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DETERMINANTS OF CREDIT RISK – THE CASE OF SERBIA

ABSTRACT: *This paper examines systemic and specific factors that increased the credit risk level in the Serbian banking sector between 2008 and 2014, by applying the vector autoregression model (VAR), logit and probit. Business cycle and RSD depreciation are the most important systemic determinants of credit risk in the corporate sector, while in the retail sector these determinants represent a deterioration of the business and financial situation, based on a rise in the unemployment rate and nonperforming loans, together with domestic currency depreciation and the effects of the solidarity tax. Banks that entered the crisis with a lower level of capital, higher level of portfolio concentration in their 50 biggest borrowers, and with restrictions on the owner supporting the bank by providing additional capital in the period of credit risk increase, have been more exposed to default and more inclined to overestimate their good assets in their reports. The influence of RSD depreciation and the economic interrelation of clients represent an increase in the credit risk level.*

KEY WORDS: *Credit Risk, NPL, Default, Systemic and Specific Determinants of Credit Risk, Business and Credit Cycle*

JEL CLASSIFICATION: E32,E51,G01, G21,G31

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1. INTRODUCTION

The emergence and development of credit risk assessment models and the identification of key credit risk determinants has a relatively long history. From the first borrower-lender relationship to the present time, there has always been an adequate way to assess credit risk. The foundations of credit risk assessment can be found in papers dating back to the 18th century and deal with the issues of uncertainty and probability, but this field expanded in the 20th century due to the development of quantitative methods and powerful IT tools for data processing. The overall development of methods and models of credit risk assessment can be described as a constant fight against the information asymmetry present in the lender-client relationship.

On several occasions to date, economic crises have provided a real stress scenario in which the quality of applied methods and models has been tested, their efficiency in reducing information asymmetry has been estimated, expert opinions on the vulnerability of the applied economic concepts in the changed economic conditions have been given, and conclusions as to further developments have been provided. The last financial crisis, which became global by being propagated through financial and real economy flows, has faced economic policy creators, financial system regulators, and economic theorists with certain tasks. The analysis of credit risk determinants and the implications of the conclusions of such analysis have become very relevant.

The subject matter of this paper is the analysis of credit risk determinants in the banking sector of the Republic of Serbia, a developing country which has faced a pronounced increase in non-performing loans: an indicator of credit risk level due to the expansion of financial crisis effects, and to certain systemic weaknesses under changed economic conditions. The central part of this paper is dedicated to empirical analysis of the systemic determinants that have effected a marked increase in non-performing loans, and to the identification of specific variables at the level of bank clients, which have a quantifiable influence on the credit risk level.

The obtained results are placed in the context of an assessment of the efficacy and efficiency of the methods that commercial banks apply to rate credit risk, and of a complete analysis of the weaknesses of models of economic growth.

The main contribution of this paper is in providing economic policymakers and bank regulators and supervisors with conclusions and the necessary answers regarding economic regulations that have affected the registered credit risk level and the influence of the credit risk level on overall economic trends in Serbia.

2. LITERATURE REVIEW

Our paper refers to earlier research dealing with the impact of systemic factors on credit risk level, especially those works that analyse the business cycle's impact on credit risk level, most often viewed through the level and share of non-performing loans. In these papers, an analysis of the impact of the business cycle – presented through movement in gross domestic product – on credit risk level – presented through the share of non-performing loans – demonstrates that the business cycle is the most important systemic determinant of credit risk level. Here we emphasise the research papers that provide quantitative evidence of the impact of the business cycle on the credit risk level in the Spanish banking system (Salas and Saurina 2002) and the Indian banking system (Rajan and Dahl 2003). Having analysed the business cycle as a factor explaining the movement of non-performing loans, Jimenez and Surina (2005) conclude that the behaviour of market participants has an important effect on the assumed credit risk level. Earlier works on the relation between the business cycle and financial movements, known as 'financial acceleration', should also be pointed out (Bernanke and Gertler 1989; Bernanke, Gertler, and Gilchrist 1996; Kiyotaki and Moore 1997; Bernanke, Gertler, and Gilchrist 1999).

We highlight a study from 2000 that stresses the interaction of credit and market risks (Jarrow and Turnbull 2000). The authors offer an overview of risk assessment models created up to that time and come to the conclusion that most of the models of credit risk assessment, such as structured and actuarial models, assume that market variables (characteristic of market risk) are constant, leave them out, and do not generate them empirically but artificially through the model. The authors conclude that these models imply separate consideration of credit and market risk and do not include possible interaction between them. The authors postulate their own reduced form of the model, which observes the interaction of market and credit risks that the introduction of the London Interbank Offered Rate (LIBOR) envisaged, and assesses its impact on the credit spread level.

A study analysing the phenomenon of spillover of exchange rate risk into credit risk is particularly important (Božović, Urošević and Živković 2009). The authors state that in developing countries, banks predominantly grant loans in foreign currency so as to protect themselves from exchange-rate risk, because the prevailing sources of financing are in foreign currency. The depreciation of the local currency increases borrowers' loan commitments and lowers loan repayments, which leads to increased credit risk.

Other research investigates the systemic determinants of credit risk in certain countries, groups of countries, or regions, such as empirical analysis for Greece (Louzis, Vouldis, and Metaxas 2010), comparative regional analysis for Central, Eastern, and South-Eastern Europe (Klein 2013), comparative analysis for several chosen countries (Ahmad and Ariff 2007), using the example of Slovenian banks (Aver 2008), using the example of a business cycle and the banking system of Austria (Boss et al. 2009), for Greece, Ireland, Portugal, Spain, and Italy (Castro 2012), using the example of underdeveloped countries (De Bock and Demyanets 2012; Diaconasu, Popescu, and Socoliuc 2014), for the group of Gulf countries (Espinoza and Prasad 2010), for the group of Baltic countries (Fainstein and Novikov 2011), in the case of the European Union countries (Mileris 2014), in new member states of the European Union (Festic, Kavkler, and Repina 2011), using the example of the banking sector of Italy (Fiori, Foglia, and Iannotti 2007), in the banking sector of the Sub-Saharan African countries (Fofack 2005), using the example of Malaysia (Janvisloo, Muhammad 2013), in the case of the Russian banking sector (Pestova and Mamonov 2013) and in the case of Bulgaria and Greece (Vogiazas and Nikolaidou 2011). We specifically underline two studies that deal with the issue of macroeconomic determinants of credit risk in the banking sector of the Republic of Serbia (Otašević 2013) and bank lending channels in a euroised economy such as Serbia's (Kujundžić and Otašević 2012).

We focus on papers that argue for the relevance of the impact of specific factors inherent to the bank itself on the credit risk level, such as cost efficiency (Podpiera and Weil 2008; Louzis et al. 2010), the existence of moral hazard in banks holding low capital (Salas and Saurina 2002; Jimenez and Saurina 2005), collateralisation of banks' portfolios and the influence of collaterals on the reduction of information asymmetry (Chan and Kanatas 1985) and frequency of portfolio monitoring (Townsend 1979; Diamond 1984; Broecker 1990; Holmström and Tirole 1997). Some research shows that when client companies do not have a close relationship with their banks or when such a relationship is inconsistent there is a marked level of information asymmetry (Petersen and Rajan 1994; Farinha and Santos 2000; DeYoung, Glennon, and Nigro 2008), and that small banks have a closer relationship with their clients, thus minimizing information asymmetry (Berger, Demirguc-Kunt, Levine, Haubrich 2004). In particular, we highlight empirical evidence supporting the claim that small, young, and indebted companies are by nature prone to have less close relationships with banks (Ongena, Smith 2001).

A special group of studies identifies and quantitatively assesses the specific factors of credit risk, mostly focusing on the identification of credit risk determinants in companies. We highlight the study in which the logit model is applied to data taken from Austria's banking sector and specific credit risk factors are analysed in the process of scoring and rating models (Hayden 2002). The study enable a comparison of the results of other scoring models, and, based on such models, establish credit risk determinants for Austria and Germany's banking sectors. Using the example of data from Turkey's banking sector, Iscanouglu (2005) creates a scoring model and identifies specific variables to explain Turkey's credit risk level. Also using data taken from Turkey's banking sector, Sezgin (2006) creates a scoring model which identifies specific factors of credit risk in the economy.

3. DATA AND VARIABLES

Analysis of systemic determinants of credit risk. The level of credit risk is determined by analysing the aggregate amount of non-performing loans (NPL), for the banking sector, corporate sector, and retail sector, covering the period 30.09.2008 to 31.12.2014 on a quarterly basis, or the period 31.12.2008 to 31.12.2014 on a monthly basis.[1]

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[1] The source of this data is aggregated reports of the National Bank of Serbia on nonperforming loans, published on the NBS website. The NBS first started to collect reports on nonperforming loans from commercial banks on 30.09.2008, and on 31.12.2008 the NBS declared it a monthly reporting obligation of banks. There are no reliable statistics on nonperforming loans in Serbia's banking sector prior to this period.

Specification of systemic variables. Consideration of the systemic factors of credit risk comprises quantification of the impact of macroeconomic variables from the real economy and the financial economy. The considered macroeconomic variables from the real economy are deseasonalised gross domestic product (GDP), deseasonalised real net salaries (SAL), and unemployment rate (UN). The macroeconomic variables from the financial economy are nominal exchange rate of the Euro (FX), reference interest rate (REF), and inflation rate (INF).

Analysis of specific determinants of credit risk at the bank level. We observed commercial banks in the Republic of Serbia for the period 30.09.2008 to 31.12.2014. Our sample comprised banks that had a capital adequacy ratio at the beginning of the first business year of the studied period that was above the legally prescribed 12%, resulting in 171 observations. We monitored if the capital adequacy ratio dropped below the legally prescribed 12% in the following year. Banks were marked 1 if yes (17 observations[2]), 0 if no (154 observations). A dependent variable was then constructed with a limitation (discrete type) and based on a binary choice (0 or 1), which differentiated between banks which as a result of increased credit risk level had a problem achieving the legally prescribed capital adequacy ratio and banks that did not. The variable is represented by *id*.

Specific variables and characteristics of commercial banks that can potentially affect the bank's credit risk level. The following variables and characteristics of commercial banks are considered in order to identify and assess specific determinants of credit risk at the bank level: type of ownership (OWN), size of bank (SIZE), efficient revenue and expense management (ROE), capital amount (CAP), non-performing loans share (NPL), concentration of claims in particular client groups (CONC), and collateralisation of credit portfolio (COL), as well as artificially formed indicators that estimate the validity of the classification of bank claims into several risk categories and assess the probability of default per risk category relative to a hypothetical reference bank that utilises a more conservative approach for measuring risk. Artificially formed indicators include

[2] Banks that had a problem with the capital adequacy ratio in the observed period were either recapitalised by their owners or their licence was revoked by the National Bank of Serbia.

an indicator of overestimation of good assets (IGA) and adjusted default indicator (PDC).

Indicator of overestimation of good assets. Our initial assumption is that there are banks that apply sufficiently conservative standards of credit risk management, so our hypothetical reference bank takes its rules from an existing conservative Serbian bank. The rules are based on National Bank of Serbia regulations on the classification of balance-sheet assets and off-balance-sheet items. In our case, categories G and D are considered bad assets (default status) and are jointly marked 4 (category 4), and good assets are marked as follows: category A is marked 1, category B is marked 2, and category C is marked 3. In our hypothetical reference bank the classification rules for balance-sheet assets and off-balance-sheet items are as follows:

- If a claim on a client in the observed bank or more banks is classified as category 4 and the total amount of category 4 claims at the level of the entire banking sector amounts to at least 20%[3] of the total claims on such a client, then the claim on such a client in the hypothetical reference bank is classified as category 4, and
- If the previously defined condition to classify as category 4 at least 20% of the exposure at the level of the banking sector is not met, the category is established as a weighted average of performed categorisations of the same client at the banking sector level.

If these classification rules for the hypothetical reference bank are applied to the clients of a chosen Serbian bank, and the categories are compared to those obtained by applying the approach of that bank, we can assess the reliability of the bank's presentation of its exposure to credit risk. In order to ascertain the reliability of each individual bank, we establish a quantitative measure of the overestimation of good assets. The indicator of overestimation of good assets measures the degree of deviation (distance) of the classification category applied by the bank, relative to the classification categories obtained by the application of the rules of the hypothetical reference bank.

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3 The criterion of 20% is based on European Banking Authority (EBA) directives that envisage giving nonperforming exposure (NPE) status to all claims on one client if at least 20% of exposure towards this client is in default.

$$IGA_{tk} = \sum_{i=1}^{4-k} w_{k \to k+i} \cdot \left(\frac{k+i}{k}\right) \tag{3.1}$$

where:

IGA_{tk} is the overestimation of good assets which the observed bank classified as k in the period t,

k is the category of classification of good assets in the observed bank (takes values 1, 2, or 3),

$k + i$ is the category of classification in the hypothetical reference bank,

$w_{(k) \to k+i}$ is the share of clients who are categorised k according to the classification rules of the observed bank, and k+i according to the classification rules of the hypothetical reference bank,

t is the year for which the indicator is being calculated.

Since the bank has three categories of good assets, a summative indicator of overestimation of good assets (I_t) is obtained in the following way:

$$IGA = \sum_{k=1}^{3} IGA_{tk} \tag{3.2}$$

The summative indicator of overestimation of good assets takes value 0 if the classification rules applied by the bank are identical to the classification rules of the hypothetical reference bank. A high value for this indicator points to a significant overestimation of good assets in the observed bank.

After defining this indicator, we investigate if a higher value of this indicator implies a higher probability of the bank adequacy ratio dropping below 12%.

Adjusted default indicator. If, based on the classification categories of the hypothetical reference bank, we calculate migration matrices for the entire banking sector, we can get the probability of default according to the classification categories of the hypothetical reference bank. The adjusted default indicator represents the probability of default according to the classification categories of an observed bank, which we obtain by applying a two-step procedure. 1) We translate the classification categories of the observed bank into the classification categories of the hypothetical reference bank by applying the approach defined in the indicator of overestimation of good assets, and 2) we apply probabilities of default calculated for the entire banking sector by applying the migration matrices of the hypothetical reference bank to the categories thus obtained. This indicator is a dynamic indicator because, apart from discrepancy between the bank's classification and the hypothetical reference bank's classification, it includes the calculation of probability of default based on the scale of the hypothetical reference bank. The adjusted default indicator is calculated separately for each category of good assets:

$$PDC_{tk} = \sum_{i=0}^{3-k} w_{k\rightarrow(k+i)} \cdot PD_{k+i} \qquad (3.3)$$

where:

$PDC_{tk}PDC_{tk}$is the adjusted default indicator for category k in the period t,

$PD_{k+i}PD_{k+i}$is the probability of a client from $k+i$ category being in default according to the scale of the hypothetical reference bank.

After defining this indicator, conditions are created to test the impact of the adjusted default indicator on the probability of the capital adequacy ratio dropping below 12%.

Analysis of specific determinants of credit risk at the client level. As companies constitute a major part of the portfolio of non-performing loans in Serbia's banking sector in the observed period, namely from September 2008 to December 2014, and data on the credit risk of individuals is scarce and unavailable, this part of the research will focus on identifying and analysing credit risk factors for companies.

The identification and analysis of companies' credit risk is based on an overview of the individual banks' 100 biggest borrowers, carried out according to the rules of the NBS reporting system, on a quarterly basis, for the period from the end of 2008 to December 2014, on data taken from financial statements, balance sheets, and profit and loss accounts relating to the listed borrowers. For the purpose of this analysis, only clients' ID numbers and classification categories were used, according to National Bank of Serbia regulations. Clients at the banking sector level are classified by applying the rules of the hypothetical reference bank, established above. After excluding clients who appear in more than one bank, financial institutions, physical persons, and companies that have data quality problems[4] or were not included in the portfolio of 100 biggest borrowers at the beginning and the end of the observed period, the variable describing the client classification category[5] comprises 1,619 companies.

Defining the credit risk indicator at the client level. A special binary variable is formed based on the previously obtained variable describing client classification category, which takes value 1 if at the end of a business year a bank's client was classified as G or D, i.e., the two worst categories according to NBS regulations, and value 0 if at the end of a business year a client was classified as A, B, or C, which represent good assets. A binary variable formed in such a way, i.e., a probability estimation that a particular homogenous group of clients has value 1 (client default) at the end of the business year, will be used as a credit-risk-level indicator to analyse the credit risk determinants at the bank client level. Of the 1,619 observed companies, 260 have status 1[6] and 1,359 have status 0.

Analysis of the influence of specific factors on companies' credit risk level. Specific factors that will be considered in this analysis include chosen qualitative factors – size of a company and economic activity sector – and quantitative factors – financial indicators calculated on the basis of data from financial reports. When choosing which financial indicators to use in the analysis, we start from two groups of indicators: 1) indicators of credit risk such as slowdown in economic activity, overborrowing, or problems in claim collection, and 2) indicators based on practically applied models, such as ratio numbers that form part of an Altman score, or other ratio numbers that that are typically referenced in the literature.

4. EMPIRICAL ANALYSIS

Analysis of the impact of macroeconomic variables on non-performing loan (NPL) level in the banking sector. The unemployment rate and the reference interest rate lose their statistical significance in the process of constructing the

4 Data from financial reports is missing, calculated ratio numbers represent extreme values, etc.

5 To form this variable, only data relevant to the estimation of borrower classification was used: default and financial standing. Quality of collateral was not taken into consideration.

6 15.5% of the companies in our analysis have status 1.

summative model, so only deseasonalised gross domestic product and nominal exchange rate of the euro have been retained in the model.

To assess the macroecnomic determinants of the level of NPLs in the banking sector, we use the following error-correction-model specification:

$$D(N\hat{P}L_t) = \beta_R R_{t-1} + \beta_{GDP} D(GDP_t) + \beta_{FX} D(FX_t) + \beta_V V_{201301} \qquad (4.1)$$

Table 1. Summary overview of results of the model

$N\hat{P}L_t$	Coefficients
R_{t-1}	-0.133
	(0.04)
$D(GDP_t)$	-2.345
	(1.06)
$D(FX_t)$	1.130
	(0.41)
V_{201301}	0.168
	(0.06)
Observations	24
Pseudo R^2	0.49
JB (Jargue-Bera) normality test (p-value)	0.35
Q test (p-value)	0.26
Remsy Reset test of model specification (p-value)	0.44

Source: *Eviews report, data calculated by the author.*

The increase in non-performing loans in the banking sector can be explained by the drop in deseasonalised gross domestic product and the rise in the nominal exchange rate of the euro during the same quarter. Application of our model can explain around 49% of the variability in the movement of non-performing loans in the banking sector.

The Vector Autoregression (*VAR)* model showed there was a one-sided causality in the impact of deseasonalised gross domestic product, nominal euro exchange rate, and unemployment rate on the level of non-performing loans in the banking sector. In contrast to the error correction model, the first-degree

VAR model finds the unemployment rate also significant in explaining non-performing loan movement in the banking sector.

Table 2. Analysis of causality

Granger causality test	**p-value**
Influence of change in deseasonalised gross domestic product, nominal exchange rate of the euro, and unemployment rate on the change in non-performing loans in the banking sector	0.00
Influence of change in non-performing loans in the banking sector, nominal exchange rate of the euro, and unemployment rate on the change in deseasonalised gross domestic product	0.55
Influence of change in non-performing loans in the banking sector, deseasonalised gross domestic product, and unemployment rate on the change in nominal exchange rate of the euro	0.35
Influence of change in non-performing loans in the banking sector, deseasonalised gross domestic product, and nominal exchange rate of the euro on the change of unemployment rate	0.17
Normality and autocorrelation tests	**p-value**
Doornik-Hansen normality test	0.94
Portmanteau autocorrelation test - Q(12)/adjusted Q(12)	0.99/0.56

Source: *Eviews report, data calculated by the author.*

Table 3. Analysis of variance decomposition

Period	**Non-performin g loans**	**Deseasonalis ed GDP**	**Nominal exchange rate of the euro**	**Unemploym ent rate**
First quarter	69.3	19.6	8.7	2.3
Second quarter	39.6	20.5	18.3	21.5
First year	33.2	17.8	30.1	18.9
Second year	32.5	17.4	31.4	18.7
Cholesky array: gross domestic product – unemployment rate – nominal exchange rate of the euro – non-performing loans				

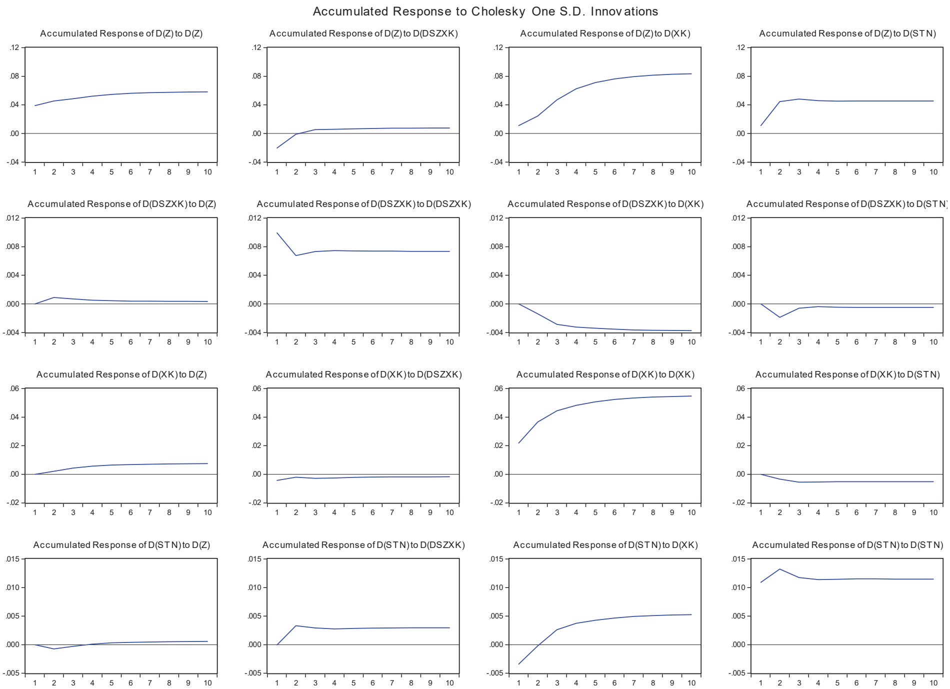
Source: *Eviews report, data calculated by the author.*

Based on an analysis of variance decomposition, we conclude that in the first quarter the change in deseasonalised gross domestic product (19.6%) had the strongest influence on the change in non-performing loans in the banking sector, disregarding the influence of the movement in the non-performing loans themselves. The influence of deseasonalised gross domestic product increased in the second quarter to 20.5%, after which it started to weaken and stabilised at the end of the second year at around 18%. Change in the unemployment rate and change in the nominal euro exchange rate had a weaker effect in the first quarter, but that effect increased rapidly in the second quarter, by 18.3% and 21.5%, respectively. After the second quarter the influence of the change in the unemployment rate became weaker, amounting to around 18% at the end of the second year, whereas the influence of the nominal euro exchange rate became stronger and was around 31% at the end of the second year. In the first quarter all three variables reached the effect of around 30%, with movements in non-performing loans in the banking sector explaining the remainder. At the end of the second year the change in deseasonalised gross domestic product, nominal euro exchange rate, and unemployment rate explains around 67.5% of the changes in non-performing loans in the banking sector, and 32.5% can be explained by their own movement.

At the end of the second year of observation, based on the analysis of decomposition of variance, the change in the banking sector in non-performing loans of around 36.1% is explained by factors from the real economy: deseasonalised gross domestic product and unemployment rate. A factor from the financial economy, the nominal exchange rate of the euro, had an impact of around 31%. If we observe these influences during the first and second years of their manifestation, we notice that the effect of factors from the real economy became markedly stronger only during the first two quarters, and thereafter started to gradually weaken, in contrast to the effect of the financial economy factor, which became stronger over the course of time. Thus, real economy factors had a primary influence on the increase in non-performing loans in the banking sector, which gradually weakened over the course of time. Financial economy factors had a secondary, progressive effect. The progressive effect of the euro's nominal exchange rate can be explained by its interaction with real economy factors; that is, by adding the effect of the financial economy factor to the effect of the real economy factors. Apart from its impact on the increase in non-performing loans, the change in factors from the real economy also affects the increase in loan repayment defaults, as shown by clients entering the default zone that immediately precedes non-performing loan status, after which even a minor change in other factors, such as a change in the nominal euro exchange rate, would push them over the line into the zone of problematic clients.

The impulse response cummulative function shows that increases in the nominal euro exchange rate and the unemployment rate of the value of a standardised random shock from one standard deviation causes an increase in non-performing loans in the banking sector, and that a drop in deseasonalised gross domestic product from one standard deviation causes an increase in non-performing loans in the first quarter. After the first quarter the influence of deseasonalised gross domestic product weakens and the influence of the unemployment rate and nominal euro exchange rate increases.

Figure 1. Impulse response cummulative function in the analysis of change in non-performing loans in the banking sector



Source: *Eviews report, data calculated by the author.*

Analysis of the impact of macroeconomic variables on non-performing loans level in the corporate sector. By gradually adding macroeconomic variables that have been proved relevant by individual modelling, we obtain a summative model that identifies deseasonalised gross domestic product and nominal euro exchange rate as relevant variables. To assess the macroeconomic determinants of the level of NPLs in the corporate sector, we use the following error correction model specification:

$$D(N\hat{P}L_{t(C)}) = \beta_R R_{t-1} + \beta_{GDP} D(GDP_t) + \beta_{FX} D(FX_{t-1}) + \beta_{V1} V_{201301} + \beta_{V2} V_{201204} \quad (4.2)$$

Table 4. Summary overview of results of the model

$N\hat{P}L_{t(C)}$	Coefficients
R_{t-1}	-0.227
	(0.08)
$D(GDP_t)$	-2.509
	(1.09)
$D(FX_{t-1})$	0.759
	(0.36)
V_{201301}	0.199
	(0.06)
V_{201204}	-0.155
	(0.05)
Observations	22
Pseudo R^2	0.57
JB(Jargue-Bera) normality test (p-value)	0.68
Q test (p-value)	0.70
Remsy Reset test of model specification (p-value)	0.45

Source: *Eviews report, data calculated by the author.*

A drop in deseasonalised gross domestic product during the same quarter and an increase in the nominal euro exchange rate with a one-quarter delay affect the increase in non-performing loans in the corporate sector. Applying the stated model can explain around 57% of changes in the movement of non-performing loans in the corporate sector. When constructing the summative model, based on the previously established model with error correction, the change in companies in bankruptcy is found to be a statistically insignificant variable for providing an explanation of movements in non-performing loans in the corporate sector.

If we include the macroeconomic variables that have been identified as relevant by individual analysis in the previously established *VAR* model for the analysis of the influence of deseasonalised gross domestic product on the change in non-performing loans level in the corporate sector, we notice that deseasonalised gross domestic product, nominal euro exchange rate, and the level of bankrupt companies remain significant variables.

Table 5. Analysis of causality

Granger causality test	**p-value**
Influence of the change in deseasonalised gross domestic product, bankrupt companies, and nominal euro exchange rate on the change in non-performing loans in the corporate sector	0.08
Influence of the change in non-performing loans in the corporate sector, bankrupt companies, and nominal euro exchange rate on the change in deseasonalised gross domestic product	0.86
Influence of the change in non-performing loans in the corporate sector, deseasonalised gross domestic product, and nominal euro exchange rate on the change in the level of ailing bankrupt companies	0.17
Influence of the change of non-performing loans in the corporate sector, deseasonalised gross domestic product, and the level of bankrupt companies on the change in nominal euro exchange rate	0.42
Normality and autocorrelation tests	**p-value**
Doornik-Hansen normality test	0.25
Portmanteau autocorrelation test - Q(12)/adjusted Q(12)	0.99/0.33

Source: *Eviews report, data calculated by the author.*

By applying the Granger causality test, we find a one-directional causality in the effect of change in deseasonalised gross domestic product, nominal euro exchange rate, and level of bankrupt companies on the change in non-performing loans level in the corporate sector. The one-directional causality is confirmed with a significance level of 8%. Although this significance level is above 5% we retain our position on the existence of significance, because the obtained result represents a marginal value that is not easy to discard for economic reasons, especially because of the previously obtained evidence of the existence of influence at the banking sector level. The obtained results are additionally checked through analysis of the decomposition of the random error variance and of the impulse response function.

Table 6. Analysis of variance decomposition

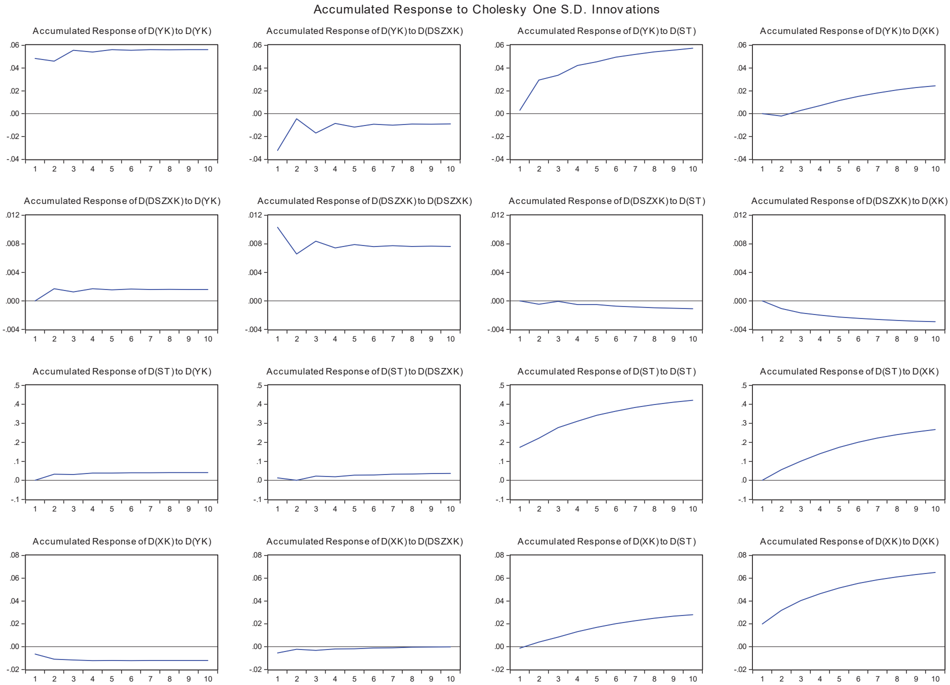
Period	Non-performing loans	Deseasonised BDP	Companies in bankruptcy	Nominal exchange rate of the euro
First quarter	62.0	31.0	0.3	6.8
Second quarter	43.2	37.5	14.5	4.8
First year	41.6	38.6	15.0	4.8
Second year	41.0	38.2	15.4	5.4
Cholesky array: gross domestic product – companies in bankruptcy – nominal exchange rate of the euro – non-performing loans				

Source: *Eviews report, data calculated by the author.*

In the first quarter the change in deseasonalised gross domestic product has an impact of around 31% on non-performing loans movement in the corporate sector. In the same quarter the influence of change in the nominal euro exchange rate is around 6.8%. After the first quarter the influence of the change in deseasonalised gross domestic product increases to around 38% at the end of the second year. It can be noticed that the influence of the change in deseasonalised gross domestic product is greater in the corporate sector than in the entire banking sector. This reaffirms the claim that deseasonalised gross domestic product has greater influence on the corporate sector than on other segments of the banking sector, such as the retail sector. The change in the nominal exchange rate of the euro weakens after the first quarter and remains at a level of around 5%. The influence of the change in the nominal exchange rate of the euro in the corporate sector is weaker than in the entire banking sector, which can be explained by the stronger influence of the change in the nominal euro exchange rate on the retail sector and the sector dominated by bankrupt companies. This is clearly seen in the analysis of the impact of the nominal euro exchange rate on the change in the level of bankrupt companies in the variance decomposition analysis. The influence of the change in the level of bankrupt companies becomes pronounced in the second quarter and remains at a level of around 15%. At the end of the second year, around 59% of the changes in non-performing loans in the corporate sector can be explained by the change in deseasonalised gross domestic product, nominal euro exchange rate, and level of bankrupt companies. Around 41% of the changes in non-performing loans in the corporate sector at the end of the second year are explained by their own movement, which supports the assumption of the impact of the economic interrelation of companies; i.e., that default of one group of companies causes default of other groups of companies.

In the case of shock from one standard deviation in the values of the chosen variables, the impulse response function shows us that the increase in the nominal euro exchange rate and the level of bankrupt companies and the drop in deseasonalised gross domestic product affect the increase of non-performing loans in the corporate sector. From the variance decomposition analysis we can see that the influence of factors from the real economy is greater than the influence of factors from the banking sector, which indicates that the corporate sector is more sensitive to changes in the real economy than other segments of the banking portfolio. At the end of the second year of observation the influence of the change in deseasonalised gross domestic product alone, as the real economy factor, explains around 38% of the changes in the non-performing loans level, whereas the influence of the change in the nominal euro exchange rate – the financial economy factor – explains around 5%. Also, a comparison of the results at the level of the banking and corporate sectors indicates that the influence of financial economy factors is more pronounced in the banking sector than in the corporate sector, which leads us to the conclusion that other parts of the banking sector portfolio, such as the retail sector, are more sensitive to change in the nominal exchange rate of the euro.

Figure 2. Cummulative impulse response function



Source: *Eviews report, data calculated by the author.*

Analysis of the effect of macroeconomic variables on the level of non-performing loans in the retail sector. Bearing in mind that the previous analysis of the effect of individual macroeconomic variables has not identified the presence of cointegration of non-performing loans in the retail sector and the observed macroeconomic variables, the construction of a summative model is based on the application of the classic linear regression model to first differences of all previously observed time series. In this way we establish that the reference interest rate and real net salaries cannot be considered significant variables in the summative model, whereas unemployment rate, nominal euro exchange rate, level of non-performing loans in the corporate sector, level of bankrupt companies, and the effect of the solidarity tax can be considered variables relevant to the explanation of the movement in non-performing loans in the retail sector.

To assess the macroeconomic determinants of NPL level in the retail sector we use the following model specification:

$$D(N\hat{P}L_{t(R)}) = \beta_0 + \beta_{UN1}D(UN_{t-6}) + \beta_{STAX}STAX_{t-4} + \beta_{FX}D(FX_t) + \beta_{NPL(C)}D(NPL_{t(C)}) + \beta_{UN2}D(UN_t) + \beta_{NPL(R)}D(NPL_{t-7(R)}) + \beta_V V_{201005} \quad (4.3)$$

Table 7. Summary overview of results of the model

$N\hat{P}L_{t(R)}$	Coefficients
C	0.007
	(0.00)
$D(UN_{t-6})$	0.786
	(0.22)
$STAX_{t-4}$	0.039
	(0.01)
$D(FX_t)$	0.354
	(0.12)
$D(NPL_{t(C)})$	0.191
	(0.19)
$D(UN_t)$	0.114
	(0.05)
$D(NPL_{t-7(R)})$	-0.160
	(0.06)
V_{201005}	0.055
	(0.01)
Observations	64
Pseudo R^2	0.71
F-statistics (p-value)	0.00
JB(Jargue-Bera) normality test (p-value)	0.99
Q test (p-value)	0.63
Breusch-Pagan-Godfrey heteroscedasticity test (p-value)	0.64
Remsy Reset test of model specification (p-value)	0.59

Source: *Eviews report, data calculated by the author.*

A rise in unemployment rate with a six-month default, introduction of the solidarity tax with a four-month default, rise in the euro rate, non-performing loans in the corporate sector, and bankruptcy status with a one-month default affect the increase of non-performing loans in the retail sector. Applying the stated model explains around 71% of variation in non-performing loans movement in the retail sector. The effect of the rise in nominal euro exchange rate during the same month confirms that the euro rate, due to its relative stability in the second part of the observed period, is more of a secondary factor that pushes clients who are already 60-90 days past-due into the status of problematic clients, as has already been confirmed in the individual analysis of this macroeconomic variable. By contrast, unemployment rate and other effects from the real economy are primary factors in determining the credit capacity of retail clients. The increase in non-performing loans in the retail sector with a seven-month default affects the decrease in non-performing loans in the retail sector, which is an indicator that individuals' increased default in loan repayment, due to different kinds of rationalisation carried out in companies after the period of seven months, results in other employees receiving more regular salaries, and consequently reduced default in loan repayments.

Due to the absence of normal distribution and the presence of autocorrelation, it is not possible to construct an adequate *VAR* model to additionally analyse causality, decomposition of random error variance, and impulse response function.

Construction of summative models for the analysis of the impact of specific variables on a bank's credit risk level. For the purpose of analysing the impact of specific variables on the credit risk level of a bank, we will apply two non-linear regression models, logit and probit. To assess the specific determinants of the credit risk level of a bank we use the following model specification:

$$D(CRB_t) = \beta_0 + \beta_1 OWN_t + \beta_2 CONC_t + \beta_3 IGA_t + \beta_4 PDC_t + \beta_5 CAP_t \quad (4.4)$$

Table 8. Summary overview of logit and probit models

$\hat{NPL}_{t(R)}$	Logit model	Probit model
C	-1.24*	-0.47*
	(2.26)	(1.22)
OWN_t	-1.06**	-0.59***
	(0.46)	(0.24)
$CONC_t$	6.75**	3.58**
	(2.91)	(1.55)
IGA_t	1.23***	0.67**
	(0.54)	(0.31)
PDC_t	29.07**	16.44***
	(11.45)	(6.47)
CAP_t	-3.86**	-2.22**
	(0.96)	(0.54)
Observations	156	156
Pseudo R^2	0.64	0.65
LR statistics	62.9	64.0
LR statistics (p-value)	0.00	0.00
Logarithm of the reliability function without limitation	-17.9	-17.4
Logarithm of the reliability function with limitation	-49.4	-49.4
Average logarithm of reliability function	-0.1	-0.1
Percentage of accurate forecasts	94.23%	94.23%
Advantage of the model in comparison with the model with a constant	40.00%	40.00%
Hosmer Lemenshow test (p-value)	0.82%	0.87%

Source: *Eviews report, data calculated by the author.*

Notes: *The asterisks ***, **, and * indicate 1%,, 5%, and 10% significance levels, respectively.*

The number of observations for the construction of the summative model is reduced to 156 due to the absence of data for some of the applied variables, so in 15 cases the dependent variable has value 1 and in 141 cases it has value 0. The application of the logit model indicates that the statistically relevant variables are type of ownership, concentration (share) of the 50 biggest clients in aggregate loans, indicator of overestimation of good assets with an up-to-one-year default, adjusted default indicator, and capital level. The logit model with these variables has a McFadden pseudo determination coefficient of 64%, and in the probit model the value of this coefficient is about 65%. Statistics based on the likelihood ratio (LR) imply that a model constructed in such a way is statistically significant.

Based on the table showing the logit model's percentage of accurate forecasts, where the defined marginal value (cut-off) is 0.5, we conclude that the forecast accuracy of the model is around 94%, and that the advantage of this model over the model that contains only a constant is around 40%. On the basis of the Hosmer Lemenshow (H-L) test, we conclude that the quality of the constructed models is good.

The quality of the constructed model is additionally tested by setting a Cumulative Accuracy Profile (CAP) curve and calculating the forecast accuracy ratio (AR). Based on the CAP curve and a calculated AR indicator of around 96.2%, we conclude it is a quality model.

Type of ownership proves to be a significant variable for explaining a bank's credit risk level. A negative mark in front of the explanatory variable indicates that the group of banks marked 1 – banks in foreign ownership where problems in business operations are registered at the level of the parent group – has the highest credit risk level, followed by the group of banks marked 2 – state banks. The group of banks marked 3 – domestic private banks – has a somewhat lower credit risk level, while the group of banks marked 4 – banks in foreign ownership where major problems have not been identified in the business operations at the level of the parent group – has the lowest level of credit risk. Based on the obtained results, we conclude that foreign-owned banks that face problems at the level of the parent group and state-owned banks show the greatest propensity to assume credit risk in the observed period.

The confirmed significance of the claims concentration index, which measures the share of the 50 biggest clients in aggregate non-performing bank loans, indicates that banks with higher claims concentration in the first 50 clients have a greater probability of their capital adequacy ratio dropping below the legally prescribed 12% due to increased credit risk. An increase in the bank's claims concentration index increases the credit risk level and the possibility of the capital adequacy ratio dropping below the legal minimum.

An increase in the indicator of overestimation of good assets, measured by a deviation in the classification of borrowers in the observed bank relative to the rules of the hypothetical reference bank, increases the probability of the capital adequacy ratio of the observed bank dropping below the legal minimum due to an increased credit risk level. This result confirms that there are banks which misrepresent their credit risk level by not accepting the reality that some clients are problematic, thus overestimating their good assets and making the bank's situation look better than it actually is, in order to postpone being given the status of an undercapitalised bank due to the increased credit risk level. Such behaviour can most often be linked to an appetite that exceeds the bank's capacity for risk assumption and weaknesses in corporate management.

An increase in the adjusted default indicator, showing the degree of default probability for clients belonging to certain classification categories, increases the probability of a bank not meeting the regulatory minimum capital adequacy ratio due to increased credit risk.

The model results indicate that banks holding low capital have a much greater chance of recording a drop in their capital adequacy ratio below the regulatory minimum than banks with medium and high levels of capital. At the same credit risk exposure level, the bank with less capacity for risk assumption, measured by the level of available capital, has a greater probability of its capital adequacy ratio dropping. When we cross this result with the result related to type of ownership, it is clear that the problems with capital adequacy ratio occur in banks that cannot get adequate support from their owners in terms of additional capital: state banks, and foreign banks in which the business operation problems are registered at the level of the parent company.

Construction of summative models to analyse the impact of specific variables on companies' credit risk levels. For the purpose of analysing the impact of specific variables on companies' credit risk levels we apply two nonlinear regression models, logit and probit. To assess the specific determinants of the credit risk level of a company we use the following model specification:

$$D(CRC_t) = \beta_0 + \beta_1 SIZE_t + \beta_2 SALES_t + \beta_3 DSCR_t + \beta_4 SLAIMS_t + \beta_5 RETA_t + \beta_6 ETA_t + \beta_7 STA_t + \beta_8 PDA_t \quad (4.5)$$

Table 9. Summary overview of logit and probit models

$N\hat{P}L_{t(R)}$	Logit model	Probit model
C	-4.53***	-2.51***
	(0.96)	(0.29)
$SIZE_t$	-0.25***	-
	(0.08)	(-)
$SALES_t$	0.47***	0.33***
	(0.12)	(0.06)
$DSCR_t$	0.51**	-
	(0.24)	(-)
$CLAIMS_t$	1.02***	0.71***
	(0.24)	(0.14)
$RETA_t$	-3.02***	-1.66***
	(0.80)	(0.38)
ETA_t	-6.22***	-3.23***
	(0.84)	(0.41)
STA_t	-0.62***	-0.30***
	(0.17)	(0.08)
PDA_t	6.77***	4.24***
	(2.08)	(1.11)
Observations	1,619	1,619
Pseudo R^2	0.32	0.30
LR statistics	460.3	429.9
LR statistics (p-value)	0.00	0.00
Logarithm of the reliability function without limitation	-483.3	-498.4
Logarithm of the reliability function with limitation	-713.4	-713.4
Average logarithm of reliability function	-0.03	-0.03

Percentage of accurate forecasts	88.45%	87.89%
Advantage of the model in comparison with the model with a constant	28.08%	24.62%
Hosmer Lemenshow test (p-value)	0.32%	0.12%

Source: *Eviews report, data calculated by the author.*

Notes: *The asterisks ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.*

On the basis of the logit model results, we conclude that the statistically relevant variables are company size (*SIZE*), revenue index (*SALES*), ratio between a company's earning capacity and leverage ($DSCR_t$), client turnover coefficient (*CLAIMS*), ratio between unappropriated profit and total assets ($RETA_t$), ratio between earning capacity and total company assets (ETA_t), ratio between sales revenue and total assets (STA_t), and average default per year (PD_t). The logit model with these variables has a McFadden pseudo determination coefficient of 32%. Statistics based on the likelihood ratio (LR) indicate that a model formed in this manner is statistically significant.

Both applied models recognise the same variables as statistically significant, except in the case of the DSCR and SIZE indicators, which lose their statistical significance in the probit model after inclusion of the variable EBIT/total assets.

Based on Table 4.9, which shows the percentage of the model's forecast accuracy and where the defined marginal value (cut-off) is 0.5, the forecast accuracy is around 88.5% for the logit model and 88% for the probit model. Their advantage over the model containing only a constant is somewhere around 28% in the case of logit model and around 25% in the case of probit model. Based on the CAP curve and AR indicator, the constructed logit model covers around 77.3% of the space between the random and perfect models, while the probit model covers around 76.1% of this space, indicating that the models are of good quality.

A slowdown in economic activity, recognised at the macro level through a drop in gross domestic product, is also confirmed at the micro level by the fall in the revenue index. Companies faced the crisis period with a high level of borrowing, which in conditions of decreasing earning capacity led to a reduced possibility of duly discharging their obligations. The quantitative evidence also confirms the existence of pronounced problems in claim collection, indicating that with a slowdown of the claim turnover coefficient, as obvious evidence of problematic collection, companies encounter severe difficulties in servicing their credit commitments. The fact that micro and small companies have higher credit risk levels, measured by the number of companies with a default status relative to the total number of companies, can only be explained by the fact that the sample for this analysis, since it involves an overview of the biggest borrowers in the banking sector, has included only those micro and small companies with a high level of leverage and consequentially a higher probability of default due to the financial crisis. The result that shows that large and medium-sized companies have a lower probability of default can be interpreted as there being some large and medium-sized companies that borrowed more reasonably and thus did not have problems discharging their credit commitments, whereas the other group of companies realised high levels of leverage, resulting in large and medium-sized companies being seen (in a value rather than a numerical expression) as carriers of the highest credit risk. A high level of accumulated reserves in the form of unallocated profit means a lower probability of default, and vice versa. A low level of earning capacity (EBIT) and sales revenue relative to total assets is a sure sign that such companies will default. A lack of a 'buffer' such as unallocated profit in the balance sheet, as an indicator of long-term positive business operations in the previous period, combined with a low level (or a slowdown) of business activity[7] and earning capacity[8] made companies vulnerable to unfavourable economic activity and led to increased probability of default.

4. CONCLUSION

The results of the econometric analysis show that recorded credit risk level/non-performing loans in the corporate sector are often affected by a drop in gross domestic product in the decline phase of a business cycle, thus confirming that this increase is the consequence of a business cycle. The recorded level of non-performing loans in the corporate sector was also affected by the depreciation of domestic currency against the euro, which under conditions of a high level of euro lending – an indicator of the high euroisation level typical of developing

7 Low level of sales revenue compared to total assets.

8 Low level of business profit compared to total assets.

countries – reduced companies' credit capacity. However, the impact of domestic currency depreciation was more pronounced in the first years of the crisis (2008-2010) than at the end of the observed period (2012-2014), and therefore it acted as a secondary factor of credit risk increase in the corporate sector. By contrast, the effect of the drop in gross domestic product increased with time. Hence the increase in non-performing loans in the corporate sector is predominantly the result of macroeconomic factors from the real economy, whose negative effects are evidence of the financial acceleration inherent in the decline stage of a business cycle, which the Serbian economy experienced after the spillover of the effects of the global financial crisis. The impact of domestic currency depreciation spillover on increased credit risk level and the quantified impact of the increase in non-performing loans in one period on the level of non-performing loans in another – the effect of economic interrelation reinforced by the presence of a pronounced concentration of companies – represent an example of the spillover of exchange-rate risk and operational risk into the recorded credit risk level.

The dominant impact of the level of non-performing loans in the corporate sector on the level of aggregate non-performing loans is not simply reflected in the share of these loans in their aggregate amount but in the impact of the slowdown in the corporate sector on the increase of non-performing loans in the retail sector. This is confirmed by the econometric modelling of the credit risk factors in the retail sector, where we particularly highlight the effect of the rise in unemployment rate as an obvious example of companies' reaction to deteriorating economic conditions due to cost rationalisation, which, with a six-month delay, influences the increase in non-performing loans in the retail sector. The results also confirm the influence of the increase in non-performing loans in the corporate sector on the increase in non-performing loans in the retail sector with a certain period of delay. Considering that net salaries are not recognised as relevant when explaining credit risk level in the retail sector, due to the pronounced influence of the level and total sum of salaries in the public sector which relativise the impact of the slowdown in the private sector, we have quantitatively measured that the moment when the solidarity tax was introduced with a time delay of four months affected the increase in non-performing loans in the retail sector. Just like in the corporate sector, the depreciation of domestic currency is found to be a significant determinant in the retail sector.

The analysis of characteristics at the bank level identifies type of ownership as an important credit risk factor. Foreign banks with identified operational problems at the group level and state-owned banks are more exposed to credit risk than privately owned domestic banks at the group level and foreign banks in which major operational problems at the group level have not been identified. In addition, banks that entered the crisis period with low capital holdings had more problems bearing the assumed credit risk level than banks that held more capital. These two findings strongly correlate the assumed credit risk level with the bank's appetite for risk assumption (capital level), thus confirming the recorded problematic credit risk level in those banks that did not have enough capital to cover the increased credit risk; that is, whose owners could not support, in terms of capital, the increase in credit risk on account of already granted loans. Banks that have a high concentration of investments in their fifty biggest clients are more exposed to credit risk, and this finding pinpoints banks that fell victim to increased credit risk due to the lack of an adequate strategy for portfolio diversification. The indicator of the overestimation of good assets, measured by the degree to which an observed bank's classification of assets into risk categories deviates from the defined rules of a hypothetical reference bank, shows that banks that were not able to cover the increased credit risk with their capital in the crisis period were prone to overestimate their good assets. An almost identical conclusion can be drawn from the quantitative evidence on the statistical significance of the adjusted default indicator, as a measure in which the calculated default probability of an observed bank is lower than the default probability that would have been calculated by the application of the rules of the hypothetical reference bank. Overestimation of good assets was a move that particular banks made to temporarily postpone facing their increased credit risk level, and also an indicator of upcoming problems, a kind of an early warning signal.

The effect of the drop in gross domestic product on increased credit risk at the system level is confirmed in the analysis of specific factors through quantification of the impact of the decrease in the sales revenue index on the increase in the probability of individual clients defaulting. Confirmation of the effect of problems in claims collection, through quantification of the impact of buyers' turnover coefficient on clients' probability of default, is more evidence of the strong effect of companies' economic interconnectedness on the credit risk level. Companies with higher levels of retained profit and a higher level of earning capacity relative to total assets had reserves that to some extent protected them from slowing economic conditions. The ratio between sales income and total assets, as a measure of total assets turnover, was found to be an important factor in credit risk, so companies with higher values of this indicator were more resilient during the crisis.

The increase in credit risk level, measured by an increase in aggregate non-performing loans, meant that banks started to reduce their credit activities, but not until the third quarter of 2012, after several years of postponing the adjustment of credit activities to the slowdown in economic activity. An important factor in the analysis of the banking sector is that the banks successfully absorbed the increased credit risk level in the crisis period, thus preserving financial stability. However, this has not completely solved the problem of the high credit risk level. Because it was successfully handled in the banking system it stopped being a central topic in the financial economy, while it continued to grow as a specific problem in the real economy. The impact of the increase in the credit risk level on the real economy is reflected both in the real flows – most once-leading companies have encountered serious business and financial difficulties – and in financial flows – the increase in the level of non-performing loans meant that banks became more risk averse and more cautious about lending to the corporate sector. The pronounced credit activity procyclicality in the crisis period raises the question of whether regulatory bodies should apply more efficient and effective countercyclical measures, and whether banks' propensity for risk in the rising phase of a business cycle is insufficiently monitored.

If we compare the results for the systemic determinants of credit risk with similar research conducted in other countries (for Spain, Salas and Saurina 2002); for India, Rajan and Dahl 2003; for Greece, Louzis, Vouldis, and Metaxas 2010; for Austria, Boss et al. 2009; for Central and Southeast Europe, Klein 2013; etc.,) we find confirmation of the significance of the business cycle as the systemic determinant of credit risk in Serbia's banking sector. As previously stated, in the case of other open and euroised economies the euro exchange rate is recognized as a significant determinant of credit risk, but, despite this experiential confirmation, few papers deal empirically with this topic in other countries. The results obtained for the banking and corporate sectors coincide with Otašević's (2013) local research on a similar topic, which uses different measures of the credit risk level (a ratio of coverage of bank assets with allowances for impairment). The introduction of the solidarity tax and of the economic connectivity of companies in the identification and quantification of the systemic determinants of credit risk makes this research specific in relation to other, comparable research.

Compared with other research, the analysis of specific determinants that affect a bank's credit risk level comprises both determinants from the literature, such as the level of a bank's regulatory capital (Salas, Saurina 2002; Jimenez, Saurina 2005; Ahmad, Ariff 2007), and new determinants, such as a specifically defined indicator of overestimation of good assets and a corrected default indicator. The specific context of this study provides a result that quantitatively confirms the significance of type of ownership as a determinant of credit risk. In addition to the standard set of quantitatively confirmed determinants of company credit risk used in the literature, and based on papers dealing with the increase of credit risk at the client level (Hayden (2002) for the Austrian and German banking sectors; Benito, Whitley, and Young (2001) for the UK banking sector), this research places greater emphasis on declining sales income as an indicator of bank clients' increased sensitivity to the decline of overall economic activity, and problems in collection due to the economic integration of clients.

The results of this research raise certain theoretical and practical issues that are not included in this paper but pose a challenge for further research. The time dimension of risk needs to be thoroughly analysed; i.e., it is necessary to investigate whether certain risks were assumed in the pre-crisis period but only materially manifested in the crisis period. The need to identify the key driving forces of economic growth in the pre-crisis period, which led to the growth of corporate sector credit that proved extremely sensitive in the crisis period via the financial accelerator mechanism, raises not just the issue of the adequacy of credit risk assessment models but also weaknesses in the applied economic concepts of the pre-crisis period.

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