-performing loans in banks with the average 98,06% accuracy. The research has confirmed that the amount of doubtful and non-performing loans in banks highly depends on macroeconomic changes in a country. The model can warn the banks in advance if the significant increase in the loan portfolio credit risk after 2 years is highly possible.

Keywords: *bank, credit risk, loan portfolio, macroeconomics, statistical analysis.*

Introduction

The credit risk management in banks requires assessing the credit risk level of every credit applicant. So banks must have the instruments that are able to classify the loan applicants into two main classes: those who are likely to keep up with their repayments and those who are likely to default on their loans (Brown & Mues, 2012). The credit risk level indicators of clients are the credit ratings determined by the internal ratings models used in banks. The credit rating of a company condenses a range of qualitative and quantitative assessments of the creditworthiness of a company and reflects the credit quality of a debtor. This credit quality can vary over time as well as among different debtors (Wozabal & Hochreiter, 2012). The developed credit risk assessment models can determine the credit rating analyzing the set of independent variables unique to each company and various systematic economical factors in the form of credit drivers (Iscoe *et al.,* 2012). Performed researches for the interrelation analysis of economic cycle and credit volume indicators, including economic growth and recession periods, confirmed close interaction between the results of credit institutions activities and country's macroeconomic indicators. Obtained results revealed that peak in total loans indicator converge with the peak in economic cycle indicators, but the peak in household loans is accessed earlier than the peak in economic cycle indicators (Lakstutiene *et al.,* 2011).

In the credit risk management it is very important to estimate the influence of macroeconomic factors not only on the amount of credits but also on the credit risk of total loan portfolio. So *the object of this research* is the macroeconomic determinants of loan portfolio credit risk in banks. *The aim of this research* is to find the macroeconomic determinants that significantly influence the changes of loan portfolio credit risk in banks and to develop the statistical model for prediction of the proportion of doubtful and non-performing loans.

The methods of this research:

1. The analysis of scientific publications about the macroeconomic factors influencing the loan portfolio credit risk.
2. The cluster analysis, logistic regression, factor analysis, probit, multiple and polynomial regression methods were applied developing the doubtful and non-performing loans prediction model.

The novelty of this paper is based on creating a new model for prediction of doubtful and non-performing loans proportion in the country's banks. The model is based on a multicriteria approach and brings together the set of macroeconomical evaluation measures. The usage of the developed model also can help to forecast the performance of banks according to the possible changes in macroeconomical environment. The model can be applied and used in different countries with low proportion of doubtful and non-performing loans (about 2,09 – 3,7 %) by various analysts as it requires information available in public sources.

Loan portfolio credit risk in banks

The banks implement very important functions in country's financial system and whole economy, so to reduce the likelihood of financial instability several countries have introduced prudential regulation frameworks, making banking one of the most heavily regulated industries. Possibly the most renowned examples are the Basel Accords (Basel I and II) that established the capital adequacy requirements, introduced additional pillars in relation to supervisory monitoring and market discipline (Ioannidis *et al.,* 2010). However the recent statistics of the EU countries about the doubtful and non-performing credits in loan portfolios of banks highlighted, once again, the importance of early warning models to forecast banking activity results and increase the soundness of individual banks.

The non-performing asset (NPA) otherwise known as the non-performing loans (NPL) is directly related to the financial performance of a bank and is the contributing factor to the credit risk of the banking system. An increase in the NPA of a bank suggests that there is a high probability of a large number of credit defaults. This in turn affects the net-worth of the bank and also erodes the value of the bank's asset. Historical evidence suggest that most bank failures are directly associated with poor management of credit risk (Thiagarajan *et al.,* 2011). The risk manager of a bank may be interested in credit risk of two types:

- Credit risk of the individual positions.
- Credit risk of the loan portfolio.

Credit risk of the individual positions is defined as the risk of loss resulting from failure of borrowers to meet their payments obligations. Among the several concepts that help analyze credit risk, the probability of default (PD) is the most critical, which is the likelihood that a loan will not be repaid and fall into default. The estimation of PD is usually obtained through taking into account the credit history of the borrower and the nature of investment (Qu, 2008). The traditional approach for assessing the companies' credit risk is mostly based on the credit risk officers' experience. This implies a certain subjectivity of the crediting process. Considering the aggressive dynamicity of the business environment, the task of the credit officers has become more and more complex. In this context, the need of using statistical methods and computerized programs for assessing the credit risk has became imperious (Cimpoeru, 2011). In addition to the loan applicant's individual characteristics there is another aspect which needs to be taken into consideration when assessing the credit risk: the status of the general economy. Business cycle can have great impact on the credit portfolio of companies. Taking macro factors into consideration when analyzing the PD is important and empirical evidence of the researches shows a negative relationship between defaults and business cycle (Qu, 2008).

The loan portfolio losses can be written as the sum of losses of individual positions: instruments, counterparties, sub-portfolios (Rosen & Saunders, 2010). Credit risk of the loan portfolio also is one of the most important areas of risk management. It plays an important role mainly for banking institutions, which try to develop their own credit risk assessment models in order to increase bank portfolio quality (Jakubik, 2007).

Together with risk management the need to evaluate the performance of banks in a more efficient way was identified and enhanced not only by supervising institutions, regulators and bank management bodies but also by clients, as their concern about the stability and sustainability of these financial institutions has grown significantly. This influences a rethink of the applicability of current performance evaluation techniques and credit risk assessment models along with their improvement (Stankeviciene & Mencaite, 2012). Macroeconomic models are also the very useful tools for central banks for research and management of banking system financial stability. Through the application of these models central banks can estimate impact changes in monetary policy or expected or unexpected macroeconomic shocks (Jakubik, 2007).

Macroeconomic factors influencing the loan portfolio credit risk

Understanding the causes of correlated credit losses is crucial for many purposes, such as managing portfolios, setting capital requirements for banks, and pricing structured credit products that are heavily exposed to correlations in credit risk. Although it is well known that credit risks across firms are correlated, there is much ambiguity regarding determinants of credit risk correlation (Pu & Zhao, 2012). Bank performance usually depends on various internal and external determinants. The internal variables are commonly bank specific determinants and the external variables are related to the economic, financial and institutional environment (Naceur & Omran, 2011).

Gaganis, Pasiouras, Doumpos, Zopounidis (2010) denote 4 main criterions of banking stability:

1. Regulations.
2. Other banking and financial sector attributes.
3. Institutional environment.
4. Macroeconomic conditions.

Figlewski, Frydman, Liang (2012) affirm that a relevant macro factor should be one that has a broad impact on most firms‘ creditworthiness. These authors group the macroeconomic risk factors into three broad classes:

1. Factors related to general macroeconomic conditions (the unemployment rate, inflation, etc.).
2. Factors related to the direction in which the economy is moving (real GDP growth, the change in consumer sentiment, etc.).
3. Factors of financial market conditions (interest rates, stock market returns, etc.).

Festic, Kavkler, Repina (2011) affirm that changes in the macroeconomic environment translate into changes in the quality of a loan portfolio in banks. Favourable macroeconomic conditions coincide with better capabilities in loan repayment, a lower probability of default (PD), a lower share of non-performing loans to total loans (the NPL ratio), etc. Hamerle, Dartsch, Jobst, Plank (2011) also agree that credit risk is correlated with macroeconomic variables or risk factors. In economic downturns, default probabilities increase and ratings deteriorate.

The Gross Domestic Product (GDP) growth is considered as an important macro determinant of bank performance and allows for controlling business cycle fluctuations. During recessions the quality of loans declines and therefore companies borrow at higher margins, therefore a negative relationship between credit spread and economic growth is to be expected. Naceur, Omran (2011) found that prevailing business cycle conditions affect net interest margins. The GDP can significantly influence the borrower's ability to repay the loans as evidences suggest that higher GDP growth will have a negative correlation with current NPA (Thiagarajan, *et al.,* 2011). According to Gaganis, Pasiouras, Doumpos, Zopounidis (2010) the GDP growth not only reduces non-performing loans, but it can also delay banking crises due to pro-cyclicality.

Economic expansion will influence the default rate for the aggregate economy as demand for goods and services increase. Accordingly, increased profitability decreases the default rate. GDP turned out to be a significant factor in explaining default risk in various countries. This is consistent with Moody‘s report on historical default rates, in which they argue that cyclical indicators are highly correlated with the number of defaults, the number of credit rating downgrades and credit spreads. Regarding Debt-to-GDP ratio, debt of general government has a positive effect on default rate (Ali & Daly, 2010).

The econometric estimations of Vazquez, Tabak, Souto (2012) presented a strong evidence of a cyclical behavior of loan quality. The estimations substantiate the existence of a robust inverse relationship between GDP growth and NPLs, with the effects operating with up to three quarter lags. The results also indicate differences in the persistence of NPLs across credit types, and in their sensitivity to economic activity. Loan quality appears to be more sensitive to GDP growth for small consumer loans, credit to agriculture, sugar and alcohol, livestock, and textile. In addition, credit for vehicle acquisition and electric and electronic equipment displayed high level of NPLs under distressed macroeconomic scenarios. Banks with relatively higher exposures to these sectors are likely to experience larger credit losses under a macroeconomic downturn (Vazquez *et al.,* 2012). Moreover, differences in the sensitivity of various NPLs categories to macroeconomic developments may be related to differential effects of the business cycle, especially economic downturns, on cash flows of a debtor and collateralized assets' values (Louzis *et al.,* 2012).

The researches have shown that in association with GDP such macroeconomic indicators as inflation, interest rates, money supply, industrial production index and other are generally used in analysis (Pilinkus, 2010). The empirical results of Wong, Wong, Leung (2010) indicated that systemic banking distress was associated with a macroeconomic environment of low economic growth, high inflation, and high real interest rates. In addition, the balance of payments crises were found to be associated with systemic banking problems. Of the 16 potential indicators considered, which mainly measure the degree of financial liberalization (e.g., money multiplier and the ratio of domestic credit to GDP), balance of payment conditions (e.g., terms of trade, real exchange rates, and reserves), the real and fiscal sector developments (e.g., industrial production and public sector deficits as a share of GDP, respectively), the three most useful indicators were found to be real exchange rates, stock prices, and the ratio of public sector deficits to GDP (Wong *et al.,* 2010).

The studies of Derbali (2011) have reported a positive association between inflation and bank profitability. High inflation rates are generally associated with high loan interest rates, and therefore, high incomes. However, if inflation is not anticipated and banks are sluggish in adjusting their interest rates, there is a possibility that bank costs may increase faster than bank revenues and hence adversely affect bank profitability (Derbali, 2011). A number of experts consider inflation to be a complicated multisided process, which depends not only on economical but also on social and political reasons. Theory of inflation considers unanimity of three components thereof: excessiveness of currency circulation; depreciation of money; redistribution of income, property and downfall of net remuneration (Kochetkov, 2012).

The important factor is the money supply in a country. The changes in money supply may lead to changes in the nominal GDP and the price level. Although money supply is basically determined by the central bank's policy, it could also be affected by the behaviour of households and banks. This factor significantly affects bank profitability (Sufian & Noor, 2012). Also one of the most important economic indicators is current account balance. As current account deficit widens for a prolonged time it points the overvalued exchange rate and uncompetitive export goods (Pilinkus *et al.,* 2011).

Finally, the results indicate that the macroeconomic indicators are determinant factors that influence bank credit risk-taking decisions. Indeed, the coefficients of rapid growth of GDP, inflation, exchange rate, interest rate and other are statistically significant with bank credit risk (Zribi & Boujelbene, 2011). The indebtedness indicator (fragility) covers the entire economy, including both the corporate and household sector. It can be assumed implicitly that the same behavioural principles are typical to both firms and households, because these two sectors are closely interconnected (Pesola, 2011). It can be concluded that the macroeconomic variables are highly significant, whether or not these variables are directly included into credit risk analysis. It has been noted that the individual default probabilities of companies and default rates (i.e. the fraction of defaulting firms in the economy) are highly correlated. Both variables also seem to be driven by the same common factors that are persistent over time and clearly related to the business cycle: in recessions or industry downturns the default probabilities and default rates are high (Bruche & Aguado, 2010). Therefore, the development of the leading indicators of banking distress and early-warning systems has long been a core interest of central banks and academics (Wong *et al.,* 2010).

The doubtful and non-performing loans prediction model

The statistics of doubtful and non-performing loans in banks was available in 22 EU countries: Austria (AT), Belgium (BE), Bulgaria (BG), Cyprus (CY), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Greece (GR), Hungary (HU), Italy (IT), Lithuania (LT), Latvia (LV), Malta (MT), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Slovakia (SK) and United Kingdom (UK).

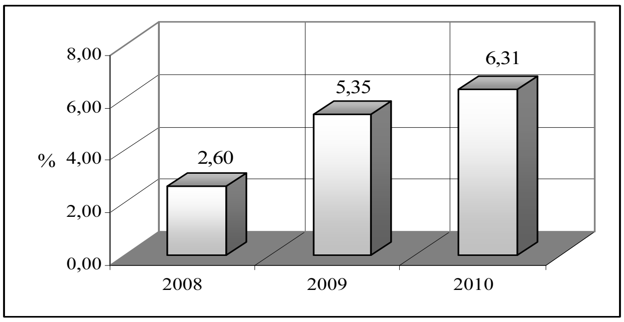

Figure 1. Average doubtful and non-performing loans in banks (22 EU countries)

According to European Central Bank in 2008 – 2010 the average percentage of doubtful and non-performing loans in banks significantly increased (Figure 1).

Table 1

Clusters of the EU countries

Cluster	Countries	%	i_{2009}	i_{2010}
C1	AT, BE, CY, DE, DK, ES, FI, FR, MT, NL, PT, SK, UK	59,09	1,32	1,42
C2	EE, GR, HU, IT, PL, RO	27,27	2,18	2,67
C3	BG, LT, LV	13,64	3,65	4,45

The increase in different countries of EU was not equal, so the cluster analysis (method of *k*-means) was accomplished in order to determine the clusters of these countries (Figure 2). The year 2008 can be considered as the datum-level because the average of doubtful and non-performing loans in all countries was in range of only 2,09 – 3,7 %. But in 2009 – 2010 the increase of this indicator in 3 clusters was different.

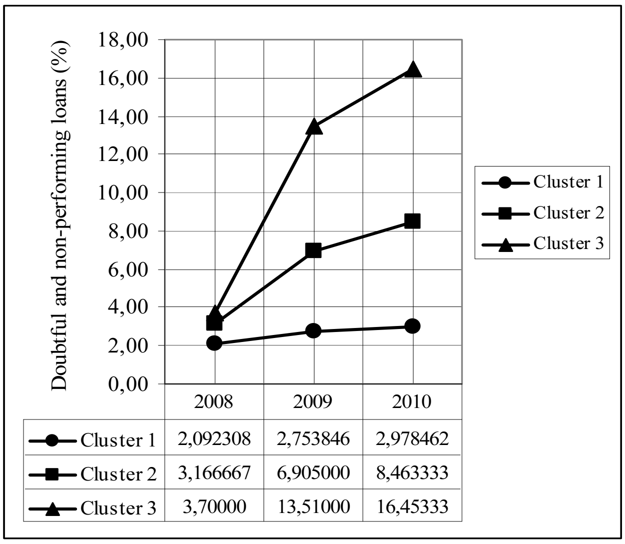

Figure 2. Plot of means for each cluster

The members of each cluster are in Table 1. The main part of countries (59,09 %) belong to Cluster 1, where the basic individual index of increase in doubtful and non-performing loans is the least (1,32 and 1,42). The higher basic index (2,18 and 2,67) have 27,27 % of the estimated countries. In 13,64 % of countries (Bulgaria, Lithuania and Latvia) the average percentage of doubtful and non-performing loans in banks increased 3,65 times (years 2008 – 2009) and 4,45 times (years 2008 – 2010).

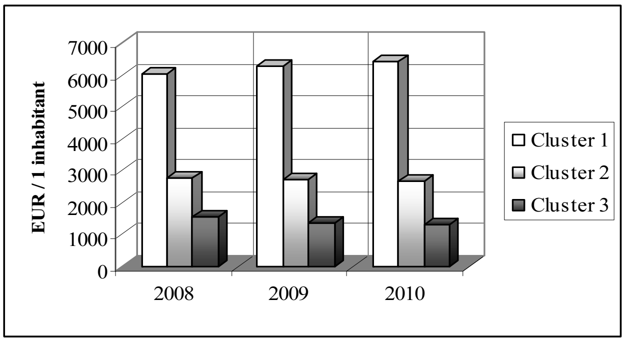

Figure 3. The average final consumption expenditure of general governments in clusters

The set of macroeconomic indicators were estimated in 22 EU countries in order to highlight their differences in 3 clusters:

- Long-term unemployment rate (%).
- Compensation of employees (EUR/1 inhabitant).
- Final consumption expenditure of households (EUR/1 inhabitant).
- Final consumption expenditure of general government (EUR/1 inhabitant).
- Gross fixed capital formation (investments, EUR/1 inhabitant).

- Exports of goods and services (EUR/1 inhabitant).
- Real GDP growth rate (%).
- Inflation rate (%).
- Imports of goods and services (EUR/1 inhabitant).

The average values of these macroeconomic indicators in clusters differ significantly. Figure 3 indicates the difference of average final consumption expenditure of general governments. Also the differences in averages of another 8 estimated macroeconomic rates were tangible, so the hypothesis was raised that it can be possible to predict the changes of doubtful and non-performing loans in banks according to the changes in a country's macroeconomics. In this research the prediction model was developed (Figure 4) where the information is needed about doubtful and non-performing loans (*DL*) in the country's banks of current year (y_0) and macroeconomic data (*MI*) of current year and two further years (y_1 and y_2). *DL* of the year y_0 must be in range of datum-level (about 2,09 – 3,7 %).

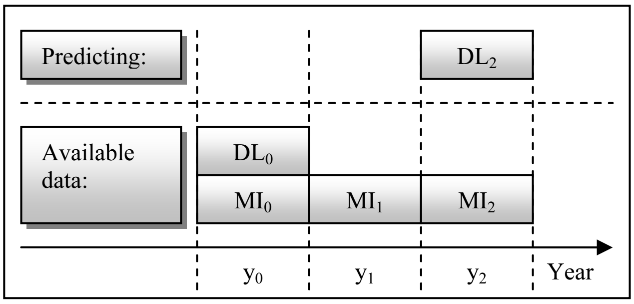

Figure 4. The period of data and predictions in the model

At first, it is necessary to classify a country into the one of 3 determined clusters. The independent variables (x_i) for the analysis are given below.

1. Real GDP growth rate (%) – GDP0, GDP1, GDP2.
2. Inflation rate (%) – INF0, INF1, INF2.
3. The changes of long-term unemployment rates (%) – LTU1, LTU2:

$$\Delta a_i = a_i - a_0 \tag{1}$$

a_i – the rates of years y_1 and y_2;
a_0 – the rate of basic year y_0.

4. The changes of compensation of employees (EUR/1 inhabitant) – CE1, CE2.
5. The changes of final consumption expenditure of households (EUR/1 inhabitant) – CEH1, CEH2.
6. The changes of final consumption expenditure of general government (EUR/1 inhabitant) – CEG1, CEG2.
7. The changes of gross fixed capital formation (investments, EUR/1 inhabitant) – GFC1, GFC2.
8. The changes of exports of goods and services (EUR/1 inhabitant) – E1, E2.
9. The changes of imports of goods and services (EUR/1 inhabitant) – IMP1, IMP2.

The changes of rates 4 – 9 were estimated by calculating the basic individual indexes:

$$i = \frac{a_i}{a_0} \tag{2}$$

The countries classification scheme is depicted in Figure 5. The 20 independent variables are being analyzed by logistic regression model:

$$Y = a + \sum_{i=1}^{n} b_i x_i \tag{3}$$

a –intercept;
b_i – the regression coefficients;
x_i – the independent variables (Table 2).

The logistic transformation of dependent variable Y allows getting results in range [0; 1]:

$$P(Y) = \frac{e^Y}{1 + e^Y} \tag{4}$$

The countries classification threshold was set to 0,5. If $P(Y) \in [0{,}5;\ 1]$ a country is classified into group G_1 and into Cluster 1. All counties (100%) that belong to Cluster 1 were classified correctly (Table 3). If $P(Y) \in [0;\ 0{,}5)$ a country is classified into group G_0 and further analysis is needed to separate the countries into Cluster 2 and Cluster 3.

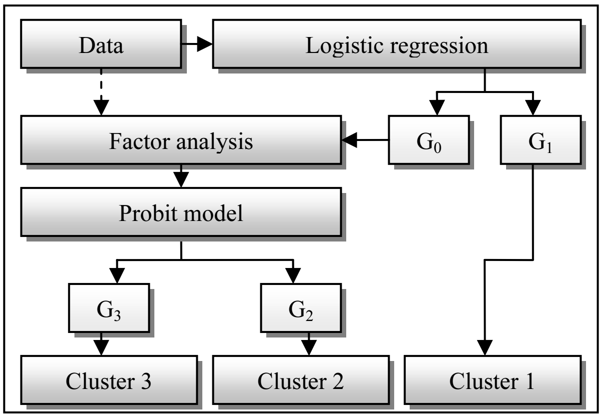

Figure 5. The countries classification scheme

For the initial variables (x_i) of countries classified into group G_0 the factor analysis was accomplished and 4 factors (F_1 – F_4) were extracted. The factor score coefficients were calculated for the each initial variable (Table 2) that allow reducing the amount of data and calculating new independent variables (factor scores) for further analysis. The common factor is expressed by the linear combination of variables under investigation:

$$F_j = \beta_{j1}x_1 + \beta_{j2}x_2 + \ldots + \beta_{jn}x_n \tag{5}$$

β_{ji} – the factor score coefficients;
x_i – the initial variables.

The factor scores of factors F_1 – F_4 were involved as independent variables and the *probit* model was developed:

$$Z = 18{,}2633 - 17{,}5493 \cdot F_1 + 10{,}5642 \cdot F_2 + 19{,}9310 \cdot F_3 + 7{,}7040 \cdot F_4 \tag{6}$$

The classification of countries according to Z value:

- If $Z \geq 0$, a country belongs to group G_2 (Cluster 2).
- If $Z < 0$, a country belongs to group G_3 (Cluster 3).

Table 2

The logistic regression model and factor score coefficients

x_i	b_i (LR)	Factor score coefficients			
		F₁	F₂	F₃	F₄
a	82,28	-	-	-	-
LTU1	14,92	0,086	-0,086	0,118	0,022
LTU2	-0,11	0,083	-0,108	0,064	-0,077
CE1	-1263,53	-0,075	-0,114	-0,087	-0,203
CE2	518,28	-0,085	-0,018	-0,032	-0,305
CEH1	388,75	-0,075	-0,135	-0,024	-0,029
CEH2	1,58	-0,096	-0,018	0,013	-0,028
CEG1	-501,55	-0,059	-0,153	-0,114	-0,014
CEG2	545,49	-0,080	-0,041	0,101	-0,285
GFC1	-68,72	-0,091	-0,012	0,039	0,052
GFC2	-122,28	-0,087	0,054	0,147	0,099
E1	34,39	-0,014	0,187	-0,047	0,219
E2	-604,71	0,036	0,181	-0,005	-0,307
GDP0	15,74	-0,034	0,148	-0,186	-0,304
GDP1	-8,40	-0,089	0,078	-0,003	0,005
GDP2	-15,81	0,004	0,068	0,360	-0,278
INF0	7,93	0,082	-0,021	-0,096	-0,228
INF1	-31,02	0,021	0,186	-0,139	0,010
INF2	3,71	-0,055	0,062	-0,208	0,059
IMP1	1197,48	-0,089	0,018	0,058	0,258
IMP2	-74,32	-0,037	0,097	0,324	0,043

According to Z values (Table 3) all countries were classified correctly into clusters *C1* and *C2*. So the classification accuracy of the developed logistic regression and *probit* models is 100 %.

Table 3

The results of logistic regression and probit models

Countries	Cluster	*P(Y)*	*Z*
AT, BE, CY, DE, DK, ES, FI, FR, MT, NL, PT, SK, UK	C1	1	-
EE	C2	3,23E-09	5,6265
GR	C2	2,42E-09	6,0442
HU	C2	2,11E-09	42,1407
IT	C2	1,56E-09	59,5936
PL	C2	2,96E-09	66,4998
RO	C2	1,55E-09	5,6388
BG	C3	1,76E-09	-5,6316
LT	C3	7,65E-10	-9,9366
LV	C3	1,7E-09	-5,6061

When a country is classified into particular cluster, secondly, the predictions of doubtful and non-performing loans can be made. Because the increase of *DL* in clusters is different, so the different prediction models were developed for each cluster. The independent variables in these models are the scores of extracted 5 factors H_1 – H_5. The factor score coefficients are given in Table 4.

Table 4

Factor score coefficients of factors H_1 – H_5

	H₁	H₂	H₃	H₄	H₅
LTU1	0,075	-0,132	0,131	-0,189	-0,040
LTU2	0,077	-0,142	0,086	-0,144	-0,228
CE1	-0,084	-0,099	-0,106	-0,091	-0,275
CE2	-0,090	0,001	-0,078	0,068	-0,260
CEH1	-0,084	-0,121	-0,015	0,022	-0,170
CEH2	-0,026	0,044	0,149	-0,349	0,058
CEG1	-0,074	-0,151	-0,120	-0,158	-0,173
CEG2	-0,090	-0,058	0,010	0,049	-0,182
GFC1	-0,092	-0,019	-0,036	-0,044	0,102
GFC2	-0,090	0,032	0,085	0,109	0,109
E1	-0,037	0,186	0,121	-0,457	0,023
E2	0,023	0,247	0,189	-0,183	-0,318
GDP0	-0,023	0,238	-0,115	0,087	-0,491
GDP1	-0,082	0,118	-0,086	-0,092	0,072
GDP2	-0,037	0,001	0,306	0,476	-0,110
INF0	0,087	0,004	-0,004	-0,003	-0,299
INF1	0,059	0,226	-0,077	0,209	0,031
INF2	0,001	0,157	-0,352	0,019	0,199
IMP1	-0,092	0,034	0,076	-0,106	0,196
IMP2	-0,065	0,096	0,292	0,112	0,126

When predicting the change of doubtful and non-performing loans in a country in year y_2, it is necessary to recalculate the 20 initial variables (x_i) into 5 factors H_1 – H_5 as new variables. According to this data the multiple regression and polynomial regression models were developed for *DL* predictions.

Prediction of *DL* change in Cluster 1 (multiple regression):

$$W_{1m} = 1{,}959084 + 0{,}664071 \cdot H_1 + 0{,}227643 \cdot H_2 - 0{,}189029 \cdot H_3 + 0{,}207129 \cdot H_4 - 0{,}232304 \cdot H_5 \qquad (7)$$

Prediction of *DL* change in Cluster 1 (polynomial regression):

$$W_{1p} = 0{,}56782 + 4{,}61692 \cdot H_1^2 + 2{,}84311 \cdot H_1 + 1{,}22570 \cdot H_2^2 - 1{,}04464 \cdot H_2 + 0{,}09222 \cdot H_3^2 - 0{,}77643 \cdot H_3 - 0{,}50051 \cdot H_4^2 - 0{,}31042 \cdot H_4 + 0{,}54477 \cdot H_5^2 + 0{,}31211 \cdot H_5 \qquad (8)$$

For the comparison of the prediction accuracy the mean square error rates (*MSE*) were calculated:

$$MSE = \frac{\sum (W_t - Y_t)^2}{n} \qquad (9)$$

W_t – the predicted basic index of *DL*;
Y_t – the actual basic index of *DL*;
n – the number of countries in each cluster.

The *MSE* values indicated that more accurate is the polynomial regression model (Table 5), so it must be used for predicting of *DL* in Cluster 1.

Prediction of *DL* change in Cluster 2 (multiple regression):

$$W_2 = -34{,}5789 + 24{,}1473 \cdot H_1 - 14{,}2356 \cdot H_2 - 43{,}6737 \cdot H_3 + 81{,}6069 \cdot H_4 - 9{,}3661 \cdot H_5 \qquad (10)$$

Prediction of *DL* change in Cluster 3 (multiple regression):

$$W_3 = 2{,}347288 + 1{,}628513 \cdot H_1 + 2{,}141657 \cdot H_2 \qquad (11)$$

The *MSE* values of models W_2 and W_3 are very low (Table 5).

Table 5

The *MSE* values of regression models

Model	W₁ₘ	W₁ₚ	W₂	W₃
MSE	0,178853	0,002673	6,874E-26	9,203E-30

The comparison of predicted and observed basic indexes of doubtful and non-performing loans is shown in Figure 6.

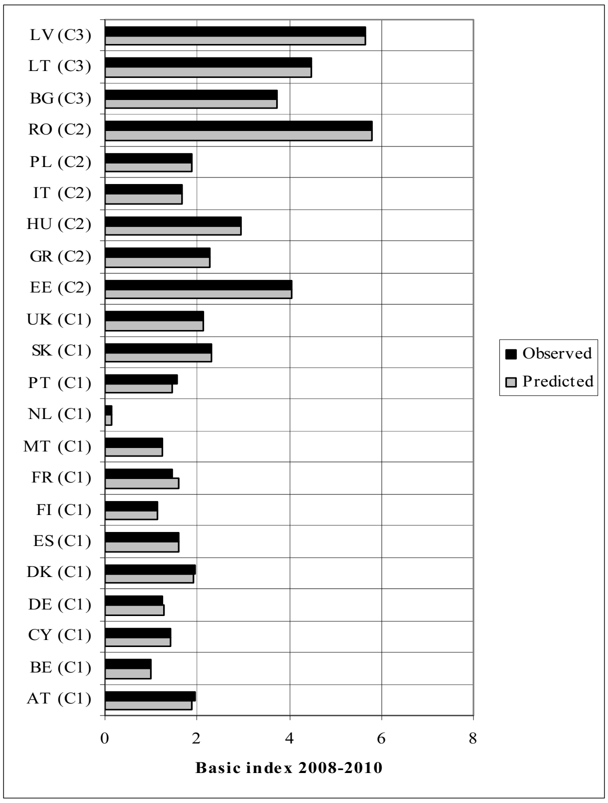

Figure 6. The predicted and observed basic indexes of doubtful and non-performing loans

The predicted variable *DL* is the relative ratio (index) so the prediction errors for every country were calculated:

$$E = |Y_t - W_t| \cdot 100\% \tag{12}$$

These errors for every country are given in Table 6.

The average prediction error:

$$\overline{E} = \frac{\sum |Y_t - W_t| \cdot 100\%}{n} = 1{,}94\% \tag{13}$$

The overall accuracy of *DL* predictions:

$$A_p = 100 - \overline{E} = 98{,}06\% \tag{14}$$

Table 6

The DL prediction errors

E (%)	Countries (%)
0,00	40,9
(0,00; 2,50]	36,4
(2,50; 5,00]	9,1
(5,00; 10,00]	9,1
> 10	4,5

Having the predicted basic index W_i of the year y_2 it is possible to predict the percentage of doubtful and non-performing loans of this year in banks:

$$DL_2 = W_i \cdot DL_0 \tag{15}$$

The research has proved that the percentage of doubtful and non-performing loans in banks for the year y_2 can be predicted with average 98,06 % accuracy. That confirms the high ability of developed model to predict the changes of doubtful and non-performing loans in banks of a country. Also the research has confirmed that the amount of doubtful and non-performing loans in banks highly depends on macroeconomic changes in a country and that this amount is exactly predictable by using statistical analysis techniques.

Conclusions

1. The scientific literature analysis and the empirical research results affirmed the significant dependency between macroeconomic determinants of a country and the loan portfolio credit risk in banks. So this research offers the statistical instrument that allows estimating the macroeconomic variables and predicting the probable changes of bank's performance in relevance to the changes in economical environment. The developed model also substantiates the predictability of loan portfolio credit risk and motivates the importance of economical environment analysis in credit risk management.
2. The cluster analysis of EU countries developing the model has shown that the particular countries have an affinity in changes of the doubtful and non-performing loans percentage in banks. This research allowed creating the set of 20 significant independent variables as factors determining the changes in amount of doubtful and non-performing loans calculated from 9 macroeconomic indicators of 3 years.
3. The developed model in this research enables to predict the percentage of doubtful and non-performing loans in banks with the average 98,06 % accuracy. The basic period for predictions must be the low proportion of doubtful and non-performing loans (about 2,09 – 3,7 %). The model is developed to forewarn banks if the loan portfolio credit risk increase impends and the equilibrium level of doubtful and non-performing loans will be imbalanced.

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Ričardas Mileris

Bankų paskolų portfelio kredito rizikos makroekonominiai veiksniai

Santrauka

Kredito rizika – viena iš pagrindinių komercinių bankų veikloje patiriamų rizikos rūšių. Gebėjimas valdyti šią riziką didele dalimi lemia banko veiklos stabilumą. Ši rizika priklauso nuo tam tikrų priežasčių, dėl kurių skolininkas ateityje gali nesugebėti įvykdyti savo finansinių įsipareigojimų bankui. Todėl bankai, prieš suteikdami kreditą, vertina klientų finansinių įsipareigojimų neįvykdymo tikimybę įvairiais kredito rizikos vertinimo modeliais. Vienas svarbiausių banko tikslų, valdant kredito riziką, yra priimtino rizikos lygio paskolų portfelio suformavimas. Kredito rizikos vertinimo tikslas yra sumažinti galimus paskolų portfelio nuostolius, atmetant paraiškas klientų, kurių rizikos lygis viršija banko nustatytą priimtiną ribą. Todėl bankams svarbu nustatyti veiksnius, leidžiančius tiksliai įvertinti kliento finansinių įsipareigojimų neįvykdymo tikimybę. Dažniausiai statistiniuose įmonių kredito rizikos vertinimo modeliuose nepriklausomų kintamųjų rinkinys suformuojamas iš įmonių finansinių rodiklių ir tam tikrų kokybinių įmonių veiklos parametrų. Tačiau keičiant klientų finansavimo politiką ar bendrą paskolų kainos lygį, svarbu, kad bankai sugebėtų numatyti viso paskolų portfelio kokybę ateityje. Todėl esminę, su šiuo prognozavimu susijusią problemą galima apibrėžti kaip statistinių duomenų analizės metodų parinkimą, kurie nustatytų abejotinų ir neveiksnių paskolų dalies portfelyje priklausomybę nuo nepriklausomų kintamųjų rinkinio (šalies makroekonominių rodiklių) pokyčių.

Šio tyrimo objektas – bankų paskolų portfelio kredito rizikos makroekonominiai veiksniai.

Tyrimo tikslas – nustatyti makroekonominius veiksnius, turinčius didelę įtaką bankų paskolų portfelio kredito rizikos pokyčiams ir sudaryti statistinį modelį, skirtą abejotinų ir neveiksnių paskolų daliai šalies bankų paskolų portfelyje, prognozuoti.

Tyrimo metodai:

1. Mokslinių publikacijų analizė.
2. Statistinių, abejotinų ir neveiksnių paskolų dalies, bankų paskolų portfelyje prognozavimo modelio formavimas, taikant klasterinę, faktorinę analizę, tiesinį tikimybių modelį, logistinę, daugialypę tiesinę ir polinominę regresiją.

Mokslinės literatūros analizės rezultatai pagrindė šalies makroekonominių rodiklių pokyčių įtaką banko klientų kredito rizikai. Teigiama, jog paskolų portfelio kokybė bankuose priklauso nuo šalies bendrojo vidaus produkto, infliacijos, rinkos palūkanų normų, pinigų pasiūlos, pramonės produkcijos indeksų, šalies mokėjimų balanso ir kitų veiksnių. Makroekonominiai veiksniai lemia atskirų ūkio subjektų šalyje veiklos rezultatus. Bankų klientų individualių finansinių įsipareigojimų neįvykdymo tikimybių didėjimas ir bendras, įsipareigojimų nevykdančių klientų skaičiaus šalyje didėjimas, yra tarpusavyje glaudžiai susiję.

Atliekant empirinį tyrimą, buvo analizuojami 22 Europos Sąjungos šalių duomenys apie bankų paskolų portfelį ir makroekonominius rodiklius. Remiantis Europos Centrinio Banko duomenimis, 2008 – 2010 m. laikotarpiu abejotinų ir neveiksnių paskolų dalis bendrai šiose šalyse padidėjo nuo 2,6 iki 6,31 proc. Šio rodiklio pokytis skirtingose šalyse buvo nevienodas, todėl atlikus klasterinę analizę *k*-vidurkių metodu, buvo suformuoti 3 valstybių klasteriai. 2008 m. reikšmė buvo laikoma atskaitos tašku, nes vidutiniškai abejotinų ir neveiksnių paskolų dalis visose šalyse sudarė 2,09 – 3,7 proc., tačiau 2009 ir 2010 m. išryškėjo rodiklio pokyčių skirtumai. Didžioji dalis valstybių (59,09 proc.) priklauso 1 klasteriui, kur bazinis abejotinų ir neveiksnių paskolų dalies pokyčio indeksas yra mažiausias (1,32 ir 1,42). Didesnė indekso reikšmė (2,18 ir 2,67) gauta 2 klasteryje, kurį sudaro 27,27 proc. analizuotų valstybių. Trys šalys (Bulgarija, Lietuva ir Latvija) sudaro 3 klasterį, kur abejotinų ir neveiksnių paskolų dalis vidutiniškai padidėjo 3,65 karto (2008 – 2009 m.) ir 4,45 karto (2008 – 2010 m.). Buvo analizuojami 22 ES šalių 9 makroekonominiai rodikliai: ilgalaikio nedarbo lygis, darbo užmokestis, namų ūkių vartojimo išlaidos, valstybės išlaidos, investicijų apimtys, bendrasis vidaus produktas, prekių ir paslaugų eksportas, importas ir infliacija. Kad būtų išvengta rodiklių nepalyginamumo dėl skirtingo valstybių dydžio, didžioji dalis rodiklių buvo perskaičiuota į rodiklių reikšmes, tenkančias vienam šalies gyventojui. Statistinės grafinės analizės metu nustatyta, kad šie rodikliai valstybių klasteriuose reikšmingai skiriasi. Todėl buvo iškelta hipotezė, jog statistiniais duomenų analizės metodais galima nustatyti priklausomybę tarp abejotinų ir neveiksnių paskolų dalies bankuose ir šalies makroekonominių rodiklių. Buvo sudarytas statistinis modelis, kuriuo galima prognozuoti abejotinų ir neveiksnių paskolų dalį šalies bankuose po 2 metų. Modeliui reikalingų nepriklausomų kintamųjų rinkinys, sudarytas iš bazinio laikotarpio (einamųjų metų), abejotinų ir neveiksnių paskolų dalies bankuose bei bazinio laikotarpio ir 2 vėlesnių metų makroekonominių rodiklių. Prognozavimas modeliu galimas, jei bazinio laikotarpio abejotinų ir neveiksnių paskolų dalis bankuose yra pusiausvyros būsenos (apie 2,09 – 3,7 proc.).

Toliau iš makroekonominių rodiklių buvo sudarytas 20 nepriklausomų kintamųjų (x_i) rinkinys, kurie įvertina rodiklių pokyčius (daugiausiai baziniai individualieji indeksai). Valstybėms klasifikuoti į klasterius, sudaryta logistinės regresijos lygtis, kuria gaunama lygties priklausomo kintamojo vertė Y. Atlikus priklausomo kintamojo logistinę transformaciją, gaunama priklausomo kintamojo reikšmė $P(Y)$ intervale [0; 1], o nustatytas klasifikavimo slenkstis – 0,5. Jei $P(Y) \in [0,5; 1]$, valstybė priskiriama grupei G_1 ir 1 klasteriui. Jei $P(Y) \in [0; 0,5)$, valstybė priskiriama grupei G_0, kur tolesnės analizės metu valstybės priskiriamos 2 arba 3 klasteriams. Į G_0 grupę patekusių valstybių nepriklausomiems kintamiesiems (x_i) buvo atlikta faktorinė analizė ir išskirti 4 faktoriai (F_1 – F_4). Suskaičiuotus faktorių įverčių koeficientus padauginus iš pradinių kintamųjų (x_i) gauti nauji nepriklausomi kintamieji (faktorių įverčiai). Analizuojant šiuos įverčius buvo sudarytas tiesinis tikimybų modelis, kurio priklausomas kintamasis Z leidžia atskirti valstybes į 2 ir 3 klasterius. Pasiektas klasifikavimo tikslumas yra 100 procentų. Kai valstybė klasifikuojama į vieną iš klasterių, toliau prognozuojama abejotinų ir neveiksnių paskolų dalis šalies bankuose po 2 metų. Tam tikslui, visų valstybių pradinių nepriklausomų kintamųjų duomenims buvo atlikta faktorinė analizė ir išskirti 5 faktoriai (H_1 – H_5). Jie naudojami kaip nauji nepriklausomi kintamieji lygtims sudaryti. Norint atlikti prognozavimą reikia faktorių įverčių koeficientus padauginti iš pradinių kintamųjų. Kiekvienam klasteriui sudarytos daugialypės tiesinės regresijos arba polinominės lygtys. Vidutinė kvadratinė paklaida (*MSE*) parodė, kad 1 klasterio valstybių abejotinų ir neveiksnių paskolų bazinio indekso prognozavimui tikslesnė yra polinominė regresijos lygtis (MSE = 0,002673), o 2 ir 3 klasterių valstybių indekso prognozavimui taikytinos daugialypės tiesinės regresijos lygtys, nes jų vidutinė kvadratinė prognozavimo paklaida atitinkamai yra tik $6,874 \cdot 10^{-26}$ ir $9,203 \cdot 10^{-30}$. Vidutinė bazinio indekso prognozavimo paklaida visuose klasteriuose bendrai yra 1,94 proc. Lygtimis gavus prognozuojamą indeksą W_i, jis dauginamas iš bazinių metų abejotinų ir neveiksnių paskolų rodiklio DL_0. Gautas rezultatas parodo prognozuojamą abejotinų ir neveiksnių paskolų dalį šalies bankų paskolų portfelyje po 2 metų.

Tyrimo rezultatai parodė, kad abejotinų ir neveiksnių paskolų pokyčiai komerciniuose bankuose 2 metų laikotarpiu, gali būti prognozuojami vidutiniškai 98,06 proc. tikslumu. Tai patvirtina sudaryto modelio praktinę reikšmę ir taikomumą. Taip pat tyrimas patvirtino, jog abejotinų ir neveiksnių paskolų apimtys bankuose, priklauso nuo makroekonominių rodiklių pokyčių, o bendrą paskolų portfelio kredito rizikos lygį galima gana tiksliai prognozuoti tyrime taikytais statistiniais duomenų analizės metodais. Todėl siekiant veiksmingai valdyti paskolų portfelio kredito riziką bankuose, būtina nuolat vertinti šalies makroekonominių rodiklių reikšmes ir jų pokyčius.

Raktažodžiai: *bankas, kredito rizika, paskolų portfelis, makroekonomika, statistinė analizė.*

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