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Banking efficiency in the Czech Republic and Slovakia using the DEA Window Analysis

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Abstract

Iveta Palečková: **Banking efficiency in the Czech Republic and Slovakia using the DEA Window Analysis.**

The aim of this paper is to apply the Data Envelopment Analysis (DEA) window analysis on the data of the Czech and Slovak commercial banks and to examine the banking efficiency of the Czech Republic and Slovakia during the period 2004-2013. The paper employed an extended DEA approach, specifically DEA window analysis for the efficiency assessment of commercial banks in the Czech Republic and Slovakia. It is based on panel data for the period from 2004 to 2013. In the Czech banking sector, the average efficiency under constant return to scale reached 66-79% and average efficiency under variable return to scale reached 77-90%. The most efficient bank were GE Money Bank and Sberbank. The lowest efficient bank was Československá obchodní banka. The group of large bank (Československá obchodní banka, Česká spořitelna and Komerční banka) was lower efficient than other banks in the banking sector. In Slovakia, the average efficiency under constant return to scale reached 77-91% and average efficiency under variable return to scale reach 83-94%. The most efficient banks were OTP, Postova banka, UniCredit Bank and Istrobanka. The lowest efficient banks were found Privatbanka and Citibank. Whereas during the period 2003-2008 the average efficiency was increasing, during the period 2010-2011 the average efficiency decreased as a result of financial crisis.

Key words

Data Envelopment Analysis, window analysis, banking sector, Czech Republic, Slovakia, commercial bank

JEL: G21, C50

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Introduction

The aim of this paper is to apply the Data Envelopment Analysis (DEA) window analysis on the data of the Czech and Slovak commercial banks and to examine the efficiency of the Czech and Slovak banking sectors during the period 2004-2013. The paper employed an extended DEA approach, specifically DEA window analysis for the efficiency assessment of commercial banks in the Czech Republic and Slovakia. It is based on panel data for the period from 2004 to 2013. There is a lack of studies in the Czech Republic and Slovakia examining banking efficiency using Dynamic Data Envelopment Analysis, which creates an opportunity for this research. Data envelopment analysis has become a popular approach in measuring the efficiency of banking industry. We use the DEA window analysis based on an input oriented model to measure banking efficiency. The contribution should be able to see the bank efficiency evolves over time and to see whether any size effect exists in the banking efficiency. This analysis provides trends of efficiency and the rank of each bank evaluated in terms of its effectiveness. The obtained results allow for an analyses of trends of the overall banking sector efficiency. By this approach, the technical efficiency is analyzed sequentially with a certain window width (i.e. the number of years in a window) using a panel data of the commercial domestic banks. The main idea is to capture the temporal impact on bank technical efficiency and see its short-run evolution from one window to another, in particular the pure technical efficiency and scale efficiency. It is the first application of the window analysis on the Czech and Slovak commercial banks during the period 2004-2013.

The structure of the paper is follow. Next section describes empirical literature regarding to banking efficiency in the Czech Republic and Slovakia. Third section presents the methodology of DEA window analysis and section 4 describe data and selection of variables. Next part of paper reveals the estimated results and last section concluded the paper.

1. Review of Empirical Literature

Several empirical analyses of the efficiency of the Czech and Slovak banking sector exist and we refer to some of them. Most empirical studies evaluated banking efficiency in the 1990s and the authors investigated whether private banks were more efficient than state-owned banks. For example, Taci and Zampieri (1998), Bonin et al. (2005), Matoušek and Taci (2005), Grigorian and Manole (2006) or Fries and Taci (2005) found that private banks were more efficient than state-owned banks and privatized banks with majority foreign ownership were more efficient than those with domestic ownership. Results of Baruník and Soták (2010) were that the foreign-owned banks were bit more cost efficient than domestic private banks, state-owned banks were significantly less cost efficient when compared to domestic private banks.

Some empirical studies e.g. reference Kosak and Zajc (2006), Yildirim and Philippatos (2007), Bems and Sorsa (2008), Matoušek (2008) or Mamatzakis et al. (2008) examined the banking efficiency in several European countries and the Czech and Slovak banking sectors was included in panel data. Stavárek and Polouček (2004) estimated efficiency and profitability in selected banking sectors, including the Czech Republic. They found that Central European Countries were less efficient than their counterparts in European Union member countries. They also found that the Czech and Hungarian banking sectors were on average evaluated as the most efficient and the Czech banking sector showed itself as the most aligned banking industry among transition countries. Their conclusion was a refutation of the conventional wisdom that foreign-owned banks are more efficient than domestic-owned banks, and that size is one of the factors that determines efficiency. To achieve greater efficiency, a bank should be large, well-known, easily accessible and offer a wide range of products and services, or if small, must focus on specific market segments, offering special products. Any other structure leads to lower relative efficiency for the bank.

Stavárek (2005) estimated commercial bank efficiency in the group of Visegrad countries (Czech Republic, Hungary, Poland, Slovakia) before joining the EU. He concluded that the Czech banking sector is the most efficient, followed by the Hungarian with a marginal gap. Although there has been an improvement in levels of efficiency in all countries since 1999, its intensity was not sufficient to converge with Western European banking sectors. He also examined the increasing value of the efficiency of the Slovak banking sector during the period 1999–2003, but they also found that Slovak banking sector was lower efficient banking sector than other Visegrad countries.

Weill (2003) found a positive influence of foreign ownership on the cost efficiency of banks in the Czech Republic and Poland. The conclusion was that the degree of openness of the banking sector to foreign capital has a positive impact on performance. It may also have a positive influence on the macroeconomic performance of these countries, because of the important role of the banking sector in the financing of these economies.

The results of Andries and Cocris (2010) showed that banks in the Czech Republic are inefficient from the perspective of costs. To improve efficiency, banks need to improve the quality of assets owned by improving the lending process and reducing the share of nonperforming loans. Staněk (2010) compared the efficiency of the banking sector in the Czech Republic and Austria. The SFA was employed to measure the efficiency of the banking sector. It was found that the efficiency of the Czech banking sector has improved in the last ten years and come closer to the efficiency of the Austrian banking sector.

Also, Staníčková and Skokan (2012) evaluated the banking sector of the Czech Republic as highly efficient. Stavárek and Řepková (2012) found that efficiency increased in the period 2000–2010 and they found that the largest banks perform significantly worse than medium-sized and small banks. The network structure of Data Envelopment Analysis models was applied to Czech banks by Jablonský (2012). Řepková (2013) used dynamic DEA for estimation of the banking efficiency in the Czech Republic.

Rossi et al. (2005) examined that the banking systems of Slovakia showed significant levels of cost and profit inefficiency, indicating that on average banks operate far above (below) from the cost (profit) efficient frontiers. But they found that cost efficiency increased between 1995 and 2002.Vincová (2006) found that the average efficiency slightly decreased and the number of efficient bank also decreased in Slovak banking sector. Iršová and Havránek (2011) estimated banking efficiency in five countries of Central and Eastern Europe including Slovakia. In Slovakia the results showed that the average cost efficiency was 51.8% and profit efficiency reached 43.2% in the years 1995–2006.

Anayiotos et al. (2010) estimated relative efficiency of banks in emerging Europe before the recent boom, just before the crisis and right after the crisis using the Data Envelopment Analysis. Their results suggested that the banking efficiency in Slovakia decreased during the pre-crisis boom and also fell during the crisis. They found the significant decreased in efficiency during the period 2004–2009.

Mentioned studies examined efficiency in several banking sector, on contrast Stavárek and Šulganová (2009) estimated banking efficiency in Slovakia. They applied the parametric Stochastic Frontier Approach and Cobb–Douglas production function on commercial banks in the period 2001–2005 and found that the average efficiency increased and their results point out a better ability of Slovak banks to use the inputs in the production process. Řepková and Miglietti (2013) and Řepková (2013) estimated the cost and profit efficiency of the Slovak commercial banks and they found that the average cost and profit efficiency was decreasing in the Slovak banking sector during the period 2003-2012. And then they found that small and medium-sized banks were more efficient than the largest banks in the Slovak banking market.

The empirical literature review concluded that only few studies examined the Czech and Slovak banking sector individually. Most of the empirical studies research several banking sector which included Slovakia and the second findings is that the most studies examined banking efficiency during 1990s. Thus, the literature review shows the motivation for this paper. This paper could fill the gap following time line in the empirical literature. Efficiency of the Czech and Slovak banking sector was estimated using the Stochastic Frontier Approach or DEA model. The contributions of this paper is the fact, that the DEA window analysis approach will be applied on the Czech and Slovak commercial banks.

2. Methodology and data

The study of the efficient frontier began with Farrell (1957), who defined a simple measure of a firm's efficiency that could account for multiples inputs. 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 objects 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 (Cooper et al., 2000).

DEA is a mathematical programming technique that measures the efficiency of a decision-making unit (DMU) relative to other similar DMUs with the simple restriction that all DMUs lie on or below the efficiency frontier (Seiford and Thrall, 1990). DEA measures the relative efficiency of a homogeneous set of DMUs in their use of multiple inputs to produce multiple outputs. DEA also identifies, for inefficient DMUs, the sources and level of inefficiency for each of the inputs and output (Charnes et al., 1995). It provides a means of comparing the efficiency of DMUs with each other based on several inputs and / or outputs. It derives its name from a theoretical efficient frontier which envelops all empirically-observed DMUs.

This analysis is concerned with understanding how each DMU performs relative to others, the causes of inefficiency, and how a DMU can improve its performance to become efficient. In that sense, the focus of the methodology should be on each individual DMU rather than on the averages of the whole body of DMUs. DEA calculates the relative efficiency of each DMU in relation to all the other DMUs by using the actual observed values for the inputs and outputs of each DMU. It also identifies, for inefficient DMUs, the sources and level of inefficiency for each of the inputs and outputs (Charnes, et al., 1995).

The CCR model is the basic DEA model, as introduced by Charnes et al. (1978) and then it was modified by Banker et al. (1984) and became the BCC model, which accommodates variable returns to scale. The CCR (Charnes, Cooper, Rhodes) model presupposes that there is no significant relationship between the scale of operations and efficiency by assuming constant returns to scale (CRS) and delivery of overall technical efficiency. The CRS assumption is only justifiable when all DMUs are operating at an optimal scale. However, firms or DMUs in practice might face either economies or diseconomies to scale. Banker et al. (1984) extended the CCR model by relaxing the CRS assumption. The resulting BCC (Banker, Charnes, Cooper) model was used to assess the efficiency of DMUs characterized by variable returns to scale (VRS). The VRS assumption provides the measurement of pure technical efficiency (PTE), which is the measurement of technical efficiency devoid of scale efficiency (SE) effects. If there appears to be a difference between the TE and PTE scores of a particular DMU, then it indicates the existence of scale inefficiency (Sufian, 2007).

As e.g. Sathye (2003) showed, the DEA has some limitations. When the integrity of data has been violated, DEA results cannot be interpreted with confidence. Another caveat of DEA is that those DMUs indicated as efficient are only efficient in relation to others in the sample. It may be possible for a unit outside the sample to achieve higher efficiency than the best practice DMU in the sample. Knowing which efficient banks are most comparable to the inefficient bank enables the analyst to develop an understanding of the nature of inefficiencies and reallocate scarce resources to improve productivity. This feature of DEA is clearly a useful decision-making tool in benchmarking. As a matter of sound managerial practice, profitability measures should be compared with DEA results and significant disagreements investigated.

Data Envelopment Analysis is performed in only one time period, hampering the measurement of efficiency changes when there is more than one time period. A DEA model is sometimes applied on a repeated basis, e.g. the so-called window analysis method (Charnes et al., 1995) when a panel data set comprising both time series and cross-section samples is available, but this produces little more than a continuum of static results, when in fact a static perspective may be inappropriate (Sengupta, 1996).

Window analysis is one of the methods used to verify productivity change over time. As Savić et al. (2012) showed, window analysis technique works on the principle of moving averages (Charnes et al., 1995; Yue, 1992; Cooper et al. 2007). DEA window analysis was proposed by Charnes et al. (1985) in order to measure efficiency in cross sectional and time varying data. Thus, it is useful in detecting performance trends of a decision making unit over time. Each DMU (i.e. bank) is treated as a different bank in a different period which can increase the number of data point. In the other word, each DMU in a different period is treated as if it were a different DMU (independent) but remain comparable in the same window (Cooper et al., 2011). Such capability in the case of a small number of DMUs and a large number of inputs and outputs would increase the discriminatory power of the DEA models (Cooper et al., 2011). Therefore, small sample sizes problem can be solved. And another advantage of DEA window analysis is that the performance of a bank in a period can be contrasted against themselves and against other banks overtime (Asmild et al., 2004).

The performance of a unit in a particular period is contrasted with its performance in other periods in addition to the performance of other units. This results in an increase in the number of data points in the analysis, which can be useful when dealing with small sample sizes. Varying the window width, that is the number of time periods included in the analysis, means covering the spectrum from contemporaneous analysis, which include only observations from one time period, to intertemporal analysis, which include observations from the whole study period (Paradi et al., 2001). A DEA window analysis, with a window width somewhere between one and all periods in the study horizon, can be viewed as a special case of a sequential analysis. It is assumed, that what was feasible in the past remains feasible, and all previous observations are included. This is not the case in the window analysis, where only observations within a certain number of time periods (i.e. a window) are considered. Once the window is defined the observations within that window are viewed in an intertemporal manner and the analysis is therefore better referred to as locally intertemporal (Tulkens and Vanden Eeckaut, 1995).

The number of firms that can be analyzed using the DEA model is virtually unlimited. Therefore, data on firms in different periods can be incorporated into the analysis by simply treating them as if they represent different firms. In this way, a given firm at a given time can compare its performance at different times and with the performance of other firms at the same and at different times. Through a sequence of such windows, the sensitivity of a firm's efficiency score can be derived for a particular year according to changing conditions and a changing set of reference firms. A firm that is DEA efficient in a given year, regardless of the window, is likely to be truly efficient relative to other firms. Conversely, a firm that is only DEA efficient in a particular window may be efficient solely because of extraneous circumstances. In addition, window analysis provides some evidence of the short-run evolution of efficiency for a firm over time. Of course, comparisons of DEA efficiency scores over extended periods may be misleading (or worse) because of significant changes in technology and the underlying economic structure (Yue, 1992).

Following Asmild et al. (2004) and Gu and Yue (2011), consider N DMUs $(n = 1,2,..,N)$ observed in T $(t = 1,2,\dots,T)$ periods using r inputs to produce s outputs. Let DMU_n^t represent an DMU_n in period t with a r dimensional input vector $x_n^t = (x_n^{1t}, x_n^{2t}, \dots, x_n^{n})'$ and s dimensional output vector $y = (y_n^{1t}, y_n^{2t}, \dots, y_n^{st})'$. If a window starts at time k $(1 \le k \le T)$ with window width w $(1 \le w \le t - k)$, then the metric of inputs is given as follows:

$$x_{kw} = \left(x_1^k, x_2^k, \dots, x_N^k, x_1^{k+1}, x_2^{k+1}, \dots, x_N^{k+1}, x_1^{k+w}, x_2^{k+w}, \dots, x_N^{k+w}\right)', \tag{1}$$

The metric of outputs as:

$$y_{kw} = \left(y_1^k, y_2^k, \dots, y_N^k, y_1^{k+1}, y_2^{k+1}, \dots, y_N^{k+1}, y_1^{k+w}, y_2^{k+w}, \dots, y_N^{k+w}\right)', \tag{2}$$

The CCR model of DEA window problem for DMU_t^k is given by solving the following linear program:

$$\min \theta, \tag{3}$$

subject to

$$\theta' X_t - \lambda' X_{kw} \ge 0, \tag{4}$$

$$\lambda' Y_{kw} - Y_t \ge 0, \tag{5}$$

$$\lambda_n \ge 0 \; (n = 1,2,\dots,N \times w). \tag{6}$$

BCC model formulation can be obtained by add the restriction $\sum_{n=1}^{n} \lambda_n = 1$ (Banker et al., 1984). The objective value of CCR model is designated technical efficiency and the objective of BCC model is pure technical efficiency. The BCC model is illustrated as:

$$\min \theta, \tag{7}$$

subject to

$$\theta' X_t - \lambda' X_{kw} \ge 0, \tag{8}$$

$$\lambda' Y_{kw} - Y_t \geq 0, \tag{9}$$

$$\sum_{n=1}^{n} \lambda_n = 1, \tag{10}$$

$$\lambda_n \geq 0 \; (n = 1,2, \dots, N \times w). \tag{11}$$

Asmild et al. (2004) point out that there are no technical changes within each of the windows because all DMUs in each window are compared and contrast against each other and suggest a narrow window width should be used. Charnes et al. (1995) found that w = 3 or 4 tended to yield the best balance of in formativeness and stability of the efficiency scores. In order to be sure that the results will be credible, a narrow window width must be used. Therefore, a 3 year window has been chosen in this paper (*w* = 3).

2.1. Data and selection of variables

The data set used in this paper was obtained from the database BankScope and the annual reports of commercial banks during the period 2004–2013. All the data is reported on an unconsolidated basis. We analyze only commercial banks that are operating as independent legal entities. As we have reliable data extracted directly from annual reports, we eliminate the risk that incomplete or biased data may distort the estimation results. We use unbalanced panel data from 14 Czech commercial banks and 12 Slovak commercial banks (with regard to mergers and acquisitions of banks).

In order to conduct a DEA window analysis estimation, inputs and outputs need to be defined. Four main approaches (intermediation, production, asset and profit approach) have been developed to define the input-output relationship in financial institution behavior. We adopted an intermediation approach which assumes that the banks' main aim is to transform liabilities (deposits) into loans (assets). Consistent with this approach, we assume that banks collect deposits to transform them, using labor, in loans. We employed two inputs (labor and deposits), and two outputs (loans and net interest income). We measure labor by the total personnel costs covering wages and all associated expenses and deposits by the sum of demand and time deposits from customers, interbank deposits and sources obtained by bonds issued. Loans are measured by the net value of loans to customers and other financial institutions and net interest income (NII) as the difference between interest incomes and interest expenses. We consider loan loss provision as undesirable output. Descriptive statistics of inputs and outputs are in Table 1.

Tab. 1: Descriptive statistics of inputs and outputs

	Czech Republic				Slovakia			
Variable	LOANS	NII	DEPOSITS	LABOR	LOANS	NII	DEPOSITS	LABOR
Mean	115313	6357	166489	2199	2219	124	2880	41
Median	45944	1749	61150	943	1168	44	1552	20
Max	472886	29460	636662	8525	7559	466	9101	113
Min	293	33	351	21	18	3	96	0
St.Dev.	129489	7836	194821	2549	2132	130	2684	37

Source: Author's calculation

3. Empirical analysis and results

We adopted DEA window analysis SBM (slack based model – non-radial) models that can evaluate the overall efficiency of decision-making units for the whole terms as well as the term efficiencies. We used the DEA window analysis to estimate efficiency under the assumptions of constant and variable returns to scale. For empirical analysis we used MaxDEA software.

Banking efficiency was estimated using DEA window analysis models, especially an input-oriented model with constant returns to scale and input-oriented model with variable returns to scale. The reason for using both techniques is the fact that the assumption of constant returns of scale is accepted only in the event that all production units are operating at optimum size. This assumption, however, is in practice impossible to fill, so in order to solve this problem we calculate also with variable returns of scale (Řepková, 2012). We used unbalanced panel data of 14 Czech commercial banks (with regard to mergers and acquisitions of banks). Thus, BancoPopolare (POPO) is now Equa bank from 2011, UniCredit Bank (UNIC) was HVB in period 2003-2006, Equa bank was called Banco Popolare during the period 2010-2007 and then IC Bank in period 2003-2006, LBBW was Dresdner Bank in 2003 and then it was called Bawag bank in 2004-2007. Sberbank was called Volksbank until 2011. And also we use panel data of 12 Slovak commercial banks (with regard to mergers and acquisitions of banks). Prima Banka was Dexia banka until 2012. Sberbank was Volksbank in period 2004-2012.

First, we estimated efficiency scores in the Czech banking sector. The results of the DEA efficiency scores under constant variable of scale are presented in Table 2.

Tab. 2: Efficiency of the Czech commercial banks in CCR model

DMU	2004-06	2005-07	2006-08	2007-09	2008-10	2009-11	2010-12	2011-13	*Mean*
CSOB	46	47	49	54	56	58	58	61	*54*
CS	63	64	67	73	77	86	84	86	*75*
KB	61	63	63	64	67	72	73	79	*68*
UniCredit	83	69	71	73	84	94	93	96	*83*
GE Money	97	99	100	97	97	99	98	98	*98*
RB	67	64	67	74	73	80	76	78	*72*
Equa bank	69	69	70	80	63	54	32	38	*59*
JT Banka	93	89	79	78	79	82	73	72	*81*
LBBW	71	79	90	86	70	60	62	73	*74*
PPF	58	67	83	95	90	87	95	92	*83*
Sberbank	88	78	84	87	86	92	92	95	*88*
ZIBA	67	59	62						*63*
Citi Bank	44	39	35	35					*38*
eBanka	39	35	33	31					*34*
Mean	*68*	*66*	*68*	*71*	*77*	*78*	*76*	*79*	

Source: Author's calculation

Moving average efficiency are shown in three-year window. During the period 2004–2013, the average efficiency calculated using the CRS ranges from 66% to 79%. This development shows that Czech banks are on average considered to be efficient, with only marginal changes over time. Thus, the average inefficiency of the Czech banking sector in the CCR model was in range 34-21%. The reason for the inefficiency of Czech banks is mainly the excess of client deposits on the balance sheet of banks.

The results of the efficiency of individual banks show that the most efficient bank were GE Money Bank and then Sberbank and PPF bank. On the other hand, the lowest efficient bank were ČSOB, Equa bank and Komerční banka. It can be seen that the group of largest bank (ČSOB, Česká spořitelna and Komerční banka) are lower efficient than other groups of bank. The reason for this inefficiency is that the group of large banks have excess of deposits in balance sheet. Thus, the excess of deposits reflected negatively to net interest income by increasing interest costs of banks.

Tab. 3: Efficiency of the Czech commercial banks in BCC model

DMU	2004-06	2005-07	2006-08	2007-09	2008-10	2009-11	2010-12	2011-13	*Mean*
CSOB	68	67	63	65	66	64	63	70	66
CS	97	96	91	94	98	97	98	100	96
KB	92	96	86	84	80	81	87	95	88
UniCredit	85	90	94	93	88	95	93	98	92
GE Money	97	99	100	100	98	99	98	98	99
RB	71	79	82	91	74	80	76	95	81
Equa bank	100	100	96	95	86	76	76	76	88
JT Banka	95	91	83	82	80	86	83	82	85
LBBW	71	79	91	86	73	66	74	84	78
PPF	61	69	84	97	91	88	99	100	86
Sberbank	88	79	89	96	86	94	95	96	90
ZIBA	68	65	71						68
Citi Bank	45	39	35	35					39
eBanka	40	35	33	32					35
Mean	77	77	78	81	84	84	86	90	

Source: Author's calculation

Table 3 presents the efficiency of individual Czech banks calculated under the variable return to scale. The average efficiency calculated in BCC model reached the value from 77 to 90%. The most efficient banks were Sberbank, GE Money Bank and Česká spořitelna. Also in BCC model, the lowest efficient bank was ČSOB. We conclude the result of Stavárek and Řepková (2012) who applied DEA methodology and found that ČSOB had average efficiency under 50% and the efficiency of ČSOB were decreasing during the period 2003-2010. We found that the main source of inefficiency was the excess of client deposits managed by banks and also the inappropriate range of operation of large banks.

Next, the estimation of the Slovak commercial banks are presented. The results of the DEA efficiency scores under constant variable of scale during the period 2004-2013 are presented in Table 4. Moving average efficiency are shown in three-year window.

Tab. 4: Efficiency of the Slovak commercial banks in CCR model

DMU	2004-06	2005-07	2006-08	2007-09	2008-10	2009-11	2010-12	2011-13	*Mean*
CitiBank	65	67	65	66	65	61			65
CSOB	51	78	89	92	93	91	83	82	82
Prima banka	57	88	87	86	91	80	78	70	79
Istrobanka	86	87	84	82	84				85
OTP	92	95	92	94	96	90	92	97	93
Postova bank	87	92	91	95	93	86	95	100	92
Privatbanka	47	62	61	58	50	45	42	39	50
SLSP	73	91	91	92	93	95	96	97	91
Tatrabanka	55	75	74	74	77	75	79	83	74
UniCredit	56	81	93	99	96	91	93	96	88
Sberbank SK	74	87	83	82	88	82	81	77	82
VUB	73	95	88	90	95	97	97	97	91
Mean	68	83	83	84	85	81	84	84	

Source: Author’s calculation

During the period 2004–2013, the average efficiency calculated using the CRS ranges from 68% to 85%. This development shows that Slovak commercial banks are on average considered to be efficient, with only marginal changes over time. The results show that the average inefficiency of the Slovak banking sector in the CCR model was in range 15-32%. The reason for the inefficiency of Slovak banks is mainly the excess of client deposits on the balance sheet of banks.

The results of the efficiency of individual banks show that the most efficient bank were OTP, Postova banka and VUB. On the other hand, the lowest efficient bank were Privatbanka, CitiBank and TatraBanka. We found that the largest banks in the Slovak banking market are lower efficient than medium-size and small banks. The reason for this inefficiency is that the group of large banks have excess of deposits in balance sheet. Thus, the excess of deposits reflected negatively to net interest income by increasing interest costs of banks.

Table 5 presents the efficiency of the Slovak commercial banks estimated under the variable return to scale. The average efficiency calculated in BCC model reached the value from 85 to 92%. The most efficient banks were OTP, VUB and Slovenska sporitelna. Also in BCC model, the lowest efficient bank were CitiBank, Tatrabanka and Prima banka.

Tab. 5: Efficiency of the Slovak commercial banks in BCC model

DMU	2004-06	2005-07	2006-08	2007-09	2008-10	2009-11	2010-12	2011-13	*Mean*
CitiBank	67	74	71	74	81	83			75
CSOB	76	79	90	95	96	91	83	82	87
Prima banka	81	92	90	88	92	84	82	76	85
Istrobanka	87	90	91	92	100				92
OTP	95	96	94	96	100	100	99	99	97
Postova bank	90	94	96	100	97	88	96	100	95
Privatbanka	89	100	94	97	94	85	92	98	93
SLSP	96	91	94	92	93	97	100	100	95
Tatrabanka	89	82	85	82	82	77	81	86	83
UniCredit	65	84	94	99	100	92	93	96	90
Sberbank SK	87	92	87	86	92	90	90	84	89
VUB	96	97	93	90	95	97	98	99	96
Mean	85	89	90	91	94	89	91	92	

Source: Author's calculation

The development of the efficiency showed that the average efficiency was increasing during the period 2003-2008. After year 2008 the average efficiency decreased. This decrease was probably as a result of financial crisis. The decrease in the net profit was registered in the balance sheet of the most Slovak commercial banks. In the last two windows 2009-2011 and 2010-2012 the average efficiency increased.

Conclusion

The aim of the paper was to apply the Data Envelopment Analysis window analysis on the data of the Czech and Slovak commercial banks and to examine the efficiency of the Czech and Slovak banking sector during the period 2004-2013. We use the DEA window analysis based on an input oriented model to measure banking efficiency. We estimated efficiency under the assumptions of constant and variable returns to scale. The research was based on unbalanced panel data for the period from 2004 to 2013.

In the Czech banking sector, the average efficiency under constant return to scale reached 66-79% and average efficiency under variable return to scale reached 77-90%. The most efficient bank were GE Money Bank and Sberbank. And the lowest efficient bank was Československá obchodní banka. We found that the group of large bank (Československá obchodní banka, Česka spořitelna and Komerční banka) was lower efficient than other banks in the banking sector. It was probably caused by the fact that these banks had excess of deposits in balance sheet and it reflected negatively to net interest income by increasing interest costs of banks.

In Slovakia, we found that the average efficiency under constant return to scale reached 77-91% and average efficiency under variable return to scale reach 83-94%. Next, it was found that the most efficient banks were OTP, Postova banka, UniCredit Bank and Istrobanka. On contrary, the lowest efficient banks were found Privatbanka and Citibank. However Privatbanka was the lowest efficient bank in assumption of constant return to scale, but it reached the 93% efficiency in assumption of variable return to scale. It can be argued that Privatbanka operate in inappropriate range of operation.

Other results of the paper is that whereas during the period 2003-2008 the average efficiency was increasing, during the period 2010-2011 the average efficiency decreased as a result of financial crisis. The results confirm the study of Anayiotos et al. (2010) who presented that the banking efficiency in Slovakia decreased during the pre-crisis boom and also fell during the crisis.

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