Conference Paper

An Exploratory Study of Financial Performance in CEE Countries

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Abstract

Our research investigates the performance of companies from Central and Eastern European (CEE) countries in the period after the Global Financial Crisis of 2007-2009 with the aim of identifying the driving factors behind accounting- and market-based performance. We include in the analysis companies from various industries in CEE countries that are European Union members and we study their performance between 2008-2016 over the following areas of performance: liquidity, solvency and indebtedness, operational profitability, global performance (through Return on assets and Return on equity), returns available to shareholders and market-based performance (through price/book value and Tobin Q ratio). Employing the hierarchical and non-hierarchical k-means cluster analysis companies are segmented into various homogeneous groups using various financial performance indicators as variables, Euclidian distances and the Ward amalgamation method. Furthermore, the resulting clusters have been grouped according to the country of origin and industry. Our findings show that specific groups of companies in these countries share common attributes, as evidenced by their performance indicators, which do not seem to be entirely based on their countries of origin and industry. Moreover, our exploration of CEE companies' performance dynamics after 2008 evidences the increased competition in all industries particularly after 2009, as well as businesses' need to adjust their activities after the losses incurred during the crisis period, but these phenomena is present with different intensities depending on country of origin and industry. At the same, we note the enhancement of global performance through improvements in the operational performance instead of financial leverage and indebtedness, which is a sound business approach by CEE companies.

Keywords: financial performance, Central and Eastern Europe (CEE), statistical cluster analysis, return to investors

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1. Introduction

The analysis of the financial performance has been the subject of discussion for decision makers as managers, economists and academic staff since long many years. It will continuously capture the interest of the economists and the accountants as a frequently debated issue in the economic field of the last decades, covering a very large spectrum of different meanings and trends. In our study we analyze the financial performance of Central and Eastern Europe (CEE) companies over the following areas: liquidity, solvability, efficiency, profitability, aggregate performance and investment performance. In the international literature that addresses companies' financial performance, different multivariate statistical techniques have been proposed, such as: cluster analysis, principal components analysis, discriminant analysis and factor analysis. Thus, [1], using non-parametric discriminant analysis, which assigns a set of weights to a linear discriminating function that consequently generates a score regarding its belonging to a group, compares the financial performances of a number of 147 companies without financial difficulties with those of 24 companies in the American energy industry. [2] examine the financial performances of companies from four Central and Eastern European countries (Czech Republic, Hungary, Poland and Romania) and from five industries (financial intermediation, beverage and food industry, energy, pharmaceuticals and chemicals), and identify natural groups, and at the same time statistically significant, of companies depending on their corporate performance. Another author, [3], uses a cluster analysis to study 208 foreign direct investments made by West-European MNEs in the Central and Eastern European region between 1996-2002 and finds that a positive relationship between psychic distance and subsidiary performance is observed only in the absence of market specific knowledge. [4] studies the successful performance of Indonesian entrepreneurs using cluster analysis to map the pattern of growth mode and strategies. [5] examine the entrepreneurial performance of transition economies in the European context using a cluster analysis of EU Member States and identify various transition economies barriers to productive entrepreneurship in the European context. [6] apply cluster modelling to firm financial data and firm bribery practices with the purpose of analyzing the relationship between `local bribery environments' and firm performance in Central and Eastern European countries. [7] investigate the impact of foreign ownership on stock market volatility in Vietnam using a K-mean cluster algorithm and hierarchical clustering methods to visualize the analysis on net trading volume, price volatility and return volatility ratio.

The present study attempts to examine financial performance in the Mining and quarrying and Manufacturing sectors, at the level of Central and Eastern European countries that are European Union members, to identify the driving factors behind their accounting and market-based performance. To achieve this purpose we implement a k-means cluster analysis using various financial performance indicators resulting from the financial reports of companies as variables, Euclidian distances and the Ward amalgamation method.

Our research is based on data with annual frequency covering the period between 2008-2016, collected from the ORBIS Database. The collected data has been analyzed and interpreted on the basis of different financial ratios. The remainder of the paper is organized as follows: Section II presents the data used in the analysis and the research methodology, Section III outlines the main results and Section IV concludes.

2. Data and Research Methodology

The data was collected from the ORBIS Database provided by Bureau van Dijk (BvD) and covers the period between 2008-2016, with annual frequency. All data is in euro. The sample includes a number of one hundred and sixty-four listed companies with available data for the entire period, in the Mining and quarrying and Manufacturing sectors.

Table 1 shows the distribution of these companies according to the specific industry and sector, based on the declared NACE main 2-digit code, and their origin countries (i.e., the countries where companies' headquarters are located). The number of companies from each industry is variable, from one (B05 - Mining of coal and lignite, B06 - Extraction of crude petroleum and natural gas, B07 - Mining of metal ores, B08 -- Other mining and quarrying, C12 - Manufacture of tobacco products, C15 - Manufacture of leather and related products) to 22 (C12- Manufacture of food products). Our research investigates the financial performance of these companies from the eleven CEE countries, European Union members - Bulgaria (BG), Croatia (HR), Czech Republic (CZ), Estonia (EE), Hungary (HU), Latvia (LV) Lithuania (LT), Poland (PL), Romania (RO), Slovenia (SI) and Slovakia (SK).

The performance of companies included in our research has been described by a number of 13 financial indicators, as follows: (1) Current ratio (CR) -- the ratio between current assets and current liabilities (a liquidity indicator); (2) Quick ratio (QR) -- the ratio between cash, short-term marketable investments and receivables, on one hand, and current liabilities, on the other hand (a liquidity indicator); (3) Solvability ratio (Solv) -- the ratio between total assets and total liabilities (a solvability indicator); (4) Total debt ratio (Debt) -- the ratio between total debt and total assets (a solvability indicator); (5) Total asset turnover (TAT) -- the ratio between turnover and net total assets (an efficiency indicator); (6) Inventory turnover (STT) -- the ratio between turnover and net inventory (an efficiency indicator); (7) EBITDA margin (Gprof) -- the ratio between EBITDA and turnover (a profitability indicator); (8) EBIT margin (Oprof) -- the ratio between EBIT and

Table 1: Selected industries, number of companies and origin countries.

NACE code	Industry	Number of companies	Origin countries
B05	Mining of coal and lignite	1	PL
B06	Extraction of crude petroleum and natural gas	1	RO
B07	Mining of metal ores	1	PL
B08	Other mining and quarrying	1	PL
B09	Mining and quarrying n.e.c.	2	HU, SI
C10	Manufacture of food products	22	EE, HR, LT, PL, RO, SK
C11	Manufacture of beverages	6	HU, LT, LV, PL, RO
C12	Manufacture of tobacco products	1	BG
C13	Manufacture of textiles	4	LT, PL
C14	Manufacture of wearing apparel	6	EE, LT, PL
C15	Manufacture of leather and related products	1	HR
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	3	BG, PL
C17	Manufacture of paper and paper products	7	BG, LT, HR, HU, PL, RO
C18	Printing and reproduction of recorded media	5	EE, HR, HU, PL, SI
C19	Manufacture of coke and refined petroleum products	5	CZ, PL, RO, SK
C20	Manufacture of chemicals and chemical products	9	BG, HR, PL
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	5	BG, HR, HU, PL, SI
C22	Manufacture of rubber and plastic products	8	BG, HU, PL
C23	Manufacture of other non-metallic mineral products	3	LV, PL
C24	Manufacture of basic metals	11	PL, RO, SK
C25	Manufacture of fabricated metal products, except machinery and equipment	7	LV, PL
C26	Manufacture of computer, electronic and optical products	4	LV, PL
C27	Manufacture of electrical equipment	13	BG, EE, LT, PL, RO, SI
C28	Manufacture of machinery and equipment n.e.c.	20	BG, HR, LV, PL, SK
C29	Manufacture of motor vehicles, trailers and semi-trailers	3	HU, PL
C30	Manufacture of other transport equipment	7	BG, HR, LV, PL, RO
C31	Manufacture of furniture	2	LT, PL
C32	Other manufacturing	6	PL
Total		**164**	CEE

*According to the EU Glossary: List of NACE codes
(http://ec.europa.eu/competition/mergers/cases/index/nace_all.html)
Source: Author's own work

turnover (a profitability indicator); (9) Return on assets (ROA) -- the ratio between net profit after taxes and net revenue (an aggregate performance indicator); (10) Return on equity (ROE) -- the ratio between net profit after taxes and shareholders' equity (an aggregate performance indicator); (11) Price/Book value (PB) -- the ratio between market price per share and book value per share (a aggregate performance indicator); (12) Tobin Q ratio (TQ) -- the ratio between market capitalization and total assets (an aggregate performance indicator); (13) Return on invest capital (ROIC) -- the ratio between net operating profit after tax and net invest capital (an investment performance indicator) (Table 2). These indicators were calculated by the authors for each company.

Table 2: Financial performance indicators.

Performance area	Financial indicators	Calculation
Liquidity	Current ratio (CR)	$\frac{\text{Current assets}}{\text{Current liabilities}}$
	Quick ratio (QR)	$\frac{\text{Cash+Short-term marketable investments+Receivables}}{\text{Current liabilities}}$
Solvability	Solvability ratio (Solv)	$\frac{\text{Total assets}}{\text{Total liabilities}}$
	Total debt ratio (Debt)	$\frac{\text{Total debt}}{\text{Total assets}}$
Efficiency	Total asset turnover (TAT)	$\frac{\text{Turnover}}{\text{Net total assets}}$
	Inventory turnover (STT)	$\frac{\text{Turnover}}{\text{Net inventory}}$
Profitability	EBITDA margin (Gprof)	$\frac{\text{EBITDA}}{\text{Turnover}}$
	EBIT margin (Oprof)	$\frac{\text{EBIT}}{\text{Turnover}}$
Aggregate performance	Return on assets (ROA)	$\frac{\text{Net profit after tax}}{\text{Net revenue}}$
	Return on equity (ROE)	$\frac{\text{Net profit after tax}}{\text{Shareholders' equity}}$
	Price/Book value (PB)	$\frac{\text{Market price per share}}{\text{Book value per share}}$
	Tobin Q ratio (TQ)	$\frac{\text{Market capitalization}}{\text{Total assets}}$
Investment performance	Return on invested capital (ROIC)	$\frac{\text{Net operating profit after tax}}{\text{Invested capital}}$

Author's own work

We use statistical cluster analysis (SCA) with the aim of detecting similarities in performance of the companies from Central and Eastern European countries in the period after the Global Financial Crisis of 2007-2009. Generally, the SCA objective resides in identifying natural groups of entities (generally called cases) according to a specific internal criterion, without knowing a priori the belonging of entities to clusters. SCA assigns entities to clusters based on their similarity depending on a set of characteristics (called variables) and the differentiation between entities included in a cluster and entities included in other clusters. SCA may be performed using a hierarchical clustering algorithm or a k-means algorithm, but in our paper we have decided to accompany the traditional hierarchical algorithm with an unsupervised learning algorithm, given our objective of detecting patterns or structure of data that cannot be easily observed, using a more sophisticated version of the K-means algorithms that is closer to the idea of neural networks. The result of SCA, in our case, is the identification of homogeneous groups of companies based on the financial performance indicators (variables) -- Current ratio, Quick ratio, Solvability ratio, Total debt ratio, Total asset turnover, Inventory turnover, EBITDA margin, EBIT margin Return on assets, Return on equity, Price/Book value, Tobin Q ratio and Return on invest capital.

Specifically, the k-means algorithm proposed by [8] and discussed in [9], assigns cases to identified clusters with or without a priori setting a number a clusters, so that the means for all variables included in the algorithm are as different as possible from each other. Cluster distances are based on simple Euclidian distances between cluster centroids (that are vectors of the means of variables included in the analysis). We chose to employ a version of the k-means algorithm under the "Generalized EM and k-Means Cluster Analysis" module of STATISTICA software, which represents a data mining tool for unsupervising learning and pattern recognition, based on Euclidian distances. These distances are calculated using transformed (or rescaled) values of variables, X_i, so that

$$X'_j = \frac{X_j - X_{max}}{Max\left(X_j\right) - Min\left(X_j\right)} \quad (1)$$

where *Min*(X_j) and *Max*(X_j) are the minimum and maximum values for variable *i*.

The main advantage of this approach is that this algorithm does not require, as in the traditional k-means clustering amalgamation, the number of clusters to be specified a priori; explicitly, we use a v-fold cross-validation scheme to identify the optimal number of clusters. This validation scheme divides the overall samples in a number of v folds, which represent sub-samples that are randomly drawn and the same procedure is successively applied to the remaining v-1 folds. The results of the clustering algorithm are applied to the fold that was not used to estimate the parameters and identify the clusters in order to calculate an index of predictive validity. Eventually, the results of all v-fold replications are aggregated into a single measure of model stability, for example, the resulting average distance of the observations from their cluster centers. All data has been standardized before the application of the clustering amalgamation techniques.

3. Results and Discussion

Before the application of clustering amalgamation techniques to financial performance data we consider necessary a brief depiction of financial performance at industries' level across the CEE countries included in our study.

In Table 3 we present the descriptive statistics of the thirteen financial indicators at CEE countries' level, based on the means and coefficient of variation values for each company, between 2008-2016. The advantage of using the coefficient of variation is that it can be compared across different variables because they are measured on the same relative scale (ratio). The first noteworthy observation is the high variability in indicators' values across CEE companies, particularly for ROE, ROIC and EBITDA and EBIT margins; for example, ROE varies between -105.18 procent and 83.15 procent, while ROIC varies between -95.71 procent and 101.06 procent. At the same time, for the majority of indicators, the sample median takes values that are lower than the sample mean, which indicates distributions that are skewed to the right. The only exceptions are ROE, ROIC and Solvability, in whose case the sample seems dominated by a few companies with higher values of these indicators.

The basic descriptive statistics of the variables show that: (i) Liquidity and solvability ratios - current ratio (CR), quick ratio (QR) and solvability ratio (Solv) have an average value of 1.2210, 1.9124 and 59.5923, respectively. This result shows that the companies included in the sample have a reasonably good ability to meet their short-term obligations and to fulfill their long-term obligations; (ii) Efficiency ratios - total asset turnover (TAT) and inventory turnover (STT) have an average value of 2.1985 and 11.4611, respectively. This result shows that the industries included in our research have good asset utilization efficiency, high inventory liquidity and the capital appropriating time is low; (iii) The average level of gross profit margin (Gprof) and operating profit margin (Oprof) indicate also good levels of profitability; (iv) The return on assets (ROA) and the return on equity (ROE) are rather small, in terms of sample mean, which suggests that the sample includes companies with very low performances. This is indicated also by the high standard deviation of ROA and, to some extent, ROE, of the sample; (v) Most likely, the small values of ROA and ROE across the sample are reflected in small values of Price/Book value (PB) and Tobin Q ratio (TQ), which indicate the reduced trust of market investors in the companies from the CEE; (vi) the high values of the ranges and standard deviation indicate that there is a large dissimilarity between CEE companies particularly for operational performance indicators, but to a lower extent for what concerns liquidity and market indicators; (vi) the positive value of skewness for almost all indicators indicates a positive or rightward asymmetry; (vii) the values of the coefficient of variation are above one for all indicators across the sample, which suggests that, on average, the volatility of financial indicators for CEE companies, as described by the standard deviation, is smaller than the average of the respective indicators. The high diversity of indicators' values within our sample is also evidenced by the Grubbs Test for outliers; with the exception of solvability means, all the other values indicate the presence of outliers in our sample. We have decided to include these outliers in our analysis, since excluding them would have dramatically reduced the number of companies available.

Table 3: Descriptive statistics of financial indicators based on 2008-2016 means and coefficient of variation values.

	Mean	Grubbs Test	Median	Minimum	Maximum	Range	Std.Dev.	Skewness
ROE_mean	1.0053	**5.0599**	3.6981	-105.1863	83.1559	188.3422	20.9871	-2.3696
ROE_CV	1.0702	**4.5079**	0.6710	-1.9371	8.2989	10.2360	1.6035	1.3895
ROA_mean	2.5035	3.5349	1.9311	-17.9829	18.3377	36.3205	5.7954	-0.4321
ROA_CV	1.0851	**5.4722**	0.6622	-2.3342	10.8830	13.2172	1.7905	2.0800
TAT_mean	2.1985	**7.9715**	1.4629	0.2096	27.9985	27.7889	3.2365	6.3935
TAT_CV	6.3354	**9.6966**	4.9578	0.4942	66.4307	65.9365	6.1976	5.9552
STT_mean	11.4611	**7.8488**	7.5232	1.5520	142.6925	141.1405	16.7199	5.5094
STT_CV	5.6743	**5.1483**	5.2183	0.4461	25.7338	25.2877	3.8963	1.6974
ROIC_mean	5.7086	**6.8669**	6.0112	-95.7140	101.0592	196.7732	14.7698	-0.6930
ROIC_CV	1.6420	**4.2402**	1.0731	-1.6494	9.6170	11.2664	1.8808	1.4970
QR_mean	1.9124	**4.6769**	1.5686	0.1874	7.5974	7.4100	1.2156	2.3082
QR_CV	5.4785	**4.1562**	4.5379	0.8895	22.3683	21.4787	4.0638	1.7285
CR_mean	1.2210	**5.5293**	1.0334	0.0617	5.8960	5.8343	0.8455	2.6031
CR_CV	4.5420	**4.2487**	3.5058	0.8207	18.8168	17.9961	3.3598	1.8286
Gprof_mean	9.8553	**4.3051**	8.9744	-13.3233	40.8342	54.1576	7.1959	0.9218
Gprof_CV	3.5152	**4.1972**	2.6807	-0.7770	17.0503	17.8273	3.2248	1.5702
Oprof_mean	4.3888	**3.7932**	4.0420	-22.0079	22.4484	44.4563	6.9590	-0.9527
Oprof_CV	1.9004	**4.0824**	1.1664	-1.7552	11.2465	13.0017	2.2893	1.5952
Solv_mean	54.2923	3.3387	54.9501	-1.6660	90.7063	92.3723	16.7606	-0.3748
Solv_CV	10.1561	**5.9052**	7.9178	-0.1517	62.2661	62.4177	8.8244	2.6694
Debt_mean	59.4876	**4.1467**	42.9543	1.2770	284.6080	283.3310	54.2891	2.0730
Debt_CV	2.8932	**9.5367**	2.2778	0.4504	30.4135	29.9631	2.8857	6.0529
PB_mean	1.2494	**8.5959**	0.9391	-1.5530	12.9717	14.5247	1.3637	4.6741
PB_CV	2.9610	**4.3332**	2.5611	-0.2087	10.3983	10.6070	1.7164	1.4806
TQ_mean	0.6761	**4.6649**	0.4759	0.0049	3.5996	3.5947	0.6267	2.1362
TQ_CV	2.9378	**4.7311**	2.5849	0.6326	10.2572	9.6246	1.5471	1.7434

Note: St. Dev -- standard deviation; Bolded Grubbs test shows statistically significant values at five procent.
Source: Author's own work

As we have shown in our research methodology, using statistical cluster analysis we group the objects, in our case the sample of 164 companies, based on the measurement of distances or similarities among them. The grouping occurs naturally, since a desired number of clusters is not required as an input. The amalgamation method starts from 164 clusters, represented by all the companies, which are to be linked progressively, relaxing the grouping criterion until it comes to one single cluster that contains all the objects. We are constructing the clusters based on the coefficient of variation for each indicator, given its ability to better compare variables that are measured differently. All the reported results that follow, for hierarchical and k-means clustering alike, are based on coefficients of variance for all the companies in the sample. Preliminary we calculated the distances among the 164 companies included in the clustering amalgamation; the lower the distance, the higher the similarity between the objects/classes. The lowest distance is found between a PANN, a Hungarian company, and CIGA, a Polish company (0.6405) and the highest between NOVI, a Polish company, and a previously created cluster that includes all the 163 companies previously grouped.

In applying the clustering algorithm, we used Ward's amalgamation method, because by this method the distribution of an object into a cluster minimizes the variance inside the cluster. The first 15 stages of amalgamation are shown in Table 4. Initially, 164 companies were distributed in 164 clusters. The first step of the amalgamation is the formation of a cluster between the first two companies. So, as a result of the first iteration, we will have 164 clusters: one formed by companies PANN (PANNERGY NYRT.), a Hungarian company from the Manufacture of rubber and plastic products sector and CIGA (CI GAMES S.A.), a Polish company from the Other manufacturing sector, and other 162 clusters formed by the other 162 companies. The next step is grouping companies VEFR (VEF RADIOTEHNIKA RRR AS), a Latvian company from Manufacture of electrical equipment sector, with ABAD (ABADON REAL ESTATE S.A.), a Polish company from Manufacture of motor vehicles, trailers and semi-trailers sector, between which there is a distance of 0.724. Now we have 162 clusters left: the one formed at the first iteration (made up by companies PANN and CIGA), the other one that resulted at the second iteration (formed by companies VEFR with ABAD), as well as other 160 clusters consisting of the remaining companies. The amalgamation goes on in a similar manner. As a result of the 163 iterations, all the 164 will form a single cluster.

On the vertical axis in Figure 1 we have the distances from the first column of Table 4 and on the vertical axis are represented the 164 iterations. We notice that the distance between clusters is rather similar for the first 150 clusters approximately, then increases significantly, particularly after the 160 iteration. This suggests a high similarity between the clusters created in the first 150 iterations of the by amalgamation algorithm and a high dissimilarity for the companies included last in the amalgamation.

Preliminarily, we were interested in observing the result of a hierarchical clustering -- see Figure 2 (the figure suggests visually where the clustering process should end naturally). The formation of three important natural clusters is evident, but within these

Table 4: Amalgamation Schedule based on Ward`s method.

No	Distances	Obj. No. 1	Obj. No. 2	Obj. No. 3	Obj. No. 4	Obj. No. 5	Obj. No. 6	....
1	0.6405	PANN	CIGA					....
2	0.7242	VEFR	ABAD					....
3	0.7659	BROD	SECO					....
4	0.7769	SILV	STAP					....
5	0.7909	ALFA	DALE					....
6	0.8057	ARCT	ZAKP					....
7	0.8119	VIDA	KCIS					....
8	0.8228	ENER	ZAME					....
9	0.8567	DITT	VEFR	ABAD				....
10	0.8568	FORM	FERR					....
11	0.8934	MANG	SYNT					....
12	0.9001	DIET	PANN	CIGA				....
13	0.9053	TIMS	VIST					....
14	0.9167	POLS	RADP					....
15	0.9520	ELZA	KGHM					....
...	....	....	....	......	......	......	......	....

Source: Author's own work

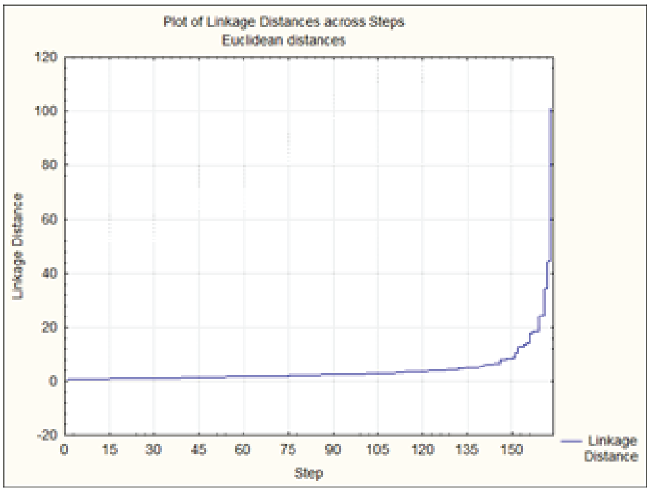

Figure 1: Plot of linkage distances across steps (Source: Author's own work).

three main clusters other smaller and more similar clusters are also formed. Overall, Figure 2 suggests that the number of clusters resulting from the clustering algorithms might vary between 2 and 15, approximately, depending on their degree of similarity. The k-means algorithm will confirm or not this result.

Rather interesting, when the k-means clustering algorithm is applied (see Table 5) it results in only 2 clusters. 36 cases are included in the first cluster (21.95% of cases) and 128 in the second (78.05%). Table 6 also shows how the 13 indicators we used are represented in each cluster's centroid and we observe that Cluster 1 centroid

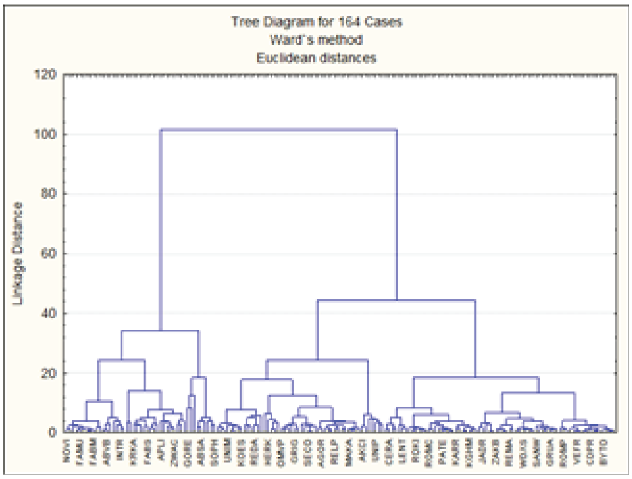

Figure 2: Tree diagram based on Ward`s method (Source: Author's own work).

has positive values for all indicators, while for Cluster 2 these values are negative. Quite straightforward, the k-means algorithm separates companies depending on their positive versus negative values for the variables included in the clustering algorithm, for example, the coefficient of variation of indicators' values between 2008-2016, with 21.95 procent of cases/companies included in Cluster 1 and the remaining 78.05 procent of them included in Cluster 2.

Table 5: Centroids for k-means clustering.

Indicators	Cluster 1	Cluster 2
ROE_CV	1.2516	-0.3520
ROA_CV	1.2100	-0.3403
TAT_CV	0.7805	-0.2195
STT_CV	0.9687	-0.2724
ROIC_CV	1.2824	-0.3607
QR_CV	0.9389	-0.2640
CR_CV	0.9586	-0.2696
Gprof_CV	1.3324	-0.3747
Oprof_CV	1.4279	-0.4016
Solv_CV	0.5289	-0.1486
Debt_CV	0.4099	-0.1152
PB_CV	0.5010	-0.1409
TQ_CV	0.3679	-0.1034
Number of cases	36	128
Percentage (%)	21.95	78.05

Source: Author's own work

At the same time, Clusters 1 and 2 seem to record a rather low dissimilarity, based on distances between clusters' centroids (shown in Table 6).

Table 6: Distance between centroids of k-means clustering.

	Cluster 1	Cluster 2
Cluster 1	0.000000	0.748128
Cluster 2	0.748128	0.000000

Source: Author's own work

Figure 3 shows the normalized means for the two clusters and we notice that cluster 1 is a a cluster with higher normalized means for all vairables, while cluster 2, that has the highest number of members, has lower normalized means for all variables. The highest differences in the normalized means of the variables between the two clusters are found for ROIC and Operational profitability, while the lowest differences are identified for Debt and TAT. Interestingly, ANOVA shows that all variables are significant differentiators within clusters and between clusters, as shown in Table 7.

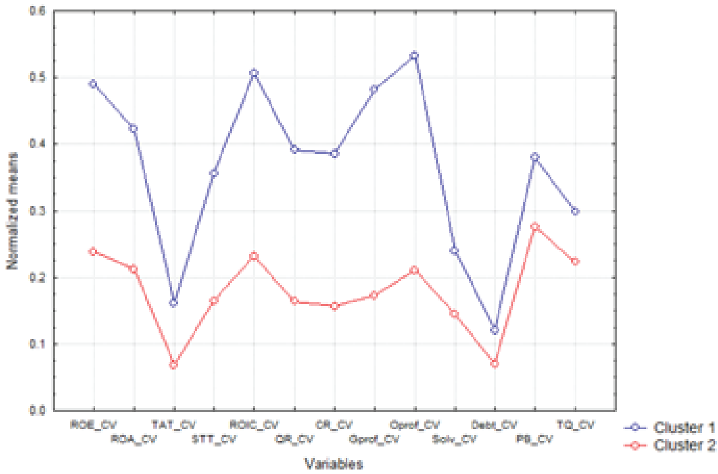

Figure 3: Graph of means for continuous variable (Source: Author's own work).

The distribution of CEE companies in the two clusters depending on their country of origin and industry of operations is presented in Table 8. As it can be easily observed, there are a few countries, such as CZ, LT, RO and SK, whose companies are present only in the second, less performing cluster. At the same time, 20 Polish companies and seven Hungarian companies belong to the more performing Cluster 1. In terms of industry, Cluster 1 includes companies from 13 out of 28 industries, the highest number of companies coming from C27 -- Manufacture of electrical equipment, followed by C10 - Manufacture of food products and C28 - Manufacture of machinery and equipment n.e.c. It is also interesting to see that almost all companies from the extractive industry are grouped in the second cluster, except for one company from B09 - Mining and quarrying n.e.c.

TABLE 7: ANOVA results for k-mean clustering.

	Between	df	Within	df	F	p value
ROE_CV	72.26622	1	90.7338	162	129.0272	0.0000
ROA_CV	67.53157	1	95.4684	162	114.5940	0.0000
TAT_CV	28.10072	1	134.8993	162	33.7460	0.0000
STT_CV	43.28763	1	119.7124	162	58.5787	0.0000
ROIC_CV	75.86646	1	87.1335	162	141.0521	0.0000
QR_CV	40.66883	1	122.3312	162	53.8567	0.0000
CR_CV	42.38550	1	120.6145	162	56.9289	0.0000
Gprof_CV	81.89503	1	81.1050	162	163.5781	0.0000
Oprof_CV	94.05185	1	68.9481	162	220.9835	0.0000
Solv_CV	12.88769	1	150.1123	162	13.9083	0.0003
Debt_CV	7.75080	1	155.2492	162	8.0878	0.0050
PB_CV	11.57827	1	151.4217	162	12.3871	0.0006
TQ_CV	6.24629	1	156.7537	162	6.4553	0.0120

Source: Author's own work

4. Conclusion

Our paper analyzed the financial performances of the companies from Central and Eastern European countries, from two main economic sectors: Mining and quarrying and Manufacturing. The objective of the research resided in identifying natural groups of companies depending on their corporate financial performance between 2008-2016. The company's financial performance was described by a set of thirteen indicators that comprehensively addressed all areas of performance: liquidity, solvability, profitability, efficiency, investment performance and aggregate performance.

Our results show the high diversity of corporate performance in CEE countries in the rather turbulent years after the Global financial crisis of 2007-2009. At the same time, both the hierarchical clustering algorithm and the k-means algorithm evidenced that what seems diverse at first sight in terms of corporate performance is actually more homogeneous when all performance indicators are taken into account. Moreover, the research methodology employed supports the conclusion that neither the country of origin nor the industry are strong differentiators of corporate performance between CEE companies. At the same time, though, all financial indicators included in our analysis discriminate between companies and sustain their inclusion in one of the two clusters.

Certainly, our research has limits that need to be addressed in further research, based on data availability. One of the limits refers to the small number of companies included in the analysis, determined by the need to work with listed companies, whose financial reports are more trustworthy and for whom data is more available. Also, the analysis included one year of the crisis -- 2008 -- and the turbulent years of the European sovereign debt crisis (after 2010), which have impacted the results of these companies. Moreover, a comparison with similar peers from the Western Europe is needed and will be further tackled.

Table 8: Companies' distribution in clusters.

Country	Cluster 1	Cluster 2	Industry	Cluster 1	Cluster 2	Industry	Cluster 1	Cluster 2
BG	1	11	B05	0	1	C19	0	5
CZ	0	1	B06	0	1	C20	1	8
EE	1	3	B07	0	1	C21	4	1
HR	7	12	B08	0	1	C22	2	6
HU	3	4	B09	1	1	C23	0	3
LT	0	9	C10	6	16	C24	2	9
LV	1	6	C11	2	4	C25	0	7
PL	20	67	C12	0	1	C26	1	3
RO	0	10	C13	0	4	C27	8	5
SI	3	1	C14	0	6	C28	6	14
SK	0	4	C15	0	1	C29	1	2
Total		164	C16	0	3	C30	0	7
			C17	1	6	C31	0	2
			C18	1	4	C32	0	6
			Total					164

Source: Author's own work

References

[1] Sueyoshi, T. (2005). Financial Ratio Analysis of the Electric Power Industry. *Asia-Pacific Journal of Operational Research*, vol. 22, no. 3, pp. 349-376.

[2] Horobet, A., Joldes, C. and Dumitrescu, D.G. (2008). A Cluster Analysis of Financial Performance in Central and Eastern Europe. *Analele Universității din Oradea, Ştiințe economice,* Tom XVII, vol. III -- ``Finances, Banks and Accountancy``, pp. 301-306.

[3] Dikova, D. (2009). Performance of foreign subsidiaries: Does psychic distance matter? *International Business Review*, vol. 18, no. 1, pp.38-49.

[4] Santi, S. (2012). Using cluster analysis study to examine the successful performance entrepreneur in Indonesia. *Procedia Economics and Finance*, vol. 4, pp. 286-298.

[5] Szabo, Z.K. and Herman, E. (2014). Productive entrepreneurship in the EU and its barriers in transition economies: A cluster analysis. *Acta Polytechnica Hungarica*, vol. 11, no. 6, pp. 73-94.

[6] Hanousek, J. and Kochanova, A. (2016). Bribery environments and firm performance: Evidence from CEE countries. *European Journal of Political Economy*, vol. 43, issue C, pp. 14-28.

[7] Ta, V. and Liu, C.M. (2016). Stock market analysis using clustering techniques: the impact of foreign ownership on stock volatility in Vietnam. *Proceedings of the Seventh Symposium on Information and Communication Technology*, Ho Chi Minh City, Vietnam, pp. 99-106.

[8] Hartigan, J. A. and Wong, M. A. (1979). A K-Means Clustering Algorithm. *Journal of the Royal Statistical Society. Series C (Applied Statistics),* vol. 28, no. 1, pp. 100-108

[9] Witten, D. (2011). Classification and clustering of sequencing data using a Poisson model. *The Annals of Applied Statistics*, vol. 5, no. 4, pp. 2493-2518.