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MACROECONOMIC DETERMINANTS OF LOAN DEFAULT RATE IN BANKING SECTOR OF THE REPUBLIC OF SERBIA

Makroekonomske determinante stope neizmirenja kredita u bankarskom sektoru Republike Srbije

Abstract

In literature, there is inconsistent view of how the size of a company affects the level of credit risk. The aim of this research is to to determine whether the exposure to systemic risk increases with the size of the borrower. Empirical analysis of the time series of loan default rates, as dependent variable, on the one hand, and macroeconomic factors, as regressors, on the other hand, is based on the error correction model. Parallel to this, a panel data analysis was applied where panel units are defined at the level of the risk segment of the loan portfolio. Research results confirm that there is statistically significant impact of macroecnomic determinants on loan default rate in banking sector of Republic of Serbia. However, in the segment of small and medium-sized enterprises, the adjustment coefficient is not statistically significant. Along with this, in the short run, there is a statistically significant negative impact of the one-quarter lagged default rate on the default rate in the SMEs segment. Based on the research results, it can be inferred that the credit risk of the SMEs segment is the most resistant to the influence of macroeconomic factors. SME are the most flexible because they are not burdened by size, and on the other hand, they are not endangered as micro businesses by the risk of concentration of one large customer and weak negotiating position in relation to creditors and suppliers.

Keywords: *banks, default rate, cyclicality of credit risk*

Rezime

U literaturi postoji neusaglašen stav kako veličina korisnika kredita utiče na stepen izloženosti kreditnom riziku. Cilj ovog istraživanja je da utvrdi da li cikličnost kreditnog rizika raste sa porastom veličine korisnika kredita. U radu je primenjen model sa korekcijom ravnotežne greške gde vremenske serije stopa neizmirenja kredita predstavljaju zavisnu promenljivu, a makroekonomski faktori nezavisne promenljive. Podaci su organizovani u formi panela gde su jedinice panela definisane na nivou segmenata kreditnog portfolija. Rezultati istraživanja potvrđuju da postoji statistički značajan uticaj makroekonomskih faktora na stopu neizmirenja kredita u bankarskom sektoru Srbije. U segmentu malih i srednjih preduzeća, koeficijent prilagođavanja nije statistički značajan. Pored toga, u ovom segmentu, u kratkom roku, postoji statistički značajan inverzan uticaj stope neizmirenja kredita sa docnjom od jednog kvartala na sopstvenu vrednost u tekućem kvartalu. Na osnovu ovih rezultata možemo da zaključimo da je kreditni rizik u segmentu malih i srednjih preduzeća najotporniji na uticaj makroekonomskih faktora. SME segment je najfleksibilniji jer nije opterećen veličinom i sa druge strane nije ugrožen kao segment mikro pravnih lica rizikom koncentracije jednog kupca i slabom pregovaračkom moći u odnosu na kupce i dobavljače.

Ključne reči: *poslovne banke, stopa neizmirenja kredita, cikličnost kreditnog rizika*

Introduction

Lending to the private sector (corporate and retail) is the main channel of financial intermediation which is the basis of economic growth of developing countries, but also a source of systemic risk [12, p. 110; 3, p. 1]. The lower the level of development of the financial system, the higher the share and importance of lending activity in the balance sheets of commercial banks, as it is almost the only way to provide external sources of financing for business entities. In such an environment, the stability of the financial system of an economy is directly related to the level of credit risk which commercial banks are exposed to, based on their lending activity.

Modeling credit risk with the default rate has been addressed in a large number of studies by foreign authors, but they all analyze the impact of specific factors at the company level [1, pp. 589-609; 23, pp. 449-470; 26, pp. 109-131; 33, pp. 59-82; 31, pp. 101-124; 10, pp. 2899-2939; 25, pp. 5932-5944]. The initial theoretical basis for credit risk analysis at the aggregate level is a model based on the portfolio evaluation (Credit Portfolio View – CPV model), developed by Thomas Wilson [34, pp. 111-117; 35, pp. 56-61]. Unlike previous models of the probability of default at the company level, in the CPV model, the aggregate default rate is for the first time modeled at the level of all industries in the USA, introducing macroeconomic factors as determinants. On the other hand, the phenomenon of financial acceleration defined by Bernanke, Gertler, Gilchrist in 1999 [5, pp. 1341–1393] was the theoretical basis for the introduction of the business cycle as one of the explanatory variables of credit risk at the aggregate level.

Irrespective of the objectively better performance of the default rate as a credit risk indicator compared to NPLs, a relatively small number of papers dealing with macroeconomic modeling of bond default rates [16, pp. 233-250; 27, pp. 28-44] and loan default rates [6, pp. 281-299; 7, pp. 219-235; 19, pp. 533-552; 11, pp. 1-19; 15, pp. 96-120] was produced after the global crisis. The reason for this is the lack of a loan default rate database at the national and international levels. Looking at the existing literature, it can be said that most countries do not have a loan default database, hence it was not possible to compare the results obtained between developing and highly developed countries. Keijsers et al. [19, pp. 533-552] in their research paper use, for the first time, the Global Credit Data[1] database formed in 2004 by 11 banks, which in 2017 counted 53 members. It was created as a result of international cooperation of banks, with a view to supporting econometric research, particularly when it comes to the implementation and improvement of regulatory framework for determining the required capital level – Advanced Internal Rating Based Approach (A-IRB approach) within the Basel II standard.

At the end of 2019, the Association of Serbian Banks, at the initiative of the largest Serbian banks, formed a national loan default rate database. It contains data at the aggregate level and by individual segments, starting from the first quarter of 2012.

The annual default rate is calculated as follows:

$$DR = N_T^D / N_{T\text{-}12m} \qquad (1.1)$$

where:

DR – default rate,

N_T^D - number of borrowers / exposure amount as of date (T-12) in default at the date T, and

$N_{T\text{-}12m}$ - borrowers/ exposure amount not in default at the date (T-12m).

The aim of this study was to determine whether there is a statistically significant difference in credit risk cyclicality with an increase in the size of the borrower. There are various inferences in the literature about the impact of a company size on the default rate. In Keijsers et al. [19, pp. 533-552] it was confirmed that there is a greater variability in the default rate and loss given default in small and medium-sized enterprises compared to large companies. This conclusion was confirmed in the following papers: Shumway [31, pp. 101-124], Bunn et al. [9, pp. 1-37], Carvalho et al. [11, pp. 1-19]. In contrast thereto, the study by Bonfim [6, pp. 281–299] found that with the increase in the size of the company, the probability of default increases. There is no explicit position in the literature, however, it is implied that with the increase in a company's size, the default rate is largely determined by macroeconomic determinants,

1 www.globalcreditdata.org

while with the decrease in company size, the influence of specific factors increases [4, pp. 1-15].

Literature Review

Bunn et al. (2003) [9, pp. 1-37] examine the impact of corporate financial position indicators and macroeconomic indicators on the default rate in the UK over the period from 1991 through 2001. The sample consists of 105,687 observations from 29,361 companies that were included in the analysis in the said period. Probit model was used in this research. The company size has also been found to be a statistically significant factor in default 0probability; hence large companies have the lowest PD.

Liou et al. [21, pp. 14-31] reported on the importance of including macroeconomic variables into default rate prediction models. Up until then, most of the models for forecasting default rates were based on specific factors, i.e., company financial performance ratios. Their research confirmed the statistically significant impact of GDP, retail price index, consumer price index, interest rate, industrial production index and stock exchange index on the default rate.

Bruneau et al. [7, pp. 219-235] use a large sample of accounting data of non-financial entities, in the period from 1991 through 2004, in order to quantify the mutual influence between macroeconomic shocks and corporate financial fragility. The VAR model was applied. The results showed that there is a mutual two-way statistically significant impact on both sides of the output gap on the default rate with a negative sign. The effects of shock last for several years, after which they disappear.

In Diane Bonfim's paper (2009) [6, pp. 281-299], the subject of research involves determinants of corporate default rates in Portugal. The determinants of the default rate were analyzed using the logit model. The highest default rate was recorded with micro businesses and large corporate clients, but it turned out that in companies with a similar financial structure the size was not a statistically significant factor in the default rate. It was found that there is a statistically significant impact, accompanied by high regression coefficients, when it comes to GDP growth (negative sign), lending activity growth rate (negative sign), lending interest rate (positive sign) and stock price variation (negative sign).

Giesecke et al. [16, pp. 233-250] quantify the impact of macroeconomic and financial factors on bond default rates, in the period from 1866 through 2008, based on annual data for the U.S. market. The study analyzes corporate bonds, i.e., nonfinancial bond issues. The research has shown that stock return, stock return volatility and GDP are the best predictors of the bond default rate. It was found that a 50% increase in stock return leads to a 0.58% increase in the bond default rate.

Atanasijević and Božović (2016) [2, pp. 228-250] examine the determinants of the corporate loan default rate (companies and entrepreneurs). The sample consists of corporate loans of a Serbian bank spanning the 2008-2012 period. The aim of the research is, first of all, to quantify the impact of the euro exchange rate against the Serbian dinar on the loan default status. A probit model was applied to panel data where panel units are defined according to the loan currency (euro-denominated loans and loans in Serbian dinars). Based on the obtained results it was concluded that the depreciation of the dinar has a statistically significant impact on the default status, regardless of whether the loan was approved in euros or in dinars (negative sign). The one-year lagged GDP growth rate has a statistically significant impact on the default status (negative sign). The research found no statistically significant impact of the company size on the likelihood of default.

Keijsers et al. [19, pp. 533-552] analyze the impact of macroeconomic factors (GDP, industrial production and unemployment rates) on the default rate and loss given default, in a period from 2003 to 2010. The authors applied the panel data analysis testing the impact of macroeconomic variables (GDP, industrial production and unemployment rate) on the default rate and loss given default, with panel units defined according to the company size and economic activities. It has been demonstrated that there is a statistically significant impact of macroeconomic factors on the default rate, that the level of credit risk in small and medium-sized enterprises is more sensitive to changes in the economic cycle and that borrowers from the financial and industrial production sectors are most sensitive to changes in the economic cycle, when it comes to the default rate level. The lowest level of the default rate sensitivity to the changes in the economic cycle phases has been recorded in companies that manufacture fast moving consumer goods.

Carvalho et al. [11, pp. 1-19] model the default rate with macroeconomic parameters on a sample consisting of 11 European countries in the period from 2007 through 2017. This study focused on answering the questions as to whether macroeconomic factors affect the default rate, whether there is asymmetry in the results obtained across the sample countries and whether the loan default rate varies significantly within economic activities. In the data analysis, a logistic regression model with panel data was applied. To test the asymmetric impact of macroeconomic factors on the default rate, a dummy variable was introduced that takes the value 1 for countries that were faced with financial crisis in the observed period (Portugal, Italy, Ireland and Spain) and 0 for all other sample countries (Austria, Belgium, Finland, France, Germany, Luxembourg and the Netherlands). It was found that all macroeconomic determinants have statistically significant impact on the default rate, with GDP growth rate standing out in particular. However, there is a pronounced asymmetric impact among the countries in GDP growth phase when the decline in the default rate is more prevalent in developing countries, i.e., countries that are more vulnerable to the stronger impact of the crisis.

Applied Methodology

Panel Unit Root Tests

The Levin, Lin and Chu test [20, pp. 1-24] and Im, Pesaran and Shin test [17, pp. 53-74] are unit root tests most commonly used in panel data analysis. The LLC unit root test is calculated based on pooled data, while the IPS unit root test is obtained as an average of ADF statistics. The LLC unit root test is based on the assumption that the residuals are independent and evenly distributed so that the mean value is equal to zero with the variance σ_u^2 and $\rho_i = \rho$ for each i. The null hypothesis claims that $H_0 : \rho = 1$, which means that all series in the panel have a unit root, while the alternative hypothesis claims $H_0 : \rho <1$, which means that all time series are stationary. As can be seen from the above, the LLC test is based on homogenous structure of all panel units, whereby the null hypothesis assumes that all observation units contain a unit root, while the alternative hypothesis assumes that all panel units are stationary. Restrictive assumptions on which the LLC unit root test was based on (homogeneity and independence of comparative data) influenced further development of unit root tests. The LLC unit root test assumes heterogeneity only in the intercept, while the IPS unit root test allows for heterogeneity in the intercept and in the regression coefficients across the units in the panel. Within the null hypothesis of the IPS unit root test, it is claimed that $H_0 : \rho_i =1$, which means that all series in the panel have a unit root. The alternative hypothesis claims that $H_1 : \rho_i <1$ for i =1,...,N_1 i $\rho_i = 1$ for i = $N_1 + 1,\ldots,N$. It follows from the above that the alternative hypothesis implies at least one panel unit is stationary (not necessarily all), which means that hypotheses testing is based on averaging of individual test statistics.

The IPS test has better performance compared to the LLC test, but there is still a drawback to it that by rejecting the null hypothesis, it is not known how many panel units have stationary properties. In the event of autocorrelation of random error, the IPS test still performs well under the condition that n and T are sufficiently large.

Panel Cointegration Tests

The *Kao test* is based on the assumption of homogeneity of cointegration vectors for all panel units [18, pp. 1-44]. The null hypothesis is based on the claim that a series of residuals from the estimated regression contains a unit root, while the alternative hypothesis assumes that the residuals are stationary. Testing is based on the use of five tests. Four tests are based on DF statistics, while one is based on the ADF statistics. The DF test variants differ depending on whether they include the assumption of strict regressor exogeneity. In order to remove autocorrelation between residuals, the model was extended using the ADF test.

Unlike the *Kao panel cointegration test*, the *Pedroni test* is based on the assumption of heterogeneous cointegration vectors, which includes the possibility of heterogeneous individual effects for different panel units. This further means that the slope coefficients, fixed effects and linear trend can vary within panel units. Pedroni [27, pp. 653-670] suggested the use of seven cointegration statistics and derived appropriate asymptotic distributions. Four statistics relate to pooling the data along the within-dimension (panel cointegration statistics) and include the pooling of autoregressive coefficients across different panel units when checking the stationarity of estimated residuals. The three statistics are based on the pooling the data along the between-dimension (mean group cointegration statistics) and involve averaging of estimated coefficients for each observation unit. For both groups of tests, the null hypothesis is the same (1, i=1,…., N), but there is a difference in the formulation of the alternative hypothesis. The first group of tests is based on the assumption of homogeneity of the coefficients of estimated residuals (, i=1,….N), while the second group of tests includes the assumption of heterogeneity of autoregressive coefficients (, i=1,….N). The first group of tests is based on the use of the following statistics: non-parametric variance ratio statistics, two non-parametric statistics proposed by Phillip and Perron (1998), which are adapted to panel data () and parametric ADF statistics. The second group of tests uses two modified non-parametric statistics (variants of Phillips-Perron test statistics) and ADF statistics. Each of the proposed seven statistics has an asymptotically normal distribution under conditions when T, N→ ∞.

Panel ARDL model

Panel ARDL model is a variant of the ARDL (p, q) model [28, pp. 1-24]:

$$\Delta Y_{it} = \Phi_i + \Sigma_{k=1}^{p} \gamma_{ij}\ \Delta Y_{i,t-j} + \Sigma_{k=0}^{q} \mu_{ij}\ \Delta X_{i,t-j} + \delta_{1ij}\ Y_{i,t-1} + \delta_{2ij}\ X_{i,t-1} + u_{it} \quad (1.2)$$

where $\delta_{1i} = -(1-\Sigma_{k=1}^{q}\lambda ij) \quad \delta_{2i} = \Sigma_{j=0}^{q}\ \omega im$ (1.3)

$$\gamma_{ij} = -\Sigma_{m=j+1}^{p}\ \lambda im \qquad \mu_{ij} = -\Sigma_{m=j+1}^{q}\ \omega im \quad (1.4)$$

where i=1,….N are panel units, t=1,….T are observation periods, Φ_i are fixed effects defined separately for each panel unit, ω_{ij} and λij are k x 1 vectors of explanatory variables and u_{it} is random error. The null hypothesis of no cointegration between variables in the model can be defined in the following way H_0: $\delta_{1i} = \ \delta_{2i} = 0$, in contrast to the alternative hypothesis claiming H_1: $\delta_{1i} \neq \ \delta_{2i} \neq 0$. An essentially null hypothesis claiming the absence of cointegration in the model can be defined as follows: H_0: $\omega_{ij} = 0$ in contrast to the alternative hypothesis H_1: $\omega_{ij} \neq 0$.

The next step, if the presence of cointegration is confirmed, the conditional ARDL long-run model for Yt can be presented as follows:

$$Y_{it} = \varphi_i + \Sigma_{k=1}^{p}\ \lambda ij\ Y_{i,t-j} + \Sigma_{k=0}^{q}\ \omega_{ij}\ X_{i,t-j} + \varepsilon_{it} \quad (1.5)$$

This requires determining of the number of lags in the ARDL (p, q) model using one of the information criteria (AIC, SBC or BIC). In the third step we define the short-run parameters of the error correction model:

$$\Delta Y_{it} = \alpha_i + \Sigma_{k=1}^{p} \gamma_{ij} \Delta Y_{i,t-j} + \Sigma_{k=0}^{q} \mu_{ij}\ \Delta X_{i,t-j} + \varphi_i ECM_{t-i} + u_{it} \quad (1.6)$$

where the random error (u_{it}) is independent, has a normal distribution with a zero mean value and a constant variance. ECM_{t-i} is the error term. φ is adjustment coefficient and shows the speed at which the dependent variable returns to the long-run equilibrium relationship path with the explanatory variables, after the effect of shock. Already based on the definition of the adjustment coefficient, it is clear the same should have a negative sign.

Methods for Estimating Heterogeneous Parameters

Pesaran et al. [28, pp. 621-634] were among the first authors to cover the heterogeneity of regression parameters in the dynamic panel models. The authors proposed the application of mean group (MG) method which involves the formation of individual equations for each panel unit estimated using OLS method to then form the average of the estimated parameters. On the other hand, pooled mean group (PMG) method constrains the long-run coefficients to be identical, while allows the constants, short-run coefficients and error variances to differ across panel units [29]. The allowed heterogeneity of the short-run coefficients affects the dynamic specification and provides the possibility of including different lags in regressions for different observation units. The PMG represents a middle-ground solution between the estimation of individual regressions, where all coefficients and error variances can vary across observation units, and traditional estimates of models with constant parameters. Unlike PMG, the

MG method does not assume heterogeneity of long-run coefficients across observation units. Using the Hausman test, a formal check is performed between the application of PMG and MG methods for estimating regression parameters. The null hypothesis of the Hausman test is based on the claim of homogeneity of the long-run coefficients. If the null hypothesis is adopted, the application of PMG method, which gives efficient and consistent estimates, has the advantage. If the null hypothesis of homogeneity of regression parameters in the long run is rejected, the PMG estimate becomes inconsistent and then the MG method should be applied, which provides consistent estimates under these conditions.

Data and Model Specifications

For the purposes of the research presented herein, two groups of data were used: (1) data on default rates and (2) macroeconomic data. The time series cover the period from 2012Q1 to 2018Q4, which means that the observation period consists of 28 observations at a quarterly level (t=28). As for the default rate (DR), we used data from the Association of Serbian Banks on the number of investments in default. In order to increase the number of observations in the sample and to test the homogeneity of regression parameters, a panel data analysis was applied. Panel units were formed according to the basic risk segments of the loan portfolio: default rates for loans extended to large corporate entities, default rates for loans extended to small and medium-sized enterprises, default rates for loans extended to individuals and default rates for loans extended to micro businesses. In this way, four panel units, i.e., four observation groups as basic components of the aggregate default rate, were obtained. The sample includes a total of 112 observations (N=112) obtained as the product of the time series length (t=28) and the number of panel units (n=4). Panel units were defined on the basis of the loan portfolio segmentation by main commercial segments, which correspond to four credit portfolio segments made based on borrower's size. Borrower's size is defined based on annaul sales turnover. The method applied for defining panel units made it possible to draw conclusions on the credit risk cyclicality at the level of the entire loan portfolio, but also to draw conclusions on the existence of heterogeneity in credit risk cyclicality among the basic risk segments of the loan portfolio. Particulars of the variables used in here presented research, as well as their abbreviations, are given in Table 1, below.

Due to the subject of the research and manner of defining panel units (main loan portfolio risk segments), we ran the regression on all panel units relative to the same time series of macroeconomic determinants. As result of this, dependent variable has two dimensions (within and between panels) while independent variables have only one dimension (within panels). Consequently, descriptive statistics of dependent variable are presented in two tables,

Table 1 Variable names and abbreviations

Number	Variable name	Abbreviation
1	Logistic transformation of the default rate (y_w) $DR_t = \ln\left(\frac{z}{1-y_t}\right)$	DR
2	Seasonally adjusted log GDP in millions of dinars	LGDP
3	Nominal log dinar-euro exchange rate	LER
4	Log key interest rate of the National Bank of Serbia	LKIR
5	Log risk premium of the Republic of Serbia measured by EMBI index (emerging market bond index prepared by JP Morgan)	LRP
6	Log year-on-year inflation rate	LCPI
7	Log seasonally adjusted real net earnings	LDRNS

Source: Author

Table 2 Descriptive statistics of the default rate with log transformation

Variable		Mean value	Standard deviation	Min	Max	Number of observations
DR	Total	-3.43164	0.54937	-4.79579	-2.27541	N=112
	Between		0.32700	-3.77275	-3.01260	n=4
	Within		0.46999	-4.87041	-2.38157	T=28

Source: Edited by the author based on the default rate database of the Association of Serbian Banks in table 2 with two dimensions and in table 3 with only one dimension i.e. as per panel units. Descriptive statistics of macroeconomic factors are presented in table 3, below.

When it comes to logistic transformation of the default rate, already based on the standard deviation between panel units and within panel units, it is clear that the main source of the total variability is variability within panel units. This means that the differences between the panel units are not the source of the total variability. Based on this result, we can expect that the assumption of homogeneity of regression parameters between the panel units is met. In order to gain a better insight into the characteristics of the default rate as a variable of interest and the characteristics of the same, but observed across panel units, in Table 3 below, the default rate is shown in its original form, i.e., in % and without any previous transformation. The same table contains descriptive statistics of macroeconomic variables in original form, before log transformation. The highest variability in the default rate is recorded in the segments of large corporate entities and micro businesses, while the lowest variability exists in the segment of loans extended to individuals is in accordance with the above.

Based on the correlation matrix of first difference of macroeconomic determinants, at significance level of 0.05, it is clear that is no statistical significant correlation between macroeconomic determinants. Consequently, there will not be multicollinearity between regressors (see Table 4 below). In addition, the panel data carry more information, have greater variability, less collinearity between variables, more degrees of freedom and greater efficiency.

Based on the fact that ECM, derived from ARDL model, was applied, there is a possibility to lose of significant numbers of degrees of freedom in the model, depending of number of lags of dependent and independent variables in ARDL (p, q) model. For that reason, in order to avoid the loss of significant numbers of degrees of freedom, two models were formed to analyze the impact of macroeconomic factors on the default rate. The panel ARDL model was applied to determine whether there are short-run and long-run relationships between the default rate, on the one hand, and macroeconomic determinants, on the other. Based on the above, two formulas were developed for each of the models (long-run and short-run part of the model,

Table 3 Descriptive statistics of the default rate expressed in % and macroeconomic factors in original measures before log transformation

	Mean value	Standard deviation	Min	Max	Median	Skewness	Kurtosis	JB test	p
DRLC	3.95	2.33	0.81	9.05	3.29	0.880141	2.600822	3.79	0.15
DRSME	3.04	1.44	1.18	6.07	3.07	0.204658	1.842179	1.75	0.41
DRR	2.31	0.55	1.33	3.05	2.30	-0.117712	1.552406	2.50	0.28
DRM	4.99	1.85	2.55	9.31	4.98	0.416738	2.296195	1.38	0.49
GDP	864.811,4	37.143,99	815.349,0	935.749,3	853.620,2	0.658744	2.296742	2.60	0.27
ER	118.3288	3.61	111.3643	123.9679	118.4453	-0.168246	2.034748	1.21	0.54
KIR	6.67	3.112013	3.00	11.75	5.67	0.253654	1.423934	3.19	0.20
RP	2.92	1.392824	1.09	6.19	2.66	0.729016	2.749446	2.55	0.28
CPI*	3.48	3.30	0.30	12.20	2.15	1.616061	4.326772	14.24	0.00
DRNS	46,003.77	2,777.45	39,134.89	50,761.77	45,758.10	-0.379	2.822616	0.70	0.70

Length of the series: 2012 Q1-2018 Q4;*non-normal distribution
Source: Author's calculations.

Table 4 Correlation matrix of first difference of macroeconomic factors (significance level of 0.05)

	LGDP	LER	LKIR	LRP	LCPI	LDRNS
LGDP	1.0000					
LER	0.1109	1.0000				
LKIR	0.0324	-0.0612	1.0000			
LRP	0.3590	0.3513	-0.1479	1.0000		
LCPI	-0.2825	0.0855	0.2624	-0.0512	1.0000	
LDRNS	0.3771	0.1681	-0.0410	0.2136	-0.1751	1.0000

Source: Author's calculations.

respectively), which were estimated simultaneously and which are shown below.

Model 1

$$DR_{it} = \varphi_i + \Sigma_{k=1}^{p} \lambda ij^*DR_{i,t-j} + \Sigma_{k=0}^{q}\omega_{ij}^* \, LGDP_{t-j} + \Sigma_{k=0}^{q}\gamma_{ij}^* \, LER_{t-j} + \Sigma_{k=0}^{q}\mu_{ij}^*LRP_{t-j} + \varepsilon_{it} \quad (1.7)$$

$$\Delta DR_{it} = \alpha_i + \Sigma_{k=1}^{p} \lambda ij\Delta DR_{i,t-j} + \Sigma_{k=0}^{q}\omega_{ij}\Delta LGDP_{t-j} + \Sigma_{k=0}^{q}\gamma_{ij}\Delta LER_{t-j} + \Sigma_{k=0}^{q}\mu_{ij}\Delta LRP_{t-j} + \varphi_{ij}ECM_{t-1} + u_{it} \quad (1.8)$$

Model 2

$$DR_{it} = \varphi_i + \Sigma_{k=1}^{p} \lambda ij^*DR_{i,t-j} + \Sigma_{k=0}^{q}\omega_{ij}^* \, LKIR_{t-j} + \Sigma_{k=0}^{q}\gamma_{ij}^* \, LCPI_{t-j} + \Sigma_{k=0}^{q}\mu_{ij}^*LDRNS_{t-j} + \varepsilon_{it} \quad (1.9)$$

$$\Delta DR_{it} = \alpha_i + \Sigma_{k=1}^{p} \lambda ij\Delta DR_{i,t-j} + \Sigma_{k=0}^{q}\omega_{ij}\Delta LKIR_{t-j} + \Sigma_{k=0}^{q}\gamma_{ij}\Delta LCPI_{t-j} + \Sigma_{k=0}^{q}\mu_{ij}\Delta LDRNS_{t-j} + \varphi_{ij}ECM_{t-1} + u_{it} \quad (1.10)$$

Results

Tables 5 and Table 6 below display results of the stationary analysis of the dependent and independent variables in this research. Dependent variable has two dimensions, between panels and within panels thus LLC and IPS unit root tests, which represent first generation unit root tests in panel models, were applied. Both test results, LLC and IPS test, show that time series of dependent variable is integrated of order I(1). Independent variables haven't dimensions between panels thus ADF and modified ADF unit root tests have been implemented. Based on both test results, conclusion is that independent variables LGDP, LER, LKIR and LRP are integrated of order I(1). On the other hand, independent variables, LCPI and LDRNS are integrated of order I(0). Modified AFD test was implemented with time series that have structural break. Existence of structural break in observed period was tested by Chow test. Structural break has time series of LGDP (2014Q3), LER (2017Q1) and LCPI (2016Q2).

The *Kao test* and *Pedroni test* were applied to test the existence of cointegration in here presented panel models (the results of the tests applied are reported in Tables 7 and 8 below). Based on the results of the *Kao test* of cointegration, the conclusion on the existence of cointegration ($p<0.05$) was made in both models, while on the basis of the results of the Pedroni test, based on the two out of the three here observed statistics, the conclusion of the existence of cointegration can be made. Based on the results of both tests, we infer that there exists cointegration in both models and we proceed with further research.

Based on the fact that there is a difference in the order of integration of the variables of interest (I(0) and I(1)), the panel ARDL model was applied to determine whether there are short-run and long-run relationships between the default rate, on the one hand, and macroeconomic determinants, on the other hand. The Bayesian information criterion (BIC) was applied to obtain the optimal lag length in the ARDL model. As the sample size grows larger, this

Table 5 Unit root tests in panel models

	LLC (Levin, Lin & Chu) test		IPS (Im-Pesaran-Shin) test	
	Order	First difference	Order	First difference
DR	1.5861	-2.6132	1.4443	-4.6782

Source: Author's calculations

Table 6 Unit root tests for macroeconomic variables

	Modifikovan ADF test		Proširen Dickey-Fuler test (ADF test)			
	U nivou		U nivou		Prva diferenca	
Promenljive	t statistika	kritična vrednost	t statistika	kritična vrednost	t statistika	kritična vrednost
LGDP	-4.57	-4.85	-1.69	-3.58	-4.87	-2.98
LER	-3.26	-5.17	-1.27	-3.58	-5.25	-2.98
LKIR	/	/	-2.77	-3.60	-3.02	-2.98
LRP	/	/	-2.68	-3.58	-5.49	-2.98
LCPI	-5.51*	-5.17	-1.70	-3.58	-3.84	-2.98
LDRNS			-4.51**	-3.58		

Source: Author; *time series stationary at a level based on the ADF test adapted for time series with structural break;**time series stationary at a level based on the augmented Dickey-Fuller test information criterion gives better results compared to other information criteria and is most often used in the panel data analysis. In model 1, the optimal number of lags in the ARDL model is (2,0,0,0), and in model 2 ARDL (1,0,1,0). In order to determine an adequate method for estimating heterogeneous parameters, i.e., to render the parameter estimates efficient and consistent, the Hausman test was applied. In both models, model 1 and model 2, based on the results of the Hausman test, the method of pooled mean groups was applied to estimate the model parameters. The test results are reported in Table 9 below. The rules of inference within the Hausman test and basic characteristics of the method for estimating heterogeneous parameters in the panel ARDL model are illustrated above under subsection Methodology.

The coefficients showing the long-run relationship in the panel ARDL model for both here defined models are shown in Table 10 below. Based on the obtained results, we infer that four out of six regressors total have a statistically significant impact in the long run on the default rate: seasonally adjusted GDP, nominal exchange rate, risk premium of Serbia and key policy rate. The direction of the impact of GDP, risk premium and key policy rate is in line with the results of prior research studies and in accordance with the economic logic. In the long run, the growth of GDP leads to a decline in the default rate, and the growth of the risk premium of Serbia and key interest rate leads to a rise in the default rate. The direction of the impact of nominal exchange rate on the default rate has a negative sign, which is not in line with the results of previous research. The result here obtained reveals that in the long run, the increases in nominal exchange rate (dinar depreciation) lead to a decline in the default rate. At first glance, the obtained result does not seem logical, but merely looking at the graphical representation of the series of the default rate calculated according to the

Table 7 Kao test and Pedroni test of cointegration - model 1

Model 1: DR=f(LGDP, LER, LRP)					
Kao cointegration test			**Pedroni cointegration test**		
Test	Statistics	p	Test	Statistics	p
Modified Dickey-Fuller test	-2.7603	0.00	Modified Phillips-Perron test	0.0242	0.49
Dickey-Fuller test	-2.5195	0.00	Phillips-Perron test	-3.6464	0.00
Augmented Dickey-Fuller test	-3.0399	0.00	Augmented Dickey-Fuller test	-1.5341	0.06
Unadjusted modified Dickey-Fuller test	-4.3201	0.00			
Unadjusted Dickey-Fuller test	-2.9830	0.00			

Source: Author's calculations.

Table 8 Kao test and Pedroni test of cointegration - model 2

Model 2: DR=f(LKIR, LCPI, LDRNS)					
Kao cointegration test			**Pedroni cointegration test**		
Test	Statistics	p	Test	Statistics	p
Modified Dickey-Fuller test	-5.78	0.00	Modified Phillip-Perron test	-1.21	0.11
Dickey-Fuller test	-3.80	0.00	Phillip-Perron test	-4.08	0.00
Augmented Dickey-Fuller test	-2.65	0.00	Augmented Dickey-Fuller test	-3.97	0.00
Unadjusted modified Dickey-Fuller test	-6.01	0.00			
Unadjusted Dickey-Fuller test	-3.84	0.00			

Source: Author's calculations.

Table 9 Results of the Hausman test for the panel ARDL model where the panel units are loan portfolio risk segments

		Test statistics	p value
Model 1	DR=f(LGDP, LER, LRP)		
	DFE vs. PMG	6.78	0.07
	PMG vs. MG	3.19	0.36
Model 2	DR=f(LKIR, LCPI, LDRNS)		
	DFE vs. PMG	0.06	0.99
	PMG vs. MG	0.26	0.96

Source: Author's calculations.

number of clients in default[2], on the one hand, and the series of the nominal exchange rate, on the other hand, it is evident that the said series have opposite direction of movement for most of the observed period (see Graph 1 below). The minimum amount of the nominal exchange rate series was recorded in 2013Q1 (111.96), when the aggregate default rate (DRT), retail default rate (DRR), small and medium-sized enterprises default rate (DRSME) and micro businesses default rate reached its maximum in 2013Q2 (3.11%), 2013Q2 (3.05%), 2013Q3 (5.20%) and 2012Q4(9.32%), respectively. This further means that in the period from 2013Q1 to 2017Q1 the nominal exchange rate increased, whereas all default rates mentioned recorded a fall. The inverse relationship between these variables, which is not in line with the economic logic, can be explained by the fact that the exchange rate in Serbia is subject to an intensive state intervention, being one of the most important channels of monetary policy due to a high degree of euroization of the Serbian economy. This further means that the price stability was achieved by the intervention of monetary authorities on the exchange rate [22, pp. 14-31]. In addition, the default rate is not cumulative as an indicator of nonperforming loans, and therefore, the impact of the said structural mismatch of the Serbian economy is pronounced even more so when it comes to the direction of the impact of the nominal exchange rate on the default rate. Atanasijević and Božović [2, p. 237] found the impact of the exchange rate, with a positive sign, on the default status to be statistically significant (1 - NPL loan; 0 – loan with regular payments), but the observation period does not coincide with the period covered herein. The authors spanned the 2008-2012 period, while the period here observed runs from 2012 through 2018. The period covered by Atanasijević and Božović [2, p. 232] is the period when the exchange rate was not in the focus of monetary authorities for achieving price stability, and that is one of the reasons behind the estimated difference in the direction of the impact of the exchange rate on the default rate. Moreover, the difference does not refer only to the observed period, but also to the method of calculating the default rate, because Atanasijević and Božović [2, p. 233] approximated the default rate through NPLs where the calculation method is cumulative. Further, it is not the first time in the literature that the negative impact of the exchange rate on the credit risk level was identified Zeman et al. [31, p. 11], which has been explained by the fact that the depreciation of a local currency tends to increase the competitiveness of domestic goods relative to foreign goods, which all depends on whether the observed country is a net exporter or importer. The stated explanation cannot be applied to the case of Serbia, because our country is a net importer. Finally, in this research default rate is on aggregate level, not on borrower's level, thus there is lot of factors than can have impact on relation between credit risk and nominal exchange rate, such as loan collateral and currency of the loan.

Based on the fact that the Hausman test determined that the method of pooled mean groups gives efficient and consistent estimates within the models defined here, it should be borne in mind that the application of this method allows for heterogeneity of parameters in the short-run part of the model across observation units, i.e., within the panel units.

In model 1, there is a statistically significant adjustment coefficient in the short run for all panel units (see Table 11 below), except for the SMEs segment. The adjustment coefficient varies between panel units from 29% (large corporate clients) to 76% and 78% (micro businesses and retail segment, respectively). In the segment of small and medium-sized enterprises, the adjustment coefficient is not statistically significant, thus we infer that there is no long-run adjustment in the SMEs default rate movement to the movement of the GDP, nominal exchange rate and risk premium of the Republic of Serbia. We can infer that credit risk in the segment of small and medium-sized enterprises is not cyclical in nature as in other three segments of the loan portfolio. Within the SMEs segment, in the short run, there is a statistically significant impact of the one-quarter lagged default rate on the default rate in this segment of the loan portfolio. The direction of the impact is negative, which means that the positive growth rate of the default rate in the previous quarter causes a negative growth rate of the default rate in the segment of small and medium-sized enterprises in the current

2 The default rate is expressed in %, in its original form, i.e., without any transformations.

quarter, and vice versa. Based on the research results, it can be inferred that the credit risk of the SMEs segment is the most resistant to the influence of macroeconomic factors. Evidently, there is an impact in the short run, but the direction of the impact of the default rate is inverse in the period up to a maximum of 3 quarters or 270 days, which can be explained by the fact that, if clients in this segment go into default, they, on the basis of various financial concessions (reprogramming, refinancing, etc.), recover rapidly and come out from the default status. We explained this by the fact that these companies are the most flexible because they are not burdened by size, and on the other hand, they are not endangered as micro businesses by the risk of concentration of one large customer and weak negotiating position in relation to creditors and suppliers. Božović got the same result in his research of loan default rate predictors for Serbian banking sector [8, pp. 22].

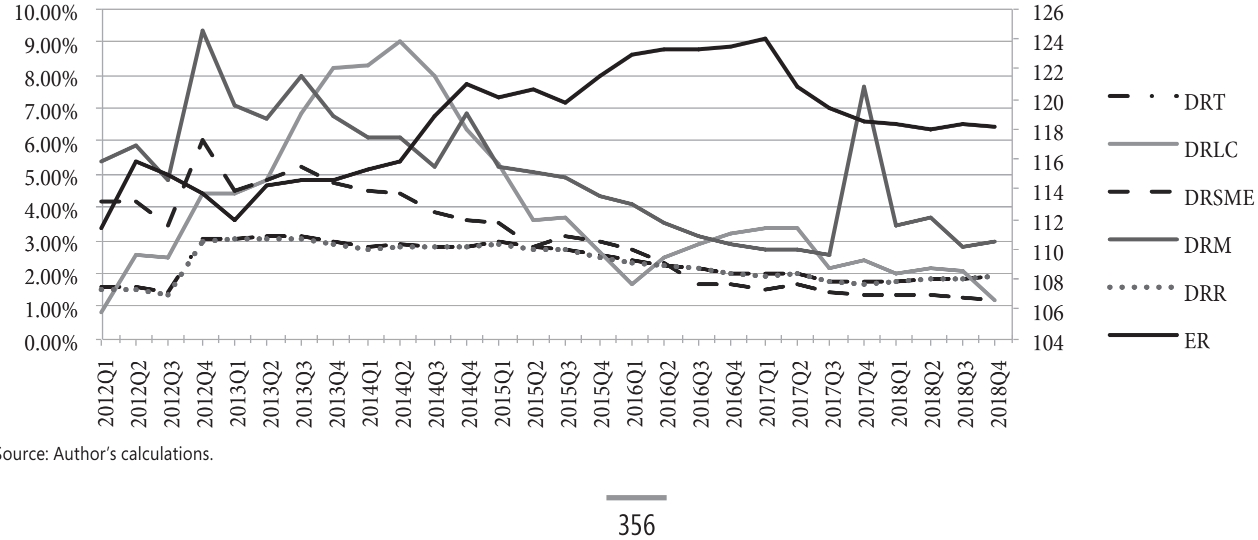
In model 2 (see Table 12 below), at the level of the panel units, adjustment coefficients in the segments of large corporate clients, small and medium-sized enterprises and individuals are found to be statistically significant in the short run. The adjustment coefficient is the highest in the corporate clients' segment (-0.36) and the lowest in the retail segment (-0.13). The adjustment coefficient in the micro businesses segment is not statistically significant. Based on the obtained results, we conclude that the default rates' movement in the long run in the segments of large corporate clients, small and medium-sized enterprises and individuals adjusts to the long-run equilibrium relationship with the key interest rate. Based on the value of the adjustment coefficient, we conclude that the default rate adjusts the fastest, i.e., in the shortest possible time, to the long-run equilibrium relationship with the key interest rate. In addition, we conclude that regardless of the homogeneity in the model parameters between panel units, there is also a statistically significant difference between panel units, when it comes to the impact of the key interest rate on the default rate across different risk segments of the loan portfolio. In the segments of large corporate clients, small and medium-sized enterprises

Table 10 Long-run regression coefficient in the panel ARDL model (model 1 and model 2)

	Variables	Coefficient	Standard error	t-Statistic	p value
Model 1	DR=f(LGDP, LER, LRP)				
	LGDP	-3.50	0.60	-5.76	0.00
	LER	-2.34	0.65	-3.6	0.00
	LRP	0.16	0.05	2.93	0.00
Model 2	DR=f(LKIR, LCPI, LDRNS)				
	LKIR	1.59	0.34	4.63	0.00
	LCPI	0.14	0.15	0.93	0.35
	LDRNS	5.04	3.25	1.55	0.12

Source: Author's calculations.

Graph 1 Aggregate default rate (DRT), retail default rate (DRR), micro businesses default rate (DRM), small and medium-sized enterprises default rate (DRSME) and large corporate entities default rate, left-hand scale, and nominal exchange rate, right-hand scale



Source: Author's calculations.

Table 11 Short-run regression coefficients in the panel ARDL model 1 (DR=f(LGDP, LER, LRP)) at the panel units level (panel units are at the level of loan portfolio risk segment)

Variables	Coefficient	Standard error	t-Statistic	p
Panel unit 1_default rate in large corporate segment (DRLC)				
ECT	-0.29*	0.12	-2.25	0.02
ΔDR_{t-1}	0.18	0.18	1.00	0.31
ΔDR_{t-2}	0.19	0.14	1.31	0.18
$\Delta LGDP_t$	-4.53	4.99	-0.91	0.36
ΔLER_t	0.65	4.61	0.14	0.88
ΔLRP_t	-0.26	0.30	-0.87	0.38
C	16.17*	7.80	2.07	0.03
Panel unit 2_default rate in SMEs segment (DRSME)				
ECT	0.04	0.12	0.36	0.71
ΔDR_{t-1}	-0.53*	0.22	-2.39	0.01
ΔDR_{t-2}	0.00	0.19	0.02	0.98
$\Delta LGDP_t$	0.78	3.11	0.25	0.80
ΔLER_t	-4.68	3.25	-1.44	0.15
ΔLRP_t	-0.08	0.18	-0.44	0.66
C	-2.48	6.71	-0.37	0.71
Panel unit 3_default rate in retail segment (DRR)				
ECT	-0.78*	0.06	-12.04	0.00
ΔDR_{t-1}	-0.11	0.07	-1.46	0.14
ΔDR_{t-2}	0.007	0.06	0.1	0.91
$\Delta LGDP_t$	1.13	1.06	1.06	0.28
ΔLER_t	-0.29	1.16	-0.25	0.80
ΔLRP_t	0.04	0.07	0.67	0.50
C	43.60*	7.18	6.07	0.00
Panel unit 4_default rate in micro businesses segment (DRM)				
ECT	-0.76*	0.32	-2.32	0.02
ΔDR_{t-1}	-0.08	0.31	-0.28	0.78
ΔDR_{t-2}	0.105	0.20	0.51	0.61
$\Delta LGDP_t$	2.13	6.04	0.35	0.72
ΔLER_t	0.02	5.47	0.00	0.99
ΔLRP_t	-0.10	0.34	-0.30	0.76
C	42.66*	19.71	2.16	0.03

Source: Author's calculations; *statistically significant coefficients ($p<0.05$)

Table 12 Short-run regression coefficients in the panel ARDL model 2 (DR=f (LKIR, LCPI, LDRNS)) at the panel units level

Variables	Coefficient	Standard error	t-Statistic	p
Panel unit 1_default rate in large corporate segment (DRLC)				
ECT	-0.36*	0.12	-2.96	0.00
ΔDR_{t-1}	-0.32*	0.15	-2.07	0.03
$\Delta LKIR_t$	0.73	0.83	0.88	0.37
$\Delta LCPI_t$	0.13	0.09	1.48	0.13
$\Delta LCPI_{t-1}$	-0.14	0.09	-1.61	0.10
$\Delta LDRNS_t$	1.49	1.55	0.96	0.33
C	-21.92	14.31	-1.53	0.12
Panel unit 2_ default rate in SMEs segment (DRSME)				
ECT	-0.27*	0.13	-2.10	0.03
ΔDR_{t-1}	-0.48*	0.15	-3.19	0.00
$\Delta LKIR_t$	-0.03	0.41	-0.08	0.93
$\Delta LCPI_t$	-0.10*	0.05	-2.09	0.03
$\Delta LCPI_{t-1}$	0.02	0.05	0.51	0.61
$\Delta LDRNS_t$	-0.35	0.82	-0.43	0.66
C	-16.78	9.40	-1.78	0.07
Panel unit 3_ default rate in retail segment (DRR)				
ECT	-0.13*	0.05	-2.27	0.02
ΔDR_{t-1}	-0.23	0.16	-1.38	0.16
$\Delta LKIR_t$	0.34	0.48	0.72	0.47
$\Delta LCPI_t$	-0.01	0.05	-0.19	0.84
$\Delta LCPI_{t-1}$	0.02	0.05	0.48	0.63
$\Delta LDRNS_t$	0.43	0.91	0.48	0.63
C	-8.14	5.51	-1.48	0.14
Panel unit 4_ default rate in micro businesses segment (DRM)				
ECT	-0.23	0.15	-1.48	0.13
ΔDR_{t-1}	-0.41*	0.20	-2.01	0.04
$\Delta LKIR_t$	-0.40	0.98	-0.41	0.67
$\Delta LCPI_t$	-0.13	0.11	-1.14	0.25
$\Delta LCPI_{t-1}$	0.11	0.11	0.98	0.32
$\Delta LDRNS_t$	-2.31	1.85	-1.25	0.21
C	-13.98	11.40	-1.23	0.22

Source: Author's calculations; * statistically significant coefficients ($p<0.05$)

and micro businesses, there is a statistically significant impact of the first difference in the logistic transformation of the one-quarter lagged default rate on its own value in the current period. The direction of the impact is negative. The default rate, as a regressor in the short run, represents the transmitter of the impact of the key interest rate, as a statistically significant regressor in the long run. This would further mean that lenders, up to a maximum of 4 quarters relative to the growth of the key interest rate, tighten the loan approval criteria, and reduce default rates by slowing lending activity (contraction). In the segment of small and medium-sized enterprises, there is also a statistically significant impact of the year-on-year inflation rate, but with a negative sign, on the default rate during the same quarter, which would mean that rising inflation devalues borrowers' liabilities and positively affects their repayment capacity.

Conclusion

Research results confirm that there is statistically significant impact of macroeconomic determinants on loan default rate in banking sector of Republic of Serbia. However, in the segment of small and medium-sized enterprises, the adjustment coefficient is not statistically significant.

Along with this, in the short run, there is a statistically significant negative impact of the one-quarter lagged default rate on the default rate in the SMEs segment. Based on the research results, it can be inferred that the credit risk of the SMEs segment is the most resistant to the influence of macroeconomic factors. The obtained results are important for economic theory, economic policy makers and top management of commercial banks.

The scientific contribution of this part of the research is a confirmation of the robustness of the recognized conclusions of the default rate cyclicality [31, pp. 101-124; 9, pp. 1-37; 19, pp. 533-552; 11, pp. 1-19] based on data related to the Serbian banking market in the period covering all phases of the economic cycle. The research presented herein is one of the first for developing countries where credit risk was approximated by the default rate. Based on the review of the available literature, this research is the first also in that it analyzes the impact of client size on the cyclical nature of credit risk, based on data from one developing country, at the level of the entire banking market. When it comes to developed countries, there is a limited number of studies that deal with this aspect of credit risk, but there is no unanimous view on how the size of the client affects the degree of credit risk cyclicality. The results of the research by Diana Bonfim [6, pp. 219-235] for the Portuguese market in the period from 1996 through 2002 show that with the growth of the size of the client, the degree of credit risk cyclicality increases. On the other hand, the results of other research [9, pp. 1-37; 19, pp. 533-552] show that the greatest degree of credit risk cyclicality is present precisely in small and medium-sized enterprises. The results obtained herein are significant because they confirm the regularity that with the increase in the size of the client, the degree of credit risk cyclicality also increases, based on the data from one developing country. In addition, it was confirmed that the most resilient sector of the economy is the sector of small and medium-sized enterprises when it comes to the impact of economic crises on the credit risk level. It is interesting that the results obtained herein coincide with the findings obtained by Diana Bonfim [6, pp. 281-299] for the Portuguese banking market, because credit risk of micro businesses, in addition to that of large corporate clients, is also sensitive to changes in the phases of the economic cycle.

Further research should be directed towards answering questions as to whether the regularity that an increase in client's size results in a rising credit risk exposure exists regardless of the level of economic development of a country. In addition, it should be examined why with the increase in the size of borrowers, the exposure to systemic risk also increases, i.e., whether the degree of exposure to systemic risk can be linked to the degree of operational and financial leverage. It is known that large corporate clients have a higher level of operational and financial leverage, which may be due to their size, but also the fact that they are managed by professional management guided by the desire to maximize the rate of return for the owner.

The obtained results are important for economic policy makers because they outline the fact that the sector of small and medium-sized enterprises is a generator of financial stability of an economy and a strong shock absorber of the negative impact of economic crises on a country's economy. The obtained result fits into the previously obtained findings on other characteristics of small and medium-sized enterprises, namely that they are the drivers of economic development of developing countries [14], that they are the most flexible part of a country's economy, that they are the most important drivers of innovation in an economy [13, pp. 30-39], etc.

As for the top management of commercial banks, one of their main goals being to enhance profitability with an acceptable level of credit risk, it is clear that lending to the segment of small and medium-sized enterprises can meet these conflicting goals.

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