Technological and Economic Development of Economy
ISSN 2029-4913 / eISSN 2029-4921
2018 Volume 24 Issue 4: 1581–1605
https://doi.org/10.3846/tede.2018.3699

MEASURING THE EFFICIENCY OF BANKS: THE BOOTSTRAPPED I-DISTANCE GAR DEA APPROACH

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Received 23 October 2017; accepted 24 April 2018

Abstract. The efficiency of the banking sector, particularly in developing countries, has captivated the attention of various researchers. Contributing to this issue, we present the results of in-depth analysis of the efficiency of Serbian banks during the period 2005–2016. Unlike previous papers evaluating the efficiency of South-Eastern European banks, we emphasize the importance of applying weight restrictions in Data Envelopment Analysis (DEA). The aim is to incorporate every aspect of a decision-making unit's performance to avoid misevaluation of a bank's efficiency. As a possible remedy to the issue, a bootstrapped I-distance is suggested as a statistically sound framework for determining weight bounds in the Global Assurance Region (GAR) DEA model. In terms of average efficiency, the banking sector of Serbia exhibits an improving trend over the period analyzed. The results show how banks can be evaluated when the impact of all the operating inputs and outputs are properly factored into the study.

Keywords: efficiency evaluation, data envelopment analysis, weight restriction, bootstrap, I-distance, banking, multivariate statistical methods.

JEL Classification: C14, C67, D24, G21.

Introduction

Efficiency in the banking sector has proved a compelling research area throughout the last decade (Aiello & Bonanno, 2017; Delis, Iosifidi, & Tsionas, 2017; Gofman, 2017; Kevork, Pange, Tzeremes, & Tzeremes, 2017). Such measurements are usually made in order to investigate how a bank is performing in comparison to other banks on the same market (Tan, Floros, & Anchor, 2017). They help the bank management identify shortcomings and improve business operations. Measuring efficiency is of particular importance to the banking sector of the developing and emerging economies (Davutyan & Yildirim, 2017) since they have a significant cost efficiency gap compared to developed countries (Nurboja & Košak, 2017).

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Throughout the years, many different methods for evaluating the efficiency of banks have been proposed. Besides stochastic frontier analysis (Huang, Lin, & Chen, 2017; Psillaki & Mamatzakis, 2017; Silva, Tabak, Cajueiro, & Dias, 2017) and non-parametric local linear maximum likelihood (Tsionas & Mamatzakis, 2017), Data Envelopment Analysis (DEA) has become the method most frequently used (Staub, Souza, & Tabak 2010; Ray & Das, 2010; Paradi & Zhu, 2013; Färe, Grosskopf, Maudos, & Tortosa-Ausina, 2015; Kumar, Charles, & Mishra, 2016). Since 1978, when it was first introduced by Charnes, Cooper and Rhodes (1978), the DEA has been applied in more than 6500 publications (Liu, J. Y. Lu, V. M. Lu, 2016).

Berger and Humphrey (1997) performed a comparative review, which included more than 120 studies related to measuring the efficiency of financial institutions. It includes studies conducted in more than 20 countries with at least five major efficiency frontier measurement techniques. Later, Berger (2007) published research which included newer applications of frontier techniques applied to bank efficiency. A recent review of studies of bank efficiency measurement shows that DEA was used in over 75% of them (Fethi & Pasiouras, 2010).

DEA allows efficiency to be measured on the basis of multiple inputs and outputs criteria (Simar, 2007; Simar & Zelenyuk, 2011), but it does not require any prior weighting of inputs and outputs in a frontier analysis (Thompson, Langemeier, C. T. Lee, E. Lee, & Thrall, 1990). The advantage to this approach is that inefficient DMUs are estimated with the most favorable set of weights. This is compelling proof that inefficient DMUs are operating badly. On the other hand, the problem of unrealistic weight dispersion can still occur when some DMUs are rated efficient, since the input and output weights have extreme or zero values (Bal, Örkcü, & Çelebioğlu, 2010). Different approaches to restricting weights are typically proposed as a possible remedy to this issue. One of the first and most important papers on weight restrictions in DEA was written by Allen, Athanassopoulos, Dyson, and Thanassoulis (1997). This paper offered a comprehensive overview of the development of weight restrictions in DEA and provided guidelines for future research in that area.

Cook and Zhu (2008) argued that the same bounds for weights should not be assigned to all DMUs, but should rather be different for a particular group of DMUs, so they proposed the CAR-DEA (Context-Dependent Assurance Regions in DEA) model. The idea was explained using the example of bank branch where they formed three groups of branches according to importance of the indicator "transaction time", based on the location of branches.

Podinovski (2005) set out to explain the economic meaning of weight restrictions. He evaluated weight bounds using production trade-offs between inputs and outputs. This approach is valid under both a constant and a variable return to scale. In his later work, he proved that for any weight restrictions, the optimal weights of the multiplier model show the DMU in the best light in comparison to the entire technology expanded by the weight restrictions (Podinovski, 2016).

It is evident that in both direct weight restrictions and virtual weight restrictions, the definition of boundaries represents a challenging task. Usually, these boundaries are formed subjectively, by appeal to expert opinion (Cvetkoska & Savić, 2017). In this way, subjective evaluation has a significant impact on final efficiency assessment, which is better avoided (Mandic, Delibasic, Knezevic, & Benkovic, 2017). Due to the lack of an adequate approach in defining weight bounds, many hybrid DEA models have emerged.

A widespread case is the hybrid AHP (Analytical Hierarchy Process) DEA model (Shang & Sueyoshi, 1995; Zhu, 1996; Seifert & Zhu, 1998; Takamura & Tone, 2003). Jain, A. Kumar, S. Kumar, and Chandra (2015) have put forward a GA-DEA model (GA – Genetic Algorithm) in cases where bounds are estimated by a larger number of experts. Mecit and Alp (2013) suggested the COR-DEA (Correlation DEA) model which generate bounds using correlation. Gonçalves, Almeida, Lins, and Samanez (2013) used CCA-DEA (CCA – Canonical correlation analysis) to avoid subjective evaluation of weight bounds from an expert.

This paper introduces a novel approach to generating weight restrictions in DEA. Our approach is based on a multivariate statistics I-distance method (Ivanovic, 1977). The restrictions for the ratios of particular virtual inputs/outputs to total virtual input/output, which will be used in a global assurance region (GAR) DEA (Cooper, Seiford, & Tone, 2006) model, are generated with the bootstrapped I-distance method (Radojicic, Savic, Radovanovic, & Jeremic, 2015). In any iteration of bootstrap, the importance (weight) of each input/output indicator is calculated. Previously, Radojicic et al. (2015) determined the range of proportion of virtual inputs/outputs by summing/subtracting the mean value of the bootstrapped weight with a 3SD/6SD value (SD-Standard Deviation). However, the key issue that emerged is the facts that lower and upper bounds were not obtained in bootstrap iterations, but rather represent a projection using the mean value and standard deviation. As a possible remedy to this issue, we propose a more comprehensive approach – selecting the minimal and maximal value of the weight of each input/output obtained during the bootstrap I-distance procedure. This approach of implementing weight restrictions also ensures that every input and output will have some, albeit small impact on the relative efficiency evaluation of each DMU. Moreover, the proposed approach overcomes the issue of possible subjectivity in *a priori* determination of weight restrictions.

The proposed approach combines bootstrapped I-distance with the GAR DEA method by incorporating a lower and an upper bound of bootstrapped I-distance weights as bounds of virtual inputs and outputs in the GAR DEA model. The proposed approach was used for the in-depth analysis of Serbian banking sector efficiency over the twelve-year period between 2005 and 2016. The results obtained will be compared with the results of the basic variable return to scale DEA model (Banker, Charnes, & Cooper, 1984). The remainder of the paper is structured as follows. This section is followed by an overview of efficiency evaluation in the banking sector with special reference to the selection of inputs and outputs. Section 2 describes the proposed bootstrapped I-distance GAR DEA approach. In section 3, the data used in the analysis is presented. Section 4 presents the results. Finally, the last section outlines the key contributions of the paper and presents ideas for the future directions of study.

1. Overview of efficiency evaluation in the banking sector

Our paper contributes to the body of articles examining the efficiency of Serbian banks. One of the first articles which dealt with this issue was (Mihailović, Bulajić, & Savić, 2009). These researchers ranked 41 banks which were operating on the Serbian market in 2005. Two methods were used – the DEA super-efficiency model (Andersen & Petersen, 1993) and I-distance. The inputs were assets, capital and number of employees. Interest revenue and revenue before taxation were chosen as the outputs. Nine banks were found to be efficient. Savic, Radosavljevic, and Ilievski (2012) measured the efficiency of Serbian banks using Window DEA analysis. Two models were presented – one for profit efficiency (ML1) and one for operating efficiency (ML2) measurement. For the profit efficiency model, the inputs were interest expense and non-interest expenses, while the outputs were interest income and non-interest income. For the operating efficiency model, the inputs were the number of employees, fixed assets and intangible investments, capital and deposits, while outputs were granted loans and deposits, and non-interest income. Both models assumed input orientation and constant return to scale. They examined the performance of 28 banks during period 2005–2011. The super-efficiency DEA model was used to rank efficient banks. They found that in ML1 only two banks were efficient during the whole period, while in ML2 no banks were efficient during the entire period. Bulajic, Jeremic, Knezevic, and Zarkic-Joksimovic (2013) performed analysis on 27 banks which were operating on the Serbian banking market from 2006 to 2010. The inputs were sources, liquid assets, cash, portfolio and number of employees, and output were core net business income and net interest income. Using the DBA (Distance Based Analysis) methodology, they found that three banks were efficient in every year. The most recent study on Serbian bank efficiency was conducted by (Marković, Knežević, Brown, & Dmitrović, 2015) and covers the period of 2007–2010. Assets, number of employees and equity were the inputs, while total revenue and earnings before tax were regarded as outputs. The study examined 33 banks, and only one bank found to be efficient during the entire period.

The first step in assessing efficiency is to determine which business indicators will be chosen as inputs and outputs. This selection directly affects the results of the analysis. There is no consensus among researchers on which indicators should be used. The various combinations of inputs and outputs which have been used in DEA for the efficiency measurement of banks are presented in Table 1.

Most controversies arise over the question of deposits. Some authors are of the opinion that deposits should be regarded as input (Barros, Chen, Liang, & Peypoch, 2011; Asmild & Matthews, 2012; Hou, Wang, Zhang, 2014) while others think that they should be seen as output (Devaney & Weber, 2002; Staub et al., 2010). Consequently, two main approaches have been developed – the intermediation approach (regards deposits as input) and the production approach (regards deposit as output). The production approach regards banks as production units which use labor and capital to produce loans and deposit account services. According to this approach, banks aim to minimize the use of resources in providing products and services. The intermediation approach regards banks as a mediators between savers and investors. Banks serve to convert deposits into loans. In this approach the bank's main objective is to raise funds (deposits) to sell (loans) in order to maximize profit (Avkiran, 2006). Berger and Humphrey (1997) concluded that neither of these two approaches is perfect because neither is capable of encompassing fully the dual role of banks. Their standpoint is that while the production approach may be better for evaluating the efficiency of bank branches, the intermediation approach is more suitable for evaluating banking activity in its entirety. We have accepted the assumption that banks collect deposits to sell them in the form of loans, thus, in this paper, we opted for the intermediation approach.

Table 1. A survey of DEA applications in the banking sector

Paper	Scope	Inputs	Outputs	Methodology
(Ferrier & Hirschberg, 1997)	94 banks in Italy, in 1986	number of employees, capital, consumer deposit accounts, commercial deposit accounts, industrial deposit accounts	loans (consumer, commercial and industrial), deposits at other financial institutions, investments, number of branches	DEA with bootstrapped confidence intervals for efficiency scores
(Kuosmanen & Post, 2001)	453 EU banks	equity capital, debt capital, operational costs	total earning assets	weight restricted DEA
(Isik & Hassan, 2002)	54 banks in Turkey, 1988–1996	labor, capital, funds	short-term loans, long-term loans, risk-adjusted off-balance sheet items, other earning assets	DEA
(Fukuyama &Weber, 2002)	141 banks in Japan, 1988–1996	labor, capital, funds	loans, other investments	Input and output-oriented DEA – Malmquist index
(Mukherjee, Nath, & Nath Pal, 2002)	68 banks in India, 1996–1999	net worth, borrowings, operating expenses, number of employees, number of branches	deposit, net profit, advances, non-interest income, interest spread	output oriented CCR DEA
(Kao & Liu, 2004)	24 banks in Taiwan, 2009–2011	total deposits, interest expenses, non-interest expenses	total loans, interest income, non-interest income	CCR DEA
(Casu, Girardone, & Molyneux, 2004)	50 banks in Europe, 1994–2000	the average cost of labor, deposits, capital	total loans, securities, the nominal value of banks' off-balance sheet items	DEA Malmquist index
(Paul & Kourouche, 2008)	10 banks in Australia, 1997–2005	interest expense, non-interest expense	net interest income, non-interest income	input-oriented DEA
(Tortosa-Ausina, Grifell-Tatjé, Armero, & Conesa, 2008)	50 banks in Spain, 1992–1998	labor, capital, purchased funds	loans, core deposits, non-interest income and income from securities	Bootstrapped efficiency score in DEA

Continue of Table 1

Paper	Scope	Inputs	Outputs	Methodology
(Sahoo & Tone, 2009)	78 banks in India, 1997–2001	fixed assets, borrowed funds, labor	investments, performing loan assets, non-interest income	DEA
(Avkiran, 2009)	15 banks in UAE	interest expense, non-interest expense	interest income, non-interest income	Network DEA
(Thoraneenitiyan & Avkiran, 2009)	110 banks in Asia, 1997–2001	deposits, labor capital, physical capital	amount of loans, investments and other earning assets, fee income, off-balance sheet items	Integrating DEA and SFA
(Staub et al., 2010)	127 banks in Brasil, 2000–2007	labor, capital, other assets	deposit, loans, investment	DEA
(Savic et al., 2012)	28 banks in Serbia, 2005–2011	number of employees, fixed assets and intangible investments, capital deposits	granted loans and deposits, non-interest income	Input oriented CCR DEA model
(Jayaraman, Srinivasan, & Jeremic, 2013)	34 banks in India, 2005–2012	equity, borrowed funds, number of employees, number of branches	deployed funds, non-interest income	Comparison between DEA and DBA (Distance Based Analysis)
(Puri & Yadav, 2013)	17 banks in India, 2010	labor, fixed assets, total expenses	interest income, other income	fuzzy DEA
(Moradi-Motlagh & Saleh, 2014)	10 banks in Australia, during 1997–2005	interest expense, non-interest expense	interest income, non-interest income	DEA with bootstrapped confidence intervals for efficiency scores
(Hou et al., 2014)	44 major banks in China, 2007–2011	deposits, fixed assets, number of employees	the total net loan, other earning assets	two-stage, semi-parametric DEA model
(Řepková, 2014)	11 banks in the Czech Republic, 2003–2012	labor, deposits	loans, net interest income	Input oriented BCC and CCR DEA models
(Kao & Liu, 2014)	22 banks in Taiwan, 2009–2011	labor, physical capital, purchased funds	demand deposits, short-term loans, medium-and-long-term loans	DEA model for multi-period efficiency
(Johnes, Izzeldin, & Pappas, 2014)	Islamic banks in 18 countries, 2004–2009	deposits and short-term funding, fixed assets, general and administrative expenses, equity	total loans, other earning assets	output oriented CCR DEA model

End of Table 1

Paper	Scope	Inputs	Outputs	Methodology
(D. Tandon, K. Tandon, & Malhotra, 2014)	44 banks in India, 2009–2012	deposits, assets	interest income, non-interest income	output oriented CCR and BCC DEA
(C. R. Chiu, Y. H. Chiu, Fang, & Pang, 2014)	23 banks in Taiwan 2008	number of employees, assets, equity	operating profit, non-performing loans	A context-dependent range-adjusted measure DEA model
(Marković et al., 2015)	33 banks in Serbia, 2007–2010	assets, equity, number of employees	earnings before tax, total revenue	Input oriented CCR DEA model – Malmquist index
(Avkiran, 2015)	49 banks in China, 2008–2010	interest expenses on customer deposit, other interest expenses, personnel expenses, other operating expenses	interest income on loans, other interest income, bet fees and commissions, other operating income	dynamic network DEA
(Kao & Liu, 2016)	22 banks in Taiwan, 2008–2013	labor, physical capital, purchased funds	demand deposits, short-term loans, medium-and-long-term loans	DEA – Malmquist index
(Fukuyama & Matousek, 2017)	72 banks in Japan, 2000–2013	number of employees, capital	loans, securities	two-stage network DEA model
(Tanna, Luo, & De Vita, 2017)	1530 banks from 88 countries, 1999–2011	fixed assets, deposit and short-term funding, personnel expenses	loans, other earning assets, non-interest income	DEA and total factor productivity
(Simper, Hall, Liu, Zelenyuk, & Zhou, 2017)	272 banks in South Korea, 2007–2011	general admin and other expenses, fee and trading expenditure, loan loss provisions, equity	non-performing loans, net interest revenue, other operating revenue	BCC DEA model
(Fukuyama & Webber, 2017)	100 banks in Japan, 2007–2012	labor, physical capital, equity capital	performing loans, securities investments	dynamic network DEA
(Kevork et al., 2017)	644 banks from 28 European countries, in 2007, 2010 and 2014	total assets, the total number of employees, total deposits	net loans, securities investments	directional distance function with DEA
(Silva et al., 2017)	65 banks in China, 2001–2012	total interest expenses, total non-interest expenses	deposits, loans, liquid assets	Comparison between DEA and SFA

2. Methodology

The bootstrapping method has recently been used in bank efficiency measurement with DEA (Hou et al., 2014; Stewart, Matousek, & Nguyen, 2016; Moradi-Motlagh & Saleh, 2014; N. Zelenyuk, V. Zelenyuk, 2014; Alhassan & Tetteh, 2017), but the bootstrap was applied to the DEA efficiency scores (Le, Harvie, & Arjomandi, 2017). All these papers rely on works elaborated by Simar and Wilson (1998, 2007). The methodology proposed in our paper is based on the bootstrapped I-distance method used for setting lower and upper bounds in GAR DEA models (Yu, 2012; Galagedera, 2014). The fundamentals of both methods, I-distance and DEA, are given in this section.

2.1. Bootstrapped I-distance

The I-distance metric (Ivanovic, 1977) easily finds a solution to the problem of incorporating various indicators of different measurement units into a single synthetic indicator (Jeremic et al., 2012). Since it can overcome issues of subjectivity in a composite indicator, the I-distance method is frequently used as the aggregation method (Jeremic, Bulajic, Martic, & Radojicic, 2011). The method itself has considerable benefits; among others, it excludes the duplicity of information. The construction of the I-distance is an iterative process, which uses the concept of total discriminant effect (Jayaraman et al., 2013).

Let $X^T = \left(X_1, X_2, \ldots X_k\right)$ be a set of indicators chosen to characterize the entities. I-distance between two entities $e_r = \left(x_{1r}, x_{2r}, \ldots x_{kr}\right)$ and $e_s = \left(x_{1s}, x_{2s}, \ldots x_{ks}\right)$ is defined as

$$D\left(r,s\right) = \sum_{i=1}^{k} \frac{\left|d_i\left(r,s\right)\right|}{\sigma_i} \prod_{j=1}^{i-1} \left(1 - r_{ji.12\ldots j-1}\right), \tag{1}$$

where $d_i\left(r,s\right)$ is the discriminative effect, the distance between the values of variable X_i for e_r and e_s

$$d_i\left(r,s\right) = x_{ir} - x_{is}, i \in \left\{1,\ldots,k\right\}, \tag{2}$$

σ_i is the standard deviation of X_i and $r_{ji.12\ldots j-1}$ is the partial correlation coefficient between X_i and X_j, $\left(j < i\right)$ (Dobrota, Bulajic, Bornmann, & Jeremic, 2016).

In addition, a frequently used square I-distance provides additional benefits (Išljamović, Jeremić, Petrović, & Radojičić, 2015). It is given as:

$$D^2\left(r,s\right) = \sum_{i=1}^{k} \frac{d_i^2\left(r,s\right)}{\sigma_i^2} \prod_{j=1}^{i-1} \left(1 - r_{ji.12\ldots j-1}^2\right). \tag{3}$$

The next phase in obtaining I-distance weights is to calculate the Pearson correlation between I-distance values and input/output indicators. Weights are formed by calculating the ratios of the Pearson correlation and the sum of correlations for all inputs/outputs:

$$w_i = \frac{r_i}{\sum_{i=1}^{k} r_i}, \tag{4}$$

where $r_i\left(i = 1,\ldots k\right)$ is a Pearson correlation between the i-th input/output variable and the I-distance value (Dobrota, Martic, Bulajic, & Jeremic, 2015).

Efron (1979) was the first to introduce the bootstrap method. It is a statistical computer-intensive approach that can provide statistic measures for a broad range of problems (Davison & Hinkley, 1997). Bootstrap is based on the idea of resampling from the original sample of data. The statistics of interest are recalculated on the basis of each sample, and the resulting "bootstrapped" measures are then used to construct a sampling distribution for the statistics of interest (Ferrier & Hirschberg, 1997).

This paper proposes using a bootstrap procedure for the I-distance method. Using a bootstrapped I-distance approach, the set of weights $w_i\left(i=1,2\ldots,k\right)$ assigned to individual indicators $X^T=\left(X_1,X_2,\ldots X_k\right)$ by calculating their lower (L_i) and upper bounds (U_i), are obtained.

The procedure for bootstrapped I-distance is as follows:

1. From the initial number of n entities, a random sample $S_s\left(s=1,\ldots,m\right)$ of size $l\left(l<n\right)$ is taken, and then calculation of I-distance is performed on that sample and values for I-distance weights w_i are obtained;
2. This process is repeated m times (usually m is no fewer than 1,000 times), and for each random bootstrapped sample S_s, I-distance weights are obtained;
3. The lower (L_i) bound for i-th variable (input/output) is determined by a minimum and the upper bound (U_i) by a maximum of all obtained I-distance weights $w_i\left(i=1,2\ldots,k\right)$, from m iterations.

The results of a bootstrapped I-distance method will be used in the next step of efficiency evaluation using DEA.

2.2. Data Envelopment Analysis – DEA

The DEA has been used for efficiency appraisal in a broad range of areas over the last 40 years (Liu, L.Y. Lu, W. M. Lu, & Lin, 2013; Emrouznejad, Banker, Lopes, & de Almeida, 2014; Emrouznejad & Yang, 2018; Scalzer, Rodrigues, Macedo, & Wanke, 2018). It was introduced by Charnes, Cooper and Rhodes (1978) assuming a constant return to scale. Suppose that $\text{DMU}_j\left(j=1,\ldots,n\right)$ uses inputs $x_{ij}\left(i=1,\ldots,m\right)$ to produce outputs $y_{rj}\left(r=1,..,s\right)$. The multiplier output-oriented DEA model is as follows:

$$\begin{aligned}
&\left(\min\right)h_k=\sum_{i=1}^{m}v_i x_{ik}\\
&s.t.\\
&\sum_{r=1}^{s}\mu_r y_{rj}=1;\\
&\sum_{i=1}^{m}v_i x_{ij}-\sum_{r=1}^{s}\mu_r y_{rj}\geq 0,\ \ j=1,\ldots,n;\\
&\mu_r\geq\varepsilon,\ \ r=1,\ldots,s;\\
&v_i\geq\varepsilon,\ \ i=1,\ldots,m.
\end{aligned}\tag{5}$$

where h_k is a measure of the relative efficiency of DMU_k, μ_r is the weight assigned to output r, v_i is the weight assigned to input i, and ε is a small positive non-Archimedean value. Model

(5) is an output-oriented model with constant return to scale (CRS). By adding the free sign variable u^* to the objective function and second constraints, the model (5) becomes an output-oriented model DEA model with a variable return to scale (VRS) (Banker et al., 1984).

2.2.1. DEA model with weight restrictions

The weight restriction is a common modification of multiplier models, implemented as the incorporation of additional inequalities on the input and output weights. The weight restrictions are helpful in practical applications since their use can significantly improve the efficiency discrimination of DEA models (Allen et al., 1997). Thompson, Singleton Jr, Thrall, and Smith (1986) were among the first to proposed weights restriction to differentiate between efficient units, while Dyson and Thanassoulis (1988), considered that restricting weights is important to avoid ignoring of some inputs or outputs.

One of the approaches of restricting weights is total weight restriction. This approach prevents some of the inputs and outputs from being over emphasized or ignored in the efficiency assessment. The constraint has the following form:

$$L_i \le v_i \le U_i, \quad i = 1,\ldots,m. \tag{6}$$

Values L_i and U_i are given by experts. The main difficulty in applying this type of weights restriction is in defining those lower and upper bounds since they can lead to an infeasible solution.

Other approaches to direct weight restrictions (Thompson et al., 1990) are based on the relationship between:

- Input-input or output-output weights – Assurance Region of type I (ARI) (Thompson et al., 1986; Zhu, 1996; Taylor, Thompson, Thrall, & Dharmapala, 1997);
- Input-output weights – Assurance Region of type II (ARII) (Thanassoulis, Boussofiane, & Dyson, 1995).

Wong and Beasley (1990) have proposed a model in which, instead of restricting actual weights, virtual input and output are restricted. This would help avoid the problem of sensitivity to the unit of measurement for inputs and outputs which occur in direct weight restriction models since virtual input/output is dimensionless. The virtual input and output of a DMU shows the relative contribution of every input and output to its efficiency. The higher the value of virtual input/output, the more significant that input/output is in evaluating the efficiency of a particular DMU (Sarrico & Dyson, 2004). The proposed constraint has the following form:

$$L_i \le \frac{v_i x_{ij}}{\sum_{i=1}^{m} v_i x_{ij}} \le U_i,\ i = 1,\ldots,m,\ j = 1,\ldots,n \tag{7}$$

under the condition that $0 \le L_i \le U_i \le 1,\ i = 1,\ldots,m$. Similar restrictions can be applied to outputs. The lower and upper bounds can be imposed subjectively based on expert opinion under the conditions $\sum_{i=1}^{m} L_i \le 1$ and $\sum_{i=1}^{m} U_i \ge 1$ if all inputs (outputs) are restricted. DEA models which have included these constraints are also known in literature as the GAR-DEA model (Yu, 2012; Galagedera, 2014).

2.3. Bootstrapped I-distance DEA methodology

As already mentioned, basic DEA models allow flexible weights determination, but this feature can lead to misevaluation of DMUs because input and output weights may have extreme or zero values. This paper suggests a statistically founded approach to determining the bounds of virtual input/output proportion (7). The main idea is to investigate the range of weight of the particular input or output which is common for all the DMUs under evaluation, based on existing data. The bootstrapped I-distance procedure, described in section 2.1., is used in the first step of the suggested procedure for this purpose. The procedure provides the range of weights which covers the whole set of DMUs. The obtained values are always in the range from 0 to 1 which corresponds to virtual inputs or outputs in DEA efficiency evaluation. DEA efficiency is measured afterwards using the presented model (5) with the integration of weights restriction (7). Therefore, the *bootstrapped I-distance DEA* procedure put forward in order to avoid subjective judgment in setting lower and upper bounds is as follows:

1. Lower and upper bounds calculation based on bootstrapped I-distance procedure given in chapter 2.1.;
2. Solving GAR DEA model (5), (7) with a constant or variable return to scale assumption;
3. Analyzing the results and comparing them to those obtained by the basic DEA models.

This procedure is used for the efficiency evaluation of banks in Serbia based on panel data for the period 2005–2016.

3. Data

The data utilized in this paper were captured from Income Statements and Balance Sheets, available on National Bank of Serbia (NBS) database (see *http://www.nbs.rs*). The dataset consists of a balanced panel of 25 banks covering a period of twelve years – from 2005 to 2016.

The choice of the inputs and outputs has been guided by choices made in previous studies (Table 2) and data availability. As we opted for measuring the efficiency of the whole bank, not just the branches of the bank, the intermediation approach was used, as explained in section 1. Thus, deposits are regarded as inputs. In addition to deposits (I4), we included three more inputs – personnel expenses (I1), fixed assets (I2), and capital (I3). For outputs, we

Table 2. Top 5 inputs and outputs used in DEA studies of banks (from Table 1)

Inputs	# Studies	Outputs	# Studies
labor/personnel expenses	14	loans	17
capital	10	non-interest income	10
deposits	10	other placements/ earning assets	7
fixed assets	10	investments	7
number of employees	8	interest income	6

employed loans (O1), other placements (O2), and non-interest income (O3). This decision is also consistent with other studies of the Serbian banking industry. Table 3 shows descriptive statistics of inputs and outputs over the whole observed period.

The inter-correlation test of all inputs and all outputs shows that the isotonicity test (Avkiran, 1999) was passed (Pearson correlations >0.30; α = 0.01). These results indicate that increasing amounts of inputs lead to increasing of outputs. The rule of thumb $m+s \leq n/3$, where m is the number of inputs, s is the number of outputs and n is the number of entities (Cooper et al., 2006), is also satisfied (7 < 25/3). Validation of the model therefore proved that input and output selection had been performed correctly.

The DEA analysis was conducted using DEA Solver software (Cooper et al., 2006), and weights were generated using in-house developed I-distance software.

Table 3. Descriptive statistics of indicators

Statistic	I1	I2	I3	I4	O1	O2	O3
Mean	1,694	2,320	12,660	41,871	50,313	10,403	2,205
Median	1,328	1,412	10,164	24,647	31,171	2,917	1,391
Max	7,574	12,345	41,760	255,449	271,750	136,124	16,190
Min	114	68	202	512	114	21	81
St.Dev.	1,322	2,309	10,299	46,630	54,619	18,926	2,343

Note: all values are presented in RSD millions (Serbian dinar).

4. Empirical findings and results

Even though the banks are homogeneous from the standpoint of structure and goals, and are operating in the same country under the same circumstances, and in spite of the fact that the data used is drawn from a balanced dataset, their size differs from small to very large. Consequently, we compared the efficiency of each bank for each year, assuming a variable return to scale. This method allows the bank under evaluation to be compared with those which operate on a similar scale of economy and at similar market strength. The results of the efficiency measurement are discussed below.

4.1. Pure technical efficiency evaluation

The dataset consists of 25 banks of various sizes, i.e. the capital varies from 202 to 41,760 million RSD. Therefore, we opted for the VRS DEA model which allows for variable returns to scale and compared units of different sizes. The first assessment of pure technical intermediation efficiency was performed using an output-oriented VRS DEA model. An overview of the results is presented in Table 4.

Table 4 shows that banks in Serbia are mainly considered efficient in the period 2005–2016. (0.869 to 0.940). The results given per year indicate that at least 11 banks are assessed as efficient. The lowest average efficiency of 86.9% with 11 banks operating below the efficiency frontier was obtained for 2010. The highest number of efficient banks (17 out of 24) was obtained in 2005, 2008 and 2013. Three banks were estimated to be efficient in each year.

Table 4. Average efficiency of banks estimated by VRS DEA model

Year	2005	2006	2007	2008	2009	2010
Average score	0.934	0.872	0.940	0.920	0.894	0.869
# efficient DMUs	17	15	16	17	16	14
# inefficient DMUs	8	10	9	8	9	11
Year	2011	2012	2013	2014	2015	2016
Average score	0.878	0.890	0.903	0.894	0.891	0.900
# efficient DMUs	16	15	17	14	11	13
# inefficient DMUs	9	10	8	11	14	12

4.2. Weight restricted DEA efficiency evaluation

The first-stage analysis shows that the average efficiency of all DMUs, obtained by the VRS DEA model tends to be very high, with more DMUs assessed as efficient than inefficient. This occurred because of the total weight flexibility and the freedom of DMUs to choose the best combinations of input and outputs. Table 5 summarizes the number of zero weights assigned to inputs and outputs. Obviously, the most ignored inputs and outputs are personnel expenses (I1), fixed assets (I2) and the output "other placements" (O2) over the observed period. This freedom of choosing only desirable inputs and/or outputs favors the banks that use more resources for producing the same level of outputs. On the other hand, they are also ignored by most of the banks in almost all the years of the observed period.

To avoid the assignment of zero weights to the inputs or outputs of DMUs, the GAR DEA output-oriented model with a variable return to scale (5, 7) was applied. The lower and upper bounds were generated as bootstrapped I-distance weights. The examples of the

Table 5. Number of zero weights assigned to inputs and outputs

Year	# DMUs	Inputs				Outputs		
		I1	I2	I3	I4	O1	O2	O3
2005	25	17	18	10	4	5	8	14
2006	25	16	17	6	10	7	20	17
2007	25	18	15	6	10	2	17	18
2008	25	16	13	4	12	1	12	9
2009	25	13	17	8	9	3	15	14
2010	25	13	18	8	8	4	19	13
2011	25	13	11	10	14	5	16	12
2012	25	7	16	17	13	6	17	7
2013	25	8	17	12	12	4	18	8
2014	25	11	20	13	11	7	15	18
2015	25	15	13	14	7	10	19	6
2016	25	11	13	11	12	4	21	8

I-distance weights obtained after 10,000 iterations of bootstrapping on 72% of the sample (18 banks in every iteration) are presented in Table 6. The lower bound (*L*) in the GAR model is determined by the minimum, while the upper bound (*U*) is determined by the maximum obtained I-distance weight.

Table 6. Weights generated using the bootstrapped I-distance method

	2005				2006				2007			
	L	U	m	σ	L	U	m	σ	L	U	m	σ
I1	0.22	0.32	0.28	0.01	0.25	0.32	0.29	0.01	0.25	0.32	0.28	0.01
I2	0.18	0.33	0.27	0.01	0.14	0.30	0.24	0.02	0.14	0.29	0.23	0.02
I3	0.17	0.31	0.22	0.01	0.15	0.28	0.20	0.01	0.18	0.28	0.22	0.01
I4	0.15	0.31	0.23	0.01	0.22	0.32	0.26	0.01	0.22	0.33	0.28	0.01
O1	0.27	0.41	0.35	0.03	0.27	0.40	0.34	0.03	0.26	0.40	0.34	0.02
O2	0.27	0.39	0.33	0.02	0.27	0.39	0.33	0.02	0.23	0.38	0.29	0.02
O3	0.28	0.39	0.32	0.01	0.28	0.41	0.33	0.03	0.31	0.41	0.37	0.02
	2008				2009				2010			
	L	U	m	σ	L	U	m	σ	L	U	m	σ
I1	0.21	0.29	0.25	0.01	0.19	0.29	0.25	0.01	0.18	0.29	0.24	0.01
I2	0.19	0.29	0.25	0.01	0.21	0.30	0.25	0.01	0.20	0.32	0.25	0.01
I3	0.18	0.28	0.22	0.02	0.17	0.28	0.22	0.01	0.20	0.28	0.23	0.01
I4	0.25	0.30	0.28	0.01	0.23	0.31	0.28	0.01	0.24	0.30	0.28	0.01
O1	0.28	0.40	0.36	0.02	0.28	0.41	0.37	0.02	0.26	0.37	0.33	0.02
O2	0.25	0.38	0.29	0.02	0.26	0.40	0.31	0.02	0.29	0.40	0.33	0.03
O3	0.30	0.42	0.35	0.02	0.27	0.38	0.32	0.01	0.29	0.40	0.34	0.01
	2011				2012				2013			
	L	U	m	σ	L	U	m	σ	L	U	m	σ
I1	0.14	0.29	0.24	0.02	0.15	0.29	0.24	0.02	0.15	0.29	0.23	0.01
I2	0.22	0.32	0.24	0.01	0.21	0.30	0.24	0.01	0.22	0.31	0.24	0.01
I3	0.18	0.29	0.23	0.01	0.19	0.28	0.25	0.01	0.19	0.28	0.24	0.01
I4	0.24	0.31	0.29	0.01	0.21	0.32	0.28	0.01	0.24	0.32	0.28	0.01
O1	0.26	0.40	0.35	0.01	0.28	0.38	0.34	0.01	0.26	0.37	0.35	0.01
O2	0.27	0.38	0.31	0.02	0.27	0.40	0.33	0.02	0.27	0.40	0.32	0.03
O3	0.27	0.41	0.34	0.01	0.28	0.38	0.33	0.02	0.27	0.39	0.34	0.01
	2014				2015				2016			
	L	U	m	σ	L	U	m	σ	L	U	m	σ
I1	0.16	0.29	0.24	0.01	0.13	0.29	0.24	0.02	0.13	0.28	0.24	0.02
I2	0.20	0.29	0.24	0.01	0.21	0.35	0.24	0.01	0.20	0.35	0.23	0.02
I3	0.21	0.27	0.24	0.01	0.21	0.27	0.24	0.01	0.21	0.23	0.24	0.01
I4	0.27	0.31	0.29	0.01	0.25	0.31	0.28	0.01	0.26	0.30	0.28	0.01
O1	0.25	0.36	0.33	0.02	0.21	0.35	0.32	0.02	0.18	0.34	0.31	0.02
O2	0.28	0.40	0.32	0.03	0.30	0.40	0.33	0.03	0.31	0.40	0.34	0.02
O3	0.27	0.40	0.35	0.02	0.27	0.41	0.35	0.02	0.29	0.41	0.35	0.01

Note: m-mean; σ-standard deviation.

Mean values of I-distance weights from Table 6 represent what should be the importance of indicators in efficiency measurement. Table 6 shows that the importance of the variable "deposits" has an increasing trend while the importance of variable "personnel expenses" has a declining trend.

The virtual input/output constraints (7) for one year are as follows:

$$L_{I1} \le \frac{v_{I1}x_{I1k}}{v_{I1}x_{I1k}+v_{I2}x_{I2k}+v_{I3}x_{I3k}+v_{I4}x_{I4k}} \le U_{I1};$$

$$L_{I2} \le \frac{v_{I2}x_{I2k}}{v_{I1}x_{I1k}+v_{I2}x_{I2k}+v_{I3}x_{I3k}+v_{I4}x_{I4k}} \le U_{I2};$$

$$L_{I3}+L_{I4} \le \frac{v_{I3}x_{I3k}+v_{I4}x_{I4k}}{v_{I1}x_{I1k}+v_{I2}x_{I2k}+v_{I3}x_{I3k}+v_{I4}x_{I4k}} \le U_{I3}+U_{I4};$$

$$L_{O1}+L_{O2} \le \frac{u_{O1}x_{O1k}+u_{O2}x_{O2k}}{u_{O1}x_{O1k}+u_{O2}x_{O2k}+u_{O3}x_{O3k}} \le U_{O1}+U_{O2};$$

$$L_{O3} \le \frac{u_{O3}x_{O3k}}{u_{O1}x_{O1k}+u_{O2}x_{O2k}+u_{O3}x_{O3k}} \le U_{O3}. \quad (8)$$

The third and fourth constraints are modified to provide more flexibility in efficiency evaluation and allow banks to use at least one, preferably input (I3 (capital) and/or I4 (deposits)) and one of the outputs (O1 (loans) and/or O2 (other placements)). This means that a DMU will not be obligated to use all of its inputs and outputs in order to evaluate its efficiency. Only personnel expenses (I1), fixed assets (I2) and non-interest income (O3) are mandatory for all DMUs. Capital is considered complementary with deposits because the main source of funds could vary between different banks. For example, banks which are co-owned by the state predominantly use capital as a principal source of funds, while purely commercial banks must gather deposits in order to sell them in the form of loans. It is similar with loans and other placements. Some banks find their primary source of profit in other placements rather than in selling loans.

Table 7 shows that with the introduction of weight restrictions the situation has changed considerably. The overall efficiency of banks in Serbia, obtained by using the bootstrapped I-distance GAR DEA model, is 57.6% for the 2005–2016 period. That is 32.3% lower than the overall efficiency shown by the basic VRS DEA model. The highest average efficiency was in 2010 (67%), with nine banks estimated as efficient. The lowest average efficiency score was in 2006 (45.1%) and with four banks on the efficiency frontier contrary to the results obtained by the VRS DEA model. The lowest average efficiency score is measured in 2010, while the highest is measured in 2007.

KBC Bank had the lowest efficiency score (0.5%) in 2013. The highest average efficiency score was obtained for Banca Intesa – 98% and the bank was estimated as efficient in every year except in 2005 and 2015. Five banks were below the efficiency frontier over the observed period. None of the banks proved efficient in every year of analysis. The lowest average efficiency score (19.1%) was observed for Findomestic Bank, contrary to its very good rank according to the VRS DEA model results.

There were only two efficient banks in 2015 – Postanska stedionica and Unicredit. The other banks which were efficient during the period prior to 2015 were below the efficiency

Table 7. Efficiency of banks estimated by the bootstrapped I-distance GAR DEA model

DMU	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
AIK Bank	1.000	1.000	1.000	1.000	0.697	1.000	0.956	1.000	0.777	0.639	0.552	0.434
Alpha Bank	0.651	0.587	0.546	0.539	0.411	0.340	0.270	0.263	0.393	0.471	0.402	0.334
BancaIntesa	0.781	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.977	1.000
Postanska stedionica	0.510	0.775	0.273	1.000	1.000	1.000	0.441	1.000	1.000	1.000	1.000	1.000
Credy Bank	0.208	0.098	0.376	0.543	0.093	0.108	0.137	0.198	0.127	0.053	0.091	1.000
Cacanska	0.102	0.075	0.104	0.612	0.702	1.000	1.000	1.000	1.000	0.830	0.255	0.293
Erste Bank	0.248	0.278	0.670	0.957	0.919	0.840	0.948	0.870	1.000	0.911	0.929	1.000
Eurobank EFG	0.136	0.214	0.321	0.625	0.684	0.737	0.626	0.596	0.517	0.500	0.515	0.542
Findomestic	0.091	0.078	0.109	0.267	0.195	0.303	0.250	0.117	0.201	0.329	0.234	0.118
Hypo Alpe-Adria-Bank	1.000	0.567	0.505	0.834	0.809	0.866	0.736	0.650	0.562	0.488	0.379	0.410
JUBMES	0.143	0.218	1.000	0.081	0.077	0.139	0.225	0.305	0.061	0.036	0.024	0.058
KBC Bank	0.901	0.130	0.082	0.112	0.157	0.247	0.234	0.305	0.005	1.000	0.063	0.112
Komercijalna Bank	0.566	0.672	0.801	0.943	0.865	0.799	1.000	0.953	0.932	0.990	0.994	0.975
Marfin Bank	0.373	0.200	0.361	0.172	0.177	1.000	0.295	0.169	0.110	0.142	0.124	0.102
Credit Agricole	0.332	0.270	0.393	0.264	0.436	0.500	0.454	0.447	0.481	0.477	0.520	0.552
NLB Bank	0.378	0.114	0.466	0.779	0.477	0.958	1.000	1.000	0.550	0.397	0.271	0.220
OTP Bank	0.966	0.443	0.424	0.631	0.569	0.402	0.755	0.339	0.426	0.297	0.319	0.367
Piraeus Bank	0.319	1.000	0.313	0.659	0.335	0.477	0.310	0.323	0.399	0.428	0.250	0.268
ProCredit	0.317	0.271	1.000	0.729	0.849	0.606	1.000	0.965	0.972	0.963	0.873	0.915
Raiffeisen	0.968	0.595	0.988	0.998	0.734	1.000	1.000	0.811	0.876	0.754	0.681	0.701
Societe Generale	0.364	0.684	0.396	1.000	1.000	1.000	1.000	0.967	1.000	0.903	0.830	0.800
Srpska Bank	1.000	0.313	0.312	0.162	0.087	0.064	0.062	0.090	0.139	0.198	0.147	0.114
Unicredit	0.671	0.195	0.385	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Vojvodjanska	1.000	1.000	0.575	0.483	0.369	0.357	0.309	0.338	0.332	0.359	0.403	0.390
Volksbank	0.235	0.489	0.183	0.994	1.000	1.000	1.000	1.000	1.000	1.000	0.738	0.919
Average score	0.530	0.451	0.503	0.655	0.586	0.670	0.640	0.628	0.594	0.607	0.503	0.545
# efficient DMUs	4	4	4	5	5	9	9	7	7	5	2	4
# inefficient DMUs	21	21	21	20	20	16	16	18	18	20	23	21

frontier in that year. The main reason for the overall inefficiency of the Serbian market during that year was the Greek bailout referendum. There are a number of Greek-owned banks operating in Serbia, and this is what caused the turbulence. Consumers were afraid of the collapse of those banks and started to withdraw their deposits, transferring them to other banks. Since we consider deposits as an input, this led to a situation where some banks increased their inputs, but at the same time did not manage to increase outputs, because there was lower demand for new loans. In contrast, the banks which had lower inputs due to the withdrawal of deposits, had to reduce the sale of loans because they lacked the funds.

Erste Bank exhibits a poor score in the first three years, followed by a period of growth, until 2013 when it started to operate on the efficiency frontier. Similar findings regarding Erste bank were made by (Savic et al., 2012). The reasons for the poor score in first two years lie in personnel expenses which were much higher in that year than in others. This is probably due to a change in a bank's majority shareholder. Before 2005, Erste Bank was predominantly owned by the state. Presumably, the bank management had to cut losses which led to downsizing, and consequently, severance payments increased personnel expenses. This is not just the case for Erste Bank. For every bank that went through a privatization process, there is a noticeable increase in efficiency.

A large increase in efficiency in 2016 for Credy bank stands out. Its average score during 2005–2015 was 18.5%, but in 2016 Credy bank operated on the efficiency frontier. This result should be interpreted in light of the fact that Credy bank changed its ownership status twice after 2012. The bank reduced its fixed assets more than 15 times during that period, while at the same time they increased other placements (reaching a peak in 2016, where they were more than double than in 2015). The results from 2016 show that the bank is on the right path of development and that it should continue its business operations modelled on recent years.

In contrast to Credy bank, Cacanska may be an example of how a change of ownership structure can cause a drastic decrease in efficiency. After the first five analyzed years when it was constantly below the efficiency frontier, Cacanska finally consolidated, and in 2010 it was efficient. The bank was efficient in the following four years, and then in 2015, when it was privatized, Cacanska started to operate again below the efficiency frontier.

It is important to emphasize that it would be wrong to compare the average efficiency of the Serbian market through years because they are measured relative to the different frontiers. It is known that the year 2008 was the year of the global financial crisis (GFC), but if we were to concluded, on the basis of an average efficiency of 65.5%, that the GFC did not affect the Serbian banking sector, we would be in danger of reaching an unsupported conclusion. The average efficiency score of 65.5% simply indicates that in that year, there may have been less variability between the banks. If we intended to examine the impact of the GFC, it would be necessary to conduct an additional study.

According to the results shown in Table 7, we can argue that Unicredit, Volksbank, Postanska stedionica and Societe Generale were prepared for the GFC, or responded effectively and took advantage of it, because from 2008 all four banks started to operate on the efficiency frontier in following years.

As stated, by using the weight restricted DEA model, the number of banks identified as efficient is reduced. Therefore, it is more evident which banks can be identified as market leaders. For the senior management of these banks, this is a good indicator that their business model is having the desired effects. Likewise, top managers at the banks which fail to achieve full efficiency have information on what aspects of their business need to improve if they are to become more competitive.

Another product of this study is the valuable information it offers regulatory bodies such as National Bank of Serbia, the Republic's central bank. The NBS is responsible for maintaining price stability and the stability of the financial system in general. Improved tools for monitoring bank efficiency, will allow the NBS more precise insight into the business operations of their banking sector and may contribute to the earlier detection of stress, thus allowing more timely and effective response.

Conclusions

The primary objective in evaluating the efficiency of banks is to see how particular actors are operating in relation to others on the same market. The results can help management identify weaknesses and improve overall business operations. This paper employs the bootstrapped I-distance GAR DEA approach to evaluate the efficiency of 25 banks operating in Serbia from 2005 to 2016. This is the first time bootstrapped I-distance weights have been used as DEA constraints. The paper also emphasizes the importance of restricting weights flexibility in classical DEA models. By implementing weight restrictions, we avoided the assignment of zero weights to the inputs and outputs of any DMUs so that every input and output had an impact on the final efficiency evaluation. This makes the bootstrapped I-distance GAR DEA approach more informative than competing methods. The Pearson correlation between the I-distance values and input/output indicators provides objective weight restriction by considering the inputs/outputs relationship. The methodology presented in this paper has potential applications in other fields of interest where efficiency measurement is called for.

Perhaps the main limitation of the paper is that the research covers only one market and a relatively small number of DMUs. Another limitation is that this kind of analysis does not allow comparison of the efficiency of the Serbian banking sector as a whole, over a period of years, because they are measured relative to the different frontier.

The paper applies the intermediation approach to measuring bank efficiency. Consequently, the results describe the banks as business entities which aim principally to maximize profit by collecting deposits and selling them in the form of loans. The study offers useful insight into the efficiency of South-Eastern European banks. On the basis of the analysis over a twelve year period, it was possible to detect the bank's reaction to the turbulence caused by both the GFC and the Greek bailout referendum. The period prior to the financial crisis (2006–2008) was one of growth and investment in the Serbian banking sector, but the financial crisis caused changes in this trend and a slight fluctuation in pure technical efficiency.

Our findings reveal that, with the introduction of weight restrictions into a DEA model with a variable return to scale, the assessment of overall average efficiency fell by more than 30%. This indicates that the results obtained with such weights restrictions are both more realistic and more comparable, and the model is properly calibrated, since the number of relatively efficient units is less than 50% (4 out of 25 in 2016).

Further avenues of research suggest themselves, for example evaluation of changes in efficiency and technical progress using the Malmquist DEA index and bootstrapped I-distance method. Another direction would be to consult bank management on use of the variable and the utility of the results from a practical perspective (Eskelinen, 2017). Finally, the production approach to bank efficiency evaluation should also be included in future work, in order to determine whether and to what extent the results are influenced by the selection of output metric (Berger & Humphrey, 1997).

Acknowlegdments

The authors gratefully thank the Deputy Editor-in Chief and the anonymous referees for their valuable comments and suggestions which have improved the paper.

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