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CLUSTERING ANALYSIS OF EMPLOYMENT SECTORS ACCORDING TO OECD COUNTRIES USING THE K-AVERAGE METHOD

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Abstract

In addition to being one of the important parameters showing the welfare level of the countries, employment shows the economic development of the countries in which sector is concentrated. The existence of industry-based employment in developed or developing countries supports this situation. In addition, the resources of countries direct the employment policy of that country. It is stated in the literature that there is generally employment in this field in countries with high agricultural resources. In this study, the employment data of 36 OECD countries between 1991 and 2019 were analysed using the Cluster analysis K-Average Method, which was obtained from the official web site of the World Bank. According to the employment data in Agriculture, Industry and Service sectors, it was analysed in which cluster OECD countries are located and whether the variables show a meaningful clustering.

Key words: Cluster Analysis, Employment, K-Average

JEL Code: C01, C40, C50

1. Introduction

The concept of employment is defined in theory in two ways as narrow and wide. While employment in a broad sense expresses all of the factors of production, employment in a narrow sense is defined as working or employing only the labour factor among the factors of production. While the fact that the factors of production other than labour does not work may only have an economic dimension, the inertness of the labour factor can cause social and political problems as well as economic problems (Köklü, 1976: 67). The development direction of the sectors in developed economies takes place from agriculture to the industrial sector and then to the service sector. Statistical data show that in countries where the industrial

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sector is not sufficiently developed, the sector development is from agriculture to the service sector (Parlaktuna, 2010: 1221).

Economic growth, which is generally accepted as the most important indicator of the welfare of the individuals living in a country, and therefore the country in general, means the development of the national economy due to the improvements in the indicators of macroeconomic variables and the increase in the welfare level due to the increase in the income obtained by the increase in production. (Alakbarov, 2018: 259).

The theses that the industrial sector is the carrier of economic growth, that RandD and technological innovations are the main source, and that a large part of international trade consists of industrial products constitute the common perspective of studies examining the economies of developed countries. However, as these studies also stated, the change in the characteristics of the sectors should also be taken into account. Although the difference between industry and service sectors has disappeared, the service sector now uses more intermediate inputs in industrial production, and the service sector also seems to have abandoned its inefficient and non-dynamic structure. The production of a significant part of the service sectors is now capital intensive, the use of technology is advanced and the labor productivity is quite high (Backer et al., 2015: 20).

In the study conducted by Bayramoğlu and Bozdemir (2018), the effect of technology use in the agricultural sector on employment was analyzed. The study was applied on the labor force participating in corn production activities in Konya province, and a test was used to examine whether the independent samples belong to the same population. The technology usage level of the enterprises in corn production, male labor force, total land width and productivity values of the labor force per unit time were analyzed by double-sided comparison. It has been observed that there is no relationship between the technology used in agriculture and these variables. It was concluded that this was mainly due to the fact that the workforce was not specialized, the level of knowledge about production techniques was low, and the technology owned was accepted as a social status factor and not used effectively.

Keskin et al. (2017) they examined the conditions of sustainability in agricultural production, taking into account the current situation of family farming and labor productivity in Turkey. In the study, the necessity of economic organization to eliminate the weaknesses of family farming is emphasized and solutions are offered. It is stated that while the most common production factor in agricultural enterprises in Turkey is labor, the capital factor is insufficient. According to the authors, the effect of many factors such as the weakness in organizing in economic terms, the education level of those who are engaged in agricultural activities and the insufficient capital accumulation are observed in the low productivity per unit area. In the study, labor productivity was found to be high in fruit and vegetable production, which require intensive labor and have a high labor demand per unit area.

Events in nature are complex situations that arise as a result of the individual or combined interactions of many interrelated variables or factors. In this complex structure, it may not be easy to determine the variables that affect the relevant event, to solve their relations with each other and to explain their formation mechanisms in a simple and comprehensible way. This is because, at a certain time and with a certain number of data, it is possible to present the event within this structure in an accurate and reliable way only by using correct statistical methods (Demir et al., 2021).

Cluster analysis is a method of grouping or classifying the variables or units in a data matrix whose natural groupings are not clearly known, into clusters that are similar to each other (Özdamar, 2004). With cluster analysis, it is aimed to obtain homogeneous groups from units or objects by using some measures of similarity or differences between variables (Özdamar, 2004; Uçar, 2010). Thus, summary information is obtained by grouping the ungrouped data according to their similarities or differences. The units in clusters obtained as a result of cluster analysis should be homogeneous and very close to each other and should be heterogeneous and distant from each other. Cluster analysis is a very useful multivariate statistical analysis method used to analyze data. In particular, it is difficult to group and make sense of the large number of data obtained in survey studies. With the cluster analysis method, it is possible to cluster all the data obtained according to the determined criteria and to obtain summary information. In clustering analysis, grouping is done by looking at the distance criteria of the variables (Hair et al., 2014).

Akat (2007) primarily focused on the military structure and the basic factors affecting it, and cluster analysis was made according to the determined factors. He touched on hierarchical and non-hierarchical clustering techniques. As a result; the structure consisting of 8 clusters was found suitable. Using different clustering methods, ward was found to be the most appropriate method. Akgöz (2010) Turkey operating in the public, private, foreign-owned banks, multivariate aspect ratio on the similarities and differences in the data produced from the financial statements have been tried to be grouped by cluster analysis method of statistical methods. The purpose of this grouping is to reveal the homogeneous structure among which banks, regardless of the distinction between public, private and foreign capital. Alkan (2012) mentioned clustering analysis theoretically in his study. With different clustering methods, they are divided into 5 clusters by taking into account the annual electricity consumption values of the households in Bingöl, Elazığ, Malatya, Tunceli provincial and district centres. Pine (2014) conveyed theoretical information on cluster analysis techniques in his study. In addition, data mining cluster analysis methods of data mining and density-based clustering algorithm has been applied to the data of patients in a hospital. Köse (2015), In his study, data mining association rules analysis and hierarchical clustering method, one of the methods of data mining association rules analysis and clustering analysis, was applied on the data obtained by collecting the shopping vouchers of an enterprise operating in 9 different provinces based in Konya.

In this study, it was analysed in which cluster 36 OECD countries are in terms of employment in Agriculture, Industry and Service sectors. The aim of the study is to examine how countries are distributed as a grouping and how long which country is in which cluster with the non-hierarchical clustering method. At the same time, analysing whether countries are in similar clusters according to their level of development is one of the other aims of the study

2. Material and Method

In the study, employment data in agriculture, industry, and service sectors of 36 OECD countries between 1991-2019 were analysed in SPSS 22 program with Cluster Analysis. Non-Hierarchical Clustering Method and K-Average Technique were used in the analysis. Country data has been obtained from the World Bank official website.

Cluster Analysis

Although classical methods used to statistically evaluate a large number of data obtained as a result of the analysis provide important information for each variable, they are insufficient to provide real information about the existence of a relationship between two or more different characteristics and do not allow the grouping of samples with homogeneous structure (Demir et al., 2016). Clustering analysis classifies very similar individuals or objects in the same cluster according to the predetermined selection criteria. As a result of the analysis, the internal homogeneity of the clusters will be high and the heterogeneity between the clusters will be low (Kalaycı, 2005). In other words; Clustering analysis is the separation of objects belonging to any data set into homogeneous groups according to their similar properties. If we sum up all these definitions; Cluster analysis is a collection of methods that can be defined as the classification of non-grouped objects in the X data matrix into subgroups according to the similarity of individuals or variables. In addition to these general purposes, they also have specific purposes.

1. Determination of real types
2. Facilitation model fitting
3. Prediction for groups
4. Testing hypotheses
5. Clarification of the data structure
6. Data reduction
7. Finding outliers (Tatlıdil, 1996).

In the application of cluster analysis techniques, data types can be applied to categorical (qualitative), numerical (quantitative) or both categorical and numerical data. While the data are indicative of some physical processes, the variables may be recorded as different values quantitatively or qualitatively.

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Similarity and Distance Measures Used in Clustering Analysis

"Similarity" is the most basic concept in cluster analysis. All of the methods discussed in the analysis are based on similarity criteria. There are different ways of measuring similarity between individuals. The two most important ways to measure similarity are measurements based on correlation and distance measurements (Junhagen, 2000). In cluster analysis, correlation measures or coefficients comparison criteria are used to classify variables or individuals according to their similarities. If the data is metric, distance is used, if not, comparison (partnership) criteria are used. In other words, distance measures are used to classify individuals and correlation measures are used to classify variables.

The regular grouping and classification of units (variables) in a data set is carried out using the distances of the units from each other. Grouping among units will make it easier to explain cause-effect relationships between variables by gathering and analysing similar units together. These values, which can take values outside the range of [0, 1] and measure the similarity or dissimilarity, are called the "Distance" value (Tatlıdil, 1996).

Table 1. Distance Measures Used in Clustering Analysis

Distance	**Equation**
Euclidean Distance	$d(x_i - y_i) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$
Squared Euclidean Distance	$d(x_i - y_i) = \sum_{i=1}^{n}(x_i - y_i)^2$
City-Block Distance	$d(x_i - y_i) = \sum_{i=1}^{n}\lvert x_i - y_i\rvert$
Chebychey Distance	$d(x_i - y_i) Max_i\lvert x_i - y_i\rvert = (\sum_{i=1}^{n}\lvert x_i - {y_i}^k\rvert)^{1/k}$
Minkowski Distance	$d(x_i - y_i) = (\sum_{i=1}^{n}\lvert x_i - {y_i}^k\rvert)^{1/k}, \quad k \geq 1$
Mahalanobis Distance	$d(x_i - y_i) = (x_i - y_i)' S^{-1}(x_i - y_i)$
Canberra Distance	$d(x_i - y_i) = \sum_{i=1}^{m}\lvert x_i - y_i\rvert / \lvert x_i - y_i\rvert$
Hotelling T^2 Distance	$d(x_i - x_j) = T^2 = \frac{n_1 n_2}{n}(\bar{x}_i - \bar{x}_j)' S^{-1}(\bar{x}_i - \bar{x}_j)$

Biserial Correlation Measure	$I_b = \frac{\bar{x}_p - \bar{x}_q}{S_t} \frac{p.q}{y}$
Pearson Correlation Measure	$r = \frac{\sum x_i y_i - \frac{(\sum x_i \sum y_i)}{n}}{\sqrt{(\sum x_i^2 - \frac{(\sum x_i)^2}{n})}\sqrt{(\sum y_i^2 - \frac{(\sum y_i)^2}{n})}}$
Spearman Rank Correlation Coefficient	$p = 1 - \frac{6 \sum d_i^2}{n(n^2-1)}$

Cluster Analysis Methods

Although cluster analysis is subdivided in many sources, there are no clear lines of subdivision basically (Grabmeir and Rudalph, 2002; Hartigan, 1975). In Clustering Analysis, which was first introduced in the literature in 1939; In the 1950s, the data was tried to be grouped hierarchically, and in the 1960s, clustering techniques were gradually developed by dividing the data into non-hierarchical subgroups. The most well-known distinction is hierarchical (staged) and non-hierarchical (non-phased) clustering. This distinction is made according to the choice of clustering method. Apart from this, methods such as two-step cluster have been used in recent years.

After the researcher decides which similarity / distance measure to use, he has to decide how the clustering process will be. There are various approaches that can be used to include units in clusters according to their similarities. One of these approaches is a hierarchical approach that starts with assigning two most similar units to the same group and ends with assigning all units to the same group. Another approach is based on assigning units with values closest to the mean values of all data to the same cluster. Apart from these two most used approaches, there are other approaches. The most important criterion in all approaches is to ensure the maximum similarity between clusters and within clusters (Blashfield and Aldenferder, 1978).

Non-Hierarchical Clustering Method: It is used when the researcher has prior knowledge about the number of clusters. If the researcher has decided on the number of clusters that could be meaningful, he may prefer non-hierarchical methods instead of hierarchical techniques that take a long time. In addition, the stronger institutional basis of these methods is another reason for preference (Selanik, 2007). Non-Hierarchical Clustering methods try to optimize a similarity criterion, which is often defined locally or universally, when creating clusters. It is not possible to try various combinations on all registers to find the best possible value of this function. Instead, algorithms are run for a few initial cases in the practical field and result sets are created by obtaining the results of these previous studies (Ünler, 2006). In this method, the separation of variables into clusters is done randomly. In non-hierarchical methods, it is aimed to gather the units in the clusters they are suitable for and to divide the n units into k clusters. After determining the number of clusters to which units can be allocated, the cluster determination criteria for clusters are determined and the assignment process is carried out (Özdamar, 2004). The two most commonly used non-hierarchical cluster analysis methods are k averages and the most likelihood method.

K-Averages Method: This technique was developed by Hartigan in 1975, after the error-squares reduction principle introduced by Forgy in 1965 and MacQueen in 1967. This technique has been the most important non-hierarchical cluster analysis technique used for many years. One of the methods used in clustering techniques is the K - Means (KO) method. It is an effective algorithm and is used in many applications running on low-dimensional and large data sets (Singhal and Shukla, 2018). It is one of the most used clustering algorithms developed by Mac Queen (Zahra et al., 2015). Usually the square error is used to evaluate the K-means method. Among the clustering results, the one with the lowest squared error is accepted as the best result (Tan et al., 2016).

Euclidean distance; according to the calculation as $\left\|x_{ij} - v_j\right\|^2, \;\; 1 \leq j \leq k$, individuals are classified to the closest cluster. Here x_{ij} is the jth object in the ith cluster; v_j refers to the center of the jth cluster. The distance measure is calculated as follows,

$$j(x; v) = \sum_{j=1}^{k} \sum_{x \in c_j} \left\|x_{ij} - v_j\right\|^2$$

The K-Average method first selects k random objects from n objects, each of which represents the centre or midpoint of a cluster. Each of the remaining objects are distributed into clusters according to the cluster centre closest to it. Thus, an object is placed in the cluster near the centre of the cluster. Then the averages are calculated for each cluster, and this calculated value becomes the new centre of that cluster. This process continues until all objects are placed in clusters. The K-Averages Method can only be used when the mean of the cluster can be defined. It can be seen as a disadvantage that users determine the value of k. The main disadvantage here is the sensitivity to the so-called outlier observations (Han et al., 2000). Tendency to converge to a weak optimum; sensitivity to scaling and other transformations; sensitivity to measurement errors and outliers; The main problems of the K-Average method are bias (ie convergence of incorrect parameter values).

3. Application and Results

In the study, analyses were performed using the K-Averages technique in the Non-Hierarchical Clustering Method used in Clustering analysis. Analyses were obtained using three clusters and 10 iterations. Below, the distance between the cluster centres, the clusters in which the countries are located, the ANOVA test to analyse whether the variables show significant clustering, the averages of the variables in the clusters and the numerical values in the clusters are listed as tables.

Table 2 shows how the variables are distributed in the three clusters discussed.

Table 2. Clustering Centers

Variable	**Cluster**		
	1	**2**	**3**
Employment in Agriculture	2.29	29.76	0.68
Employment in Industry	36.52	29.66	10.81
Employment in the Service	61.19	40.58	88.51

When Table 2 is examined, it is observed that the employment intensity in the agricultural sector is in cluster 2, the employment intensity in the industrial sector is in cluster 1, and the employment intensity in the service sector is in cluster 3. Table 3 includes the distances between the formed clusters.

Table 3. Distance Between Cluster Centres

Cluster	**1**	**2**
2	15.491	
3	10.655	25.885

When Table 3 is examined, it is observed that the longest distance is between Cluster 3 and Cluster 2, and the shortest distance is between Cluster 1 and Cluster 3. Therefore, it can be said that 1 and 3 show much more similarity than 2 and 3. Table 4 shows the distribution of countries according to clusters and how many years in which cluster between 1991 and 2019.

Table 4. Clustering of Countries

Cluster 1	**Cluster 2**	**Cluster 3**
Austria (1997-2019), USA (1991-2001), Australia (1991-1996), England (1991-2002), France (1991-2006), Germany (2000-2019), Italy (2002-2019), Belgium (1991-2007), Sweden (1991-2002), Denmark (1991-2006), Chile (2016-2019), Netherlands (1991-1998),	Austria (1991-1996), Germany (1991-1999), Italy (1991-2001), Japan (1991-2000), Ireland (1991-2000), Spain (1991-2003), S. Korea (1991-2003), Portugal (1991-2012), Turkey (1991-2019), Greece (1991-2004), Slovakia (1991-2019), Mexico (1991-2019), Czech Republic (1991-2019),	Australia (1997-2019), USA (2002-2019), England (2003-2019), Belgium (2008-2019), Denmark (2007-2019), France (2007-2019), Netherlands (1999-2019), Ireland (2011-2019), Spain (2013-2019), Sweden (2003-2019), Switzerland (2004-2019), Iceland (2007-2019),

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Switzerland (1991-2003), Japan (2001-2019), Ireland (2001-2010), Spain (2004-2012), Portugal (2013-2019), Iceland (1991-2006), Canada (1991-1992), Luxembourg (1991-1996), Norway (1991-2000), S.Korea (2004-2019), Greece (2005-2015), Finland (1991-2012), New Zealand (1991-2009), Hungary (2009-2019), Estonia (2010-2019), Israel (1991-1998), Latvia (2008-2019), Lithuania (2008-2019)	Hungary (1991-2008), Poland (1991-2019), Chile (1991-2015), Estonia (1991-2009), Slovenia (1991-2019), Latvia (1991-2007), Lithuania (1991-2007	Canada (1993-2019), Luxembourg (1997-2019), Norway (2001-2019), Greece (2016-2019), Finland (2013-2019), New Zealand (2010-2019), Israel (1999-2019)

Table 4 shows in detail how many years OECD countries are in which cluster according to their employment sectors. When the table is examined, it is seen that the densities are in cluster 1, cluster 2 and cluster 3, respectively. In Table 2, the clusters in which the employment is concentrated in the sectors; The result was that the industrial sector was in cluster 1, the agriculture sector in cluster 2, and the service sector in cluster 3. In this case, it can be said that OECD countries create more employment in the industrial sector. According to Table 4, it gives the conclusion that the employment in the sectors varies according to the years in this situation where countries experience transition between clusters according to years. In Cluster 1, the country with the highest employment in the industrial sector is Austria (1997-2019) and the country with the lowest is Canada (1991-1992). Countries with the highest employment in the agricultural sector in Cluster 2; Turkey, Slovakia, Mexico, Czech Republic, Hungary, Poland, Estonia and Slovenia (1991-2019). These countries were completely in cluster 2 between the years discussed. The country with the lowest employment intensity in the agricultural sector is Austria (1991-1996). In cluster 3, the country with the highest employment in the service sector is Canada (1993-2019) and the country with the lowest is Greece (2016-2019).

Table 5 contains the statistical information about the variables as a result of using the K-Averages method.

Table 5. ANOVA

	Cluster		**Error**		**F**	**Sig.**
	Mean Square	**df**	**Mean Square**	**df**		
Employment in Agriculture	7866.290	2	19.094	1041	411.976	0.001
Employment in Industry	11501.006	2	13.605	1041	845.356	0.001
Employment in the Service	37611.187	2	15.590	1041	2412.509	0.001

Table 5 presents the statistical information on the variables obtained by using the K-Averages method. The ANOVA table is used to see whether the variables are meaningful in clustering. When the table is examined, it is seen that all variables are significant in clustering (Sig.≤0.05). In addition, when the F values are examined, it is seen that the most effective variable in clustering is Employment in Service. The least effective variables are Employment in Agriculture and Employment in Industry, respectively. The reason for this result is that the difference between clusters is maximized by cluster analysis. Consequently, the distribution of the observations in clusters is not random. Table 6 shows the number of rows in the clusters.

Table 6. Row Values in Cluster

Clusters	**Number of Rows**	**Total**
Cluster 1	382	1044
Cluster 2	363	
Cluster 3	299	

When Table 6 is examined, it is observed that numerical data are mostly in Cluster 1. The cluster with the least numerical data is the third cluster. Cluster two contains 363 numerical data in total. A total of 1044 numerical data can be seen in the table in which the analysis is included.

4. Discussion and Conclusion

Sustainable economic growth is one of the main goals of all country economies in the world. Economic growth theories developed from past to present, which are classical production factors; It reveals that land, labour, capital and entrepreneur factors are insufficient at the point of sustainability of economic growth. Although physical factors are important in determining a permanent and sustainable economic growth according to the growth theories developed, it is pointed out that the labour factor, which can be transformed into a window of opportunity for each country in terms of human capital, is of vital importance. The contribution of the workforce to permanent and sustainable economic growth in human capital is of great importance due to its efficiency-enhancing effect.

Since the development level, demographic structure and labour market characteristics of each country differ, the employment policies applied can also differ from country to country. For this reason, in this study, employment data in agriculture, industry and service sectors were analysed using Cluster Analysis K-Average method in order to analyse how OECD countries showed employment similarities in sectors between 1991-2019.

In the study, it was observed that the employment sectors of the countries changed over the years. According to years, there were 30 countries in cluster 1, 20 in cluster 2 and 19 countries in cluster 3. It has been observed that the countries in cluster 1 are in the industrial sector as the employment sector and they are developed countries. It is seen that countries in cluster 2 generally experience employment intensity in the agricultural sector. In addition, Turkey, Slovakia, Mexico, Czech Republic, Estonia and Slovenia in the second set was observed to have an important place. There are 19 countries in the cluster 3 where the service sector is intense. Canada has a large density in cluster 3 with the lowest density.

In the study, it was observed that countries cluster according to the employment policies they use and the resources they have. From this situation, it can be inferred that developed countries are generally distributed in the same cluster and follow similar policies. To make more investments in the industrial sector set to take place in Turkey's developed countries and developing policies in this area will be in Turkey's favor. In the globalizing world, where competition is intense and countries develop policies to take part in this competition will be in favour of countries.

When the literature research is done, the effect of employment on economic growth in general has been investigated. In particular, studies on employment in the industrial and agricultural sector have obtained the result that employment has a positive effect on economic growth (İşleyen, 2019; Timur and Doğan, 2015; Ertuğrul and Uçak, 2013). In this study, unlike the literature, whether OECD countries show similarities in the employment sectors was examined with the cluster analysis. When the studies conducted with cluster analysis are examined, we think that this study differs and will contribute to the literature in this respect.

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