ESTIMATION OF BANKING EFFICIENCY IN THE CZECH REPUBLIC: DYNAMIC DATA ENVELOPMENT ANALYSIS

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Abstract

This paper estimates the efficiency of Czech commercial banks during the period 2001 to 2011. We applied Dynamic Data Envelopment Analysis (DEA) to data from Czech commercial banks. The DEA measures the relative efficiency of a homogeneous set of decision-making units (DMUs) in their use of multiple inputs to produce multiple outputs. Dynamic Data Envelopment Analysis is a new approach which estimates the performance of a group of DMUs during several periods of time. The results of Dynamic DEA models showed that the average efficiency computed under the assumption of constant returns to scale reached a value of 86.7% and that the average efficiency estimated under the assumption of variable returns to scale was 95.7%. Efficiency slightly increased in the period analysed. The result of scale efficiency found that the main source of inefficiency is the inaccurate size of the biggest banks and also the excess client deposits managed by Czech banks.

Keywords

Efficiency, Dynamic Data Envelopment Analysis, Czech Banking Sector, Commercial Banks

I. Introduction

The Czech financial system can be characterized as a bank-based system and banks play an important role in the economy for corporations and businesses as well as for households. The transformation and consolidation of the Czech banking sector was carried out during the 1990s. From 1998–2001, a second round of privatization occurred with the sale to foreigners of majority equity interests in four large Czech banks: Československá obchodní banka (ČSOB), Česká spořitelna (ČS), Komerční banka (KB) and Investiční a poštovní banka (IPB). These Big Three (Československá obchodní banka, Česká spořitelna and Komerční banka) are still the dominant players in the market. Their combined market share in terms of assets is about 50% and they have an extensive networks of branches.

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From 2000–2011, the number of banks was almost constant. In 2011, the number of banking institutions included 18 banks (four large banks, eight medium-sized banks and six small banks), five building societies and 21 foreign bank branches. There were several mergers and acquisitions in the Czech banking market during the years analysed. The Czech banking sector has an almost stable shareholder structure. The Czech Republic joined the European Union (EU) in 2004 and in 2009 the small and open Czech economy was hit hard by the global financial and economic crisis. Thanks to its very strong deposit base and the very small percentage of loans denominated in foreign currency, the banking sector remained stable throughout the global financial crisis. Overall financial stability in the Czech Republic seems stable².

The aim of the paper is to estimate the efficiency of Czech commercial banks during the period 2001–2011. In order to achieve this aim, we applied a Dynamic Data Envelopment Analysis (DEA) to data from Czech banks.

The structure of the paper is as follows. The next section describes the theoretical background of banking efficiency and presents the dataset used in the empirical part of the paper. Section 4 reveals the estimated results and the last section concludes the paper with a summary of key findings.

II. Literature review

Several empirical analyses of the efficiency of the Czech 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) used a parametric technique, the distribution-free approach, to investigate the cost efficiency of Czech banks. Efficiency was analysed in conjunction with size and ownership structure (private or public) and it was found that private banks have a higher mean efficiency score, supporting rapid privatization.³

Bonin, Hasan, Wachtel (2005) investigated the impact of bank privatization in transition countries. They found that foreign-owned banks were most efficient and government-owned banks were least efficient.⁴

Matoušek and Taci (2005) examined the cost efficiency of the Czech-banking system in the 1990s by applying the distribution-free approach model. They found that the efficiency of the Czech-banking sector increased during the period analysed. The results indicated that foreign banks were on average more efficient than other banks, although their efficiency was comparable with the efficiency of ‘good’ small banks in the early years of their operation. Based on these results, it was argued that the early privatisation of state-owned commercial banks and a more liberal policy towards foreign banks in the early stages of transition would have enhanced efficiency in the banking system.⁵

Weill (2003) found a positive influence of foreign ownership on the cost efficiency of banks in the Czech Republic and Poland. His conclusion was that the degree of openness

² Otýpková (2012).

³ Taci, Zampieri (1998).

⁴ Bonin, Hasan, Wachtel (2005).

⁵ Matoušek, Taci (2005).

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 economies⁶.

Fries and Taci (2005) found that banking systems in which foreign-owned banks have a larger share of total assets have lower costs and that the association between a country's progress in banking reform and cost efficiency is non-linear. Early stages of reform were associated with cost reductions, while costs tend to rise at more advanced stages. They argued that private banks are more efficient than state-owned banks, but there are also differences among private banks. Privatised banks with majority foreign ownership were the most efficient and those with domestic ownership were the least⁷. The results of Andries and Cocris (2010) showed that banks in the Czech Republic are inefficient from the perspective of costs⁸. To improve efficiency, banks need to improve the quality of assets owned by improving the lending process and reducing the share of nonperforming loans.

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.⁹

Stavárek (2005) estimated commercial bank efficiency in the group of Visegrad countries (Czech Republic, Hungary, Poland, Slovakia) before joining the EU. A Stochastic Frontier Approach and Data Envelopment Analysis were applied to data from the period 1999 to 2003. 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.¹⁰

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.¹¹

⁶ Weill (2003).

⁷ Fries, Taci (2005).

⁸ Andries, Cocris (2010).

⁹ Stavárek, Polouček (2004).

¹⁰ Stavárek (2005).

¹¹ Staněk (2010).

Also, Staníčková and Skokan (2012) evaluated the banking sector of the Czech Republic as highly efficient¹². 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 banks¹³.

There is a lack of studies in the Czech Republic examining banking efficiency using Dynamic Data Envelopment Analysis, which creates an opportunity for this research. The network structure of Data Envelopment Analysis models was applied to Czech banks by Jablonský (2012)¹⁴.

III. Measures of banking efficiency

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. He proposed that the efficiency of any firm consists of two components: technical efficiency and allocative efficiency. Technical efficiency is the ability of the firm to maximize outputs from a given set of inputs. Allocative efficiency is the ability of the firm to use these inputs in optimal proportion given their respective prices. Combining these two measures provides a measure of productive efficiency.¹⁵ Technical efficiency for a firm is its success in producing maximum output from a given set of inputs and this measure is relative to the set of firms from which the efficient production frontier is estimated¹⁶.

Farrell illustrated his ideas using a simple example involving firms that use two inputs (x_1 and x_2) to produce a single output (y). If the isoquant of the benchmark efficient firm is known, the efficiency of any firm can be calculated. In Figure 1, the isoquant is represented by SS' . If a firm uses quantities of inputs defined by P to produce the output, the technical inefficiency is given by distance QP, which is the amount by which all inputs could be reduced without a reduction in outputs. This can be measured in percentage terms as QP/OP. Therefore the technical efficiency (TE) of the firm operating at P is measured by the ratio OQ/OP. A value of one in this ratio means that the firm is technically efficient.¹⁷ If the input price ratio is also known, the allocative efficiency may also be calculated. The allocative efficiency of the firm operating at P is the ratio OR/OQ, where RQ represents the reduction of the production costs that would occur at the allocatively (and technically) efficient point Q', instead of the allocatively inefficient point Q. Finally, the overall efficiency (EE) is the ratio OR/OP, where RP is reduction of cost if a firm at P moves to R (technically impossible because it is under the isoquant).¹⁸

¹² Staníčková, Skokan (2012).

¹³ Stavárek, Řepková (2012).

¹⁴ Jablonský (2012).

¹⁵ Farrell (1957).

¹⁶ Sengupta (1996).

¹⁷ Farrell (1957).

¹⁸ Farrell (1957).

Figure 1: Technical and allocative efficiency (in input-oriented model)

Source: author's compilation

These efficiency measures assume that the production function of a benchmark efficient firm is known, but this is really an unknown and therefore has to be estimated from sample data. In empirical literature, the two general approaches are used to assess the efficiency of an entity, parametric and non-parametric methods, which employ different techniques to envelop a data set with different assumptions for random noise and for the structure of the production technology. The nonparametric methods are Data Envelopment Analysis and Free Disposal Hull, which are based on linear programming tools. The parametric methods most widely used in empirical estimations are Stochastic Frontier Approach, Distribution-Free Approach and Thick Frontier Approach, which assume a specific functional form for the cost function or production technology and allow for an error term composed from symmetrically distributed random error term and a truncated inefficiency term.

Data Envelopment Analysis 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.¹⁹ DEA measures the relative efficiency of a homogeneous set of decision-making units 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 output²⁰. Kamecka (2010) defined DEA as a method of obtaining total factor productivity measures.²¹ As such, 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

¹⁹ Seiford, Thrall (1990).

²⁰ Charnes et al. (1995).

²¹ Kamecka (2010).

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 outputs²².

The term DEA was first introduced by Charnes et al. (1978)²³ based on the research of Farrell (1957)²⁴. The CCR model is the basic DEA model, as introduced by Charnes et al. (1978). This model was modified by Banker et al. (1984)²⁵ and became the BCC model, which accommodates variable returns to scale.

The CCR²⁶ 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, Charnes and Cooper (1984) extended the CCR model by relaxing the CRS assumption. The resulting BCC²⁷ 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.²⁸

Figure 2: Comparison of constant and variable returns to scale

Source: author's compilation

²² Charnes, Cooper, Rhodes (1995).

²³ Charnes, Charnes, Cooper (1995).

²⁴ Farrell (1957).

²⁵ Banker, Charnes, Cooper (1984).

²⁶ Charnes, Cooper, Rhodes (1978).

²⁷ Banker, Charnes, Cooper (1984).

²⁸ Sufian (2007).

Figure 2 shows the comparison of constant and variable returns to scale in an input-oriented model. Efficiency of scale reflects the amount which the bank has to increase to achieve point B, or technically optimal efficiency. Given that $OD/OE = GE/GD$, the distance measures could be used to assess differences in efficiencies. The technical efficiency of firm D, the distance D in VRS is $TE_{VRS} = GE/GD$, while the distance from technically efficient point E in CRS equals $SE = GF/GE$, $TE_{CRS} = GF/GD$ in TE_{VRS} . In cases using multiple inputs and multiple outputs, this would be only a generalization of this idea. DEA modelling allows the analyst to select inputs and outputs in accordance with managerial focus. This is an advantage of DEA since it opens the door to what-if analysis. Furthermore, the technique works with variables of different units without the need for standardisation (e.g. number of transactions, number of staff). Fried and Lovell (1994) have given a list of questions that DEA can help to answer.²⁹ However, 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.³⁰

DEA begins with a relatively simple fractional programming formulation. Assume that there are n DMUs to be evaluated. Each consumes different amounts of i inputs and produces r different outputs, i.e. DMU _{j} consumes x_{ji} amounts of input to produce y_{ji} amounts of output. It is assumed that these inputs, x_{ji} , and outputs, y_{ji} , are non-negative, and each DMU has at least one positive input and output value. The productivity of a DMU can be written as:

$$h_j = \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}}, \quad (1)$$

In this equation, u and v are the weights assigned to each input and output. By using mathematical programming techniques, DEA optimally assigns weights subject to the following constraints. The weights for each DMU are assigned subject to the constraint that no other DMU has efficiency greater than 1 if it uses the same weights, implying that efficient DMUs will have a ratio value of 1.

The objective function of DMU _{k} is the ratio of the total weighted output divided by the total weighted input:

$$\max h_0(u, v) = \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{i=1}^m v_i x_{i0}}, \quad (2)$$

²⁹ Fried, Lovell (1994).

³⁰ Sathye (2003).

subject to

$$\frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1, \quad j = 1, 2, \dots, j_0, \dots, n, \quad (3)$$

$$u_r \geq 0, \quad r = 1, 2, \dots, s, \quad (4)$$

$$v_i \geq 0, \quad i = 1, 2, \dots, m, \quad (5)$$

where h_0 is the technical efficiency of DMU₀ to be estimated,
 u_r and v_i are weights to be optimized,
 y_{rj} is the observed amount of output of the r^{th} type for the j^{th} DMU,
 x_{ij} is the observed amount of input of the i^{th} type for the j^{th} DMU,
 r indicates the s different outputs,
 i denotes the m different inputs,
and j indicates the n different DMU_s.

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 method³¹ 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 inappropriate³².

Window analysis and the Malmquist index were the first methods used to verify productivity change over time. The Malmquist index evaluates efficiency change over time. The original idea of the MI was proposed by Malmquist (1953)³³ who suggested comparing the input of a firm at two different points of time in terms of the maximum factor by which the input in one period could be decreased such that the firm could still produce the same output level of the other time period. The MI, based on DEA models, is one of the most prominent indexes for measuring the relative productivity change of DMUs in multiple time periods. However, these models do not capture the effect of carry-over activities (links) between two consecutive time periods. These models have inputs and outputs for each period, but linking activities between the periods are not computed explicitly³⁴.

The Dynamic Data Envelopment Analysis model proposed by Fare and Grosskopf (1996) is the first innovative system that formally addresses activities in different interconnected time periods³⁵. Thus, Dynamic DEA is a new approach which estimates the performance of a group of DMUs during several periods of time. The Dynamic DEA model takes into account the internal heterogeneous organizations of DMUs for which divisions are mutually connected by link variables and trade internal products with each other. Additionally, each DMU has carry-over variables that take into account a positive or negative factor

³¹ Charnes, Cooper, Rhodes (1994).

³² Sengupta (1996).

³³ Malmquist (1953).

³⁴ Costa, Ramos, Souza (2012).

³⁵ Fare, Grosskopf (1996).

in the previous period. This model has the huge advantage of being able to evaluate the policy effect on the individual divisions of each DMU³⁶.

Tone and Tsutsui (2010) pointed out a concept of carry-over³⁷. Figure 3 presents the Dynamic DEA model described by Tone and Tsutsui (2010).

Figure 3: Dynamic DEA model

Source: Author's compilation

In this paper we adopted the Dynamic DEA model proposed by Sengupta (1996)³⁸ or Tone and Tsutsui (2010)³⁹ and Tone (2001)⁴⁰. The mathematical formulation of the Dynamic DEA model was described, e.g. by Sengupta (1996)⁴¹ or Lotfi and Poursakhi (2012)⁴². The Dynamic DEA model can easily be written as:

$$\max(T - 1) = \sum_{t=0}^{T-1} \sum_{j=1}^n w'(t) \lambda_j(t), \quad (6)$$

subject to

$$\sum_{j=1}^n A_j(t) \lambda_j(t) \leq X_k(t), \quad (7)$$

$$\lambda_j(t) \geq 0, \quad \text{all } t = 0, 1, 2, \dots, T - 1, \quad (8)$$

where $\lambda_j(t)$ is the output vector for each DMU, X_k is current input, $A_j(t)$ is the corresponding input coefficient matrices, and $w(t)$ is a non-negative weight vector for the multiple outputs of each DMUs.

³⁶ Kawaguchi, Tone, Tsutsui (2013).

³⁷ Tone, Tsutsui (2010).

³⁸ Sengupta (1996).

³⁹ Tone, Tsutsui (2010).

⁴⁰ Tone (2001).

⁴¹ Sengupta (1996).

⁴² Lotfi, Poursakhi (2012).

We estimated the dynamic model in the slacks-based measure (SBM) framework, called Dynamic SBM (DSBM). The SBM model is non-radial and can deal with inputs/outputs individually, contrary to radial approaches that assume proportional changes in inputs/outputs.

IV. 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 2001–2011. All the data is reported on an unconsolidated basis. We analysed 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. One important point is that the calculation of Dynamic DEA requires strictly balanced panel data. We use panel data from 11 Czech commercial banks (with regard to mergers and acquisitions of banks).

In order to conduct a Dynamic DEA estimation, inputs and outputs need to be defined. Four main approaches have been developed to define the input-output relationship in financial institution behaviour. Firstly, the intermediation approach, which can also be referred to as the asset approach, was introduced by Sealey and Lindley (1977) and assumes that the banks' main aim is to transform liabilities (deposits) into loans (assets). Secondly, the production (service-oriented) approach (Sherman and Gold, 1985), which can also be referred to as the value-added or production approach, focuses on the services banks provide to their clients. It assumes that the banks' aim is to produce liabilities (deposits) as well as loans (assets) and other services. The production approach thus has two main disadvantages in that it does not take interest costs into account and second, it requires information about the number of accounts and cost allocation (Kamecka, 2010). Third, the asset approach recognizes the primary role of financial institutions as creators of loans. In essence, this stream of thought is a variant of the intermediation approach, but instead defines outputs as the stock of loan and investment assets (Favero and Papi, 1995). Last, the profit approach, which is the newest of the approaches. It is based on Berger and Mester (2003) who stated that use of the profit approach may help take into account unmeasured changes in the quality of banking services by including higher revenues paid for improved quality, and may help capture the profit maximization goal by including both costs and revenues. Such changes are expected to occur, in particular, following any significant changes in the disposable income of citizens (Kamecka, 2010).

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 labour, in loans. We employed two inputs (labour and deposits), and two outputs (loans and net interest income). We measure labour 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. Descriptive statistics of inputs and outputs are in Table 1.

Table 1: Descriptive statistics (in mil. CZK) Rate of unemployment and inflation rate in the Czech Republic

Variable	Deposits	Labour	Loans	NII
Mean	131036.41	1808.24	86920.10	4990.97
Median	45428.2	551.3	32213.6	1332
Max	595092	8525	441587	29460
Min	332.8	20	185.3	32.9
St.Dev.	170844.24	2371.13	104273.75	6793.29

Source: Author's calculation based on annual reports of individual banks

V. Empirical analysis and results

We adopted Dynamic SBM models that can evaluate the overall efficiency of decision-making units for the whole terms as well as the term efficiencies. We used Dynamic DEA 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 Dynamic DEA 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. One important point is that the calculation of Dynamic DEA requires strictly balanced panel data. We use panel data of 11 Czech commercial banks (with regard to mergers and acquisitions of banks). The results of the Dynamic DEA efficiency scores are presented in Table 2.

Table 2: Efficiency of the Czech banking sector

	CRS	Inefficiency	VRS	Inefficiency
2001	0.8644	0.1356	0.9556	0.0444
2002	0.8983	0.1017	0.9837	0.0163
2003	0.8924	0.1076	0.9725	0.0275
2004	0.8744	0.1256	0.9414	0.0586
2005	0.8002	0.1998	0.8985	0.1015
2006	0.8543	0.1457	0.9353	0.0647
2007	0.8549	0.1451	0.9809	0.0191
2008	0.8651	0.1349	0.9758	0.0242
2009	0.9158	0.0842	0.9628	0.0372
2010	0.8580	0.1420	0.9520	0.0480
2011	0.8574	0.1426	0.9691	0.0309
Mean	0.8668	0.1332	0.9571	0.0429

Source: Author's calculation

During the period 2001–2011, the average efficiency calculated using the CRS ranges from 80% to 92% and the average efficiency computed using the VRS ranges from 90%

to 98%. This shows that Czech banks are on average considered to be efficient, with only marginal changes over time. Average efficiency calculated under the assumptions of constant returns to scale reaches the value of 87% and the average efficiency computed under the assumptions of variable returns to scale was 96%. The results of the CCR model and the BCC model show that the model with VRS achieves a higher degree of efficiency than the model with CRS by eliminating that part of the inefficiency that is caused by a lack of size of production units. The average inefficiency of the Czech banking sector in the CCR model was 13% and the average inefficiency in the BCC model reached 4%. The reason for the inefficiency of Czech banks is mainly the excess of client deposits on the balance sheet of banks.

The development of average efficiency shows that the efficiency score was increasing in the period 2001–2003. In the period 1999–2001, large Czech banks were privatized and the new owners and managers probably learnt to adapt to the new environment. Reflecting this process is the gradual increase in efficiency in the Czech banking sector. Average efficiency decreased in 2005. This decrease was influenced by decreasing of loans and net interest income in ČSOB, Banco Popolare (in 2005 called IC bank) or LBBW (in 2005 it was BAWAG bank). It was probably caused by the fact that the CNB increased the basic interest rate in 2005. During the period 2006–2009, the efficiency of the Czech banking sector was increasing and the structure of the financial market was stabilized. In 2010, when average efficiency decreased, we can suppose that this development was a result of the financial crisis. Because the analysed outputs (loans and net interest income) decreased in the balance sheet of individual banks.

Table 3: Efficiency of Czech commercial banks

DMU	Technical Efficiency Score (CRS)	Pure Technical Efficiency Score (VRS)	Scale Efficiency Score
CS	0.7842	1.0000	0.7842
CSOB	0.6633	0.8625	0.7691
GE MONEY	0.9850	0.9953	0.9897
JT BANK	0.9166	0.9610	0.9538
KB	0.7601	0.9798	0.7758
LBBW	0.8847	0.9001	0.9830
POPO	0.8742	1.0000	0.8742
PPF	0.8978	0.9194	0.9765
RB	0.8333	0.9110	0.9147
UNICREDIT	0.9373	1.0000	0.9373
VOLKSBANK	0.9983	0.9984	0.9999
Mean	0.8668	0.9571	0.9053

Source: Author's calculation

The efficiency of individual banks, especially technical efficiency, pure technical efficiency and scale efficiency, is shown in Table 3. The highest average efficiency was achieved Volksbank and GE Money Bank. The banks with the lowest efficiency in the CCR model were ČSOB, Komerční banka and Česká spořitelna. The lowest values of the scale

efficiency also reached these three banks. The banks mentioned are among the largest banks in the national banking sector. Thus, largest banks were the least efficient in the analysed period. These large banks attained higher values in the BCC model; thus large banks in the market are too large and have improperly chosen their size (range of operation). Česká spořitelna achieved 100% in the BCC model. Also, Banco Popolare and UniCredit bank were 100% efficient under the assumption of variable returns to scale.

VI. Conclusion

The aim of this paper was to estimate the efficiency of Czech commercial banks during the period 2001–2011. We applied Dynamic Data Envelopment Analysis to data from Czech commercial banks. We estimated efficiency under the assumptions of constant and variable returns to scale. In the period analysed, average efficiency was calculated using constant returns to scale ranging from 80% to 92% and average efficiency computed using variable returns to scale ranged from 90% to 98%. The average inefficiency of the Czech banking sector in the CCR model was 13% and average inefficiency in the BCC model reached 4%. The reason for the inefficiency of Czech banks was mainly an excess of client deposits in the balance sheet of banks. We found that the efficiency score increased in the period 2001–2003. This increase was probably caused by better management in privatized banks. In 2005, average efficiency decreased. This was influenced by a decrease in loans and net interest income in several banks, a situation which was probably caused by the fact that the CNB increased the basic interest rate in 2005. During the period 2006–2009, the efficiency of the Czech banking sector was increasing and the structure of the financial market stabilized. In 2010 and 2011, average efficiency decreased as a result of the financial crisis.

We found that the highest value achieved for average efficiency was for Volksbank and GE Money Bank. In contrast, the lowest bank efficiency in the CCR model was represented by ČSOB, Komerční banka and Česká spořitelna. These banks, which are the three largest banks in the Czech banking sector, reached the lowest values in scale efficiency. Thus, the largest banks are the least efficient in the Czech banking industry. These large banks reached a higher value in the BCC model, demonstrating that large banks are too large and have improperly chosen their size (range of operations).

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