BANKING EFFICIENCY IN VISEGRAD COUNTRIES: A DYNAMIC DATA ENVELOPMENT ANALYSIS

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Abstract


The aim of the paper is to examine the efficiency of the banking sectors in Visegrad countries during the period 2009–2013. The group of Visegrad countries includes the Czech Republic, Hungary, Poland and Slovakia. We apply Dynamic Data Envelopment Analysis (DEA) to data on commercial banks in the group of Visegrad countries. Next, we calculated average efficiency of the groups of banks according the total assets. Average efficiency was slightly decreased during the period 2010–2011 and significantly decreased in 2012 which was probably as a result of financial crisis. In 2013 average efficiency increased. The Czech and Hungarian banking sector was the highest efficient. Considering the group of banks according total assets, the group of small banks was the most efficient in CCR model and the group of medium-sized banks was the most efficient in BCC model.

Keywords: banking sector, commercial banks, Dynamic Data Envelopment Analysis, efficiency, Visegrad countries, constant return to scale, variable return to scale

INTRODUCTION

The aim of the paper is to examine efficiency of the banking sectors in Visegrad countries during the period 2009–2013. The group of Visegrad countries (V4) includes the Czech Republic, Hungary, Poland and Slovakia. In order to achieve this aim, we apply Dynamic Data Envelopment Analysis (DEA) to data from commercial banks. We also estimated average efficiency of the groups of banks according the total assets. 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. Each DMU has carry-over variables that take into account a positive or negative factor in the previous period.

In empirical analysis there is a lack of studies in banking sectors examining efficiency using the Dynamic DEA, which creates an opportunity for this research. According to the author’s awareness, in empirical literature exists only a few studies which applied the Dynamic DEA on the banking sector. Řepková (2013a) estimated the Czech banking sector using the Dynamic DEA and Shafiee et al. (2013) examined the Iranian banking industry using dynamic slacks-based measure model in DEA. The motivation of this paper is to apply the Dynamic DEA analysis approach on the data of commercial banks in V4 and this paper could fill the gap in empirical literature.

The structure of the paper is following. First literature review and theoretical background of banking efficiency will be described. Next section will present the methodology and dataset used in the empirical part of the paper. Next section presents the estimated results and last section concludes the paper.

Literature Review

Several empirical analyses of the efficiency of the Visegrad countries’ banking sectors exist and we refer to some of them. Some empirical studies e.g. Kosak and Zajc (2006), Bems and Sorsa...
(2008), Matoušek (2008), Mamatzakis et al. (2008)
Koutsomanoli-Filippaki et al. (2009), Barunik and
Sotáš (2010) or Brissimis et al. (2010) examined
the banking efficiency in several European countries
and the Czech, Slovak, Polish and Hungarian
banking sectors were included in panel data.
Stavárek and Polouček (2004) found that the Czech
and Hungarian banking sectors were on average
evaluated as the most efficient. Anayiotos et al.
(2010) found the significant decreased in efficiency
in emerging European countries during financial
crisis. Tsionas et al. (2015) estimated the efficiency
of European banks during the pre-crisis and post-
crisis periods, Stavárek (2005) estimated commercial
bank efficiency in the group of Visegrad countries
before joining the EU and concluded that the Czech
banking sector is the most efficient, followed by
the Hungarian with a marginal gap. Also Melecký
and Staněk (2010) estimated banking efficiency
of Visegrad region and evaluated the banking sector
of the Czech Republic as highly efficient.
Weill (2003) found a positive influence of foreign
ownership on the cost efficiency of banks in
the Czech Republic and Poland. Erina and Erins
(2013) evaluate cost-benefit efficiency of the banks
of seven CEE states (the Czech Republic, Hungary,
Latvia, Lithuania, Poland, Slovakia, Slovenia) in
estimated banking efficiency in five countries of
Central and Eastern Europe.
Stanek (2010) found that the efficiency of the
Czech banking sector has improved. Stavárek
and Repková (2012) found that efficiency increased
Rossi et al. (2005) examined that banking systems
of Slovakia showed significant levels of cost and profit
inefficiency. Vincová (2006) found that banking
inefficiency slightly decreased in Slovakia. Repková
(2013b) found that average cost and profit banking
efficiency decreased in Slovakia within the period
2003–2012. Also e.g. Stavárek and Sulganová (2009)
or Zimková (2014) examined efficiency of the Slovak
banking sector.
Hasan and Marton (2003) examined the cost and
profit inefficiency of Hungarian banking sector
within the period 1993–1998 and found that
banks with foreign involvement were found to be
significantly less inefficient than their domestic
counterparts. Among the foreign-involved
institutions, a higher share of foreign ownership was
associated with lower inefficiency.
Nikiel and Opiela (2002) estimated banking efficiency in Poland and found that foreign banks are more cost-, profit-, and operationally efficient than domestic or owned or domestic private banks. Large banks were more efficient than small banks in Poland. Havrylychyk (2006) found that banking efficiency has not improved in Poland during the analysed period. Wozniewska (2008) estimated efficiency of the Polish banking sector within the period 2000–2007.
The empirical literature review concluded
that only few studies examined the banking
sectors of Visegrad countries individually. Most
of the empirical studies research several banking
sector which included the group of Visegrad
countries 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. Banking
efficiency was estimated using the Stochastic
Frontier Approach or DEA model. There is a lack
of studies examining banking efficiency using
dynamic methods, which creates an opportunity
for this research.

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 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). The 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 outputs (Charnes et al., 1995).
The analysis is performed in only one time period,
hampering the measurement of efficiency changes
when there is more than one time period. Detailed
description of DEA model is presented in Stavárek
and Repková (2012).

Window analysis and the Malmquist index were
the first methods used to verify productivity change
over time. However, these models do not capture
the effect of carry-over activities (links) between
two consecutive time periods. The Dynamic DEA
model proposed by Fare and Grosskopf (1996) is
the first innovative system that formally addresses
the activities in different interconnected time
periods. Thus, Dynamic DEA is a new approach
which estimates 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 in the previous period.
This model has the huge advantage of being able to
evaluate the policy effect on the individual divisions
of each DMU (Kawaguchi et al., 2013).

The CCR (Charnes, Cooper and Rhodes, 1978)
model presupposes that there is no significant
relationship between the scale of operations
and efficiency by assuming constant returns to
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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. Banker at al. (1984) extended the CCR model by relaxing the CRS assumption. The resulting BCC (Banker, Charnes and Cooper, 1984) 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.

Tone and Tsutsui (2010) developed Fare and Grosskopf (1996) model into a slacks-based measure (SBM) framework. Tone and Tsutsui (2010) pointed out a concept of carry-over. In this paper we adopted the Dynamic DEA model proposed by Sengupta (1996) or Tone and Tsutsui (2010) and Tone (2001). Mathematical formulation of the Dynamic DEA was described e.g. by Sengupta (1996) or Lotfi and Poursakhi (2012). The Dynamic DEA model can easily be written as:

$$ \text{max} \, z(T-1) = \sum_{j=1}^{n} \sum_{t=1}^{T} w(t) \lambda_j(t), $$

subject to

$$ \sum_{j=1}^{n} A_{j}(t) \lambda_j(t) \leq X_i(t), $$

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

where $z$ is efficiency of DMU to be estimated, $\lambda_j$ is the output vector for each DMU, $X_i$ is current input, $A_{j}(t)$ is the corresponding input coefficient matrix, and $w(t)$ is a non-negative weight vector for the multiple outputs of each DMU, $j$ indicates the $n$ different DMU, and $t$ denotes time. 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 the radial approaches that assume proportional changes in inputs/outputs.

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 2009–2013. All the data is reported on unconsolidated basis. We analyzed only commercial banks that are operating as independent legal entities, because we need homogenous data set. One important point is that the calculation of the Dynamic DEA requires strictly balanced panel data. We use balanced panel data from 12 Czech commercial banks, 13 Hungarian commercial banks, 28 Polish commercial banks and 9 Slovak commercial banks.

For the definition of inputs and outputs, we adopted intermediation approach. This approach assumes that the banks’ main aim is to transform liabilities (deposits) into loans (assets). We employed three inputs (labor, fixed assets 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. Descriptive statistics of inputs and outputs are in Tab. I.

### 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 the Dynamic DEA model to estimate efficiency under the assumptions of constant and variable returns to scale. For empirical analysis we used MaxDEA software. One important point is that the calculation of the Dynamic DEA requires strictly balanced panel data. We use panel data of 12 Czech commercial banks, 13 Hungarian commercial banks, 28 Polish commercial banks and 9 Slovak commercial banks.

We divided banks into three groups of banks according total assets amount. We distinguish between small, medium-sized and large banks based on the amount of their total assets. Following Vodová (2012) we define large banks as banks with total assets greater than 6% of the total assets of the banking sector. Medium-sized banks have total assets of between 2% and 6% of total assets. Small banks are banks with total assets of less than 2% of the total assets of the banking sector.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Deposits</th>
<th>Labor</th>
<th>Fixed assets</th>
<th>Loans</th>
<th>NII</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>389443</td>
<td>6515</td>
<td>8211</td>
<td>315250</td>
<td>20534</td>
</tr>
<tr>
<td>Median</td>
<td>23978</td>
<td>391</td>
<td>193</td>
<td>19740</td>
<td>925</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.00</td>
<td>2.22</td>
<td>0.09</td>
<td>0.00</td>
<td>0.29</td>
</tr>
<tr>
<td>Maximum</td>
<td>7876341</td>
<td>204277</td>
<td>261523</td>
<td>7047179</td>
<td>656202</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>1092663</td>
<td>23278</td>
<td>33382</td>
<td>933918</td>
<td>81557</td>
</tr>
</tbody>
</table>

Source: author’s calculation
The results of the Dynamic DEA efficiency scores of the group of V4 are presented in Tab. II. We calculate the average efficiency score in CCR model and BCC model as well as average efficiency in group of small banks, medium-sized banks and large banks. Average efficiency calculated in assumption of CRS reach the value 51–68%. On the other hand, average efficiency with VRS was between 63 to 78%. The BCC model decomposes efficiency into two components: pure technical efficiency and efficiency 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. This situation may occur when a bank, which has been marked as ineffective in the CCR model due to its inaccurate size, will be marked as an efficient in the BCC model.

Comparing the group of banks we can state that the group of small banks in V4 was the most efficient in CCR model, but the lowest efficiency in BCC model. In BCC model the group of medium-sized banks reached the highest average efficiency.

Tab. III shows average efficiency scores of the Czech commercial banks. We estimated efficiency in CCR model and BCC model. In model with constant return to scale average efficiency reached the value between 50–72%. In BCC model average efficiency was 61–88%.

The highest value of average efficiency was registered in 2009 and then average efficiency was slightly decreasing. Average efficiency rapidly decreased in 2012. This decrease was probably as a result of financial crisis. The decrease in loans and net interest income were registered in the balance sheet of the most Czech commercial banks. In 2013 the average efficiency again increased. When we compare analysed group of banks, we can see that the group of medium-sized banks was the most efficient in CCR and BCC model. In BCC model, the most of medium-sized banks operated in 100% efficiency frontier besides year 2012.

Average efficiency of the Hungarian banking sector is presented in Tab. IV. The development of the Hungarian banking efficiency is similar as development in the Czech banking sector. Average efficiency decreased in 2011 and 2012 as a result of a financial crisis. In CCR model, the highest average efficiency was registered in the group of small banks within the period 2009–2010, since 2011 the highest efficient has been the group of large banks. In BCC model the most efficient was the group of medium-sized and large banks. Large banks attained the highest value of efficiency in BCC model. Thus large banks in the market are too large and have improperly chosen their size (range of operation).

In the Polish banking sector (Tab. V), average efficiency was increasing during the period 2009–2011. Banking efficiency decreased in 2012 and then

<table>
<thead>
<tr>
<th>II: Banking efficiency of Visegrad countries (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Return to scale</strong></td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Median</td>
</tr>
<tr>
<td>Min</td>
</tr>
<tr>
<td>Max</td>
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<tr>
<td>St. Dev.</td>
</tr>
<tr>
<td>Small banks</td>
</tr>
<tr>
<td>Medium-sized banks</td>
</tr>
<tr>
<td>Large banks</td>
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</tbody>
</table>

Source: author’s calculation

<table>
<thead>
<tr>
<th>III: Efficiency of the Czech banking sector (in %)</th>
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<tbody>
<tr>
<td><strong>Return to scale</strong></td>
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<tr>
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<td>Median</td>
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<td>Large banks</td>
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</table>

Source: author’s calculation
efficiency increased in 2013. Estimation of efficiency in the group of banks showed that the most efficient were small banks in CCR and BCC models. The group of large banks was the lowest efficient in both models.

Tab. VI presents average efficiency in the Slovak banking sector in CCR and BCC model. The development of average efficiency is similar as in other analyzed banking sectors. Average efficiency was increasing within the period 2009–2011. Decreased of average efficiency in 2012 was probably caused by a financial crisis. In 2013 average efficiency increased and attained the highest value in both models. Average efficiency in CCR model was ranged between 49–70% and in BCC model was 60–82%. In CCR model the most efficient were medium sized banks, but in BCC model were the most efficient small banks.

### DISCUSSION AND CONCLUSION

The aim of the paper was to examine the efficiency of the banking sectors in Visegrad countries during the period 2009–2013. The results show that average efficiency was slightly decreasing within the period 2010–2011. But significant decrease in efficiency in 2012, it was probably as a result...
of financial crisis. Then average efficiency increased in 2013. This finding confirms results of Anayiotos et al. (2010) who presented that banking efficiency decreased during the crisis period. The values of efficiency computed by BCC model reach higher values than efficiency computed by CCR model by eliminating the part of inefficiency that is caused by a lack of size of production units. We found that the Czech banking sector was the highest efficient under the assumptions of constant return to scale. On the other hand, the Hungarian banking sector was the most efficient under the assumptions of variable return to scale. Because the Hungarian banking sectors was the lowest efficient in CCR model, it shows that the Hungarian commercial banks, especially large banks in the market, have improperly chosen their size. The lowest efficient were the Polish and Slovak banking sectors. Our result is consistent with the conclusion of Stavárek and Polouček (2004), Stavárek (2005) or Melecký and Staníčková (2012) who evaluated the Czech banking industry as the highest efficient. The reason of the inefficiency of the banks were the excess of clients deposit in banks’ balance sheet. To improve efficiency banks should reduce deposits in balance sheet and reduce fixed assets. The result of DEA estimation shows that the reduction of inputs would lead to higher efficiency more than increasing of outputs. Thus banks should orient to reduction of their inputs rather than increasing their outputs.

Next, we distinguish between efficiency of the group of large banks, medium-sized banks and small banks in Visegrad countries as well as in the Czech Republic, Hungary, Polish and Slovakia. Results show that the group of small banks was the most efficient in CCR model and the group of medium-sized banks was the most efficient in BCC model. The group of small banks was the most efficient in Poland. In the Czech Republic and Slovakia, medium-sized banks were the most efficient and large banks were the most efficient in Hungary. On the contrary, Nikiel and Opiela (2002) found that large banks were more efficient that small banks in Poland during 1990s. Our results show that small banks were the most efficient in the period 2009–2013. Difference in results can be due to different periods.

In Slovakia we confirm the result of Řepková (2013b) that large banks were the lowest efficient. Result of the paper is consistent with Stavárek and Řepková (2012) who found that largest banks performed significantly worse than medium-sized and small banks. Result indicates that banks operate in an incommensurate size. It could recommend that banks should concentrate to operate in optimal range of operation to increase banking efficiency. The further research could also focus on estimating the reason and determinants of the low efficiency of the large banks in Czech Republic, Slovakia and Poland. The further research could also include the dividing the DMUs into groups according their belonging to a financial conglomerate.

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