Measuring the efficiency in the Czech banking industry: Data Envelopment Analysis and Malmquist index

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Abstract. This paper estimates the technical efficiency and the efficiency change in the Czech commercial banks during the period 2001–2010. We applied the Data Envelopment Analysis and the Malmquist index on the data of the Czech banks. We simultaneously use two alternative specifications of DEA approach, specifically CCR model and BCC model that differ in returns to scale assumption. The results of DEA models show that the average efficiency computed under the assumption of constant returns to scale ranges from 49 to 85 % and the average efficiency estimated under the assumption of variable returns to scale ranges from 71 to 87 %. The results of the Malmquist index reached an annual average negative growth of -4.7%. This negative change can be dichotomized into efficiency change and technological change. Technological change reached an average annual negative growth of -5.6% and technical efficiency change improved average by 1%.

Keywords: efficiency, Data Envelopment Analysis, Malmquist index, Czech banking sector.

JEL Classification: G21, C58
AMS Classification: 62P20

1 Introduction

The two general approaches used to assess efficiency of an entity, parametric and non-parametric 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 and Free Disposal Hull, 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 observed in the data. The parametric methods most widely used in empirical estimations are Stochastic Frontier Approach, Distribution Free Approach and Thick Frontier Approach, which assume specific functional form for the cost function or production technology.

The aim of this paper is to estimate the technical efficiency and the efficiency change in the Czech commercial banks during the period 2001–2010. For the estimation we applied the Data Envelopment Analysis (DEA) and Malmquist index (MI) on the data of the Czech banks. The MI is determined in order to investigate the levels of and the changes in the efficiency of the Czech banks over the analyzed period. 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. We simultaneously use two alternative specifications of DEA approach, specifically CCR model and BCC model that differ in returns to scale assumption. The structure of the paper is follow. Next section presents methodology and data, the Data Envelopment Analysis and the Malmquist index and selection of variables are described. Section 3 reveals and discusses the estimated results and Section 4 concludes the paper with summary of key findings.

2 Methodology and data

2.1 Data Envelopment Analysis

The Data Envelopment Analysis is a mathematical programming technique that measures the efficiency of a decision-making unit relative to other similar DMUs with the simple restriction that all DMUs lie on or below the efficiency frontier [9]. DEA also identifies, for inefficient DMUs, the sources and level of inefficiency for each of the inputs and outputs [4].

The CCR [3] 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

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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. [1] extended the CCR model by relaxing the CRS assumption. The resulting BCC [1] 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 (SE) effects. If there appears to be a difference between the technical efficiency (TE) and PTE scores of a particular DMU, then it indicates the existence to scale inefficiency [11].

DEA begins with a fractional programming formulation. Assume that there are n DMUs to be evaluated. $\mathrm{DMU_j}$ consumes x_{ij} amounts of input to produce y_{rj} amounts of output. It is assumed that these inputs, x_{ij}, and outputs, y_{rj}, are non-negative, and each DMU has at least one positive input and output value. The productivity of a DMU can be written as:

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

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 is the ratio of the total weighted output divided by the total weighted input:

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

subject to

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

$$u_r \ge 0, r = 1,2, \dots, s,$$

$$v_i \ge 0, i = 1,2, \dots, m,$$

where h_0 is the technical efficiency of $\mathrm{DMU_0}$ 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 $\mathrm{DMU_s}$.

2.2 Malmquist index

The Malmquist index [8] evaluates efficiency change over time. The MI, based on DEA models, is one of the prominent indexes for measuring the relative productivity change of DMUs in multiple time periods. This index breaks down into various components. The index provides a useful way of distinguishing between changes in technical efficiency, pure technical efficiency, scale, total factor productivity (TFPC) and shifts in the efficiency frontier (technological change) over time. This index is the geometric mean of two TFPC indices, one evaluated with respect to the technology (efficiency frontier) in the current period t and the other with respect to the technology in the base period s [5]. One extension with DEA is to apply MI to panel data to estimate changes in technical efficiency, technological progress and total factor productivity.

The original idea of the MI was proposed by [8] 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. [2] extended the original Malmquist input index and introduced the first type of the Malmquist index, and then [6] showed that the Malmquist index can be calculated using a nonparametric DEA-like approach, given that suitable panel data are available and they applied DEA for measuring the Malmquist index. They assumed constant returns to scale and identified the technological change and the change of technical efficiency as two components of the productivity changes over time. Next, [7] considered variable return to scale and offered an extended decomposition of the Malmquist index with another important factor capturing change in scale efficiency.

Following [7] we use DEA to construct an input based MI between period t (the base period) and period s:

$$M_I(y^s, x^s, y^t, x^t) = \left[\frac{D_I^t(y^s, x^s)}{D_I^t(y^t, x^t)} x \frac{D_I^s(y^s, x^s)}{D_I^s(y^t, x^t)}\right]^{\frac{1}{2}},$$

where $M_I(\cdot)$ is the input-oriented MI, $D_I^t(y^s, x^s)$ is the distance function showing a maximal proportional reduction of the observed period *s* inputs under the period *t* technology. The distance function is defined as follows:

$D_I^t(y^s, x^s) = \min_{\theta,\lambda} \theta$

subject to

$$y_{is} \leq \lambda Y^t$$

$$\theta x_{is} \geq \lambda X^t$$

$$\lambda_i \geq 0, i = 1, \dots n$$

where θ is a scalar and λ is a vector of constants. The value of θ obtained is the component score of the *i*-th firm. *X* and *Y* are input and output vectors, and the amounts of the i^{th} input consumed and output generated by the DMU_0, are denoted by *x* and *y*.

2.3 Data and selection of variables

The data set used in this study was obtained from the annual reports of commercial banks during the period 2001–2010 and all the data is reported on unconsolidated basis. We analyzed 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.

In order to conduct the 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 (intermediation, production, asset and profit approach). We adopt intermediation approach which assumes that the banks' main aim is to transform liabilities (deposits) into loans (assets). Consistently with this approach, we assume that banks use the two inputs. The bank collects 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 as the difference between interest incomes and interest expenses.

3 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 DEAP 2.1 software (A Data Envelopment Analysis Computer Program), which was written by Tim Coelli. 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 [10]. 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 are presented in Table 1. Dresdner Bank has the efficiency score of 100% in 2001–2003 and then BAWAG has the average efficiency score 84%. Volksbank, GE Money Bank and JT bank are 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 has the efficiency scores of 100% in 2002, 2004 and 2006. IC bank has the average efficiency 97% and Banco Popolare has the average efficiency 96%. eBanka, ČSOB, Česká spořitelna and Komerční banka have the average efficiency score less than 50%.

It can be concluded 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. One of the advantages of DEA is that the model identifies sources of lower efficiency. In the Czech banking sector, 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.

DMU	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
CSOB	0.70	0.28	0.79	0.40	0.68	0.02	0.41	0.29	0.01	0.08	0.37
CS	0.38	0.07	0.83	0.74	0.44	0.31	0.22	0.22	0.16	0.22	0.36
KB	0.23	0.17	0.94	0.32	0.18	0.12	0.08	0.36	0.32	0.23	0.29
HVB	0.87	1.00	0.99	1.00	0.85	1.00					0.95
UNIC							0.73	0.88	0.76	0.28	0.66
ZIBA	0.63	0.68	0.67	0.75	0.79	0.90					0.73
GEM	0.75	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.87	0.28	0.89
RB	0.76	0.72	0.67	0.86	0.75	0.88	0.88	0.82	1.00	0.42	0.78
IC	1.00	1.00	0.95	1.00	0.95	0.92					0.97
POPO							0.95	0.89	1.00	1.00	0.96
JTB	0.66	0.85	1.00	1.00	1.00	1.00	0.89	0.92	1.00	0.78	0.91
DRESD	1.00	1.00	1.00								1.00
BAWA				0.65	0.71	1.00	1.00				0.84
LBBW								1.00	1.00	0.64	0.88
PMB	0.83	0.95									0.89
PPF			0.93	0.94	0.58	0.64	1.00	1.00	0.55	1.00	0.83
VOLKS	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.55	0.48	0.90
CITI	1.00	0.73	0.75	0.63	0.53	0.43	0.37				0.63
EBAN	0.30	0.20	0.43	0.63	0.61	0.50	0.44				0.44
Mean	0.72	0.69	0.85	0.78	0.72	0.69	0.69	0.76	0.66	0.49	

Table 1 Efficiency of the Czech banks in CCR model

Table 2 reports efficiency scores obtained relative considering variable returns to scale for each year. HVB bank, IC bank, Banco Popolare and Dresdner bank and then LBBW bank have efficiency score of 100% in all analyzed years. UniCredit bank, GE Money Bank, Raiffeisenbank, JT Bank, BAWAG bank and Volksbank are considered to be fully efficient with the efficiency scores of 100% over all analyzed years. Česká spořitelna and Komerční banka have the efficiency score of 100% in 2010. ČSOB, Česká spořitelna, Komerční banka and eBanka have the average efficiency score less than 50%. Efficiency scores of almost all large banks improve when the assumption of variable returns of scale built in BCC model is used.

DMU	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
CSOB	1.00	0.34	0.79	0.41	0.68	0.03	0.42	0.38	0.05	0.09	0.42
CS	0.55	0.08	0.83	0.76	0.45	0.33	0.24	0.28	0.18	1.00	0.47
KB	0.29	0.17	0.94	0.34	0.20	0.14	1.00	0.44	0.42	1.00	0.49
HVB	1.00	1.00	1.00	1.00	1.00	1.00					1.00
UNIC							1.00	1.00	1.00	0.31	0.83
ZIBA	0.67	0.68	0.67	0.76	0.86	0.92					0.76
GEM	0.75	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.33	0.91
RB	0.91	0.82	0.73	0.91	0.85	0.91	1.00	0.96	1.00	0.82	0.89
IC	1.00	1.00	1.00	1.00	1.00	1.00					1.00
POPO							1.00	1.00	1.00	1.00	1.00
JTB	0.72	1.00	1.00	1.00	1.00	1.00	0.93	0.93	1.00	0.84	0.94
DRESD	1.00	1.00	1.00								1.00
BAWA				0.65	0.75	1.00	1.00				0.85
LBBW								1.00	1.00	1.00	1.00
PMB	0.95	1.00									0.97
PPF			0.97	0.95	0.60	0.65	1.00	1.00	0.59	1.00	0.84
VOLKS	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.91	0.72	0.96
CITI	1.00	0.79	0.80	0.64	0.55	0.43	0.39				0.66
EBAN	0.44	0.22	0.44	0.63	0.61	0.50	0.44				0.47
Mean	0.81	0.72	0.87	0.79	0.75	0.71	0.80	0.82	0.74	0.74	

Table 2 Efficiency of the Czech banks in BCC model

In the Czech banking sector, there are several common features, which are valid over the whole analyzed period. The DEA model indicates that the reason of lower efficiency in the Czech banking industry is persistently low efficiency of utilization of fixed assets. Banks hold excessive fixed assets mainly in the form of buildings. Generally, during the period 2001–2010, the average efficiency calculated using the CRS ranges from 49 to 85% and the average efficiency computed using the VRS ranges from 71 to 87%. It shows that the Czech banks are in average considered to be efficient with only marginal changes over time.

The results of the CCR model and the BCC model show that the model with VRS achieves higher degree of the efficiency than the model with the CRS. Number of efficient banks is higher in the model with VRS. [11] argued this is because the BCC model decomposes inefficiency of production units into two components: the pure technical inefficiency and the inefficiency to scale. The values of efficiency computed by the BCC model reach higher values than efficiency computed by the CCR model by eliminating the part of the inefficiency that is caused by a lack of size of production units.

The large volume of information derived from DEA may be difficult to summarize and evaluate. Therefore, it is often helpful to break down the information using the Malmquist index. We calculate MI from the DEA scores between adjacent periods. The application of the MI is also conducted in DEAP 2.1 software. The Malmquist change indices are computed using DEA. The indices measure TFPC for sampled banks in adjacent year during the period of 2001/2002 and 2009/2010. Its decomposition into technical efficiency change (TEC), technological change (TCC), pure technical efficiency change (PTEC) and scale efficiency change (SEC) components are also derived. The VRS or CRS option has no influence on the MI because both are used to calculate the various distances used to construct the Malmquist indices.

One important point is that the calculation of the Malmquist TFPC index requires strictly balanced panel data. That means all DMUs must be observed in all time periods. But this study has an unbalanced panel. One way of dealing with the unbalanced panel data is to find out as many DMUs as possible that are observed in the longest common periods. This method has been the most commonly used by many researchers, but it has one existing shortcoming of this method – greatly reducing the research sample size. We use panel data of 11 Czech banks (with regard to mergers and acquisitions of banks). Table 3 presents the results of the average Malmquist indices in the analyzed period.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
TEC	0.763	0.757	1.664	1.089	0.973	0.995	0.956	0.976	1.154	1.01
TCC	1.142	2.902	0.509	0.77	0.963	0.998	1.057	0.923	0.745	0.944
PTEC	0.91	0.995	1.049	0.982	0.971	1.007	0.989	0.99	1.084	0.997
SEC	0.839	0.761	1.586	1.109	1.002	0.988	0.967	0.986	1.064	1.013
TFPC	0.872	1.439	0.847	0.839	0.937	0.993	1.011	0.901	0.859	0.953

Table 3 Malmquist index of the sample banks

The average efficiency change reaches the -4.7 %. This negative efficiency change can be dichotomized into its catch-up and frontier-shift components. The mean value of TEC (catch-up or recovery component) registered 1.01, or under 1.00 indicating progress or positive efficiency change. The catch-up effect is comprised of pure and scale efficiency changes. Pure efficiency change represents core efficiency due to improved operations and management while scale efficiency change is associated with returns to scale effects. PTEC reached below 1 on average for the period suggesting regress in terms of operations and management, and SEC reached value under 1 showing the positive scale economies effects. Technological change or frontier-shift represents the innovation in the banking system that has been developed, adapted or absorbed by the players. Technological change is average 0.944. The results of the Malmquist index reached an annual average negative growth of -4.7%. This negative change can be dichotomized into efficiency change and technological change. Technological change reached an average annual negative growth of -5.6% and technical efficiency change improved average by 1%.

	CSOB	CS	KB	UNIC	GEM	RB	POPO	JTB	LBBW	PPF	VOLKS
TEC	1.024	1.031	1.027	1.034	1.01	1.016	1	1	0.992	1	0.976
TCC	0.91	0.991	0.888	0.95	0.964	0.937	0.929	1.042	0.933	0.929	0.918
PTEC	1	0.99	0.973	1.016	1	1	1	1	0.984	1	1
SEC	1.024	1.041	1.056	1.017	1.01	1.016	1	1	1.009	1	0.976
TFPC	0.932	1.021	0.912	0.982	0.974	0.952	0.929	1.042	0.926	0.929	0.896

Table 4 Malmquist index of the individual banks

The individual banks' Malmquist indices are given in Table 4. The average efficiency change achieved the negative growth in most banks (besides Česká spořitelna and JT banka) indicating that analyzed banks registered negative efficiency growth in the Czech banks. We decomposed the efficiency change into the catch-up and frontier-shift effects and found that the catch-up effect was primarily accountable for the productivity growth rather than the frontier-shift effect, suggesting that the industry has lacked innovation or technological progress in the past 10 years. Technological efficiency change register below 1.00 in all analyzed banks. It means that technology has a negative effect on the total efficiency change. The values of catch-up registered values under 1.00 in most banks (besides LBBW), which indicate the progress or positive efficiency change. PTEC and SEC reached values under 1 in the most Czech banks, which suggest progress in terms of operations and management, and positive scale economies effects.

4 Conclusion

The aim of this paper was to estimate the technical efficiency and the efficiency change in the Czech commercial banks during the period 2001–2010. For the estimation we applied the Data Envelopment Analysis and the Malmquist index on the data of the Czech banks. In the paper it was found that the average efficiency computed under the assumption of constant returns to scale ranges from 49 to 85 % and the average efficiency estimated under the assumption of variable returns to scale ranges from 71 to 87 %. We found that the efficiency scores from the BCC model reached 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. Large banks in the market appeared to be inefficient. In the Czech banking sector, the main source of inefficiency is the excess of client deposits managed by banks. The results of the Malmquist index reached an annual average negative growth of -4.7%. It was found that the catch-up effect was primarily accountable for the productivity growth rather than the frontier-shift effect, suggesting that the industry has lacked innovation or technological progress in the past 10 years. The average efficiency change achieved the negative growth in most banks (besides Česká spořitelna and JT banka). This negative change can be dichotomized into efficiency change and technological change. Technological change reached an average annual negative growth of -5.6% and technical efficiency change improved average by 1%.

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