UDC 338.2:336.76 JEL Classification: C10, F33, O31

Peker Sinem,
PhD, Assistant Professor, Department of Mathematics, Faculty of Science and Letters, Yasar University (Izmir, Turkey);
Aktan Bora,
PhD, Associate Professor, College of Business Administration, Faculty of Commerce and Business Administration, University of Bahrain, Kingdom of Bahrain & Future University in Egypt (New Cairo, Egypt);
Tvaronavičienė Manuela,
PhD, Professor, Vilnius Gediminas Technical University (Vilnius, Lithuania)

CLUSTERING IN KEY G-7 STOCK MARKET INDICES: AN INNOVATIVE APPROACH

Investment in stock market requires taking risk. Investors typically buy several stocks to create a portfolio which targets to maximize the return while keeping a certain level of risk. In today's information-rich financial markets, one of the main challenges for individual investors in particular is to allocate the scarce sources appropriately within the wide range of investment alternatives that grouping the multiple assets based on their similar characteristics would be useful to take it out. In this paper, stock markets of the Group of 7 (G-7) countries consisting of France, United Kingdom, Germany, Italy, United States, Canada and Japan are examined over the period of 2011 and 2016 and some hierarchical clustering methods are applied on key indices namely, CAC 40 (France), FTSE 100 (UK), DAX (Germany), FTSE MIB (Italy), S&P TSX Composite (Canada), S&P 500 (USA), NIKKEI 225 (Japan) to identify the groups based on risk and return characteristics.

Keywords: G-7 countries, hierarchical clustering, k-means, twostep clustering, stock market, innovative approach.
DOI: 10.21272/mmi.2017.1-27

Introduction and background. Integration among the major stock exchanges of the financial world has always been attracted attentions due mainly to globalization efforts and innovations in the sector that the financial markets have become more integrated and complicated in today's head to head competitive investment environment. However, so-called integrated and information-rich markets do not continuously follow the same patterns due mainly to the local market conditions where advance quantitative methods through econometric models are required using to forecast the behaviors. Moreover, understanding those models is almost impossible for individuals eager to making better investment decisions [4; 16; 17; 18].

Clustering, which was first used as a term by Tyron (1939), is a widely held multivariate analysis which is practiced in a number of fields such as biology, medical sciences computer vision, sociology, urban planning, marketing, and so forth [7; 9; 13; 33; 34; 36;]; for example, Li et al., (2015) distinctly grouped the sports gamblers according to the demographic and behavioral characteristics in China who bought sports lottery tickets more than once in a year by developing a typology based upon the scale of assessing problem gambling [22].

The method, which is relatively new and innovative approach in empirical finance, like factor analysis and multi-dimensional scaling, can be used to facilitate the selection process in portfolio management to solve abovementioned problem. In this analysis, objects or variables are separated into a small number of similar categories and relationships between objects and subjects are explored without a dependent variable being identified [5; 30]. In finance, cluster analysis unlike factor analysis is applied seldomly. The finance literature documents a small number of studies applying different clustering methods to given financial classification problems for instance, [1; 3; 6; 14; 26; 28;] and more recently, [8; 15; 19; 25]. Stock exchanges of G-7 countries can be seen as a leading group not only for their market capitalizations within the world's total value of equities but also for the solidity in today's multifaceted investment environment, in particular, for individual investors. Despite this, some studies on predictability of G-7 countries' stock markets such as Lim and Hooy (2013)'s presented evidence that G-7 markets are usually unpredictable but not all the time [23]. Therefore, still many ongoing researches being worked on developed markets are existed where complex econometric techniques are applied by academics and researchers.

In the existing literature, some studies focus on developed markets, for instance, Basalto et al (2005) applied pairwise version of the chaotic map clustering algorithm to the firms indexed in Dow Jones to identify the similar behaviors from 1998 to 2002 [3] and Directed Bubble Hierarchical Tree, a type of hierarchical clustering method was applied by Musmeci et al (2015) to the US stock prices for a fifteen year period and results were compared with other clustering methods such as the single, the average and the complete linkages together with k-medoids [25]. They specified that the applied method showed dissimilar performance in retrieving the economic information encoded in the Industrial Classification Benchmark and suggested that these dissimilarities would be connected to different degrees of sensitivity to the market mode dynamics [25]. Laval (2016) interestingly examined the relationship between frequency of annual general meetings and stock returns in UK and found a significantly negative relationship between stock returns and the monthly frequency of annual general meetings [21].

Some concentrate on emerging markets, for instance, Long et al, (2014) tested an efficient multi-objective portfolio optimization model adopting Fuzzy C-means clustering and Multi-objective genetic algorithm for 570 stocks listed on Thailand Stock Exchange over a short period from 2011 and 2012 and suggested that the model would be useful to investor to pick stocks which have similar characteristics basing on risk and return [24]. Jung and Chang (2016) implemented agglomerative clustering form of hierarchical clustering approach to the monthly data of listed firms on Korean Stock Exchange for a decade from 2004 to 2014 and indicated that the firms were grouped under the same sector based upon their market returns [15]. Nanda et al (2010) used stock returns at different time scales together with their valuation ratios from Bombay Stock Exchange over a short period from 2007 to 2008 to build a portfolio providing minimum risk. In order to classify the stocks, Self-organizing map, k-means and Fuzzy C-means methods were implemented. They pointed out that k-means cluster analysis builds the most compact clusters as compared to others and suggested using a hybrid system for efficient portfolios based on the data from 106 stocks [26].

Recently, a broad cluster analysis on global equity markets was carried out by Esmalifalak et al (2015) by using weekly returns of 41 indices from 40 countries over the period of March 2011 and December 2013. They found that the proposed methods were able to capture (a) hierarchy of interrelated clusters embedded in a complex network of objects; (b) different integration and disintegration levels amongst selected equity indices and (c) abnormal seasons and indices in terms of time and regional horizons [8]. Lahmiri (2016) investigated if cluster structures were similar by analyzing the listed firms on Casablanca Stock Exchange adopting hierarchical clustering to different sectors namely transportation, construction, banking, insurance, communications, financing, distribution and food for three market regimes so-called ups and downs, falling and rising trends during 2009, 2010, and 2011 time periods. He observed that the general structure of stock exchange topology was considerably changed over time periods and also stated that interrelationships among sectors differ throughout the time periods thus Casablanca Stock Exchange complex structure is dynamic and changes with market regime [19].

In this paper, stock markets of the Group of 7 (G-7) countries consisting of France, United Kingdom, Germany, Italy, United States, Canada and Japan are examined over the period of 2011 and 2016 and some hierarchical clustering methods are applied on widely followed stock market indices namely, CAC 40 (France), FTSE 100 (UK), DAX (Germany), FTSE MIB (Italy), S&P TSX Composite (Canada), S&P 500 (USA), NIKKEI 225 (Japan) to identify the groups based on risk and return characteristics. The remainder of the paper is as follows: Section 2 describes the data and methodology, Section 3 presents the empirical results and Section 4 concludes.

Data and methodology. Daily closing data of stock market indices is obtained from Datastream internatonal over the period of 2011 and 2016 [11; 37]. Returns are computed as logarithmic price relatives. The single linkage, complete linkage, average linkage, centroid and Ward's hierarchical clustering methods are performed on daily index returns; the k-means clustering and twostep clustering are performed on the means and the risk measured by standard deviations of daily returns over the studied period.

In the identification of clusters, similar records with respect to some characteristics take part in the same group; however, each group should be different from other groups considering the related characteristics [20; 27; 31]. In the literature, a lot of clustering methods have been developed such as partitioning methods, hierarchical clustering methods, density based methods, grid-based methods, and model based methods [12; 38]. The partitional clustering involves many clustering families [27]. Some of them are k-means, k-medoids, k-medians, k-modes clustering. The choosing the initial centroids, and the number of clusters are the main factors which can affect the performance of k-means algorithm. Some methods that may be used for the estimation of the correct number of clusters in k-means clustering are Gab statistics, Akaike information criteria, Bayesian information criteria, Duda and Hart method [29]. In the hierarchical clustering, there are agglomerative and divisive methods [2]. Divisive methods begin with a single cluster that involves all objects and the objects are separated successively such that at the last stage, each cluster involves a single object. Agglomerative methods begin with clusters such that each object form each cluster at the beginning and the objects are merged until obtaining a single cluster which is formed by all objects at the end [32]. Both divisive and agglomerative methods use dendrogram. Some agglomerative hierarchical clustering methods are single linkage, complete linkage, average linkage, centroid and Ward's method [10; 32]. Some used statistics for the appraising of the cluster solution at any step are root-mean-square standard deviation of new cluster, semipartial R-squared, R-squared, distance between two clusters. The reliability and external validity of a cluster solution can be evaluated by a cross-validation procedure and the comparison of the results from cluster analysis with an external criterion, respectively [31].

3. Empirical Results. Returns are computed as logarithmic price relatives: $y_t = ln(p_t / p_{t-1})$, where P_t is daily value at time t and statistical properties of the data are given in Table 1.

Table 1 – Statistical properties

	CAC 40	DAX	FTSE MIB	FTSE 100	NIKKEI 225	S&P 500	S&P/ TSX
Mean	0,00033	0,00057	0,00019	0,00026	0,00059	0,00050	0,00014
Median	0,00060	0,00113	0,00015	0,00047	0,00072	0,00049	0,00058
Standard Deviation	0,01316	0,01292	0,01716	0,00955	0,01431	0,00896	0,00804
Variance	0,00017	0,00017	0,00029	0,00009	0,00021	0,00008	0,00006
Kurtosis	2,69578	1,87474	3,77519	1,88737	3,55533	2,16573	1,75766
Skewness	-0,20019	-0,18274	-0,45417	-0,08257	-0,34039	-0,17357	-0,18229
Range	0,14474	0,12278	0,19718	0,08419	0,15679	0,08262	0,07115
Minimum	-0,08384	-0,07067	-0,13331	-0,04779	-0,08253	-0,04021	-0,03174
Maximum	0,06089	0,05210	0,06386	0,03639	0,07426	0,04240	0,03941
Sum	0,40977	0,68937	0,22979	0,31000	0,66838	0,58753	0,16459
Count	1234	1214	1194	1193	1131	1171	1181
Largest (1)	0,06089	0,05210	0,06386	0,03639	0,07426	0,04240	0,03941
Smallest (1)	-0,08384	-0,07067	-0,13331	-0,04779	-0,08253	-0,04021	-0,03174

The line chart of daily index returns is given in Figure 1.

The Ward's hierarchical clustering method is performed on daily index returns by using SPSS. In the clustering, the squared Euclidean distance is used. The agglomeration schedule and the dendrogram of clustering are shown in Table 2 and Figure 1, respectively.

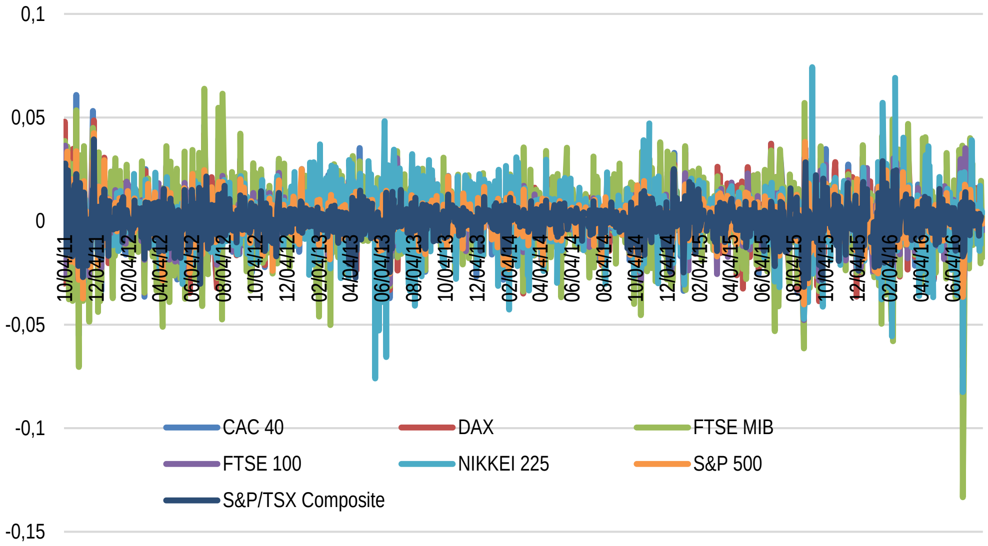

Figure 1 – Time series lines of daily index returns

Table 2 – Agglomeration schedule

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	1	2	,011	0	0	3
2	6	7	,029	0	0	5
3	1	4	,058	1	0	4
4	1	3	,123	3	0	5
5	1	6	,242	4	2	6
6	1	5	,447	5	0	0

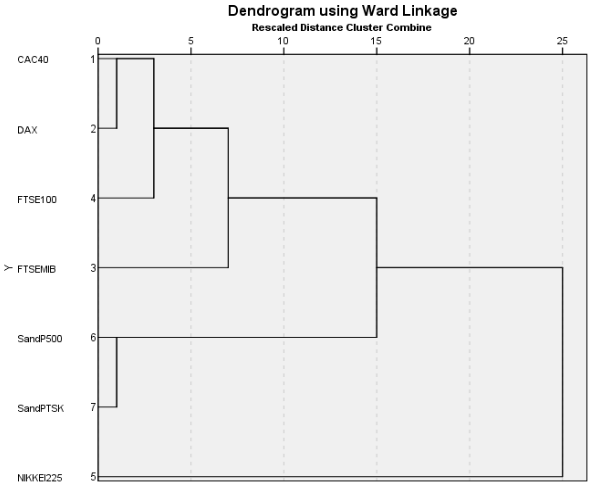

Figure 2 – Dendrogram using Ward's method

The time series lines of daily index returns of CAC 40 and DAX, S&P 500 and S&P/TSK Composite are given in Figure 3 and Figure 4, respectively.

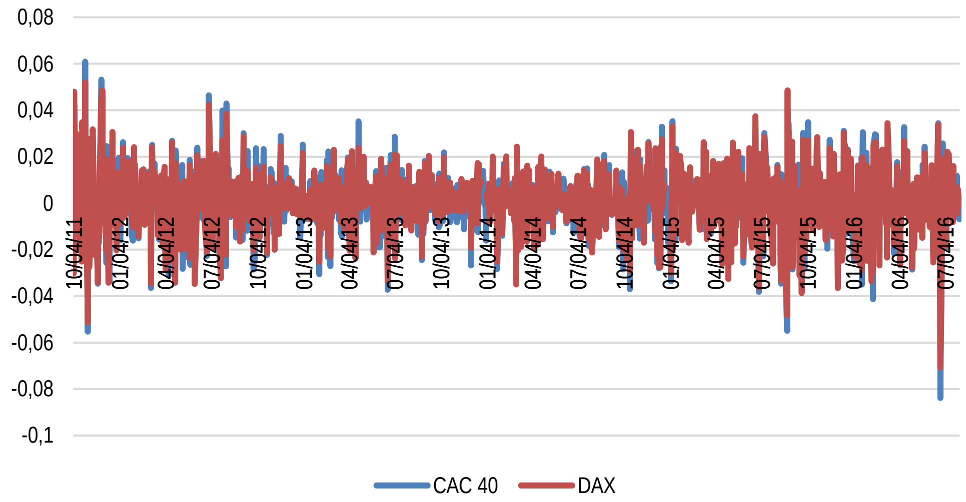

Figure 3 – Time series lines of daily index returns for CAC 40 and DAX

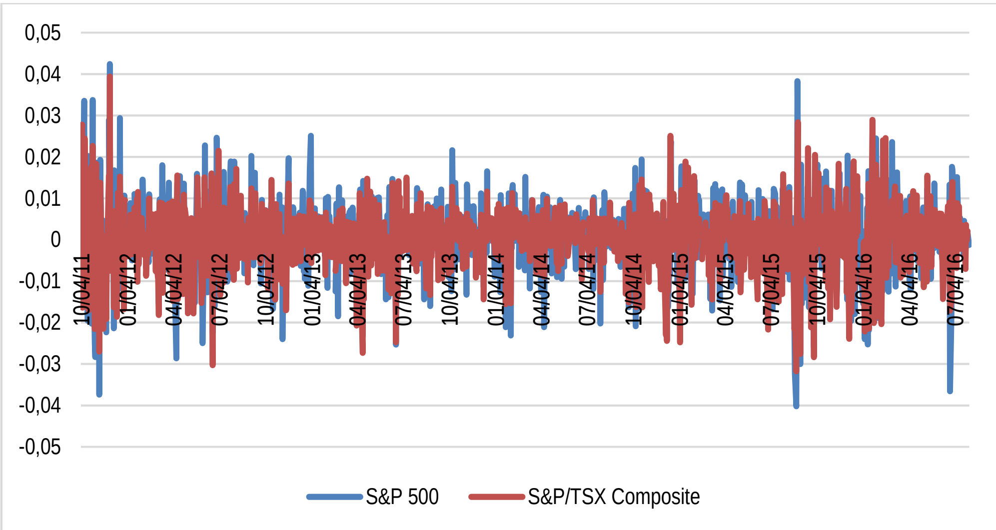

Figure 4 – Time series lines of daily index returns for S&P 500 and S&P/TSK Composite

The other dendrograms obtained by the average linkage, single linkage, complete linkage, centroid hierarchical methods as shown in Figures 5-9. There are some differences between dendrograms obtained by some methods. However, the all performed dendrograms in this study indicate that CAC 40 is merged with DAX, S&P is merged with S&P/TSK Composite at the first stages; lastly NIKKEI 225 is merged with the group of CAC 40, DAX, FTSE 100, S&P 500, S&P/TSK Composite, FTSE MIB at the last stage.

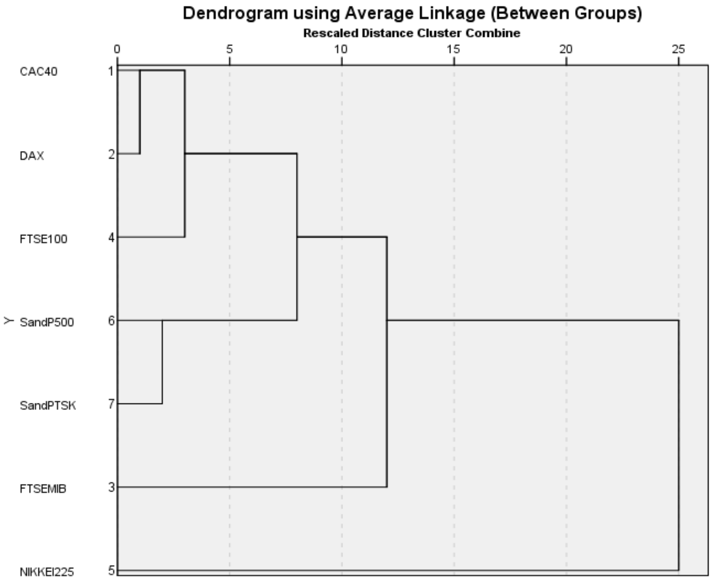

Figure 5 – Dendrogram using Average Linkage (Between Groups)

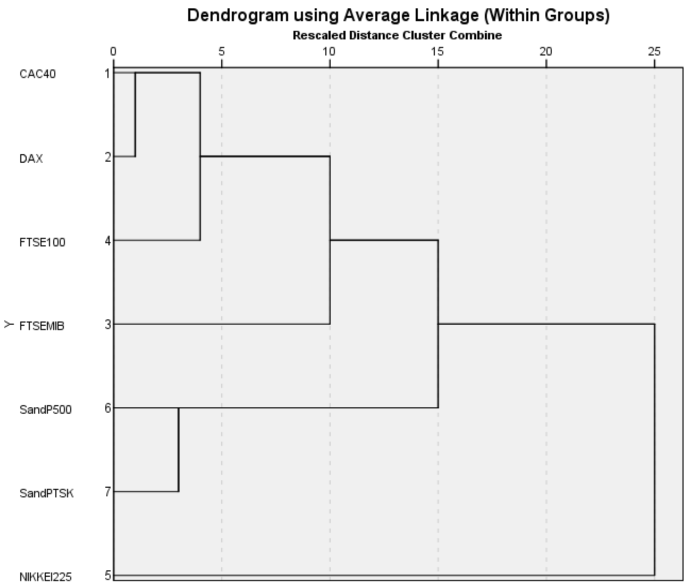

Figure 6 – Dendrogram using Average Linkage (Within Groups)

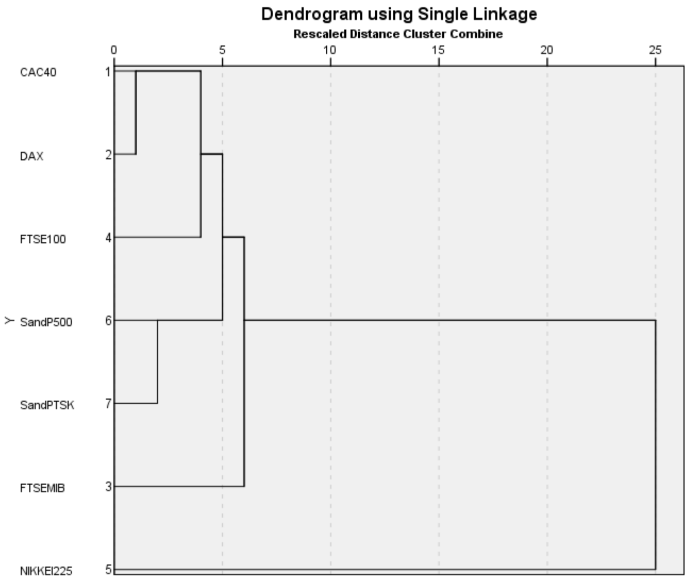

Figure 7 – Dendrogram using Single Linkage

The scatterplot for indices based on mean and standard deviations is obtained as given in Figure 10 over the studied period.

Twostep clustering is processed on the means and standard deviations of daily returns over the period 04.10.2011-01.08.2016. AIC and BIC criterias result that the appropriate number of cluster is k=1.

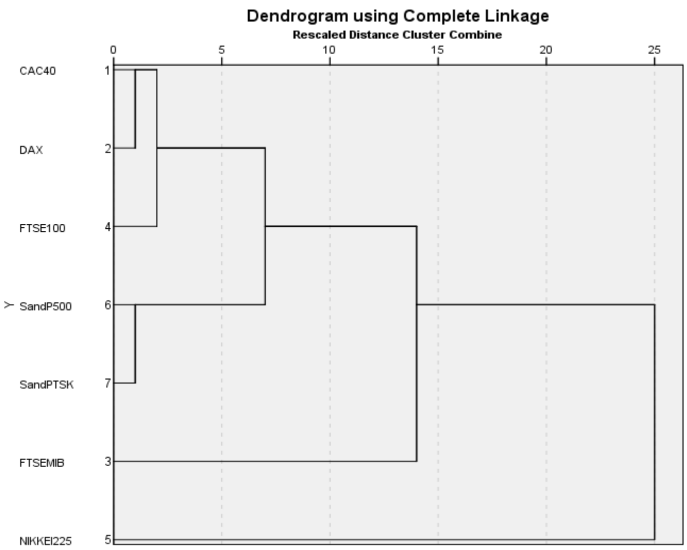

Figure 8 – Dendrogram using Complete Linkage

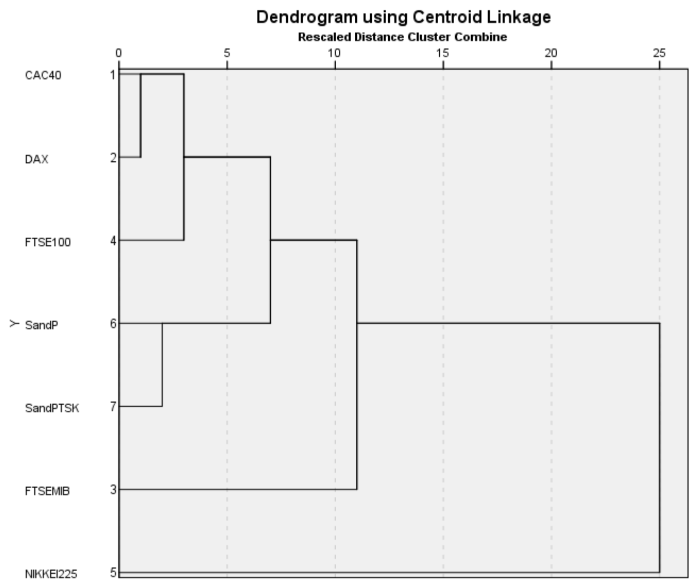

Figure 9 – Dendrogram using Centroid Linkage

Considering Duda and Hart Method, the hierarchical clustering is performed on the means and standard deviations of daily returns to choose the correct cut of level in the dendrogram. Accordingly, it is decided that the appropriate number of clusters may be 3. In this context, the k-means clustering is performed on the means and standard deviations of daily returns over the period 04.10.2011-01.08.2016 and the following results are obtained for k = 3.

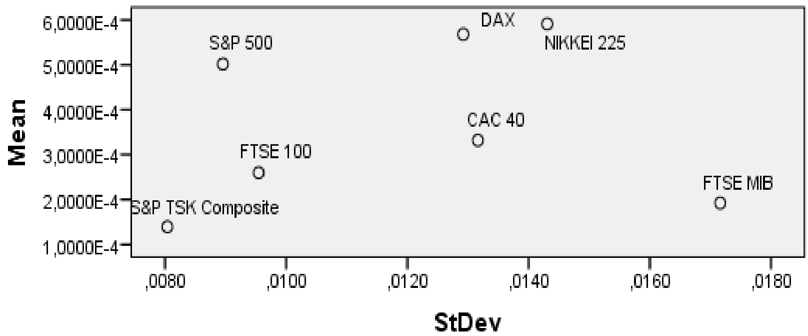

Figure 10 – Scatter plot of indices 2011-2016

As seen in Table 3, CAC 40, DAX, NIKKEI 225 form a group; FTSE 100, S&P 500, S&P TSK Composite form another group, and FTSE MIB form a group for the period. When twostep cluster is applied for k = 3, the results in Table 4 is evaluated for the related period.

The same results given in Table 4 are found when the standardized values of the mean and the standard deviations are used and when the unstandardized values of the mean and the standard deviations are used in twostep clustering. In the k means clustering, if the standardized values of mean and standard deviations are used, again the similar cluster memberships are obtained as given in Table 4 for the related period.

Table 3 – Cluster Membership according to k-means clustering for k = 3

Case Number	Indices	Cluster	Distance
1	CAC 40	1	,000
2	DAX	1	,001
3	FTSE MIB	3	,000
4	FTSE 100	2	,001
5	NIKKEI 225	1	,001
6	S&P 500	2	,000
7	S&P TSK Composite	2	,001

Table 4 – The Cluster memberships according to twostep clustering for k=3

Case Number	Indices	Cluster
1	CAC 40	1
2	DAX	2
3	FTSE MIB	1
4	FTSE 100	3
5	NIKKEI 225	2
6	S&P 500	2
7	S&P TSK Composite	3

According to Table 4, CAC 40 and FTSE MIB form one group; FTSE 100, S&P TSK Composite form another group; while DAX, NIKKEI 225 and S&P 500 form the third group for the period.

Conclusion. Cluster analysis is an innovative and a very useful method to help make sense of data. In this paper, we investigated the Group of 7's stock markets over the period of 2011 and 2016. The single linkage, complete linkage, average linkage, centroid and Ward's hierarchical clustering methods are performed on widely followed stock market indices namely, CAC 40 (France), FTSE 100 (UK), DAX (Germany), FTSE MIB (Italy), S&P TSX Composite (Canada), S&P 500 (USA), NIKKEI 225 (Japan) to identify the groups based on risk and return characteristics.

Although, the differences exist at some stages, the all performed dendrograms, in this study, demonstrated that CAC 40 is merged with DAX whereas S&P 500 is merged with S&P/TSK Composite at the first stages. At the last stage, NIKKEI 225 is merged with the group of CAC 40, DAX, FTSE 100, S&P 500, S&P/TSK Composite and FTSE MIB for the studied period. Additionally, the k-means clustering is performed on means and standard deviations of daily returns. The analysis showed that CAC 40, DAX and NIKKEI 225 form a group; FTSE 100, S&P 500 and S&P TSK Composite form another group, and finally FTSE MIB itself form a group during the examined period. When twostep clustering is performed for k=3, CAC 40 and FTSE MIB form one group; DAX, NIKKEI 225 and S&P 500 form another group, and FTSE 100 and S&P TSK Composite form the third group for the related period. Results partly showed similarity by the study of [8] since the dendrograms which was obtained through the average linkage method.

1. Aktan, B. (2013). An Empirical Examination of Clustering at Bahrain Bourse. *International Research Journal of Finance and Economics, 110*, 149-154 [in English].

2. Azzalini, A., & Scarpa, B. (2012). *Data Analysis and Data Mining: An Introduction*, Oxford University Press, USA [in English].

3. Basalto, N., Bellotti, R., De Carlo, F., Facchi, P., & Pascazio, S. (2005). *Clustering stock market companies via chaotic map synchronization, Physica A, 345*, 196-206 [in English].
4. Bikas, E., & Bikas, E. (2016). Towards sustainable financial markets: impact of structured securities on portfolio management, *Journal of Security and Sustainability Issues 6(2)*, 275-288. http://dx.doi.org/10.9770/jssi.2016.6.2(7) [in English].
5. Čábelková, I., Strielkowski, W., & Mirvald, M. (2015). Business influence on the mass media: a case study of 21 countries. *Transformations in Business & Economics, 14(1),* 65-75 [in English].
6. Chiabai, A., Platt, S., & Strielkowski, W. (2014). Eliciting users' preferences for cultural heritage and tourism-related e-services: a tale of three European cities. *Tourism Economics*, *20(2),* 263-277. http://dx.doi.org/10.5367/te.2013.0290 [in English].
7. Demainea, E.D., Emanuel, D., Fiat, A., & Immorlica, A. (2006). *Correlation clustering in general weighted graphs, Theoretical Computer Science, 361*, 172-87 [in English].
8. Esmalifalak, H., Ajirloub, A.I., Behrouz, S.P., & Esmalifalak, M. (2015). (Dis)integration levels across global stock markets: A multidimensional scaling and cluster analysis. *Expert Systems with Applications, 42*, 8393-8402 [in English].
9. Fuschi, D.L., & Tvaronavičienė, M. (2016). A network based business partnership model for SMEs management, *Entrepreneurship and Sustainability Issues, 3(3),* 282-289. http://dx.doi.org/10.9770/jesi.2016.3.3(5) [in English].
10. Gan, G., Ma, C., & Wu, J. (2007). *Data Clustering: Theory, Algorithms, and Applications*, SIAM, Philadelphia [in English].
11. Google Finance. (2016). *www.google.com.* Retrieved from https://www.google.com/finance [in English].
12. Han, J., & Kamber, M. (2001). *Data Mining: Concepts and Techniques*, Morgan Kaufmann [in English].
13. Ignatavičius, R., Tvaronavičienė, M., & Piccinetti, L. (2015). Sustainable development through technology transfer networks: case of Lithuania. *Journal of Security and Sustainability, 4(3)*, 261-267. DOI: http://dx.doi.org/10.9770/jssi.2015.4.3(6) [in English].
14. Ingram, M., & Margetis, S. (2010). A practical method to cost of equity capital for a firm using cluster analysis. *Managerial Finance*, 36 (2), 160-67 [in English].
15. Janda, K., Rausser, G., & Strielkowski, W. (2014). Determinants of Profitability of Polish Rural Micro-Enterprises at the Time of EU Accession. *Eastern European Countryside*, *19*, 177-217. https://doi.org/10.2478/eec-2013-0009 [in English].
16. Jurevičienė, D., & Skvarciany, V. (2016). Camels+t approach for banks' assessment: evidence from the Baltics. *Entrepreneurship and Sustainability Issues, 4(2)*, 159-173. http://dx.doi.org/10.9770/jesi.2016.4.2(4) [in English].
17. Kaźmierczyk, J., & Aptacy, M. (2016). The management by objectives in banks: the Polish case. *Entrepreneurship and Sustainability Issues, 4(2),* 146-158. http://dx.doi.org/10.9770/jesi.2016.4.2(3) [in English].
18. Kulišauskas, D., & Galinienė, B. (2015). Stock evaluation methods and their applicability in Lithuania ensuring sustainable capital market development. *Journal of Security and Sustainability Issues 5(1)*, 73-86. http://dx.doi.org/10.9770/jssi.2015.5.1(6) [in English].
19. Lahmiri, S. (2016). Clustering of Casablanca stock market based on hurst exponent estimates*. Physica A: Statistical Mechanics and its Applications, 456*, 310-318 [in English].
20. Larose, D.T. (2005). *Discovering Knowledge in Data: An introduction to Data Mining*, Wiley [in English].
21. Lawal, T. (2016). Clustering of annual general meetings and stock returns: UK evidence, *Journal of Behavioral and Experimental Finance, 11,* 9-12 [in English].
22. Li, H., Mao, L.L., Zhang, J.J., & Xu, J. (2015). Classifying and profiling sports lottery gamblers: A cluster analysis approach. *Social Behavior and Personality, 43 (8)*, 1299-1318 [in English].
23. Lim, K.P., & Hooy, C.W. (2003). Non- Linear Predictability in G7 Stock Index Returns. *The Manchester School, 81 (4)*, 620-637 [in English].
24. Lisin, E., & Strielkowski, W. (2014). Modelling new economic approaches for the wholesale energy markets in Russia and the EU. *Transformations in Business & Economics*, 13(2B), 566-580 [in English].
25. Musmeci, N., Aste, T., & Di Matteo T. (2015). Relation between Financial Market Structure and the Real Economy: Comparison between Clustering Methods. *PLoS ONE 10 (3),* 1-24 [in English].
26. Nanda, S.R., Mahanty, B., & Tiwari M.K. (2010). Clustering Indian stock market data for portfolio management. *Expert Systems with Applications, 37(12)*, 8793-8798 [in English].
27. Nandi, A.K., Abu-Jamous B., & Fa R. (2015). *Integrative Cluster Analysis in Bioinformatics*. John and Wiley Sons, India [in English].
28. Pattarin, F., Paterlini, S., & Tommaso, M. (2004). Clustering financial time series: An application to mutual funds style analysis. *Computational Statistics and Data Analysis, 47*, 353-72 [in English].
29. Reddy, C.K., & Vinzamuri B. (2014). *Data Clustering: Algorithms and Applications*, *Chapter 4,* edited by Charu C. Aggarwal, Chandan K. Reddy, CRC Press, Boca Raton [in English].
30. Saunders, J. (1994). Cluster Analysis. *Journal of Marketing Management, 10*, 13-28 [in English].
31. Sharma, S. (1996). *Applied Multivariate Techniques*, Wiley [in English].
32. Strielkowski, W., & Weyskrabova, B. (2014). Ukrainian labour migration and remittances in the Czech Republic. *Tijdschrift voor Economische en Sociale Geografie, 105(1),* 30-45. http://dx.doi.org/10.1111/tesg.12052 [in English].
33. Tvaronaviciene, M., Razminiene, K., & Piccinetti, L. (2015). Approaches towards cluster analysis, *Economics and Sociology, 8 (1),* 19-27 [in English].
34. Tvaronavičienė, M., & Černevičiūtė, J. (2015). Technology transfer phenomenon and its impact on sustainable development, *Journal of Security and Sustainability Issues 5(1),* 87–97. DOI: http://dx.doi.org/10.9770/jssi.2015.5.1(7) [in English].

35. Tvaronavičienė, M., Razminienė, K., & Piccinetti, L. (2015). Cluster efficiency study through benchmarking. *Entrepreneurship and Sustainability Issues* 3(2), 120-128. http://dx.doi.org/10.9770/jesi.2015.3.2(0) [in English].
36. Tyron, R. (1939). *Cluster Analysis*, McGraw Hill, New York [in English].
37. Yahoo finance. (2016). *finance.yahoo.com.* Retrieved from https://finance.yahoo.com [in English].
38. Zhou, Z.H. (2012). *Ensemble Methods: Foundations and Algorithms*, CRC Press, Boca Raton [in English].

С. Пекер, PhD, асистент, кафедра математики, факультет природничих наук і літератури, Університет Яшар (м. Ізмір, Туреччина);
Б. Актан, PhD, доцент, Коледж бізнес-адміністрування, факультет комерції і бізнес-адміністрування, Університет Бахрейну, Королівство Бахрейн і майбутній університет в Єгипті (м. Нью-Каїр, Єгипет);
М. Тваронавісіене, PhD, професор, Вільнюський технічний університет ім. Гедімінаса (м. Вільнюс, Литва)

Кластеризація ключових показників на фондових ринках країн “Великої сімки”: інноваційний підхід

Інвестиції на фондовому ринку вимагають прийняття ризику. Інвестори зазвичай намагаються сформувати свій інвестиційний портфель таким чином, щоб забезпечити отримання максимальної віддачі при збереженні прийнятного рівня ризику. У сучасних умовах для інвестора першочерговим завданням стає визначення найкращих джерел фінансування серед альтернативних варіантів шляхом групування активів з аналогічними характеристиками. У статті досліджено фондові ринки країн “Великої сімки” – Франції, Великобританії, Німеччини, Італії, США, Канади та Японії за період 2011-2016 рр. З метою поділу відповідних показників фондових ринків, зокрема CAC 40 (Франція), FTSE 100 (Великобританія), DAX (Німеччина), FTSE MIB (Італія), S&P TSX Composite (Канада), S&P 500 (США), NIKKEI 225 (Японія), на групи за критерієм “прибутковість – ризик” були використані окремі ієрархічні методи кластеризації.

Ключові слова: країни “Великої сімки”, ієрархічна кластеризація, k-засоби, TwoStep-кластеризація, фондовий ринок, інноваційний підхід.

С. Пэкер, PhD, ассистент, кафедра математики, факультет естественных наук и литературы, Университет Яшар (г. Измир, Турция);
Б. Актан, PhD, доцент, Колледж бизнес-администрирования, факультет коммерции и бизнес-администрирования, Университет Бахрейна, Королевство Бахрейн и будущий университет в Египте (г. Нью-Каир, Египет);
М. Тваронависиене, PhD, профессор, Вильнюсский технический университет им. Гедиминаса (г. Вильнюс, Литва)

Кластеризация ключевых показателей на фондовых рынках стран “Большой семерки”: инновационный подход

Инвестиции на фондовом рынке требуют принятия риска. Инвесторы обычно пытаются сформировать свой инвестиционный портфель таким образом, чтобы обеспечить получение максимальной отдачи при приемлемом уровне риска. В современных условиях для инвестора первоочередной задачей становится определение оптимальных источников финансирования среди альтернативних вариантов путем группировки активов с аналогичными характеристиками. В статье исследованы фондовые рынки стран “Большой семерки” – Франции, Великобритании, Германии, Италии, США, Канады и Японии за период 2011-2016 гг. С целью разделения соответствующих показателей фондовых рынков, в частности, CAC 40 (Франция), FTSE 100 (Великобритания), DAX (Германия), FTSE MIB (Италия), S&P TSX Composite (Канада), S&P 500 (США), NIKKEI 225 (Япония), на группы по критерию “доходность – риск” были использованы отдельные иерархические методы кластеризации.

Ключевые слова: страны “Большой семерки”, иерархическая кластеризация, k-средства, TwoStep-кластеризация, фондовый рынок, инновационный подход.

Отримано** 01.12.2016 **р.