International Journal of Economics and Financial Issues
Vol. 4, No. 2, 2014, pp.336-343
ISSN: 2146-4138
www.econjournals.com

Development of European Union and China Bilateral Trade After The 2008 Financial Crisis: A Cluster Analysis

Serkan TASTAN
Department of Management and Information Systems
Cumhuriyet University, Sivas, Turkey.
Email: stastan@cumhuriyet.edu.tr

Halil OZEKICIOGLU
Department of Labor Economics and Industrial Relations,
Cumhuriyet University, Sivas, Turkey.
Email: hozekicioglu@cumhuriyet.edu.tr

ABSTRACT: China and European Union are two economic zones realizing a significant part of the world trade. These two economic zones have been subject to shrinkage after the 2008 crisis. The objective of this article is to reveal the status of foreign trade of both economic zones after the 2008 crisis by means of cluster analysis. In light of both export and import data, the countries are collected in three clusters and the only difference observed in cluster structures is that England is placed in the third cluster with Belgium, France, Netherlands, Spain and Italy in terms of export.

Keywords: Trade Flows; Bilateral Trade; Cluster Analysis
JEL Classifications: C38; F14; F15

1. Introduction

Strengthening of relations between European Union (EU)[*] and China is the outcome of development of economic and commercial relations by the increase in interdependence as a result of globalization. After initiation of diplomatic relations between EU and China in 1975, the first Commercial Agreement has been signed between the two parties on April 3, 1978. And by the "Economic and Commercial Cooperation Agreement" signed in 1985, it was aimed to take the economic cooperation farther, and to enhance economic relations between EU and China. Besides, joining of China to World Trade Organization (WTO) in 2001 has increased commercial relations between the two zones considerably (Akses, 2014).

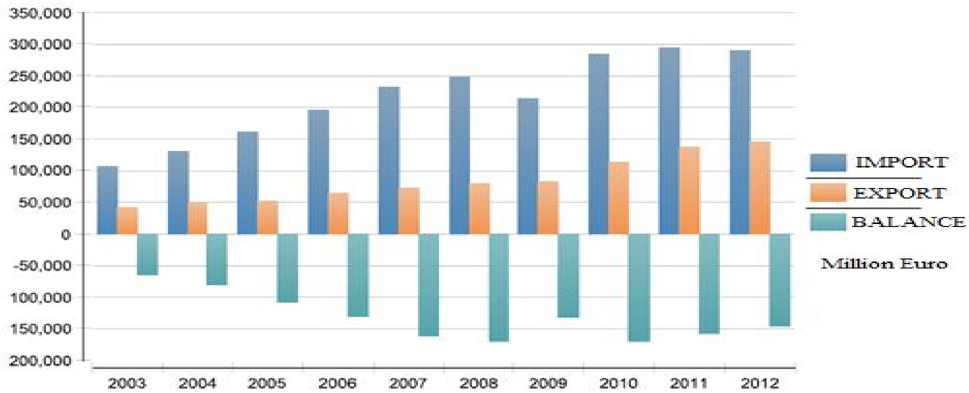
The change of ineffective planned economy in China began in 1978; and economic reforms are evaluated in five phases. The reform in agricultural area (household responsibility system) created a new form of unlimited company (town and village companies, corporations) and contributed directly to household earnings acquired from planned production level in the first phase (1978–1984). Accordingly, agricultural production and productivity increased in the first years. In the second phase (1985-1988), the reforms were realized mainly in industrial sector; therefore prices and wages were liberalized, companies were provided with opportunities to enable endurance of their earnings for finance. Open door policy, which supported China's integration to world economy both via trade and foreign direct investments (FDIs), needs to be particularly indicated in this phase. In the third and fourth phases (1988–91 and 1992–97), economic reforms influenced all sectors; the role of market economy and private ownership were officially approved in the Communist Party Convention realized in 1992. Next phase (from 1998 up to now), comes to the forefront especially by the increase of foreign expansion in Chinese economy after admission in the WTO (Hölscher et al., 2010).

[*] The term EU hereinafter covers EU-27.

2. Overview on EU and China Bilateral Trade

EU and China come to the forefront as two significant trade zones in world trade. As seen in Figure 1, recently EU carries out about 250-300 billion USD of import activities and about 150 billion USD of export activities with China. Balance of trade has decreased to a certain extent in 2009 by reduction of EU in import after 2008 crisis, yet trade flows continue in favor of China. EU zone has displayed a current account deficit of about 150 billion USD in 2012.

Figure 1. EU-China Trade Flow and Balance (2003-2012)



Source: European Commission Report (ECC, 2013)

When we see export and import structure of the trade between EU and China according to SITC[***] classification in Table 1; EU carries out import activities of 9569 million Euro in primary products, of 279099 million Euros in manufactures and of 809 million Euros in other products. Again, according to SITC classification, export structure displays 20257 million Euros of primary products, 121815 Euros of manufactures, and 1142 million Euros of other products. When considered proportionally, highest import rate is observed in primary products with 96.3 % and highest export rate is observed again in primary products with 84.7%. These figures indicate that EU imports agricultural, forestry, fishery and mining products from China; treats these products, consumes some of them in EU, and exports a significant part of these after converting them into final products.

Table 1. SITC Product Groups (Million Euro)

	Import		Export	
Primary products	9569	%3.3	20257	%14.1
Manufactures	279099	%96.3	121815	%84.7
Other products	809	%0.3	1142	%0.8

Source: European Commission Report (ECC, 2013)

When we consider sub-product groups based on EU's SITC product classification according to above analyzed figures, S6, S7 and S8 sub product groups[****] come to the fore in import from China whereas S5, S6, S7, S8 sub product groups appear in export, as you can see in Figure 2.

3. Literature Review

The studies performed by using cluster analysis are summarized below. Kılıç (2005) has attempted to measure the economic performances in terms of EU member countries and candidate countries in this research. The model used in this study indicates that Bulgaria, Romania, Turkey,

[***] **SITC (Standard International Trade Classification):** Product classification determined by the World Trade Organization (WTO). There are three classifications according to STIC including; 1-Primary products (unprocessed fishing, mining, agricultural and forestry products), 2-Manufactures (Chemicals used in production, machinery and transport equipment, other goods used in production), 3- Other non-classified products (WTO, 2010).

[****] S5: Chemical products, S6: Semi-manufactures, S7: Machinery and transport equipment, S8: Miscellaneous manufactures

Czech Republic, Estonia, Latvia, Lithuania, Poland, Slovenia, and Slovakia are at a lower level compared to other EU countries in terms of economic performance.

Figure 2. Trade flows from EU to China According to SITC Sub Groups

Source: European Commission Report (ECC, 2013)

In the study of Bircan (2006), carried out considering export values, Turkey's export countries are clustered. Some countries center in some clusters whereas some other countries constitute a cluster on their own. This indicates that we carry out intensive trade activities with certain countries; yet we do not have significant trade with many countries except for some product groups. Considering this we conclude that Turkey's foreign trade is not homogeneous worldwide and that it has a fragile structure.

Tunç and Öner (2009) used cluster analysis and discriminant analysis in their study; and applied 25 socio-economic variables of 27 EU member countries and Turkey. The classification structure gathering these countries together within the Union is analyzed.

Kaya et al. (2009) evaluate the macro economic performance exhibited by Turkish economy in after 2002. This evaluation is based on analysis of 10 selected macroeconomic performance criteria of 17 emerging market economies by "non-hierarchic clustering" method. Cluster analysis has proven that high interest rates are the most important indicators of Turkish economy.

Berberoğlu (2011) has studied the effects of 2008 crisis on EU countries by cluster analysis. As to the results of the analysis, Germany, France, Italy and England fell into the same cluster in 2006; Spain and Netherlands fell into another cluster; and Turkey and other EU countries fell into one other cluster. 2007 results indicated that the same clustering structure continued. Yet, in 2008, England was not clustered with Germany, France and Italy; but with Spain.

Göçer (2012) has made the effect of 2008 global financial crisis generally on world economy and specifically on economies of USA, five European countries and Turkey. He has proven that crisis influenced economic growth by private consumption expenses. The countries, affected mostly by the crisis were USA, Italy and Greece.

Kaya and Türkmen (2013); similar or diverging reactions of 23 high or middle income group countries against 2008 crisis attempted to be revealed by cluster analysis in this study. The dealt countries were classified in 5 clusters. Turkey, Uruguay, and Costa Rica displayed similar reactions against crisis as a cluster.

4. k –Means Method

Cluster analysis attempts to identify subgroups (clusters) in a data set so that observations in each subgroup to be as much similar as possible with each other while observations in separate groups to be as much different as possible. One of the most common methods, among many other developed for this purpose, is k-means clustering method developed by MacQueen (1967). In k-means method, after deciding the number of clusters in a data set, a center vector is determined depending on the number of variables for each cluster. Each observation is assigned to a cluster considering the closest center. The purpose in the clustering process is to minimize within-cluster variation; here within-cluster variation can be calculated with reference to the square of Euclidean distances between all observations in a cluster and the center of the cluster (James et al., 2013). In this context, the best result is the one which gives the minimum value of the function:

$$E=\sum_{j=1}^{k}\sum_{i\in C_j}\left\|x_i-m_j\right\|^2 \quad (1)$$

In the equation, x_i corresponds to observations whereas Cj and m_j represent the clusters and their centers respectively. The number of clusters is expressed by k. An optimum solution can be obtained for the above defined objective function by following the below given steps; in other words, clustering can be performed by dividing the observations in the data set to k different groups.

1) Observations as the number of clusters are randomly selected as the cluster centers. Each observation in a data set is assigned to a cluster according to the closest cluster center. These are the initial cluster assignments.

2) The two following steps are repeated until cluster assignments of each observation remain the same.

a) A cluster center is calculated for each cluster by using the following formula.

$$m_j=\frac{1}{n_j}\sum_{i=1}^{n_j}x_i \quad (2)$$

b) All observations in the data set are again assigned to a cluster according to the closest cluster center.

Since the solution obtained by following the above defined steps addresses a local optimum and is mostly influenced by initial cluster assignments, the algorithm needs to be run multiple times for different initial clusters and the trial yielding the lowest value of the objective function needs to be used (James et al., 2013).

In order to use the k-means method, the number of clusters needs to be priory determined. Among many techniques which might be used for this purpose, the two with the best performance for continuous data are the ones suggested by Calinski and Harabasz (1974), and Marriot (1971) which can be calculated as given below respectively (Everitt et al., 2011):

$$C(k)=\frac{trace(B)}{(k-1)}\bigg/\frac{trace(W)}{(n-k)} \quad (3)$$

$$marriot=k^2\left|W\right| \quad (4)$$

In the equations, B and W are the between-cluster and within-cluster dispersion matrixes respectively. While m represents the center of the data matrix and n_j represents the number of observations in j. cluster, they can be calculated as;

$$W=\sum_{j=1}^{k}\sum_{i\in C_j}(x_i-m_j)(x_i-m_j)^T \quad (5)$$

$$B=\sum_{j=1}^{k}n_j(m_j-m)(m_j-m)^T \quad (6)$$

Calinski and Harabasz recommends to use the k value which gives the biggest C(k) value whereas Marriot recommends to select the k value which gives the smallest value of (4) as the number of clusters. The number of clusters can be determined with reference to the graphic to be drawn between the within-cluster sum of squares and the number of clusters. The bending point in the graphic can be used for determination of appropriate number of clusters. Besides, it is possible to determine the number of clusters for small data sets simply with the formula: $k=\sqrt{n/2}$.

After determining the number of clusters and clustering the data set via k-means method, efficiency of the clustering can be measured with the silhouette value. Silhouette value for an observation in a data set can be calculated as (Rousseeuw, 1987);

$$s(i)=\frac{b(i)-a(i)}{\max\left(a(i),b(i)\right)} \quad (7)$$

In the equation, a(i) signifies average dissimilarity between i. observation and all other observations in the same cluster; b(i) is the smallest average dissimilarity separately calculated for each cluster between the i. observation and the observations in all clusters except the cluster where i.

exists. In case there is no other observation in the cluster where the observation is assigned, silhouette statistics equals to zero. Silhouette value takes a value between -1 and 1. If the mentioned value is close to 1 then the observation is well classified; if the mentioned value is close to -1 then the observation is in the wrong cluster; if the value is close to 0 then there is an uncertainty whether the observation should be assigned to the existing cluster or to the closest neighboring cluster. On the other hand, the average of silhouette values of the observations in a cluster defines the goodness for that cluster, and the average of all silhouette values defines the goodness of clustering.

5. Data Set and Findings

The data set of the study consists of export and import values between the EU and China. The data obtained from the official web site of Eurostat cover a four years period between 2009 and 2012 in terms of million Euros. The countries included in the study are Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, England, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Poland, Portugal, Romania, Sweden, Slovenia and Slovakia. The trade activities between countries are studied with reference to the data collected according to international trade SITC standards. Therefore, 10 variables are used in the study in accordance with relevant standard. All analysis are performed in R (R Core Team, 2013) statistical software using Cluster (Maechler et al., 2013), and NbClust (Malika et al., 2013) packages.

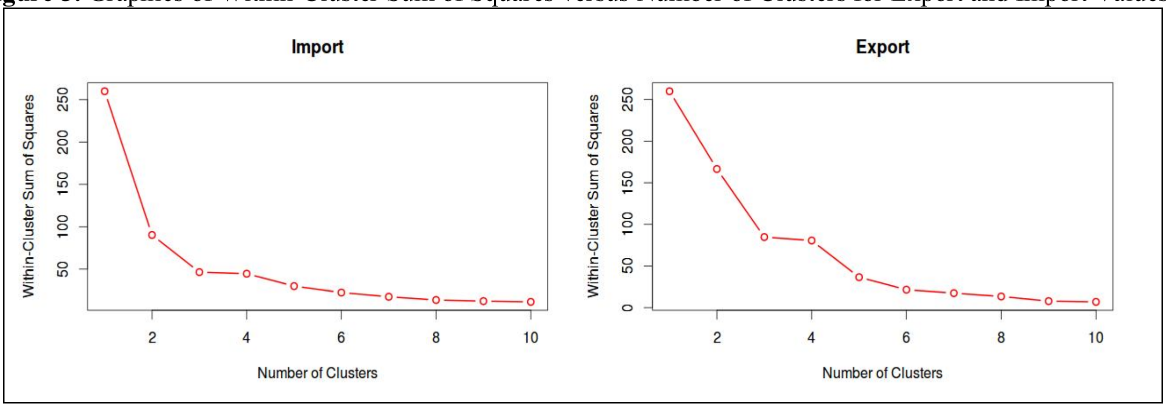
For clustering of the data set via k-means method, numbers of clusters are determined as the first step. For this purpose, the criteria measured according to the above defined techniques are given in Table 2. Besides, graphics of within-cluster sum of squares versus number of clusters are drawn for both export and import values (Figure 3).

Table 2. Number of Clusters According to the Criteria

	Number of Clusters (k)		
	C(k)	Marriot	$\sqrt{n/2}$
Import	3 (55.15)	3 (203.98)	4
Export	9 (73.02)	3 (304128.60)	4

Note: The criteria values are given in parentheses.

Figure 3. Graphics of Within-Cluster Sum of Squares versus Number of Clusters for Export and Import Values



In Table 2, suitable number of clusters is three for both criteria for the import data. For export data, suitable number of clusters is nine according to Calinski and Harabasz criteria, and three according to Marriot criteria. In the same table, number of clusters is measured as four by $k = \sqrt{n/2}$ formula for both import and export data. On the other hand, when graphics for both data are examined, suitable number of clusters is two or, in line with the results in Table 2, three for import data; and three in compliance with Marriot criteria or five for export data. Therefore, the number of clusters is determined to be three for both data by jointly evaluating the results in the tables and the graphics. In accordance with the best results obtained from the cluster analysis performed by designating 100 different initial clusters for both data considering k=3; clustering distributions of export and import activities of countries with China are given in Table 3. Besides, graphics of relevant distributions obtained by using discriminant analysis are given in Figure 4. Table 4 indicates the cluster centers measured for both data.

Table 3. Distribution of Countries According to Clusters

	Cluster 1	Cluster 2	Cluster 3
Import	Austria, Bulgaria, Cyprus, Sweden, Estonia, Czech Republic, Denmark, Finland, Greece, Hungary, Ireland, Lithuania, Luxembourg, Latvia, Malta, Poland, Portugal, Romania, Slovenia and Slovakia.	Germany and England	Belgium, France, Netherlands, Spain and Italy
Export	Austria, Bulgaria, Cyprus, Sweden, Estonia, Czech Republic, Denmark, Finland, Greece, Hungary, Ireland, Lithuania, Luxembourg, Latvia, Malta, Poland, Portugal, Romania, Slovenia and Slovakia.	Germany	Belgium, France, Netherlands, England, Spain and Italy

Figure 4. Distribution of Countries According to Clusters

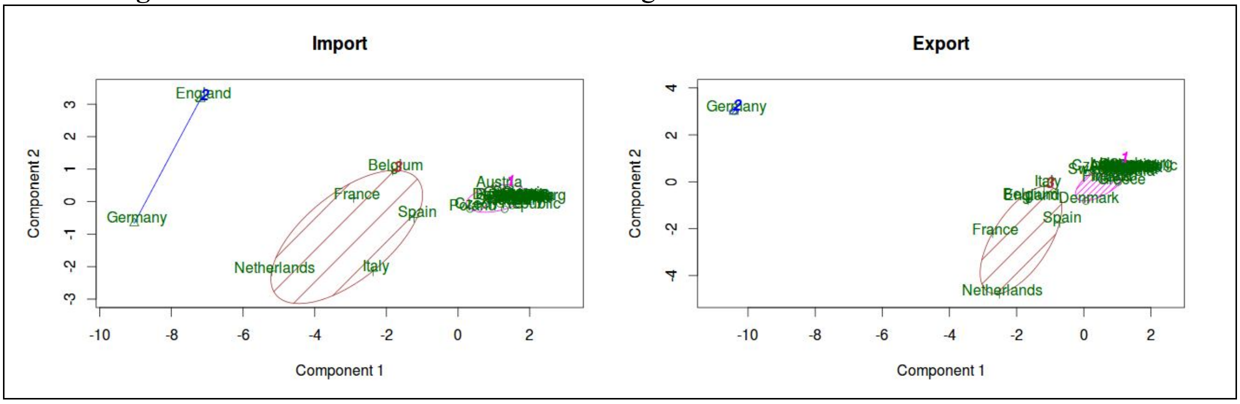


Table 4. Centers of Clusters for Export and Import Values (Million Euro)

	Import			Export		
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3
S0	122.84	2924.78	1442.37	99.41	923.49	749.16
S1	5.23	119.49	49.01	4.51	211.38	627.88
S2	76.25	1726.52	1107.67	401.58	4520.90	3429.35
S3	5.68	234.52	139.14	23.50	407.78	571.58
S4	0.86	52.76	14.91	2.38	15.63	64.94
S5	325.61	7774.15	4570.64	396.69	18889.06	4570.46
S6	1182.00	22536.61	12407.28	512.76	17043.08	3292.79
S7	5937.87	87780.51	48537.24	1975.36	161884.61	13839.81
S8	2390.58	66687.12	30652.33	243.51	15590.79	2209.30
S9	23.64	1067.37	109.26	16.45	2770.53	260.33

When countries are divided into clusters as given in Table 3, the average silhouette values measuring goodness of the clustering for import and export data are defined as 0.79 and 0.66 respectively. Therefore, achieved cluster structures are sufficient in terms of evaluation of export import relation especially between EU countries and China.

When considered in terms of import, Germany and England form the second cluster. These countries have the highest import figures with China. But England carries out import activities mostly from Germany and Germany, on the other hand, carries out import activities mostly from USA and then China. Germany and England import greater amounts of raw material investment goods from China. In other words, export income contains added value generated from import activities. Therefore, export income of these two countries contains production arising out of import from China.

Belgium, France, Netherlands, Spain and Italy which also have considerably high import figures with China form the third cluster. Remaining 20 European Union countries are accumulated in the third cluster with the lowest import figures. When considered in terms of export, the clusters can be evaluated like the previous case in terms of export volume. In addition, the only difference observed in cluster structures according to imports is that England, which was in the second cluster before, is in the third cluster with a lower export volume.

When centers of clusters are examined, significant differences are observed between clusters especially in S5, S6, S7, S8 product subgroups prominent in export activities between European Union and China. In S7 subgroup which has the biggest share in export amount of Germany is 161884.61 million Euros; which is 11 times the average of the third cluster countries, and 82 times the average of the first cluster countries. Similar proportional differences, though not this much dramatic, can be observed in other important export product subgroups including S5, S6 and S8. When product subgroups (SITC Sections) are considered in export, chemical products, manufactures, machines (office goods) and transport equipment (road equipment) as well as manufacture based products (furniture, shoes, bags etc.) become prominent.

In terms of import, second and third cluster countries are better balanced than export template terms of S6, S7 and S8 product subgroups which are prominent in import activities between China and European Union. Yet, first cluster countries are in a much lower level in these subgroups compared to other two cluster countries. The reason of this is that first cluster countries carries out import activities mostly from China for production and display foreign trade deficit with China. In light of the data of 2012, the only country having foreign trade surplus is Germany. Here, we have to distinguish Germany which differs from other EU countries in terms of import and especially export activities, and constitutes solely a cluster in the clustering performed according to export values. Germany, thanks to its strong industry and knowledge level, has the highest trade activity figures with China both in terms of export and import. In terms of trade activities of Germany with China, there are also problems including (Akses, 2014); China's holding its currency, Renminbi, at a low value; violating intellectual property rights; implementing some bureaucratic procedures which obstruct access of European investors to China market; and implementing damping and subvention.

6. Conclusion

The study suggests that EU countries cannot be differentiated in terms of foreign trade activities with China. In light of both export and import data, the countries are collected in three clusters and the only difference observed in cluster structures is that England is placed in the third cluster with Belgium, France, Netherlands, Spain and Italy in terms of export. Another significant difference is that in product subgroups of intensive export activities the cluster formed by Germany has much bigger export figures compared to other two clusters.

Germany and England import more raw materials and investment goods compared to other EU countries. Export income of these two countries contains added value generated from import activities, in other words contains production arising out of import from China. The fact that England carries out import activities mostly from Germany, places England in the same cluster with the other 5 countries in the 3rd Cluster carrying out intensive trade activities with China. Germany, on the other hand, carries out import activities mostly from USA and then China. In this context it is an understandable result that Germany separated from other EU countries by means of the trade surplus, forms a cluster alone in cluster analysis which was performed by using export data.

References

Akses, S. (2014), *Trade Between The European Union And China And Investment Relations, Economic Development Foundation*, 80, http://www.ikv.org.tr

Berberoğlu, B. (2011), *Analysing The Effects of 2008 Global Crises On Turkey And European Union With Cluster Analysis,* Anadolu University Journal of Social Sciences, 11(1), 105–130.

Bircan, H., Zontul M., Yüksek G. (2006*), A Study on Som-Type Using Neural Networks Turkey's Cluster of Exporting Countries,* Atatürk University, Journal of Economics and Administrative Sciences, 20(2), 219-237.

Calinski, R.B., Harabasz, J. (1974), *A Dendrite Method For Cluster Analysis,* Communications in Statistics, 3, 1–27.

Everitt, B.S., Landau, S., Leese, M., Tahl, D. (2011), *Cluster Analysis,* John Wiley & Sons.

Göçer, İ. (2012), *Causes And Effects On Selected Countries Economies of 2008 Global Economic Crisis: An Econometric Analysis,* Journal of Economic and Management Research, 17, 18-37.

Hölscher J., Marelli, E., Signorelli, M. (2010), *China and India in the Global Economy*, Economic Systems, 34, 212-217.

James, G., Witten, D., Hastie, T., Tibshirani, R. (2013), *An Introduction to Statistical Learning: with Applications,* R. Springer Science & Business.

(ECC,2013), *European Union, Trade in goods with China*, European Commission Report, http://trade.ec.europa.eu/doclib/docs/2006/september/tradoc_113366.pdf, 1-12, 07.11.2013, (Access Date: 01.02.2013).

(WTO,2010), *Statistical Appendix*, World Trade Organisation Report, http://www.wto.org/english/res_e/booksp_e/anrep_e/wtr10-2g_e.pdf, 204-228, (Access Date: 14.12.2013).

Kaya V. , Türkmen, A. (2013), *Macroeconomic Implications/Reflections of the Global Crisis on Upper Middle Income Countries,* Atatürk University, Journal of Economics and Administrative Sciences, 27(4), 317-338.

Kaya V., Yılmaz, O., Talaş, E. (2009), *Emerging Market Economies and Turkey, 1990-2006: Where are we?*, Atatürk University, Journal of Graduate School of Social Sciences,13(1), 315-342.

Kılıç, S.B. (2005), *European Union Member States And Candidate Countries Some Basic Macro By Economic Classification Criteria: A Model Based on Multi-Criteria Decision Analysis Forecast*, Çukurova University, Journal of Social Sciences Instutie, 14(2), 339-352.

MacQueen, J.B. (1967), Some Methods for Classification and Analysis of Multivariate Observations, Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, pp.281–297.

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., Hornik, K. (2013), *Cluster: Cluster Analysis Basics and Extensions.* R package version 1.14.4.

Malika C., Nadia, G., Veronique B., Azam, N. (2013), *NbClust: An examination of indices for determining the number of clusters : NbClust Package*, R package version 1.4. Retrieved from http://CRAN.R-project.org/package=NbClust

Marriott, F.H.C. (1971), *Practical Problems in A Method of Cluster Analysis*. Biometrics, 27, 501–514.

R Core Team (2013), *R: A language and environment for statistical computing. R Foundation for Statistical Computing,* Vienna, Austria. Retrieved from http://www.R-project.org/.

Rousseeuw, P.J. (1987), *Silhouettes: A Graphical Aid To The Interpretation And Validation of Cluster Analysis.* Journal of Computational and Applied Mathematics, 20, 53–65.

Tunç T., Öner, Y. (2009), *The Evaluation of The European Union Countries And Turkey With Multivariate Statistical Analyses In Terms of Some Socio-Economic Variables*, E-Journal of New World Sciences Academy, 4(1), 12-25.