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ANALYSIS OF BANK EFFICIENCY IN THE REPUBLIC OF SERBIA: DEA APPROACH

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Abstract: *The structure of Serbian banking system has substantially changed over the past decade as a result of a comprehensive reform which has regulated the banking system and reduced the number of banks. With the arrival of foreign banks banking environment has become more competitive. Therefore, bank management should focus on improving efficiency which will consequently lead to the improvement of the competitive position. This paper uses Data Envelopment Analysis (DEA) to examine and evaluate the efficiency of Serbian banks during the period 2014–2016. The analysis will show which of the banks operate efficiently and which of the banks have efficiency that is not at a satisfactory level, as well as the potential reasons of inefficiency.*

Keywords*: Banking system, Efficiency, Data Envelopment Analysis.*

1. Introduction

Financial system stability is of crucial importance for the overall economic development. Given that the banks play an important role in the Serbian financial system and contribute substantially to the finance of the national economy, the state of the economy and the structure of the banking system are closely related to the stability of the financial system. The competition among banks has increased mainly due to appearance of banking institutes from the other countries, primarily EU counties and due to technological improvement. In order to remain competitive in individual markets, banks must constantly compare themselves with their competitors, recognize the best and strive to learn from.

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In contemporary conditions frequent analyses of the bank's operations and analysis of the whole competitive market are necessity and the development of an appropriate model for efficiency assessment is one of the biggest challenges. An adequate analysis of banks' operations and the identification of factors that cause inefficiency can greatly facilitate decision-making for managers. In practice, analysis based on financial indicators is often used, however, this approach in modern conditions does not provide a satisfactory amount of information. In order to carefully identify economic reality, in view of its complexity, it is ever more often necessary to seek out and make use of the methods and tools based on econometrics, statistics or operations research (Barburski, 2013). In the recent years one of the most commonly used methods for efficiency evaluation of banks is Data Envelopment Analysis.

Therefore, the main objective of this paper is to examine and evaluate the efficiency of Serbian banks during the period 2014–2016 in order to follow the dynamics of efficiency of each of the banks. The analysis will show which of the banks operate efficiently and which of the banks have efficiency that is not at a satisfactory level, as well as the potential reasons of inefficiency.

Based on the given objective, the paper is structured so that, in addition to the introduction and conclusion, it contains the following components: (1) Literature review and methodology; (2) Characteristics of the banking sector of the Republic of Serbia; (3) Model formulation and analysis of the results.

2. Literature review and methodology

In the literature interest in the measurement of comparative efficiency of banks has grown. There are a number of papers that use non-parametric methods for determining the efficient banks. Silva et al. (2017) apply both data envelopment analysis (DEA) and stochastic frontier approach (SFA) to investigate the efficiency of Chinese local commercial and rural banks. Hemmati et al. (2013) use two methods of DEA and TOPSIS for measuring the relative efficiencies of banks in one of the Iranian provinces and the results have indicated that 9 out of 16 banks were efficient. Staub et al. (2010) investigate cost, technical and allocative efficiencies for Brazilian banks in the recent period with the use of DEA to compute efficiency scores. Their results show that Brazilian banks have low levels of cost efficiency compared to banks in Europe and in the US. DEA can be also used in the assessment of the impact of internet banking on the performance of Romanian banks (Stoica, 2015). Several studies published in the recent years have been devoted to measurement of efficiency at the branch level. DEA has been successfully applied in many bank branch performance evaluations using traditional intermediation, profitability and production approaches. Aggelopoulos and Georgopoulos (2017) use bootstrap input-oriented profit DEA to measure efficiency change of bank branches under external environment deterioration. Thilakaweera et al. (2016) assess changes in the technical efficiency of commercial banks in Sri Lanka following the end of armed conflict in 2009 by application of weighted aggregate-efficiency framework based on data envelopment analysis. Portela and Thanassoulis (2007) have used data envelopment analysis and they have developed a novel way to assess the performance of bank branches focusing on three dimensions of performance: transactional, operational and profit. Camanho and Dyson (2005) focuse on the assessment of cost efficiency in branch operational activity and they develop a method for the estimation of upper and lower bounds for the cost efficiency measure in situations of price uncertainty. The assessments under price uncertainty are based on extensions to the DEA model. LaPlante and Paradi (2015) have provided a comprehensive approach to measurement of bank branch efficiency that identifies the growth potential of their branches. A number of studies try to explain the market's reaction to bank mergers. Sherman and Rupert (2006) analyse merger benefits based the comparison of the branch operating efficiencies in the merged bank and pre-merger banks. When it comes to assessing the efficiency of the Serbian banking sector, there are not many papers dealing with this issue. Mihailović (2016) has used one non-parametric (Data Envelopment Analysis) and one parametric method (I-distance) in order to evaluate and rank banks in Serbia according to their efficiency, Savić and Radosavljević (2012) use an extended DEA - Window analysis for the efficiency assessment of banks in Serbia based on panel data for the period from 2005 to 2011.

The term Data Envelopment Analysis was originally introduced by Charnes et al. (1978) based on the research of Farrell (1957). DEA is a non-parametric linear programming approach, capable of handling multiple inputs as well as multiple outputs (Asmild et al., 2004). This methodology allows handling different types of input and output together. A DEA model can be constructed either to minimize inputs or to maximize outputs. An input orientation is focused at reducing the input amounts as much as possible while keeping at least the present output levels, while an output orientation aims at maximizing output levels without increasing the use of inputs (Savić, & Radosavljević, 2012)

DEA models are widely used as a tool for evaluation of efficiency, performance or productivity of homogenous decision making units. These effects can be denoted as the outputs of the decision making units (Halkos, & Salamouris, 2004). There are a number of DEA models. We use the two most frequently used ones are the CCR model (after Charnes, Cooper and Rhodes, 1978) and the BCC model (after Banker, Charnes and Cooper, 1984). The main difference between the two models is the treatment of returns-to-scale (Jemric, & Vujcic, 2002): BCC allows for variable returns-to-scale while CCR assumes that each DMU operates with constant returns-to-scale. In CCR model a measure of efficiency for each decision making unit (DMU) is obtained as a maximum of a ratio of weighted outputs to weighted inputs. Formally the efficiency measure for DMU can be calculated by solving the following linear programming model (Jemric, & Vujcic, 2002):

$$\max_u z_0 = \sum_{r=1}^{s} u_r y_{r0} \tag{1}$$

subject to

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, j = 1,2 \ldots, n \tag{2}$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \tag{3}$$

$$u_r \geq 0, r = 1,2 \ldots s \tag{4}$$

$$v_i \geq 0, i = 1,2 \ldots m \tag{5}$$

where x_{ij} is the observed amount of input of the i^{th} type of the j^{th} DMU and y_{rj} is the observed amount of output of the rt^{h} type for the j^{th} DMU. For the above linear programming model, the dual can be written as (Jemric, & Vujcic, 2002):

$$\min_\lambda z_0 = \theta_0 \tag{6}$$

subject to:

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1,2 \dots s \tag{7}$$

$$\theta_0 x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, i = 1,2 \dots m \tag{8}$$

$$\lambda_j \geq 0, j = 1,2 \dots n \tag{9}$$

Both linear problems produce the optimal solution θ_0*, which is the efficiency score (so-called technical efficiency or CCR efficiency) for the particular DMU. DMUs for which θ_0* < 1 are relatively inefficient and those for which θ_0*= 1 are relatively efficient.

To allow for variable returns-to-scale, it is necessary to add a convexity condition for *X*, i.e. to include in the previous model the constraint (Jemric, & Vujcic, 2002):

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{10}$$

The resulting DEA model is called the BCC model. The input-oriented BCC model for the DMU can be written formally as (Jemric, & Vujcic, 2002):

$$\min_\lambda z_0 = \theta_0 \tag{11}$$

subject to:

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1,2 \dots s \tag{12}$$

$$\theta_0 x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, i = 1,2 \dots m \tag{13}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{14}$$

$$\lambda_j \geq 0, j = 1,2 \dots n \tag{15}$$

These scores are also known as "pure technical efficiency scores", since they are obtained from a model that allows variable returns-to-scale and hence eliminates the "scale part" from the analysis (Jemric, & Vujcic, 2002). Generally, for each DMU the CCR efficiency score will not exceed the BCC efficiency score.

3. Characteristics of the banking sector of the Republic of Serbia

The Serbian banking industry has undergone a substantial development over the last decade. In the reform of the banking sector, which began in 2000, besides the reduction of the number of state banks, one of the primary goals was the construction of a competitive banking system, as well as restoration of the trust of the population to the banks.

During the decade preceding the reforms of the banking sector, banks have lost their primary function - mobilization of free funds and their placement in profitable projects. In contrast, they were considered to be the main bearers of the realization of the current economic plans at that time. Public confidence in the banking sector was lost due to the inability of the depositors to dispose with their assets, as well as due to bad experiences with several pyramid banks during that decade. Due to hyperinflation, dinar deposits completely lost their value, foreign currency savings were frozen, and loans were available only to a narrow circle of economy and citizens, while payment cards did not exist.

The financial situation of the banking sector was characterized by a high level of insolvency and insolvency of the largest banks, a high level of non-performing loans and a low level of real interest-bearing assets, frozen deposited foreign currency savings and low profitability (Jović, 2012).

Credit activity was limited, or directed almost entirely to a narrow circle of related parties in the presence of significant political influence, highly concentrated in the absence of an adequate credit risk assessment, which resulted in a significant underestimation of the incurred and potential losses and reserves for their coverage.

The evolving process of the banking system started in 2001 along with the transition of the Serbian economy when the country had approximately 90 banks. Since that year, until now (for approximately 15 years) the number of banks is more than halved, so that the current number of 31 banks is the result of revoking operating licenses, rehabilitation measures and administration measures undertaken by the National Bank of Serbia, mergers with other banks and the issuance of new licenses for banks. Ownership transformation of the banking sector was carried out primarily through the process of taking over private or privatizing state-owned banks, with strict criteria for assessing the creditworthiness of investors and also with the disabling of the establishment of a monopoly position.

The banking system of The Republic of Serbia consists of the Central Bank (National Bank of Serbia) and commercial banks. Banks in Serbia are independent in their pursuit of profit-oriented business activities based on the principles of solvency, profitability and liquidity (Savić, & Radosavljević, 2012). At the end of March 2017, the banking sector of Serbia consisted of 31 banks with work permit, with an organizational network of 1,716 business units (3 business units less compared to the end of the previous quarter) and 23,798 of employees (49 less compared to the end of the previous quarter) (Banking sector in Serbia: Report for the 1st quarter of 2017).

The banking sector is highly liquid and solvent - an indicator of capital adequacy at the end of 2016 was over 19% and share of capital in total sources is around 20%.

The banking sector of the Republic of Serbia operated profitable in 2016, with a net financial result before taxation in the amount of 21.3 billion dinars, which represents an improvement over the net profit before tax in the previous year (Banking sector in Serbia: Report for the 4th quarter of 2016). Return on Assets (ROA) at the end of the fourth quarter of 2016 was 0.68% (increase by 0.36% compared to the same period in 2015), while return on equity (ROE) amounted to 3.40% (growth by 1.82% compared to the previous year) which means that these indicators are at a satisfactory level.

4. Model formulation and analysis of the results

The variables included for the input oriented CRS/VRS models are drawn from the balance sheets and income statements of the banks under examination for the period 2014–2016. The following variables have been used: interest expenditure (IntExp), total assets (Tasset), number of employees (Labour) and operating expenditures (OE) as inputs, and, interest income (IntInc) and profit before tax (ProfitBT) as outputs. The choice of variables was performed in accordance with the model proposed by Halkos & Salamouris (2004).

At the stage of designing the model, if highly correlated variables are identified among inputs and outputs and these highly correlated variables appear in the same input or output group then they are omitted from the model in order to keep the model's discrimination power high (Avkiran, 1999). On the other hand, Rhodes and Southwick (1993) and Charnes et al. (1994), argue that highly correlated inputs or outputs can remain in the DEA models without distorting the efficiency scores at the expense of lower discrimination power. Therefore, high correlation coefficients do not prevent us from running a DEA model because of the non-parametric nature of DEA, which is supposed to mitigate this effect (Halkos, & Salamouris, 2004).

Table 1. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
IntExp	87	847,00	7925793,00	1475299,4023	1685130,35583
Tasset	87	1325764,00	551415772,00	106116245,5517	123440928,33067
Labour	87	66,00	3032,00	843,9885	765,70321
OE	87	1460,00	13894410,00	3905778,0115	3348018,00634
IntInc	87	45487,00	27838612,00	5829044,1494	6267684,26460
ProfitBT	87	,00	10781396,00	1228736,7011	2315878,44943

Source: Authors' calculation

Table 2. Correlation coefficients on input–output data

		IntExp	Tasset	Labour	OE	IntInc	ProfitBT
IntExp	Pearson Correlation	1	,855**	,790**	,795**	,915**	,600**
	Sig. (2-tailed)		,000	,000	,000	,000	,000
Tasset	Pearson Correlation	,855**	1	,902**	,939**	,979**	,807**
	Sig. (2-tailed)	,000		,000	,000	,000	,000
Labour	Pearson Correlation	,790**	,902**	1	,949**	,898**	,598**
	Sig. (2-tailed)	,000	,000		,000	,000	,000
OE	Pearson Correlation	,795**	,939**	,949**	1	,926**	,683**
	Sig. (2-tailed)	,000	,000	,000		,000	,000
IntInc	Pearson Correlation	,915**	,979**	,898**	,926**	1	,792**
	Sig. (2-tailed)	,000	,000	,000	,000		,000
ProfitBT	Pearson Correlation	,600**	,807**	,598**	,683**	,792**	1
	Sig. (2-tailed)	,000	,000	,000	,000	,000	

Source: Authors' calculation

Since there is a large dispersion in data, it is necessary to solve the problem data imbalance. One of the best ways of making sure there is not much imbalance in the data sets is to have them at the same or similar magnitude. A way of making sure the data is of the same or similar magnitude across and within data sets is to mean normalize the data as proposed by Sarkis (2007). All efficiency measures have been calculated using the Efficiency

Measurement System (EMS) software developed by Holger Scheel at University of Dortmund, Germany.

Table 3. Efficiency scores

Bank	2014			2015			2016		
	VRS	CRS	Scale	VRS	CRS	Scale	VRS	CRS	Scale
AIK	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Alpha	0,75	0,68	0,91	0,82	0,78	0,96	0,75	0,73	0,97
Halkbank	0,73	0,73	1,00	0,73	0,71	0,97	0,81	0,79	0,98
Credit Agricole	0,66	0,62	0,94	0,71	0,69	0,97	0,82	0,79	0,96
mts	1,00	1,00	1,00	0,71	0,52	0,73	0,77	0,70	0,91
Erste	0,84	0,78	0,94	0,91	0,86	0,95	0,86	0,84	0,98
Eurobank	0,98	0,87	0,88	0,98	0,97	0,99	0,91	0,91	1,00
Findomestic	0,81	0,78	0,95	1,00	1,00	1,00	1,00	1,00	1,00
Addico	0,73	0,71	0,98	0,71	0,70	0,99	0,70	0,68	0,97
Intesa	1,00	0,95	0,95	1,00	0,94	0,94	1,00	0,95	0,95
JUBMES	0,86	0,63	0,74	0,96	0,72	0,75	0,96	0,71	0,74
Jugobanka	1,00	1,00	1,00	1,00	1,00	1,00	0,96	0,87	0,90
KBM	0,63	0,56	0,89	0,61	0,58	0,95	0,66	0,54	0,82
Komercijalna	0,86	0,78	0,90	0,79	0,75	0,95	0,82	0,79	0,96
Marfin	0,64	0,59	0,92	0,70	0,63	0,91	0,61	0,53	0,87
NLB	0,55	0,54	0,99	0,92	0,91	0,99	1,00	1,00	1,00
Opportunity	1,00	1,00	1,00	1,00	0,99	0,99	1,00	1,00	1,00
OTP	1,00	0,91	0,91	0,98	0,92	0,94	0,87	0,84	0,96
Piraeus	0,68	0,68	1,00	0,79	0,78	0,99	0,61	0,56	0,91
Poštanska	0,89	0,68	0,77	0,82	0,76	0,93	0,83	0,80	0,96
Procredit	1,00	1,00	1,00	0,97	0,96	0,99	0,92	0,91	0,99
Raiffeisen	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Sberbank	0,95	0,94	0,99	0,91	0,90	0,99	0,88	0,86	0,98
Societe	1,00	0,90	0,90	0,99	0,94	0,95	0,95	0,94	0,99
Srpska	0,70	0,62	0,89	1,00	1,00	1,00	1,00	0,83	0,83
Telenor	0,82	0,62	0,76	0,64	0,34	0,54	0,62	0,42	0,67
Unicredit	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,98	0,98
Vojvođanska	0,70	0,63	0,89	0,78	0,68	0,88	0,76	0,72	0,95
VTB	1,00	0,92	0,92	0,98	0,78	0,80	1,00	0,68	0,68
Average	0,85	0,80	0,93	0,88	0,82	0,93	0,86	0,81	0,93

Source: Authors' calculation

Based on the obtained results, it can be determined that, under the assumption of the VRS 11 banks in 2014 operated effectively, 8 in 2015 and 9 in 2016. Under the assumption of CRS, the number of banks that efficiently operated in 2014 is 7, 6 in 2015, while 5 banks operated efficiently in 2016. Given the fact that the subject of the analysis was efficiency of 87 banks (29 per year) it can be concluded that more than two thirds of the banks operated inefficiently in the analysed period.

Further, scale scores are analysed. Scale scores are calculated as ratio of technical efficiency (CRS) and pure technical efficiency (VRS). As stated in Thanassoulis (2001), if the technical efficiency (CRS) and pure technical efficiency (VRS) of a DMU are equal then scale efficiency is 1 and whether or not we control for its scale size we reach the same view on the DMU's technical efficiency. We may identify no adverse impact of scale size on its productivity. If, however, the DMU has lower CRS efficiency compared to VRS efficiency ratings then its scale efficiency will be below 1. The lower CRS compared to VRS efficiency scores suggests that the DMU is more productive in the former case and less productive when we control for scale size and this means that scale operation does impact the productivity of the DMU effect (Halkos, & Salamouris, 2004). Therefore, the larger the divergence between VRS and CRS efficiency scores the lower the value of scale efficiency and the more adverse the impact of scale size on productivity.

Further on, the results of efficiency for 2016 will be analysed in more detail. As can be seen, several banks (Alpha bank, Halkbank, Credit Agricole, mts, Erste bank, Addico bank, Komercijalna, OTP, Piraeus, Poštanska štedionica and Sberbank) have low efficiency VRS scores (below 0.9) and relatively high scale efficiency (above 0,9). That means that the overall inefficiency of the bank in the CRS model (less than 0.85) is attributed mainly to inefficient operations or management.

On the other hand, if a bank has a fully efficient VRS score and low scale score that may mean that the global inefficiency of the bank under CRS is attributed to disadvantageous conditions. An example of this case can be Srpska bank which has an optimal VRS score of 1 and a relatively low scale score of 0.83. The same holds also for other banks such as Intesa, Unicredit and VTB.

5. Conclusion

The aim of this paper was the determination of the relatively best performing banks and relatively worst performing banks with the application of Data Envelopment Analysis to analyse efficiency of the banks in the Serbian banking market in the period 2014-2016. The results indicated that almost two-thirds of banks operated inefficiently in the observed period, while the main causes of inefficiency were identified inefficient operations or management or disadvantageous conditions. The DEA method is one of the potential ways of evaluating the performance of banks that has certain advantages over the traditional method of measuring the efficiency using financial indicators. The advantage of using DEA compared to financial ratios is that DEA gives a complete unbiased numerical score, ranking, and efficiency potential improvement targets for each one of the inefficient units.

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ANALIZA EFIKASNOSTI BANAKA U REPUBLICI SRBIJI: DEA PRISTUP

Apstrakt: Struktura srpskog bankarskog sistema bitno je izmenjena u poslednjoj deceniji kao posledica sveobuhvatne reforme kojom je regulisan bankarski sistem i smanjen broj banaka. Sa dolaskom stranih banaka, bankarsko okruženje postalo je konkurentnije. Stoga, rukovodstvo banke treba da se fokusira na poboljšanje efikasnosti što će posledično dovesti do poboljšanja konkurentske pozicije. U ovom radu biće primenjena Analiza obavijanja podataka (DEA) za ispitivanje i procenu efikasnosti poslovanja srpskih banaka tokom perioda 2014-2016 godine. Analiza će pokazati koja od banaka funkcioniše efikasno, kod kojih banaka efikasnost nije na zadovoljavajućem nivou, kao i potencijalne razloge neefikasnosti.

Ključne reči: bankarski sistem, efikasnost, Analiza obavijanja podataka.