Comparison of the efficiency of selected European banking sectors

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Abstract: *There is no generally accepted concept of efficiency nor is there a uniform system of indicators for measuring bank efficiency. It is even possible to use the method of financial analysis to measure bank efficiency. In this paper, the following ratios are used for measuring bank efficiency: ROA, ROE, total assets, nonperforming loans/total loans, quick liquid assets/total assets, quick liquid assets/short-term liabilities, loans/deposits, and capital adequacy. The goal of this paper is to assess the efficiency of Czech banks using cluster analysis on the basis of selected ratios and to conduct a comparison with bank efficiency in Poland, Austria, Greece, Portugal, France, and Slovakia. The collective ratios for the entire banking sector will be compared for the selected countries for the years 2010–2014. The cluster analysis demonstrates that the Czech banking sector is the most similar to the Slovakian sector. According to a combination of selected ratios, it is possible to designate the cluster composed of the Czech and Slovak banking sectors as being the cluster with the highest banking sector efficiency. It differs extensively from the cluster of Greece and Portugal.*

Keywords: bank, banking sector, banks efficiency, cluster analysis, the Principal Components Analysis

JEL codes: G14, G21, C38

1 Introduction

The banking system has become an important component in the economic sector of each country. Like other industries, the banking industry has its own unique characteristics and specifics that adapt by internal and external influences economic sector. Each state is required for the proper functioning of the economy needs a reliable a stable banking system, because the problems in the banking sector may have an impact on the entire financial sector. Each banking system of each country has its own specifics that influence global globalization. It operates on banking systems around the world. Each state receives it but in different ways. Some states retain more of their traditional banking features that arose during the development of the system, in turn, take some elements of the globalized economy.

Banks are an inseparable part of life for all economical subjects. The bank stability and efficiency is an important assumption for function the financial markets (Teplý et al., 2010 or Černohorský, 2014). For qualified analysis, it is necessary to work with a time series of ratios and monitor the trends of their development over past periods of time (Tokarčíková et. al., 2014). The aim of the article is to undertake a cluster analysis of efficiency of chosen banking sectors in the countries of Eupean Union – Slovak, Poland, Austria, Czech Republic, France, Portugal and Greece. The selected countries are countries represented in the European Union, which have variously developed financial markets and banking sectors. Based on a cluster analysis, the creation of clusters would result, in which individual banking sectors will exhibit similar values in the selected criteria.

Based on current research literature on the efficiency of banks, it is evident that in terms of evaluating the efficiency of banks, that there is a wide range of views and measuring the efficiency is therefore very difficult. There are numerous methods of measuring efficiency and the fundamental question is what indicators can we use to measure that efficiency.

Efficiency is often understood in the same sense as performance and profitability (such as Atemnkeng and Nzongang, 2006 or Molyneux and Thornton, 1992). Where banks are run efficiently, the operational costs are reduced, leading to an increase in profits realised by the banks. The authors Richard, Devinney, et al. (2009) found an analysis of more than 213 articles in leading international journals which use particular indicators based on accounting data to measure efficiency; these indicators mainly include cash flow, financial results, revenues and their growth and asset profitability indicators .

In measuring the efficiency of banks, profitability was used, for example, by Altunbas (1998), Bonin and Hasan (2005), Abbasoglu, Aysan and Günes (2007) and Berger et al. (1993). These authors evaluate the profitability of banks using return on assets (ROA) or return on equity (ROE). Bonin and Hasan (2005) also monitored the amount of total deposits, total assets, loans and liquid assets. The size of a bank is judged by its total assets (Dabla-Norris and Floerkemeier (2007), Fuentes and Vergara (2003)). Indicators of total assets, loans, and total loans/total deposits are used to assess the efficiency of banks, in addition to ROE and ROA, as well as Berger et al. (1993). Groenveled and de Vries (2009) use the capital ratio when measuring the efficiency of banks. Very often the efficiency of banks is evaluated by means of their ownership structure (Fuentes and Vergara (2003), Bonin and Hasan (2005), Mester (1993)). Some authors take into account the cost of labour when measuring the efficiency of banks (Stavárek (2013), Tulekns (2006), Berger et al. (1993)) and the cost of capital (Berger et al. (1993)). Another factor influencing the efficiency of banks is the interest margin (Stavárek (2013) or Dabla-Norris and Floerkemeier (2007)). These last authors also use the indicator of quickly nonperforming loans/total loans, liquid assets/total assets and quick liquid assets/short-term liabilities.

2 Methodology and Data

Evaluating bank efficiency is a relatively complicated analytical problem. There is no generally accepted concept of efficiency nor is there a uniform system of indicators for measuring bank efficiency. It is even possible to use the method of financial analysis to measure bank efficiency. The goal of financial analysis is to evaluate the financial ratios for efficiency and competitiveness that were achieved in prior periods of time. In this paper, the following ratios are used for measuring bank efficiency: ROA, ROE, total assets, nonperforming loans/total loans, quick liquid assets/total assets, quick liquid assets/short-term liabilities, loans/deposits, and capital adequacy. The collective ratios for the entire banking sector will be compared for the selected countries for the years 2010–2014. The necessary data were obtained from the Bankscope database and were chosen with regard to the specifics of the selected banking sectors, international accounting standards and information requirements for the banks. A comparison was made of the average values of the selected indicators in individual banking sectors. Further scientific study could use a longer time series of selected indicators of selected banking sectors for a more detailed analysis. It would be possible to monitor factors which affect the efficiency of banking sectors (such as the period before the financial crisis, the impact of the financial crisis on selected criteria and subsequently track the clusters created, etc.).

The peer analysis allows make a comparison of the financial variables according to the tables and graphs. For this peer analysis will used the traditional methods of multiple statistical analysis, especially cluster analysis and principal components analysis. The method of cluster analysis was used to compare the efficiency of the Czech banking sector with the banking sectors of the other selected European countries. Cluster analysis divides the selected countries into clusters according to similarity. Using the method of principal component analysis, it was determined that there are two main components that jointly explain nearly three-quarters of the variability.

2.1 Cluster analysis

The primary access for determining the similarity of quantitative variables is the factor analysis. It is based on principal component analysis, which is used to reduce the size of the job (instead of many variables for further calculations determined by a small number of principal components, which can be expressed as linear combinations of the original variables).

The Principal components analysis is computed by the Singular Value Decomposition of X. (Friedman et al. (2013)) The general formula (2) is:

$$X = UDW^T \tag{2}$$

where

D … diagonal matrix consisting of the set of all eigenvalues of C along its principal diagonal, and 0 for all other elements

U … an n-by-n matrix, the columns of which are orthogonal unit vectors of length n called the left singular vectors of X;

W … a p-by-p whose columns is orthogonal unit vectors of length p and called the right singular vectors of X.

In the Principal Components Analysis (PCA), the data are summarized as a linear combination of an orthonormal set of the vectors. The first principal component accounts for as much of the variability in the data as possible, and each successive component represents as much of the remaining variability as possible (Zou (2006)). Components accounting for maximal variance are retained while other components accounting for a trivial amount of variance are not retained. These techniques are typically used to analyse groups of correlated variables representing one or more common domains. The result of PCA enters into the factor analysis. It is aim to assess the structure and relationships of selected indicators to see if allowed by their division into groups, in which the indicators chosen from the same groups together more than correlated variables from different groups.

Cluster analysis is a collective term covering a wide variety of techniques for delineating natural groups or clusters in data sets. The article will be used hierarchical agglomerative clustering.

Hierarchical agglomerative clustering start at the bottom and at each level recursively merges a selected pair of clusters into single clusters. This produces a grouping at the next higher level with one less cluster. Algorithm of hierarchical agglomerative clustering begins with every observation representing a singleton cluster. At each of the N-1 steps the closest two (least dissimilar) clusters are merged into a single cluster, producing one less cluster at the next higher level. (Friedman et al., 2013)

In the first phase clustering calculated the relative distances of objects and writes them into a matrix. This leads to a square symmetric matrix $\mathbf{D} = \{d\ (R,S)\}$ which has zeros on the main diagonal. It used for calculating the metric distance matrix is normally used and it called a Euclidean method. It is based on the geometric model (Klímek, 2005). The objects characterized by p characters are assigned to the points p-dimensional Euclidean space Ep, then two dots (R,S) it is defined by the Euclidean distance given by general formula (3):

$$d(R,S) = \sqrt{\sum_{i=1}^{p} (x_{ri} - x_{si})^2}\ . \tag{3}$$

On the basis of the distance matrix can be launched the second phase calculations, also clustering. Clustering method was used furthest neighbour (called too complete linkage). Complete linkage agglomerative clustering takes the intergroup dissimilarity to be that of the furthest (most dissimilar) pair according to formula (4):

$$d(R,S) = \max_{\substack{O \in R \\ O \in S}} \{d(O_i, O_j)\} \text{ for } R \neq S \quad (4)$$

where

R, S … represent two such groups

$d(R,S)$ … represent dissimilarity between R and S in computed from the set of pairwise observation dissimilarities $d(O_i, O_j)$, where one member of the pair O_i is in R, and the other O_j is in S.

Methods of clustering is selected based on the degree of credibility, and it cophenetic correlation coefficient "CC". The higher the value of the correlation coefficient cophenetic (a value close to 1), the greater the credibility and the choice of a suitable model cluster. (Friedman et al. (2013), Romesburg (2004))

The result is graphical figure called a dendogram with provided a highly interpretable complete description of the hierarchical agglomerative clustering.

3 Results and Discussion

The basic condition for performing cluster analysis is rejected claim that the data are affected by multicollinearity. Multicollinearity could very significantly affect the final quality of the clustering and classification of the individual elements in the resulting clusters. It is necessary to establish the correlation matrix. Then eliminate those criteria in assessing the relationship reaching the correlation coefficient higher than 0.7. If left criterion which the correlation coefficient is above 0.7. It is necessary to provide a justification for its further occurrence of cluster analysis. For more information see Friedman et al. (2013).

Based on the results of the correlation matrix, the ratio of nonperforming loans/total loans was removed from the analysis. This indicator showed very high levels of correlation with ROE, as well as the proportion of quick liquid assets/short-term liabilities, which is highly correlated with ROA.
To obtain information on the impact of these indicators, the principal components method was applied followed by a factor analysis. Both methods are used for visualising data and obtaining input information.

3.1 Visualization of date using factor analysis

The principal component method determined that there are two main components which together explain nearly three quarters of variability (Table 1).
The first principal component depletes approximately 47.96% of the total variability in the data, the second approximately 25.81%. The results of the factor analysis bring Table 1 and Figure 1. Table 1 shows which criteria are important for further exploration in terms of classification into certain objects, respectively clusters (bold face type).

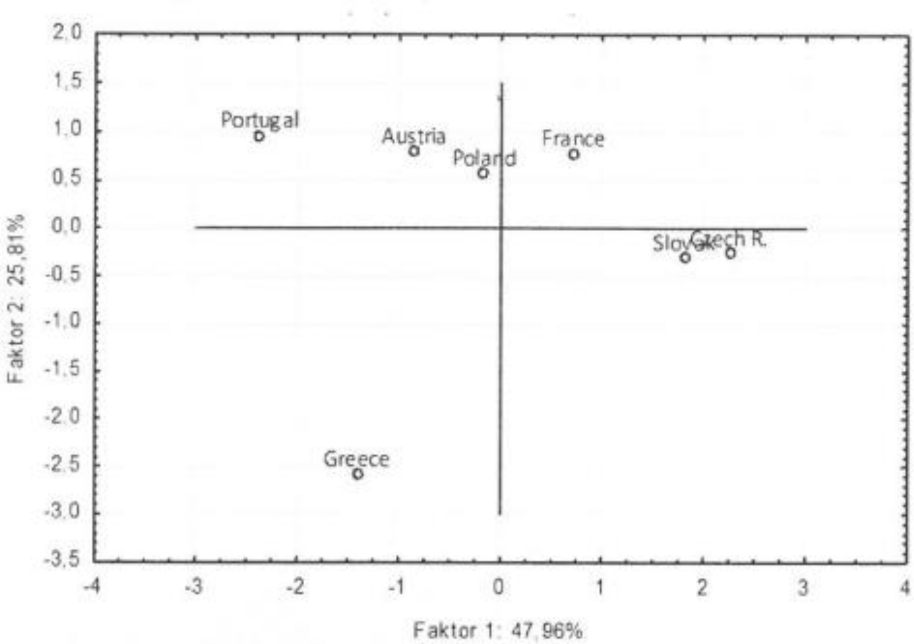
Table 1 The result of the factor analysis – two main components

	First principal component 1	**Second principal component 2**
Total assets	0.39	**0.80**
Liquid assets/total assets	**0.77**	0.26
Loans/Deposits	0.60	0.04
Capital adequacy	0.62	0.64
ROA	**0.91**	-0.12
ROE	-0.19	**0.97**

Source: own calculation

Graphic representation of the data visualisation from the factor analysis assumes the possible creation of approximately four relevant clusters (Figure 1).

Figure 1 Factor analysis – number of clusters



Source: own calculation

3.2 Result of cluster analysis

The cluster analysis method was used in comparing selected banking sectors. This analysis divides the selected countries into clusters according to their similarities. To perform a cluster analysis, we have assumed an agglomerative hierarchical clustering. For more information see Romesburg (2004). It was followed by selecting the clustering procedures, namely, a clustering method (the furthest neighbour method, or complete linkage clustering using statistical software), and the distance calculation method (Euclidean distance). The clustering method was selected based on the degree of credibility, namely, a correlation coefficient. The degree of credibility, or closeness degree, has been verified by the correlation coefficient. The higher the value (i.e., approaching 1), the greater the credibility and the choice of a suitable cluster model. The correlation coefficient was chosen on the basis of achieving a value approaching 1 with the furthest neighbour method. A prerequisite to performing the cluster analysis is that the data is not affected by multicollinearity.

Determining the relevant number of clusters was started from the clustering schedule, which determined the degree of distance of approximately 60%. Below this level, the relevant number of clusters was determined (Figure 2). The division of the countries into four clusters with the values of the individual indicators can be seen in Table 2.

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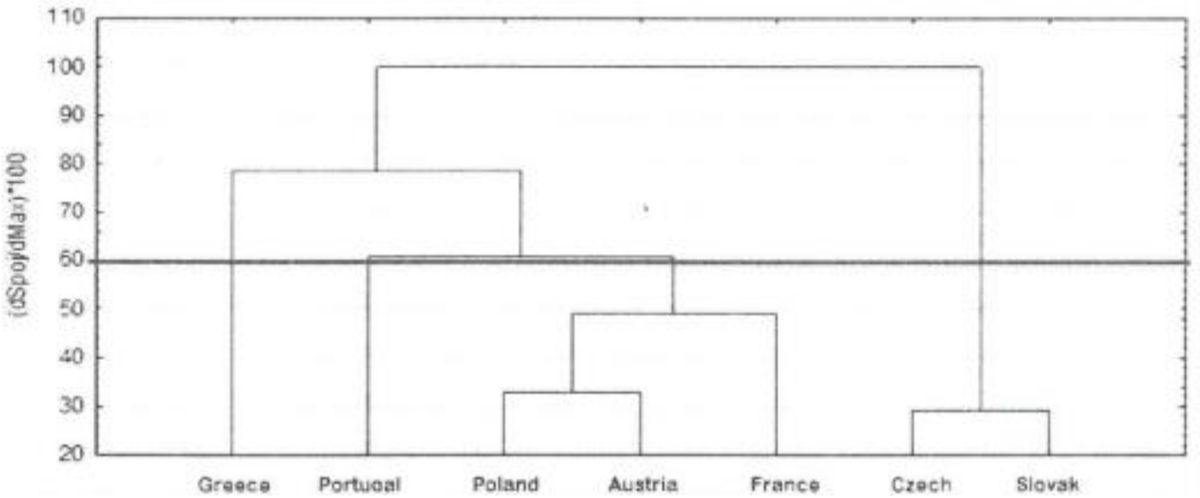
Figure 2 Dendogram (Wards method)



Source: own calculation

Table 2 Average values of chosen indicators (in %)

		Change in total assets	**Liquid ass./Total assets**	**Loans/ Deposits**	**Capit. adeq.**	**ROA**	**ROE**
First cluster	Slovak	1.4	36.2	110	17.93	1.3	9.1
	Czech R.	8.9	33.8	132	17.08	1.27	16.2
Second cluster	France	9,6	39.1	81	15.03	0.5	8.4
	Austria	-5.8	24.5	87	15.83	0.1	5.5
	Poland	4	21.4	90	14.91	1.1	14
Third cluster	Portugal	-7.7	16.9	117	13.20	-0.7	-11
Fourth cluster	Greece	-10.8	29.9	89	13.50	1.4	-169
	Average total	-0.06	26.44	88.14	15.35	0.71	-18.1

Source: own calculation by Bankscope

4 Conclusions

Based on the cluster analysis, four clusters were created. From the point of view of the efficiency of the banking sectors using selected indicators with the first principal component, which explains almost 48% of the variability of the investigated group, the greatest correlations were the ratio of liquid assets to total assets and ROA. In the ratio of liquid assets to total assets, the best values were achieved by France, the Czech Republic and Slovakia. The Czech Republic and Slovakia faultlessly exceeded the average ROA limit, but not France. The average ROA value was also exceeded by Poland, but which does not record comparable results to those countries in the ratio of liquid assets/total assets. The first cluster is formed by the Czech Republic and Slovakia. Because France and Poland lag behind in one or the other indicators, they are clustered into another cluster together with Austria. The third cluster consists of only one country - Portugal. Portugal achieved the worst results in both indicators listed above. The Greek banking sector achieved better results than Portugal, but because it achieved very low levels in the indicator corresponding to the second part of the component, it forms a separate cluster. Especially in terms of ROE, it achieved high negative values, which prevents it from being compared to other countries, and thus Greece and forms the fourth separate cluster.

Depending on the combination of selected indicators, the cluster composed of the Czech Republic and Slovakia can be qualified as a cluster with the highest possible efficiency in the banking sector. The first cluster achieves significantly better values of the indicators monitored than other banking sectors. These two banking sectors were not impacted by the global financial crisis (compared to Greece and Portugal, and to some extent, France). The average values of the monitored indicators of the first cluster are significantly above the average for all the markers in the selected banking sectors.

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