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Differences in Efficiency between Banks in Financial Conglomerates and other Banks in the Banking Sectors in Visegrad Countries

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Abstract

Palečková Iveta: **Differences in Efficiency between Banks in Financial Conglomerates and other Banks in the Banking Sectors in Visegrad Countries**

The aim of this paper is to estimate the differences in efficiency between banks in four financial conglomerates and other banks in the banking sectors in Visegrad countries within the period 2005-2015. In line with the aim of the paper, the research question is stated as follows: Are banks that belong to financial conglomerates more efficient than other banks in the banking sectors in the Visegrad countries? We analysed banks from four financial conglomerates: Erste Group, Société Généralé Group, UniCredit Group and KBC Group. Moreover we estimated the efficiency of commercial banks in the Visegrad countries using the Dynamic Data Envelopment Analysis (DEA) approach. We did not find the statistical significant differences in efficiency between banks that belong to a financial conglomerate and other banks in the banking sectors in the Visegrad countries.

Key words

efficiency, Dynamic Data Envelopment Analysis, banking sector, financial conglomerate, propensity score matching, Visegrad countries

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Introduction

A financial conglomerate is an economic group comprising financial institutions that are subject to supervision in terms of Community Law. In economic theory, it is assumed that the relative advantage of financial conglomerates stems from economies of scale. Furthermore, the financial conglomerates can take advantage of the separate capital requirements for their constituent divisions by transferring assets between divisions to avoid high capital charges. Another important aspect is that an affiliation of a financial conglomerate can influence a bank's behavior (Goldberg, 2016). In this study we focus on the efficiency of commercial banks in a financial conglomerate and other banks in the banking sectors.

The aim of this paper is to estimate the differences in efficiency between banks in four financial conglomerates and other banks in the banking sectors in Visegrad countries within the period 2005-2015. Visegrad countries include Czechia, Slovakia, Hungary and Poland. In line with the aim of the paper, the research question is stated as follows: Are banks that belong to financial conglomerates more efficient than other banks in the banking sectors in the Visegrad countries? We analysed banks from four financial conglomerates: Erste Group, Société Généralé Group, UniCredit Group and KBC Group. Moreover we estimated the efficiency of commercial banks in the Visegrad countries using the Dynamic Data Envelopment Analysis (DEA) approach. Banking efficiency is very often investigated using the static methods (traditional models of Data Envelopment Analysis). In the empirical literature there are only limited number of studies applied the Dynamic DEA model. This study is focused on estimating differences in technical efficiency between banks in financial conglomerates and other banks in the banking sectors in Visegrad countries. Several empirical studies research European banking sectors which included the group of Visegrad countries (e.g., Kosak and Zajc, 2006; Bems and Sorsa, 2008; Matoušek, 2008; Mamatzakis et al.; 2008; Koutsomanoli-Filippaki et al., 2009; Baruník and Soták, 2010; Brissimis et al., 2010; Anayiotos et al., 2010; Iršová and Havránek, 2011 or Erina and Erins, 2013). Moreover in the empirical literature, most of studies examined banking efficiency during 1990s or during the beginning of 2000s. Thus, it shows the motivation for this study. This paper could fill the gap following time line in the empirical literature. There is a lack of studies examining banking efficiency using dynamic methods, which creates an opportunity for this research. Therefore, the Dynamic Data Envelopment Analysis is employed for estimation banking efficiency using the slack-based measure method with variable return to scale.

Next, we analyse whether commercial banks in financial conglomerates are more or less efficient than other banks in the banking sectors. We used a matching method, namely propensity score matching, for estimation of the differences between these two groups of banks in Visegrad countries. Moreover we consider other factor to match the banks: bank's size, level of capitalization, level of liquidity and credit risk.

Moreover, only a few studies have focused on the efficiency of financial conglomerates. Vander Vennet (2002) examined the cost and profit efficiency of European conglomerates and universal banks and found that conglomerates were more efficient than their specialized competitors. However, this study investigated cost efficiency. The effect of financial conglomerates was examined, for instance, Palečková (2017), who assessed efficiency and efficiency change using the Malmquist index in the group of Visegrad countries during the 2009–2013 period. She determined that there were differences in banks in the financial conglomerates across Visegrad countries.

The structure of the paper is as follows. First chapter defines the methodology and the data used. Next chapter presents the empirical analysis and results. The last section concludes the paper.

1. Methodology and Data

The Data Envelopment Analysis is an approach for evaluating the performance of a set of peer entities (DMUs) which convert multiple inputs into multiple outputs (Cooper et al., 2011). The term DEA was first described by Charnes et al. (1978) and it was model with assumption of constant return to scale. Next, this model was modified by Banker et al. (1984) and became the BCC model which accommodates variable returns to scale.

Moreover, the criterion for the classification of DEA models is possible orientations in DEA models. Input-oriented model represent models where the DMUs produce a given quantity of outputs with the minimum possible amount of controllably inputs (Hančlová et al., 2015). Output-oriented model is the model that attempts to maximize outputs while using no more than the observed amount of any inputs (Cooper et al., 2007). Non-oriented (additive) models are based on the optimal mix of inputs and outputs, it is combination both orientations in a single model (Cooper et al., 2007).

We employed the non-oriented Slacks-Based Model (SBM) introduced by Tone (2001) who proposed a slacks-based measure (SBM) of efficiency in the Data Envelopment Analysis. The SBM model maximizes the average improvements of relevant factors (inputs / outputs) for the evaluate DMU to reach the frontier (Tone, 2001). Tone and Tsutsui (2010) developed Dynamic DEA model in to a slacks-based measure framework for measuring the dynamic efficiency of relative DMUs over several terms. Authors pointed out a concept of carry-over and accounted the effect of interconnecting activities between two consecutive terms. We adopted the Dynamic DEA model proposed by Tone and Tsutsui (2010) and Tone and Tsutsui (2014). The Dynamic DEA model can easily be written as:

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

subject to

$$\sum_{j=1}^{n} A_j(t)\lambda_j(t) \leq X_k(t), \tag{2}$$

$$\lambda_j(t) \geq 0, \qquad \text{all } t = 0,1,2,\dots,T-1, \tag{3}$$

where z is efficiency of DMU to be estimated, $\lambda_j(t)$ 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 DMU$_j$, j indicates the n different DMU$_s$

and t denotes time. We estimated the dynamic model in the slacks-based measure (SBM) framework, called Dynamic SBM (DSBM).

1.1. Matching methods

Next, we estimated the difference in efficiency between banks in a financial conglomerate and other banks in the banking sector. We used the matching method, especially the propensity score matching. Matching methods were developed in the 1940s and have gradually increased in complexity and in use. The development of a theoretical basis for these methods began with papers by Cochran and Rubin (1973) and Rubin (1973 a,b).

Stuart (2010) defined matching as any method that aims to equate (or balance) the distribution of covariates in the treated and control groups. One of the most common method, which is also the easiest to implement and understand, is nearest neighbour matching (Rubin, 1973a). This method is generally the most effective method for settings in which the goal is to select individuals for follow-up. Nearest neighbour matching nearly always estimates the average effect of the treatment on the treated, as it matches control individuals to the treated group and discards controls that are not selected as matches.

Rosenbaum and Rubin (1983) introduced propensity scores defined as the probability of receiving the treatment given the observed covariates. Propensity Score Matching (PSM) is an approach that estimates causal treatment effects. Propensity scores collapse all of the covariates into one scalar: the probability of being treated. The propensity score for individual *i* is defined as the probability of receiving the treatment given the observed covariates. PSM is estimated by using probit or logit regression with the covariates collected from the participants as *X* and participants' status on the treatment variable as *Y* (Rosenbaum, 1987). This approach can significantly reduce bias in observational study (Rosenbaum, 1987; Rubin and Thomas, 1992). It also confirms Rosenbaum and Rubin's (1983, 1985 a, b) approach that suggests the use of the propensity score – the probability of receiving a treatment conditional on covariates – to reduce the dimensionality of the matching problem.

As Oh et al. (2009) stated, the concept of propensity score matching requires satisfying the conditional independence assumption (CIA). One possible identification strategy is to assume that given a set of observable covariates X, which are not affected by the treatment, the potential outcomes are independent of the treatment assignment. It means that conditioned on the observable characteristics (X variables) of possible participants, the decision to participate in the program should be independent of the outcome measures. A propensity score indicates a conditional probability of applicants to participate in a program when the observable characteristics of applicants are given:

$$(Y_1, Y_0) \perp D \mid X \tag{4}$$

where Y_1, Y_0 are potential outcomes, *D* is treatment and *X* is observable characteristics. In our case, potential outcome is efficiency score and observable characteristics are level of bank's capitalization, liquidity risk, bank's size and credit risk.

The second assumptions underlying PSM is that for each value of X, there is a positive probability of being either treated or untreated:

$$0 < P(D = 1 \mid X) < 1 \tag{5}$$

As Melkamu and Mesfin (2015) stated, this equation implies that the probability of receiving a treatment for each value of *X* lies between 0 and 1. By the rules of probability, it means that the probability of not receiving a treatment lies between the same values. Then, the proportion of treated and untreated individuals must be greater than zero (positive) for every possible value of *X*. The average treatment effect is given by the difference in expenditure patterns between the two groups. Therefore, one group is the group of banks that belong to the financial conglomerate and the second group consist of other commercial banks in the banking sectors. The PSM approach could be used since it helps to reduce the selection bias associated with the existence of observed differences in profitability between banks in a financial conglomerate and other banks in the banking sector.

A very important step in using matching methods is to test the quality of the resulting matched samples. All matchings should be followed by an assessment of the covariate balance in the matched groups, where balance is defined as the similarity of the empirical distributions of the full set of covariates in the matched treated and control groups (Stuart, 2010). All diagnostics are described in Stuart (2010).

1.2. Data

The dataset used in the paper was obtained from the database Orbis Bank Focus and from annual reports of commercial banks of the Visegrad countries during the period 2005–2015. All the data were reported on an unconsolidated basis. The Dynamic DEA model requires strictly balance panel data. Therefore we used balanced panel data from commercial banks of the Visegrad group. The total assets of selected commercial banks covered more than 70% of the total assets of the banking sector. The dataset is representative, and we can present results for the banking sectors of the Visegrad countries.

For estimation of banking efficiency we adopted the asset-oriented intermediation approach. This approach assumes that the commercial bank collects deposits and transform them into loans. We employed three inputs and two outputs (Tab. 1). It was mentioned that Dynamic DEA model included carry-over variable and we chose loan loss provision as a proxy for non-performing loans.

Tab. 1: Inputs and Outputs in Dynamic DEA Model

Inputs	Outputs
Total deposits	Total loans
Physical capital	Other earning assets
Number of employees	

Source: author’s compilation

2. Empirical Analysis and Results

First, we estimated the banking efficiency using Dynamic DEA model. We used the SBM non-oriented model with variable return to scale. The average values of the efficiency in banking sectors are presented in Figure 1. The average efficiency shows that the most efficient were Hungarian and Czech banking sectors. On the other hand the least efficient was Slovak banking sector. There were differences in efficiency between commercial banks in individual banking sectors.

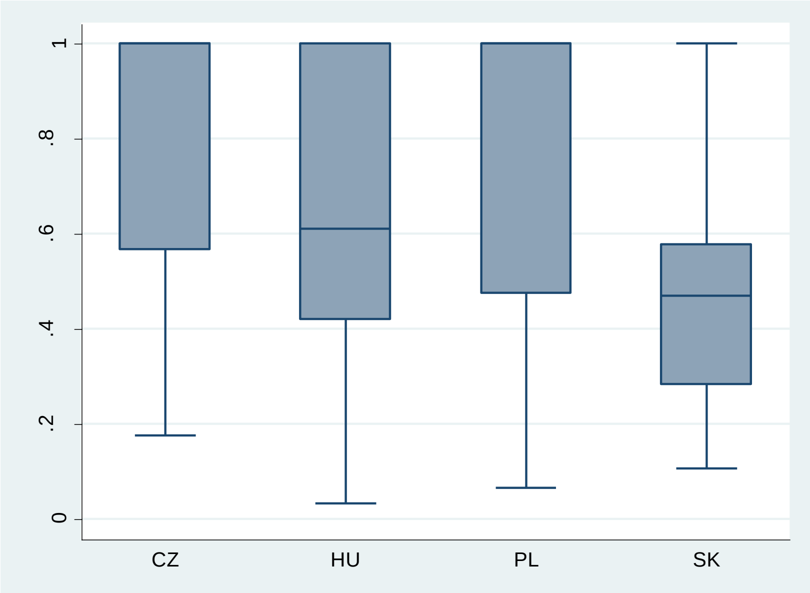

Fig. 1: Boxplot analysis of technical efficiency in the banking sectors in V4 during the period 2005-2015 (in %)
(Source: author's calculation)

Figure 2 presents the development of efficiency in the banking sectors in Visegrad countries during analyzed period. The development of average efficiency could be divided into two phases. The first phase was characterized by increase in average efficiency during 2005-2012. In the second phase the average efficiency decreased during the period 2013-2014 and we can see the increase in 2015. A significant decrease was registered during the period 2013-2014 especially due to the decrease of efficiency of Hungarian commercial banks.

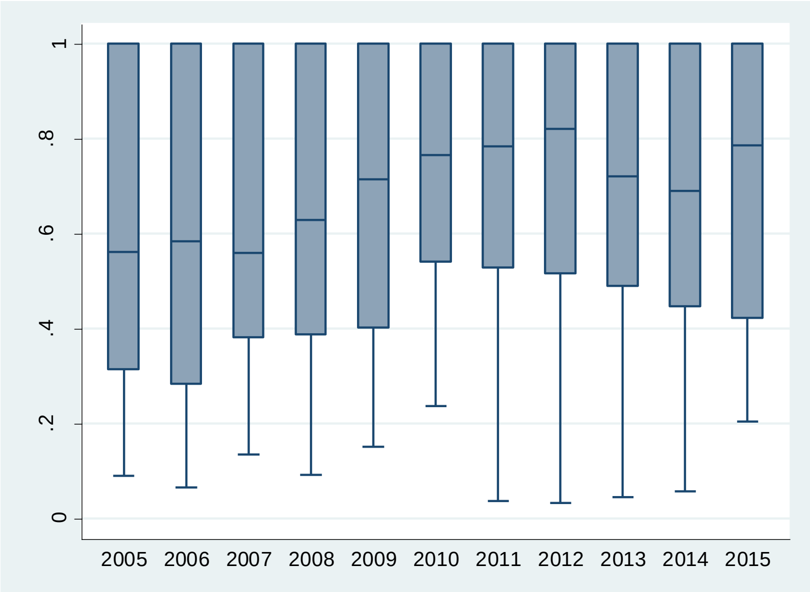

Fig. 2: Boxplot analysis of technical efficiency in the banking sectors in V4 during the period 2005-2015 (in %)
(Source: author's calculation)

Next, we estimate the differences in efficiency between banks in financial conglomerates and other banks in the banking sectors. When we only compare the average value of commercial banks in financial conglomerate we can registered that the average efficiency of commercial banks in financial conglomerates was 74% and average efficiency of other banks was 67%. We can conclude that the difference is 7 b.p. Although the simple difference compared only average values of groups of banks. There is not obvious whether this difference is due to the affiliation with the financial conglomerate. We compare the banks with other characteristics.

Moreover, we used the propensity score matching method, which allows us to construct a comparison group by matching twin banks based on the propensity score in the population of bank groups. We estimate the difference between the efficiency of banks that belong to a financial conglomerate and other banks in the banking sectors of the Visegrad countries from 2005 to 2015. For empirical analysis we used STATA Data Analysis and Statistical Software. We divided banks in the Visegrad countries into two groups: one group consisted of banks that belong to a financial conglomerate, and the other group consists of other commercial banks in the banking sectors. We considered several bank-specific factors in matching. We considered the bank's size, level of capitalization, level of liquidity and credit risk to estimate the difference in efficiency in the two groups of banks. Banks size was measured by total assets. Level of capitalization is measured by the ratio of total capital to total assets. Liquidity risk is measured by the ratio of liquid assets to total assets. Credit risk is the share of the loan loss provision to the total assets of the bank (this proxy for the measurement of credit risk was used, in e.g., Košak and Čok, 2008). Table 2 presents the differences in efficiency in groups of banks in Visegrad group countries during the period 2005-2015.

Tab. 2: Difference in efficiency in groups of banks in V4 during the period 2005-2015

Financial conglomerate (1 vs 0)	Coefficient	Std. Err.	z
Efficiency	0.0555	0.03731	-1.49
Number of obs.=616, estimator: propensity-score matching, treatment model = logit			

Source: author's calculation

The coefficient shows us the statistical insignificance difference between these two groups of banks. The results show that there is not the statistical significant difference in efficiency between banks in financial conglomerates and other banks in the banking sectors. The propensity score matching did not show the statistical significant differences between banks in financial conglomerate and other banks in the banking sectors in Visegrad group countries. This results do not confirm the results of Palečková (2017) who concluded that there were differences in banks in the financial conglomerates in the Visegrad countries. This research cannot confirm the results of Vander Vennet (2002), who found that conglomerates were more efficient than their specialized competitors.

Conclusion

The aim of the paper was to estimate the differences in efficiency between banks in four financial conglomerates and other banks in the banking sectors in Visegrad countries within the period 2005-2015.

First, we found that the Hungarian and Czech banking sector were the most efficient banking sector. The lowest average efficiency achieved the Slovak banking sector. We did not find the statistical significant differences in efficiency between banks in financial conglomerates and other commercial banks in the banking sectors in Visegrad countries. We found using simple comparing that there were differences in the group of banks that belong to a financial conglomerate compared to other banks in the banking sector. We found that the banks in financial conglomerates were more efficient than other banks in Visegrad countries. This results showed only simple comparison of average value and it could be influenced by the fact that banks in the financial conglomerate belong to the group of large banks in the banking sectors.

Using a matching method (propensity score matching) that took into account bank size, level of capitalization and level of liquidity, we did not confirm that commercial banks that belongs to a financial conglomerate were more efficient than other banks. The differences between these two groups of banks were not statistically significant in Visegrad group countries during analysed period.

In further research, we would like to focus on the reasons for these differences between the groups of commercial banks by focusing on other indicators that influence the efficiency of commercial banks.

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