ACTA UNIVERSITATIS AGRICULTURAE ET SILVICULTURAE MENDELIANAE BRUNENSIS

Volume LX 47 Number 2, 2012

EFFICIENCY IN THE CZECH BANKING INDUSTRY: A NON-PARAMETRIC APPROACH

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Received: November 30, 2011

Abstract

STAVÁREK, D., ŘEPKOVÁ, I.: *Efficiency in the Czech banking industry: A non-parametric approach.* Acta univ. agric. et silvic. Mendel. Brun., 2012, LX, No. 2, pp. 357–366

This paper estimates the efficiency of the Czech commercial banks in the period 2001–2010 using the non-parametric Data Envelopment Analysis. We simultaneously use two alternative specifications – CCR model and BCR model – that differ in returns to scale assumption. Differences in estimated efficiency scores of individual banks are quite large up to 70 percentage points. Largest banks perform significantly worse than mid-size and small banks. This efficiency gap decreases if variable returns to scale are considered in the estimation. The average efficiency in the banking sector remained nearly unchanged during the analysed period. Although each year is estimated separately one can observe a deterioration of average efficiency during the recent crisis period.

efficiency, Data Envelopment Analysis, banking sector, Czech Republic, CCR model, BCR model

The Czech Republic's financial system is bank-based and banks play an important role in the economy. At the beginning of 1990s, the Czech Republic started to transform from centrally planned into market oriented economy. Banking has experienced dramatic changes over the last decades. Deregulation, financial innovation and privatization have been major forces impacting on the performance of the banking sector. In such context, banks have become increasingly concerned about controlling and analyzing their costs and revenues, as well as measuring the risks taken to produce acceptable returns. The Czech Republic joined the European Union in 2004. Thus the analysis of efficiency in industry with so many important development milestones is of high interest.

The aim of the paper is to estimate efficiency in the Czech banking sector during the period 2001–2010. For the practical estimation we applied the non-parametric method, especially the Data Envelopment Analysis (DEA). We can use this approach because we have reliable data extracted directly from annual reports and, hence, we eliminate the risk of non-parametric methods that incomplete or biased data may distort the estimation results.

The structure of the paper is follow. Next section describes theoretical background of the banking efficiency. The literature review is presented in the section 3 and the Data Envelopment Analysis is described in the section 4. Section 5 presents the dataset used in the empirical part. Section 6 reveals and discusses the estimated results and Section 7 concludes the paper with summary of key findings.

Efficiency of the banking sector

The two general approaches used to assess efficiency of an entity, parametric (econometric) and non-parametric (mathematical programming) methods, 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 (DEA) and Free Disposal Hull (FDH), which are based on linear programming tools. The efficiency frontier in nonparametric estimations is formed as a piecewise linear combination of best-practice observations. The main drawback of nonparametric methods is that they are not robust to measurement errors and luck (temporary better performance) observed in the data.

The parametric methods most widely used in empirical estimations are Stochastic Frontier Approach (SFA), Distribution Free Approach (DFA) and Thick Frontier Approach (TFA), which assume specific functional form for the cost function or production technology and allow for an error term composed from symmetrically distributed random error term and truncated inefficiency term. The main criticism of parametric methods is that they impose particular functional form on the behavior of economic variables (Poghosyan and Borovička, 2007).

The essential differences and the sources of advantages of these approaches can be grouped under two categories. (1) The econometric approach is stochastic and attempts to distinguish the effects of noise from the effects of inefficiency; it is based on sampling theory for the interpretation of essentially statistical results. The programming approach is non-stochastic, and hence groups noise and inefficiency together and calls this combination inefficiency. It is built on the findings and observation of population and assesses efficiency relative to other observed units. (2) The econometric approach is parametric and confounds the effects of misspecification of functional form with inefficiency. The programming model is non-parametric and population-based and hence less prone to this type of specification error (Lovell, 1993).

Literature review

Empirical analyses of the Czech banking efficiency exist several. We mention some of them. Taci and Zampieri (1998) used parametric technique, the distribution free approach, to investigate the cost efficiency of Czech banks. Efficiency was analyzed 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.

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 increases during the analysed period. Results indicated that foreign banks were on average more efficient than the other banks, although their efficiency was comparable with the 'good' small banks' efficiency in early years of their operation. Based on the estimated results it was argued that early privatisation of state-owned commercial banks and more liberal policy towards foreign banks in the early stage of transition would have enhanced the efficiency in the banking system.

Weill (2003) found positive influence of foreign ownership on cost efficiency of banks in the Czech Republic and Poland. His 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.

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 differences among private banks. Privatised banks with majority foreign ownership were the most efficient and those with domestic ownership are the least.

Stavárek and Polouček (2004) estimated efficiency and profitability in the selected banking sectors, including the Czech Republic. They found that Central European Countries were less efficient than their counterparts in the 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 the refutation of the conventional wisdom of higher efficiency from foreign-owned banks than from domestic-owned banks, and size is one of the factors that determine efficiency. To achieve high efficiency, a bank should be large, well known, and easily accessible and offering a wide range of products and services, or if small, must focus on specific market segments, offering special products. Any other structure of a bank leads to lower relative efficiency.

Stavárek (2005) estimated commercial banks` efficiency in the group of Visegrad countries (Czech Republic, Hungary, Poland, Slovakia) before joining the EU. It was employed Stochastic Frontier Approach and Data Envelopment Analysis on data from the period 1999–2003. 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 level of efficiency in all countries since 1999, its intensity was not sufficient to converge with the Western European banking sectors.

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 efficiency of the Czech banking sector has improved in the last ten years and got closer to the efficiency of the Austrian banking sector.

Data Envelopment Analysis

The 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 (Seiford and Thrall, 1990). Kamecka (2010) defined DEA as a method of obtaining total factor productivity measures. 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 is performing 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 term DEA was first introduced by Charnes *et al.* (1978) based on the research of Farrell (1957). CCR model is the basic DEA model as introduced by Charnes *et al.* (1978). This model was modified by Banker *et al.* (1984) and became the BCC model which accommodates variable returns to scale.

The CCR model presupposes that there is no significant relationship between the scale of operations and efficiency by assuming constant returns to scale (CRS) and it delivers the 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. Thus, if one makes the CRS assumption when not all DMUs are operating at the optimal scale, the computed measures of technical efficiency will be contaminated with scale efficiencies. Banker *et al.* (1984) extended the CCR model by relaxing the CRS assumption. The resulting BCC 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 the scale efficiency (TE) effects. If there appears to be a difference between the TE and PTE scores of a particular DMU, then it indicates the existence to scale inefficiency (Sufian, 2007).

DEA modelling allows the analyst to select inputs and outputs in accordance with a 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. 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 a 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 (Sathye, 2003).

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:

$$h_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}. \tag{1}$$

In this equation, u and v are the weights assigned to each input and output. By using mathematical programming techniques, DEA optimally assigns the 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:

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

subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \; j = 1, 2, \ldots, j_0, \ldots, n \tag{3}$$

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

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

where
h_0 .... is the technical efficiency of DMU_0 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 and selection of variables

The data set used in this study was obtained from the annual reports of commercial banks. All the data is reported on unconsolidated basis. The data set consists of data of banks that represent about 90% of the Czech banking sector. We analyzed only commercial banks that are operating as independent legal entities. All foreign branches, building societies, mortgage banks, specialized banks or credit unions were excluded from the estimation data set. As we have reliable data extracted directly from annual reports we eliminate the risk that incomplete or biased data may distort the estimation results.

In order to conduct a DEA estimation, inputs and outputs need to be defined. In the empirical literature four main approaches have been developed to define the input-output relationship in financial institution behavior. Firstly, the intermediation approach, which can also be referred to as 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, production (service-oriented) approach (Sherman and Gold, 1985), which can also be referred to as 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 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 the improved quality, and may help capture the profit maximization goal by including both the costs and revenues. Such changes are expected to occur, in particular, following any significant changes in the disposable income of citizens (Kamecka, 2010).

We adopt intermediation approach which assumes that the bank collects deposits to transform them, using labor and capital, in loans. We employed three inputs (labor, capital and deposits), and two outputs (loans and net interest income). We measure labor by the total personnel costs (PC) covering wages and all associated expenses, capital by fixed assets (FA), and deposits by the sum of demand and time deposits from customers, interbank deposits and sources obtained by bonds issued (TD). Loans are measured by the net value of loans to customers and other financial institutions (TL) and net interest income as the difference between interest incomes and interest expenses (NII). Descriptive statistics of inputs and outputs are in Tab. I.

EMPIRICAL ANALYSIS AND RESULTS

DEA can be used to estimate efficiency under the assumptions of constant and variable returns to scale. For empirical analysis we use EMS 1.3.0 software (Efficiency measurement system) created by Holger Scheel. The DEA method is suitable in the banking sector because it can easily handle multiple inputs-outputs producers such as banks and it does not require the specification of an explicit functional form for the production frontier or an explicit statistical distribution for the inefficiency terms unlike the econometric methods (Singh *et al.*, 2008).

The banking efficiency have been estimated using the DEA models, input-oriented model with constant returns to scale and input-oriented model with variable returns to scale. The reason for the using of 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, in practice it is impossible to fill, so in order to solve this problem we calculate also with variable returns of scale.

The results of the DEA efficiency scores based on constant returns to scale (CCR model) are presented in Tab. II. Volksbank CZ is considered to be efficient with the efficiency scores of 100%, implying that it had produced its output on the efficiency frontier in most analyzed years. HVB bank has the efficiency scores of 100% in 2001–2004 and it has the efficiency score over 89% in the years 2005–2006. Dresdner

I: *Descriptive statistics of inputs and outputs (in CZK mln)*

	TD	PC	FA	TL	NII
Mean	122 545	1 765	3 009	77 901	4 689
Median	41 411	544	442	29 827	1 230
Min	333	20	9	107	33
Max	568 199	8 525	17 532	422 468	28 332
Std. Dev.	163 230,9	2 339,35	5 014,36	96 981,29	6 528,981

Source: Authors' calculations

II: *Efficiency estimation of Czech banks in CCR model (in %)*

bank	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
CSOB	65	54	54	58	36	38	37	36	33	33	44
CS	61	64	68	77	63	60	64	67	69	67	66
KB	62	52	49	53	50	50	48	58	58	62	54
UNIC							81	81	70	100	83
HVB	100	100	100	100	99	89					98
ZIBA	50	57	60	72	74	70					64
GEM	36	78	89	100	100	100	100	100	82	78	86
RB	93	81	73	97	100	100	91	88	100	84	91
IC		69	66	100	88	80					81
POPO							95	87	100	47	82
JTB	64	77	54	71	83	77	81	79	100	100	79
DRESD	100	100	100								100
BAWA				63	61	64	82				67
LBBW								76	63	78	72
PMB	83	66									74
PPF			73	86	85	95	96	100	100	100	92
VOLKS	100	100	100	100	100	98	100	100	92	100	99
CITI	100	78	85	100	100	100	100				95
EBAN	21	9	40	62	60	49	44				41
Mean	72	70	72	81	79	76	78	79	79	77	

Source: Authors' calculations

Bank has the efficiency score of 100% in 2001–2003. Citibank has the efficiency score of 100% in 2001 and 2004–2007 and the average efficiency of the Citibank is 95%. In 2001 and 2005–2006, Raiffeisenbank has the efficiency score of 100% and in other years the efficiency score was over 70%. The efficiency of PPF bank increase over the analyzed period and PPF bank has reached the efficiency score of 100% in 2008–2010.

The average efficiency of GE Money bank is 86%, the average efficiency of UniCredit bank is 83%, the average efficiency score of Banco Popolare is 82% and the average efficiency of JT bank is 79 %, so that these banks could be considered to be efficient. ČSOB bank and eBanka have the average efficiency score less than 50%. Generally, we can conclude that the largest banks in the market appeared to be least efficient. Considerable inefficiency was also revealed in mid-sized banks that are building up the market position and using aggressive business strategies.

Tab. III reports efficiency scores obtained relative considering variable returns to scale (BCR model) for each year. PPF bank, HVB bank, UniCredit bank, Dresdner bank, IC bank and Banco Popolare are considered to be fully efficient with the efficiency scores of 100% over all analyzed years. Česká spořitelna has the efficiency score of 100% in 2002–2010 and Volskbank CZ has the efficiency score of 100% in most of analyzed years. Komerční banka, Raiffeisenbank, PPF bank, Citibank, GE Money bank were efficient over the whole period. Efficiency scores of almost all large banks improve when the assumption of variable returns of scale built in BCC model is used. However, there is one and surprising exemption, which is ČSOB. The efficiency score of ČSOB decrease over the period. This development is opposite to development of other large banks as well as efficiency change in the whole banking sector.

Persistently low efficiency of ČSOB (largest bank in the Czech Republic) is one the most striking and surprising findings of this paper. It is worth to mention that low efficiency does not necessarily mean fragile financial situation of the bank or bankruptcy thread. We should remind that having robust and reliable estimation results requires appropriate number of inputs and outputs involved in the estimation in relation to the number of banks in dataset. The fact that the Czech banking sector is relatively small and consisted of limited number of banks automatically restricts comprehensiveness of the model. Three inputs and two outputs cannot capture the banking business completely and, hence, the efficiency scores obtained may not be absolutely optimal. Nevertheless, one can observe a dynamic accumulation of clients' deposits in the ČSOB's balance sheet over the period 2004–2007. This increase on the inputs' side was not accompanied by a similar increase of volume of loans disbursed. Furthermore, net interest income as the second output exhibits stagnation during the last four years.

III: *Efficiency estimation of Czech banks in BCR model (in %)*

bank	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
CSOB	100	100	100	79	69	62	63	55	50	33	71
CS	92	100	100	100	100	100	100	100	100	100	99
KB	93	89	76	71	98	100	100	100	100	100	93
UNIC							100	100	100	100	100
HVB	100	100	100	100	100	100					100
ZIBA	57	62	64	73	74	70					67
GEM	38	83	100	100	100	100	100	100	87	81	89
RB	94	82	73	97	100	100	100	100	100	93	94
IC		100	100	100	100	100					100
POPO							100	100	100	100	100
JTB	100	81	56	71	83	78	81	80	100	100	83
DRESD	100	100	100								100
BAWA				63	62	64	82				68
LBBW								77	74	83	78
PMB	100	100									100
PPF			100	100	100	100	100	100	100	100	100
VOLKS	100	100	100	100	100	98	100	100	93	100	99
CITI	100	78	87	100	100	100	100				95
EBAN	50	10	41	63	61	50	45				46
Mean	86	85	85	87	89	87	90	92	91	90	

Source: Authors' calculations

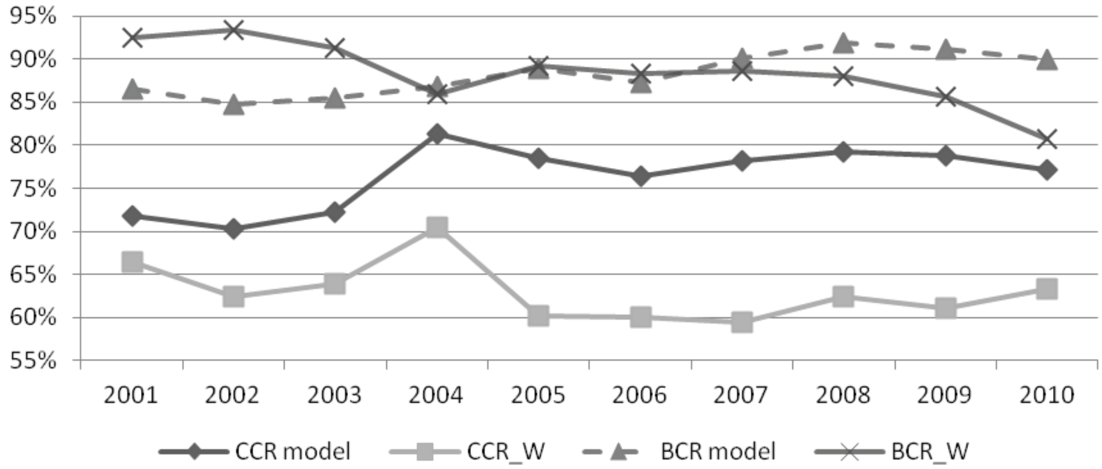
IV: *Average efficiency of banks' groups (in %)*

CCR model											
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
Large banks	62	67	68	72	62	59	58	60	57	65	63
Medium-sized banks	80	79	85	89	89	89	97	94	91	81	87
Small banks	67	64	58	80	79	75	83	88	91	85	77
BCR model											
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
Large banks	95	97	94	87	92	90	91	89	87	83	91
Medium-sized banks	81	81	87	89	89	89	100	100	93	87	90
Small banks	88	78	74	83	86	82	85	91	93	97	86

Source: Authors' calculations

One of the advantages of DEA is that the model identifies sources of lower efficiency. In the Czech banking industry, the main source of inefficiency is the excess of client deposits managed by banks. To a lesser degree, low weight in calculation process was often assigned to net interest income. The excess of deposits reflected negatively to net interest income by increasing interest costs of banks. The models also warn that the reason of lower efficiency of largest banks and ČSOB in particular is persistently low utilization of fixed assets. Banks hold excessive fixed assets mainly in the form of buildings, which also increases on operational risk (Rippel and Teplý, 2011). Because the estimates of the efficiency consist of three inputs, it indicates a tendency to minimize the impact of fixed assets to estimate efficiency.

Next, we calculate average efficiency scores derived from both models for three groups of banks classified according to volume of total assets. We adopt the categorization system applied by the Czech National Bank and on distinguish between large, medium-sized and small banks. Under the assumption of CRS small banks experienced the largest improvement of average efficiency. On the other hand, the group of large banks exhibits very stable development of average efficiency with only minor changes. Negative effect of financial crisis is evident mainly in the group of medium-sized banks.



1: *Average efficiency score for the Czech banking sector*

In terms of BCR model that allows for VRS, the average efficiency scores look quite different. First, large banks seem to be frequently most efficient due to elimination of scale inefficiency. Second, one can observe a worsening of average efficiency during the financial crisis in the group of large and medium-sized banks. Obtaining inverse or substantially different results by using both model specifications is an interesting common finding for many studies of efficiency in banking sector. While smaller banks usually occupy the efficiency frontier in the CCR model under VRS assumption the efficient frontier banks are generally much larger. All large banks included in our analysis become more efficient in conditions of non-increasing returns to scale. It indicates that these banks have chosen inappropriate scale of operation and simply use too many inputs or produce too few outputs.

Fig. I presents the results the average score of efficiency using the CCR model and the BCR model in the period 2001–2010. The development of average efficiency was almost constant in the period 2001–2010. During the period 2001–2010, the average efficiency computed using the constant returns to scale (CCR model) ranges from 70 to 81% and the average efficiency computed using the variable returns to scale (BCR model) ranges from 85% to 92%. It shows that the Czech banks are in average considered to be highly efficient with only marginal changes over time. The development trend of the efficiency is similar in both models. We can see a phase of increasing efficiency in the period 2002–2005 that followed a wave of privatization, consolidation and restructuring in the banking sector. After a temporary worsening of efficiency in 2006, the trend of efficiency improvement continued until 2008. Then, we can observe a deterioration that can be attributed to worsened conditions in banking sector due to financial crisis.

We incorporate the effect of a bank's size also to Fig. I and present development of weighted average efficiency for both models (CCR_W and BCR_W). Volume of total assets served as basis for weights used in calculation. Fig. I gives evidence that size matters mainly in the CCR model. When considering weighted average we come to opposite conclusion on total change of average efficiency between 2001 and 2010 than the ordinary average indicates. Whereas the ordinary averages point to slight improvement of efficiency the weighted averages show deterioration.

SUMMARY

The aim of the paper was to estimate the level of the efficiency in the Czech banking sector during the period 2001–2010. For this purpose, this paper uses two basic Data Envelopment Analysis models, particularly the CCR and BCR model

The efficiency scores from the BCR model reach higher values than efficiency scores from the CCR model by eliminating the part of the inefficiency that is caused by an inappropriate size of production units. Dresdner bank has the efficiency score of 100 % over the whole estimated period in the CCR model and next five banks (HVB, Raiffeisenbank, PPF bank, Volksbank CZ and Citibank) had the average efficiency score over 90% during the entire estimated period. ČSOB and eBanka has the average efficiency score under 50% in the CCR model. In the BCR model, six Czech banks (UniCredit bank, HVB bank, IC bank, Banco Popolare, Dresdner bank and PPF bank) have the efficiency score of 100%. Five more banks (Česká spořitelna, Komerční banka, Raiffeisenbank, Volksbank CZ, and Citibank) had the average efficiency score over 90%. DEA model indicates that the reasons of lower

efficiency are the excess of client deposits managed by banks that has also negative implications on net interest income and persistently low efficiency of utilization of fixed assets in the case of large banks.

We revealed that size of a bank is a key factor that should be taken into account in calculation as well as interpretation of results. Large banks appear to be inefficient under the assumption of constant and non-decreasing returns to scale. By contrast, if we allow for non-increasing returns to scale efficiency of large banks increases substantially. The lowest differences between efficiency scores obtained from alternative specifications of the DEA model were found for medium-sized banks. This implies that they perform at almost optimal scale of operation.

The average efficiency in the Czech banking sector remained nearly unchanged during the period of estimation. While ordinary average efficiency scores indicate a negligible increase the weighted averages point to deterioration of average efficiency. Most of the computed average efficiency scores exhibit negative effect of financial crisis, particularly in year 2009 and 2010.

Acknowledgement

Research behind this paper was supported by the Student Grant Competition of Silesian University within the project SGS/25/2010 'Financial integration in the EU and its effect on corporate sector'.

REFERENCES

BANKER, R. D., CHARNES, A., COOPER, W. W., 1984: Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, Vol. 30, No. 9, 1078–1092. ISSN 1526-5501.

FARRELL, M. J., 1957: The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society (Series A)*, Vol. 120, No. 2, 253–281. ISSN 0964-1998.

FAVERO, C. A., PAPI, L., 1995: Technical Efficiency and Scale Efficiency in the Italian Banking Sector: A non-parametric Approach. *Applied Economics*, Vol. 27, No. 3, 385–395. ISSN 1466-4283.

FRIES, S., TACI, A., 2005: Cost Efficiency of Banks in Transition: Evidence from 289 Banks in 15 Post-communist Countries. *Journal of Banking and Finance*, Vol. 29, No. 1, 55–81. ISSN 0378-4266.

FRIED, H. O., LOVELL, C. A. K., 1994: Enhancing the Performance of Credit Unions: The Evolution of a Methodology. *Recherches Economiques de Louvain*, Vol. 60, No. 4, 421–447. ISSN 0770-4518.

CHARNES A., COOPER, W. W., LEWIN, A. Y., SEIFORD L. M., 1995: *Data Envelopment Analysis: Theory, Methodology and Applications*. New York: Springer-Verlag, 513 p. ISBN 9780792394808.

CHARNES, A., COOPER, W. W., RHODES, E., 1978: Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, Vol. 2, 429–444. ISSN 0377-2217.

LOVELL, C. A. K., 1993: Production Frontiers and Productive Efficiency. In: FRIED, H., LOVELL, C. A. K., SCHMIDT, S. (ed.) *The Measurement of Productive Efficiency: Techniques and Applications*, London: Oxford University Press. ISBN 978–0195072181.

KAMECKA, M., 2010: *Bank efficiency in CEE*. Doctoral thesis, WU Vienna University of Economics and Business, 165 p.

MATOUŠEK, R., TACI, A., 2005: Efficiency in Banking: Empirical Evidence from the Czech Republic. *Economic Change and Restructuring*, Vol. 37, No. 3, 225–244. ISSN 1573-9414.

POGHOSYAN, T., BOROVIČKA, J., 2007: Banking Efficiency in Emerging Economies: The Impact of Ownership Endogeneity and EU Accession, CERGE-EI Discussion Paper No. 2007-189, 1–39.

RIPPEL, M., TEPLÝ, P., 2011: Operational risk – scenario analysis. *Prague Economic Papers*, Vol. 20, No. 1, 23–29. ISSN 1210-0455.

SATHYE, M., 2003: Efficiency of banks in a developing economy: The case of India. *European Journal of Operational Research*, Vol. 148, No. 3, 662–671. ISSN 0377-2217.

SEALEY, C. W., LINDLEY, J. T., 1977: Inputs, Outputs and a Theory of Production and Cost at Depository Financial Institutions. *Journal of Finance*, Vol. 32, No. 8, 1251–1266. ISSN 1540-6261.

SEIFORD, L. M., THRALL, R. M., 1990: Recent developments in DEA: the mathematical programming approach to frontier analysis. *Journal of Econometrics*, Vol. 46, 7–38. ISSN 0304-4076.

SHERMAN, D. H., GOLD, F., 1985: Bank Branch Operating Efficiency: Evaluation with Data Envelopment Analysis. *Journal of Banking and Finance*, Vol. 9, No. 3, 297–315. ISSN 0378-4266.

SINGH, G., SINGH, P., MUNISAMY, S., 2008: A Cross Country Comparison of Banking Efficiency: Asia Pacific Banks. International Review of Business Research Papers, Vol. 4, No. 3, 73–95. ISSN 1832-9543.

STAVÁREK, D., 2005: *Restrukturalizace bankovních sektorů a efektivnost bank v zemích Visegrádské skupiny.* Karviná: SU OPF, 156 p. ISBN 80-7248-319-6.

STAVÁREK, D., POLOUČEK, S., 2004: Efficiency and Profitability in the Banking Sector. In: POLOUČEK, S. (ed.) *Reforming the Financial Sector in Central European Countries*. Hampshire: Palgrave Macmillan Publishers, 74–135. ISBN 1-4039-1546-6.

STANĚK, R., 2010: Efektivnost českého bankovního sektoru v letech 2000–2009. In: *Konkurenceschopnost*

a stabilita. 1. ed. Brno: Masarykova univerzita, 81–89. ISBN 978-80-210-5336-6.
SUFIAN, F., 2007: The Efficiency of Islamic Banking Industry: a non-parametric analysis with non-discretionary input variable. *Islamic Economic Studies*, Vol. 14, No. 1–2, 53–78. ISSN 1319-1616.
TACI, A., ZAMPIERI, E., 1998: Efficiency in the Czech Banking Sector. *CERGE-EI Discussion Paper 4*. Prague: CERGE-EI.
WEILL, L., 2003: Banking efficiency in transition economies: The role of foreign ownership. *Economics of Transition*, Vol. 11, 569–592. ISSN 0967-0750.

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