Operational Research in Engineering Sciences: Theory and Applications
Vol. 4, Issue 2, 2021, pp. 102-123
ISSN: 2620-1607
eISSN: 2620-1747
DOI: https://doi.org/10.31181/oresta20402102y

ROBUST MAHALANOBIS DISTANCE BASED TOPSIS TO EVALUATE THE ECONOMIC DEVELOPMENT OF PROVINCES

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Received: 07 April 2021
Accepted: 07 June 2021
First online: 01 July 2021

Research paper

Abstract: *In this paper, 81 Turkish provinces with different development levels were ranked using the TOPSIS method. To evaluate the ranking with TOPSIS, we presented an improvement to Mahalanobis distances, by considering a robust MM estimator of the covariance matrix to deal with the presence of outliers in the dataset. Additionally, the homogenous subsets, which were obtained from the robust Mahalanobis distance-based TOPSIS were compared with robust cluster analysis. According to our findings, robust TOPSIS-M scores reflect the inter-class differences in economic developments of provinces spanning from the extremely low to the extremely high level of economic developments. Considering indicators of economic development, which are often used in the literature, İstanbul ranked first, Ankara second, and İzmir third according to the Robust TOPSIS-M method. Moreover, with the Robust Cluster analysis, these provinces were diagnosed as outliers and it was seen that obtained clusters were compatible with the ranking of Robust TOPSIS-M.*

Keywords: *Economic Development, Mahalanobis Distance, Robust Clustering, Robust TOPSIS-M, Outliers.*

1. Introduction

In today's world where globalization and competition are rapidly increasing, countries are trying to gain an advantage with both their economic activities and social policies. To increase the international competitiveness of the countries, it is aimed to keep the economic indicators in the national context. Because it has been observed that regional and local economies also affect the global economy and increase competition (Kılıç et al., 2011). Economic development has generally been

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conceptualized as a balance increase in per capita income (Ascani et al., 2012). However, studies draw attention to the importance of determining the factors affecting per capita income. For regional development, the necessity of both increasing exports and following import substitution strategies have been put forward (Shaffer, 1989; Blair and Carroll, 2008; Cooke and Watson, 2011). Exports are generally considered in two dimensions as the export of goods and services. Advanced technology and advanced industrial facilities used in developed countries increase the sales potential for the foreign market by enabling these countries to produce fast and high quality (Contractor and Mudambi, 2008). On the other hand, developing countries, follow a policy that will increase exports by utilizing their raw materials and underground resources. The service sector has been identified as a new growth engine for both developed and developing countries (Noland et al., 2012, Akın and Özsağır, 2012). Regions and provinces in the country carry out export activities according to the characteristics of their geographical location, production, and service types. According to these characteristics, there are important differences between the export capacities of the provinces and the development levels accordingly.

Economic development, in another definition, focuses on increasing wealth (Mathur, 1999). According to this view, domestic savings are one of the most important sources of development. The positive relationship between saving and growth has been noted in studies of many countries (Room, 2002; Carroll and Weil, 1994). In recent years a decline was observed in domestic savings in Turkey. This decline causes a negative impact on the economy through a deficit and it has led to the emergence of domestic savings again. (Peace and Space, 2015).

Another factor that is thought to have an impact on economic development is population. However, the direction and strength of the relationship between economic development and population are still under debate. While some argue that rapid population growth has a negative effect on economic development (Srinivasan, 1988; Kentor, 2001), there are also studies showing that the relationship between them is not significant (Easterlin, 1967). The population-oriented economic growth hypothesis, which states that population growth supports economic development, also maintains its validity. It is seen that population growth has positive effects on economic development, especially in developing countries (Furuoka, 2009). Increasing population brings some needs with it. The most important of these is the need for housing. With the sale of housing, not only the construction sector but also many sub-sectors such as cement, ready-mixed concrete, iron, and steel are affected. Specifically, when the economic contraction begins in developing countries, a way out of this bottleneck is sought by increasing investment expenditures in the construction sector. Thus, economic recovery is provided.

TOPSIS (Technique for Order Preference by Similarity to Solution) method makes it possible to assess the objects concerning multidimensional economic phenomena based on the group of economic variables (Yoon and Hwang, 1995; Balcerzak and Pietrzak, 2016). Most economists think that international comparisons of the level of sustainable development must be done with an application of quantitative methods (Balcerzak and Pietrzak, 2016). TOPSIS is referred to be a very useful and informative technique for ranking and selecting variables (Shih et al., 2007; Bhutia and Phipon, 2012, Kizielewicz et al. 2021). For this reason, TOPSIS is widely used in studies that are based on the comparisons of economic and financial performances and real-world problems. Eyüboğlu (2016) compared the developing countries considering macro performances as economic growth, inflation rate, unemployment rate, and the current account balance/GDP using Analytic Hierarchy Process (AHP) and TOPSIS methods. Using similar variables, Dinçer (2011) ranked both European Union members and candidate countries using TOPSIS and similarly, Kuncova (2012) made the comparisons of European countries in terms of e-commerce. TOPSIS method was also preferred to evaluate economic performances of countries during the financial crisis period (Mangır and Erdoğan, 2011) and used to examine the development achievement by European countries in the field of implementing the concept of sustainable development (Balcerzak and Pietrzak, 2016). TOPSIS method was employed to evaluate the good governance development in the European Union countries for the years of 2007-2017 (Ardielli, 2019). To assess the e-Government in the countries TOPSIS was used (Ardielli and Halaskova, 2015). Besides the comparisons of countries, municipalities were evaluated considering environmental sustainability using DEMATEL based TOPSIS (Kiliç and Yalçın, 2020). Slovak municipalities were assessed according to management criteria using TOPSIS (Vavrek, et al, 2015). Different from the listed studies here, TOPSIS was also used to identify suitable health indicators to evaluate the efficiency of Slovak municipalities (Vavrek et al., 2021).

In this study, it was aimed to evaluate the level of economic competition of 81 Turkish provinces considering the economic indicators using TOPSIS-M (Mahalanobis distance-based TOPSIS) which is based on the robust covariance matrix. The TOPSIS method is used to construct the ranking of items considering many variables and it is based on Euclidean distance that assumes the criteria of monotonically increasing or decreasing and this approach disregards the dependence among variables. Conversely, TOPSIS-M uses dependencies between variables considering the correlation matrix. However, in the presence of outliers, the use of methods based on covariance matrix should be approached with attention. Because the covariance matrix can be manipulated by outliers and give misleading results.

TOPSIS method is based on the distances from the model values ("positive ideal solution" and "negative ideal solution") and in case of the existence of outliers in a dataset, the maximum and minimum values of the variables affect the model values inevitably and this leads to excessive remoteness from typical values of the considered variables that narrow the range of variability of the constructed synthetic measure (Luczak and Just, 2020). Several studies in the literature suggested limiting the effect of outliers on the TOPSIS method. Khalif, et al. (2017) proposed the Spearman correlation matrix to handle outlier effects in the TOPSIS method. Luczak and Just (2020) used robust standardization and spatial median to make the TOPSIS method resistant against outliers. De Andrede, et al. (2020) used Singular Value Decomposition (SVD) TOPSIS approach to decrease the impacts of outliers while evaluating the performance of TV programs.

In this study, different from the previous approaches we presented an improvement to TOPSIS-M by using robust Mahalanobis distances which are resistant to outliers. To make Mahalanobis distances resistant to outliers, a robust covariance matrix was used. The covariance matrix employed in this study is based on the MM estimator. However, MCD, OGK, and S estimators were also evaluated, but since the results were very similar, only the results based on the MM estimator are included here.

To evaluate the level of economic competition of provinces in this study, per capita GDP, the trade deficit (import-export), the population, the total housing sales numbers, and the total bank deposit accounts were determined as variables. Since this dataset includes socioeconomic variables belonging to the provinces, due to the provinces with different development levels, the existence of outliers and dependency between variables are expected. Therefore, in the first stage of the application, descriptive statistics and correlation matrices were used to evaluate the dataset and outliers were diagnosed. In the next stage, the findings obtained from TOPSIS, TOPSIS-M, and robust MM covariance matrix based TOPSIS-M were evaluated. In addition to rank the provinces by taking into account the economic indicators, it was also included to classify provinces with robust cluster analysis. At the final stage, findings of robust cluster analysis were compared homogenous subsets obtained from robust Mahalanobis distance-based TOPSIS.

2. Methodology

TOPSIS method, originally developed by Hwang and Yoon (1981), is a simple and efficient Multi-Criteria Decision-Making (MCDM) method to identify solutions from a finite set of alternatives. The main idea is based on determining the best alternative which should have the closest geometric distance from the ideal solution. However, there are some main disadvantages in the traditional TOPSIS model: (i) correlations between criteria, (ii) uncertainty in obtaining the weights only by objective and subjective methods, finally, (iii) possibility of alternative closed to positive and negative ideal points concurrently (Li et al., 2011). Additionally, when the data set does not only include regular observations, outliers may have effects on the definition of ideal solutions and the calculation of distances it is important to consider robust estimators to deal with outliers. Because of the listed disadvantages, traditional TOPSIS can lead to biased estimation of relative significances of alternatives and can cause inaccurate ranking results.

To overcome the deficiency of correlation between criteria in the TOPSIS model, Mahalanobis distance-based TOPSIS was preferred. Mahalanobis distance is a measure that takes into consideration the correlation in the data by using the covariance matrix. However, outliers have a major influence on the covariance matrix. Because covariance matrix is known as a low breakdown estimator. Outliers attract mean and inflate variance towards its direction (Becker and Gather, 1999). To make Mahalanobis distances resistant against outliers, robust estimates of the covariance matrix are preferred to use (Rocke and Woodruff, 1996). Robust estimators are used to reducing and limiting the effect of outliers and strong asymmetry when calculating Mahalanobis distance. The robustness of an estimator can be evaluated by considering breakdown points and influence function properties (Huber, 1981; Maronna et. al., 2006). Minimum Covariance Determinant (MCD) estimator, S-estimators, Orthogonalized Gnanadesikan-Kettenring (OGK) estimator, and MM-estimators are well-known high-breakdown robust estimator of mean and covariance matrix. The covariance matrix employed in this study is based on the MM estimator.

2.1. Mahalanobis Distance-Based TOPSIS (TOPSIS-M)

The Euclidean distance approach used by the TOPSIS method is insufficient in terms of investigating the relationship between the criteria in the MCDM problem and including it in the decision process. Therefore, it is more appropriate to use Mahalanobis distance in calculating the deviations from the ideal solutions. TOPSIS-M method is a type of analysis in which deviations are computed using Mahalanobis distance in traditional TOPSIS algorithm.

Mahalanobis distance measurement also takes into account the correlation between variables in measuring the distance between two points. This measurement was proposed by Mahalanobis in 1936 and is used under his name. Mahalanobis distance between x_1 and x_2 points is calculated with the help of the following equation:

$$d\left(x_1, x_2\right) = \sqrt{\left(x_1 - x_2\right)^T C^{-1} \left(x_1 - x_2\right)} \tag{1}$$

C in Eq. (1) shows the variance-covariance matrix of the X set consisting of x values. (Xiang et al., 2008).

Analysis of the decision problem with the TOPSIS-M method consists of the following steps.

Step 1. As in all MCDM problems, the analysis process in the TOPSIS method starts with generating a decision matrix in which is the performance score of the alternative according to the criterion is expressed together. The A matrix created by the decision-maker is shown as below:

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & \cdots & \cdots & a_{mn} \end{bmatrix} \tag{2}$$

Step 2. Since the performance values created in the decision matrix represent different units or sizes according to different criteria, the evaluation process is continued by standardizing the decision matrix. Standardized performance scores to standardize the decision matrix, represented by r_{ij}, are obtained as follows:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \qquad i = 1, 2, \ldots, m \;\; j = 1, 2, \ldots, n \tag{3}$$

R standardized decision matrix is obtained by making use of Eq. (3).

Step 3. As mentioned in the definition of the TOPSIS-M method, it is based on the principle of proximity calculation to ideal solutions. In this step of the TOPSIS-M method, in which the ideal solution is handled in two directions, the ideal positive solution and the ideal negative solution sets are created, and the process continues. While creating the ideal solution clusters, the attributes of the criteria included in the decision problem are taken into account, considering the benefits and cost conditions.

In the TOPSIS-M method, the positive ideal solution set is calculated with Eq. (4), and the negative ideal solution set is calculated with the help of Eq. (5).

$$A^{*} = \left\{ (\max_{i} v_{ij} \middle| j \in J), (\min_{i} v_{ij} \middle| j \in J^{'} \right\} \tag{4}$$

$$A^{-} = \left\{ (\min_{i} v_{ij} \middle| j \in J), (\max_{i} v_{ij} \middle| j \in J^{'} \right\} \tag{5}$$

In the equations, J refers to Benefit Index and J' refers to Cost Index.

Step 4. In the TOPSIS-M method, the Mahalanobis distance approach is used to calculate deviations from ideal solution sets. As a result of the process, ideal separation values are calculated for each solution set.

The Positive ideal discrimination measure S_i^* is calculated using Eq. (6) and the negative ideal discrimination measure S_i^- is calculated using Eq. (7).

$$S_i^* = d\left(x_i, A^*\right) = \sqrt{\left(A^* - x_i\right)^T \Omega^T C^{-1} \Omega \left(A^* - x_i\right)} \tag{6}$$

$$S_i^- = d\left(x_i, A^-\right) = \sqrt{\left(x_i - A^-\right)^T \Omega^T C^{-1} \Omega \left(x_i - A^-\right)} \tag{7}$$

The C value in the equations represents the variance-covariance matrix of the X decision matrix of *mxn*, and Ω represents the square root of the elements of the weight vector on the diagonal matrix. The diagonal matrix Ω is obtained using Eq. (8).

$$\Omega = diag\left(\sqrt{w_1}, \sqrt{w_2}, \ldots, \sqrt{w_n}\right) \tag{8}$$

Step 5. In the calculation of the C_i^* value, which expresses the relative proximity of each alternative to the ideal solution, the ideal separation measures obtained in Step 5 are used.

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}, \quad 0 \le C_i^* \le 1 \tag{9}$$

As the C_i^* values that take values between 0 and 1 grow, it expresses the absolute proximity to the positive ideal solution. The C_i^* value obtained as a result of the analysis steps is ranked in descending order and a ranking based on the closeness of the alternatives to the ideal is obtained (Wang and Elhag, 2006).

2.2. Robust MM Estimator

The MM-estimator is a high breakdown value estimator, and it is an extension of the S-estimator (Maronna et. al., 2006). S-estimator was proposed by Rousseeuw and Leroy (1987). S-estimators of location μ and covariance S are defined such that the determinant of the matrix S is minimized under the constraint (Maronna et. al., 2016):

$$\frac{1}{n}\sum_{i=1}^{n}\rho\sqrt{\left(X_i-\mu\right)^{'}S^{-1}\left(X_i-\mu\right)}=b \tag{10}$$

where b is a constant and $\rho(X)$ is the loss function. A popular choice loss is Tukey's bi-weight function (Hubert and Rousseeuw, 2013):

$$\rho(x)=\begin{cases}\frac{k^2}{6}\left(1-\left(1-\frac{x}{k}\right)^2\right)^3 & , \quad |x|\le k\\ \frac{k^2}{6} & , \quad |x|>k\end{cases} \tag{11}$$

For the estimation of the MM estimator the following steps should be considered (Maronna et. al., 2006.):

a) Define a loss function ρ to compute the S-estimators of location and covariance, ($\tilde{\mu}$ and $\tilde{\Sigma}$).

b) Calculate $\hat{\sigma}=\left|\tilde{\Sigma}\right|^{1/2p}$

c) Find the MM-estimator of the location and the shape parameter, $(\hat{\mu},\hat{\Gamma})$, that minimize:

$$\frac{1}{n}\sum_{i=1}^{n}\rho_1((X_i-\mu)^{'}\Gamma^{-1}(X_i-\mu))^{1/2}/\hat{\sigma}) \tag{12}$$

d) Compute the MM-estimator of the covariance matrix $\hat{\Sigma}=\hat{\sigma}\hat{\Gamma}$

2.3. Robust Cluster

Cluster analysis is based on identifying homogeneous clusters with large heterogeneity among them. Many studies emphasize outliers may impair clustering ability and clustering methods need to be robust if they are to be useful in applications (García-Escudero et al. 2010, Ruwet et al. 2012). For handling outliers, robustness in cluster analysis is needed because outliers appear many times joined together (Garcia-Escudero et.al. 2011). To refrain from the outlier effects García-Escudero et al. (2008) introduced the TCLUST approach. The TCLUST approach performs robust clustering to find clusters with different distribution structures and weights (Ruwet et al. 2012). The TCLUST algorithm allows for Eigenvalue Rate restriction and trimming of a specific observation rate determined by the researchers to eliminate the effect of outliers. The T-CLUST method is known as the trimmed k-means technique. In this study, TCLUST was used to identify clusters with trimming a rate of 5%.

The flowchart in Figure 1 summarizes the steps followed throughout the methodology. As can be seen from the flow chart in the first stage, Mahalanobis distances based on the solid MM covariance matrix were calculated using the first decision matrix and these distances were used for ranking in the TOPSIS process. Similarly, based on this decision matrix, TOPSIS scores, and TOPSIS-M scores based on the classical covariance matrix were obtained. In the last step, provinces were classified using robust cluster analysis and the findings were evaluated considering the MM covariance-based TOPSIS-M, TOPSIS-M, and TOPSIS rankings.

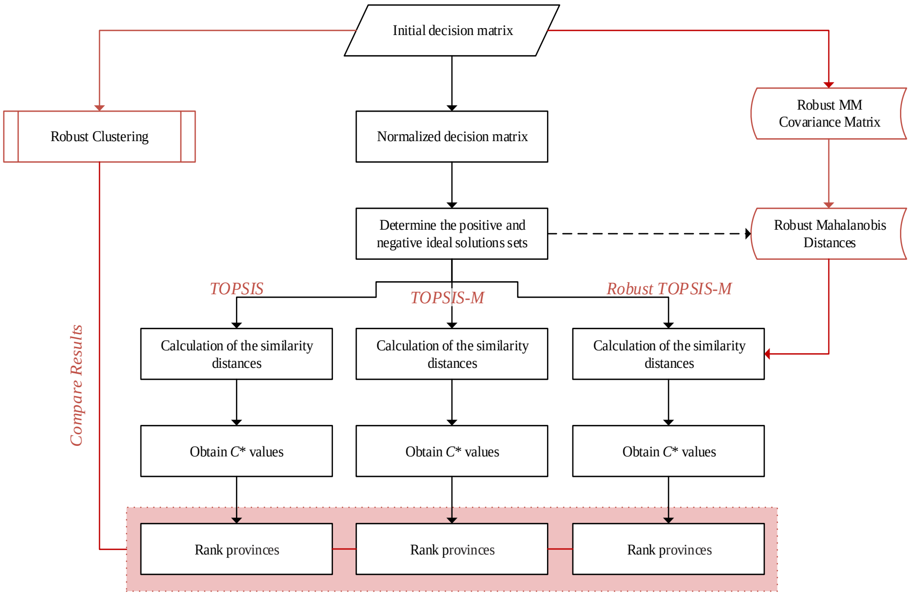

Figure 1. Flowchart of the evaluation methodology used.

3. Dataset and Results

In this study, the variables of GDP per capita, the trade deficit of the provinces (import-export), the population of the provinces, the total housing sales figures in the provinces, and the total bank deposit accounts of the provinces are used for the years 2019 and 2020. Datasets have been created through the official web page of the Turkish Statistical Institute and the Banking Supervision and Regulatory Agencies.

The reason why the TOPSIS method based on Mahalanobis distance was preferred in this study is the strong correlation coefficients between the variables. When the correlation values in Table 1 are examined, it is seen that there is a strong relationship. However, it was observed that the relationships were slightly weaker in the MM correlation matrix.

Table 1. Pearson Correlation Matrix

	Population	GDP per capita	Housing Sales	Trade deficit	Bank deposit
Population	1.00				
GDP per capita	0.52	1.00			
Housing Sales	0.97	0.61	1.00		
Trade deficit	0.85	0.39	0.77	1.00	
Bank deposit	0.96	0.52	0.93	0.94	1.00

Descriptive statistics were presented in Table 2. As can be seen from Table 2, the difference between mean and median values of variables (except GDP per capita) seem significantly different. This raises the suspicion of the existence of outliers. As a matter of fact, in a way to confirm this situation, outlying observations can be seen in Figure 2. Figure 2 corresponds to the distance-distance plot defined by Rousseeuw and van Zomeren (1991). This plot is based on classical Mahalanobis distances versus robust Mahalanobis distances (based on MM covariance estimator), it enables the classification of regular observations and outliers. The dashed line depicts the points where both distances are equal. The vertical and horizontal lines were drawn at the points ($\chi^2_{df=5,\ 0.975}$). Observations beyond these lines (Istanbul, Ankara, and Izmir) are defined as outliers.

Table 2. Descriptive statistics of development indicators

Variables	Mean	Std. Dev.	Median	MAD
Bank deposit	45353637,4	171658598	9715929	8497261
Housing Sales	18510,07	35694,54	7625	7168,37
Population	1032276,07	1872575,82	537762	419343
Trade deficit	-402315,83	4976466,74	35118	142794
GDP per capita	39506,76	13648,03	36820,7	10774,7

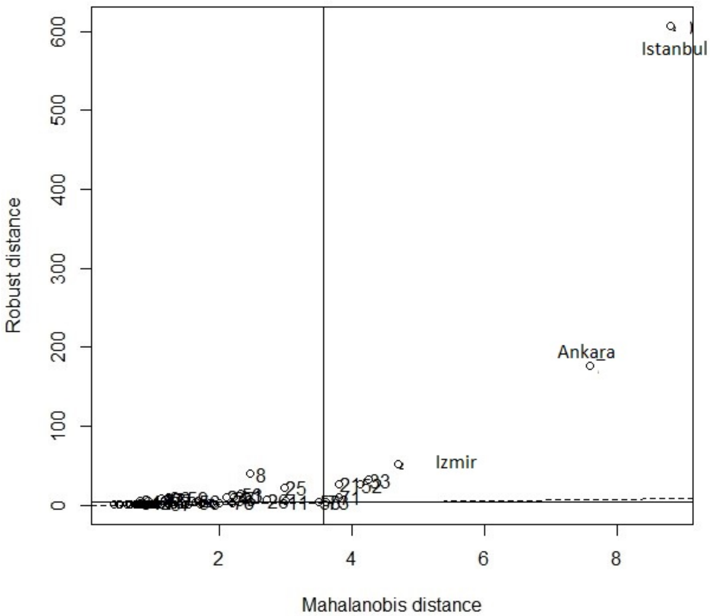

Figure 2. Distance-Distance plot (detection of outlying provinces).

Robust TOPSIS-M analysis steps and final scores of 81 provinces which obtained based on robust MM covariance matrix, are included in the Appendix. However, in Figure 3, provinces are divided into homogeneous groups based on these robust TOPSIS-M scores. As can be seen from this map, the provinces with the highest scores are respectively Istanbul, Ankara, Izmir, and Antalya. The scores with the lowest provinces are Ardahan, Bayburt, and Tunceli. These rankings are consistent with the actual values, considering the development levels of the provinces. Robust TOPSIS-M scores reflect the inter-class differences in the economic developments of provinces. Figure 3 presents ten classes of provinces, spanning from the extremely low to the extremely high levels of economic development.

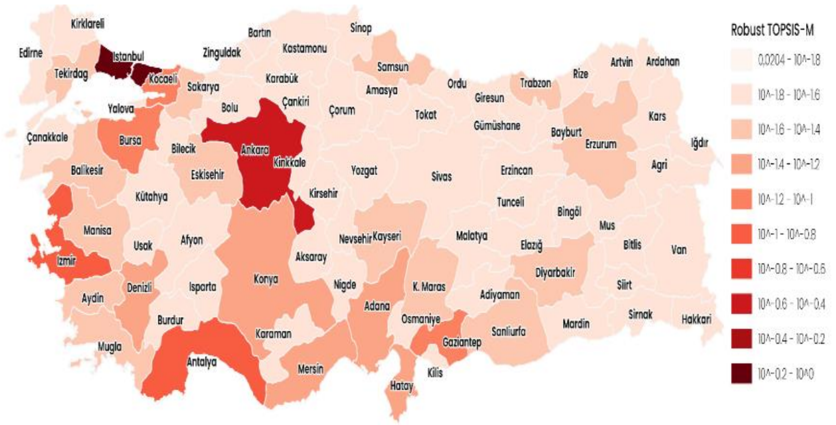

Figure 3. Classification of provinces according to Robust TOPSIS-M scores.

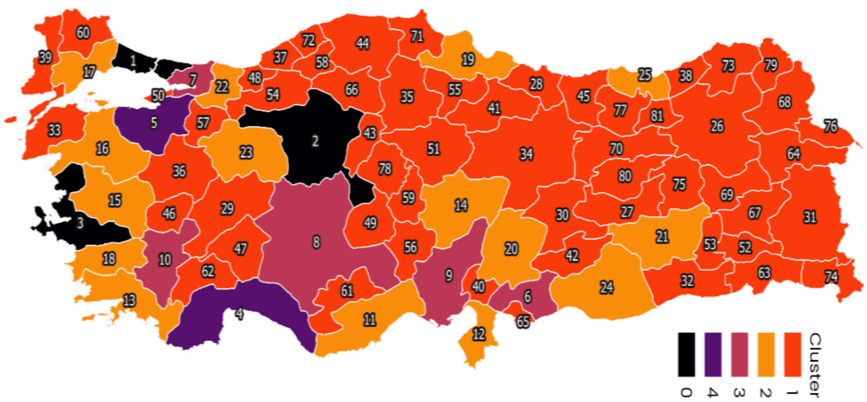

Figure 4. Classification of provinces according to robust clustering.

In Figure 4, robust clustering results were given. According to the TCLUST algorithm, four clusters and an outlier group were obtained. Cluster 0 consists of the outlying provinces. The map in Figure 4 also includes rank values of provinces according to robust TOPSIS-M scores. As can be seen, provinces were divided into four groups according to the robust clustering. Following the "distance-distance plot" in Figure1, Istanbul, Ankara, and Izmir have been determined as outliers here as well, and these provinces are in the top three with the robust TOPSIS-M ranking.

It is seen that the homogeneous groups defined based on robust TOPSIS-M scores in Figure 3 are compatible with the clusters in Figure 4. Although there are fewer clusters in Figure 4, only four clusters, these clusters can show the inter-class differences in terms of development indicators.

Table 3 presents the ranking of provinces according to TOPSIS, TOPSIS_M, and TOPSIS-MM approaches. This table also contains information about the cluster to which each province belongs. Rankings of provinces in the same cluster in Table 3 are expected to be close to each other. Although the order of provinces falling into clusters with 0 and 4 codes is close to each other in all three approaches, the order of provinces in clusters with codes 1-2 and 3 seems compatible only in TOPSIS-MM. Denizli, Kocaeli, Şırnak, Hatay, and Çorum are not compatible in the clusters in which they are ranked according to TOPSIS and TOPSIS-M approaches.

Table 3. Ranking of Provinces based on TOPSIS, TOPSIS-M, and TOPSIS-MM approaches

Province	TOPSIS	TOPSIS -M	Robust TOPSIS -M	Robust Cluster	Province	TOPSIS	TOPSIS -M	Robust TOPSIS -M	Robust Cluster
İstanbul	1	1	1	0	Adıyaman	47	50	42	1
Ankara	2	2	2	0	Kırklareli	35	39	43	1
İzmir	3	3	3	0	Kastamonu	42	38	44	1
Antalya	5	5	4	4	Giresun	40	42	45	1
Bursa	4	4	5	4	Uşak	45	36	46	1
Gaziantep	6	9	6	3	Isparta	37	35	47	1
Kocaeli	12	6	7	3	Düzce	41	52	48	1
Konya	7	8	8	3	Aksaray	44	37	49	1
Adana	10	7	9	3	Yalova	38	40	50	1
Denizli	14	15	10	3	Yozgat	57	46	51	1
Mersin	8	10	11	2	Siirt	64	75	52	1
Hatay	24	13	12	2	Batman	54	54	53	1
Muğla	17	11	13	2	Bolu	46	51	54	1
Kayseri	9	12	14	2	Amasya	55	60	55	1
Manisa	19	16	15	2	Niğde	53	59	56	1
Balıkesir	16	14	16	2	Bilecik	49	65	57	1
Tekirdağ	13	19	17	2	Karabük	68	49	58	1
Aydın	15	17	18	2	Nevşehir	59	44	59	1
Samsun	21	20	19	2	Kırşehir	63	57	60	1
Kahramanmaraş	25	25	20	2	Karaman	52	55	61	1
Diyarbakır	20	23	21	2	Burdur	51	56	62	1
Sakarya	11	22	22	2	Şırnak	39	73	63	1
Eskişehir	22	18	23	2	Ağrı	67	70	64	1
Şanlıurfa	18	27	24	2	Kırıkkale	56	64	65	1
Trabzon	23	21	25	2	Çankırı	62	67	66	1
Erzurum	36	43	26	1	Bitlis	74	76	67	1
Elazığ	32	34	27	1	Kars	72	69	68	1
Ordu	30	30	28	1	Muş	65	72	69	1
Afyonkarahisar	27	28	29	1	Erzincan	58	61	70	1
Malatya	28	29	30	1	Sinop	66	63	71	1
Van	31	45	31	1	Bartın	70	62	72	1
Mardin	26	58	32	1	Artvin	60	66	73	1
Çanakkale	29	26	33	1	Hakkari	77	78	74	1
Sivas	33	31	34	1	Bingöl	73	68	75	1
Çorum	81	32	35	1	Iğdır	71	74	76	1
Kütahya	34	41	36	1	Gümüşhane	78	77	77	1
Zonguldak	75	24	37	1	Kilis	76	79	78	1
Rize	50	47	38	1	Ardahan	79	80	79	1
Edirne	43	33	39	1	Tunceli	69	71	80	1
Osmaniye	61	53	40	1	Bayburt	80	81	81	1

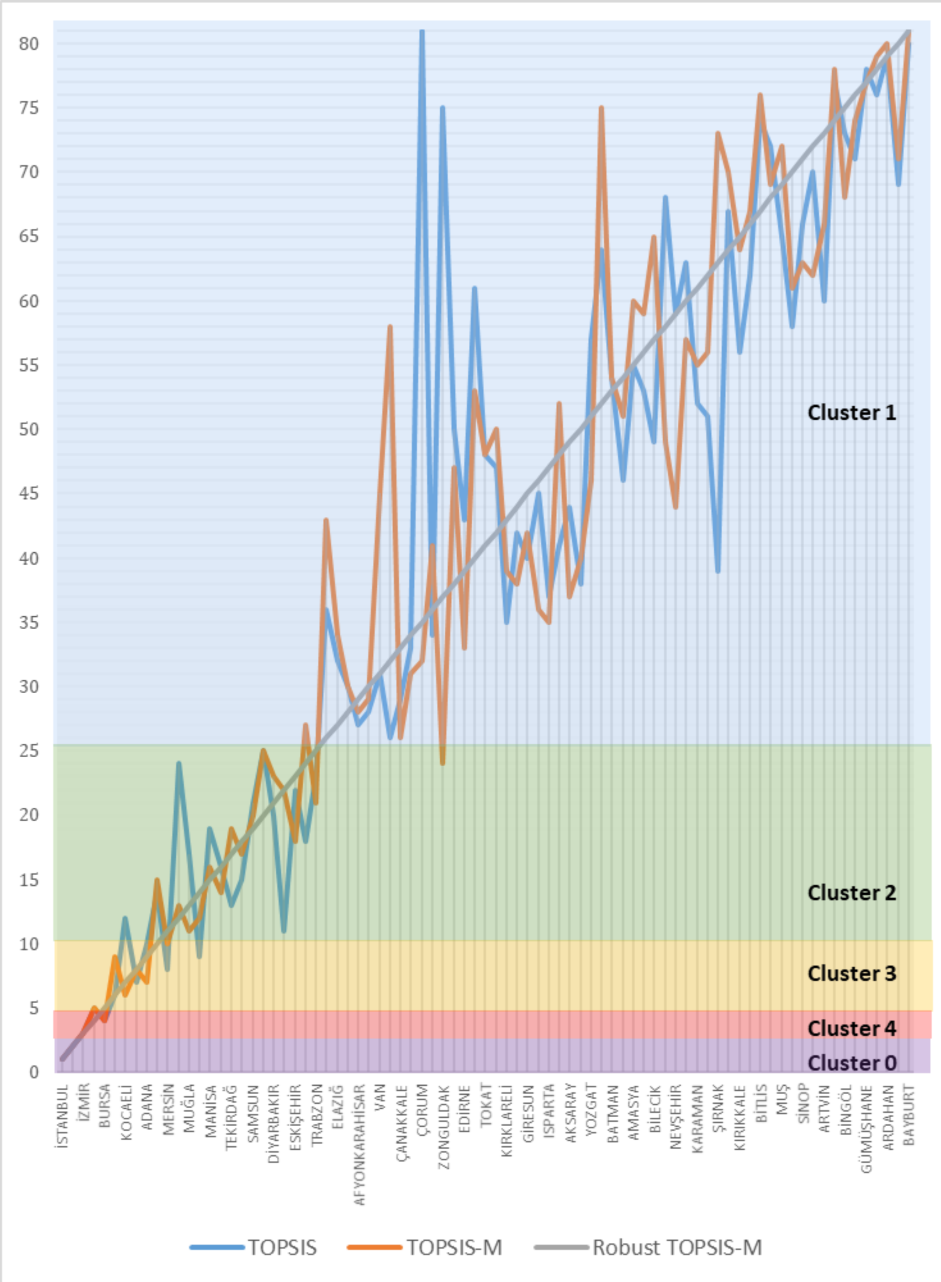

Figure 5. Comparision of TOPSIS, TOPSIS-M, and Robust TOPSIS-M results

The provinces that exists in cluster 0 and cluster 4 are also consistent in terms of rankings. While Denizli and Kocaeli should be in the third cluster, they are in the second cluster according to TOPSIS and TOPSIS-M rankings. The province of Zonguldak, which should be in the first cluster, falls in the second cluster according to the TOPSIS and TOPSIS-M rankings, and Şanlıurfa, which should be in the second cluster, falls into the first cluster. However, as can be seen in Figure 5, there is no inconsistency between Robust TOPSIS-M and clusters.

4. Conclusion

The TOPSIS method is an MCDM method that is frequently used to sort the observations and divide them into homogeneous groups, considering various variables. However, the TOPSIS method is calculated based on the Euclidean distance and ignores the relationship between variables. The TOPSIS-M method calculated based on the Mahalanobis distance takes into account the dependency structure between variables. However, since Mahalanobis distances are calculated based on the covariance matrix, these distances calculated when there are outliers in the data set give misleading results. In this study, it was proposed to make the TOPSIS-M method resistant with the use of the MM covariance matrix, which is resistant to outliers. Robust Mahalanobis distances are used frequently in the literature by using robust covariance matrix. However, to the best of our knowledge, this approach has not been applied to the TOPSIS-M method in studies conducted so far.

In this study, it was aimed to rank 81 Turkish provinces by taking into account the variables of per capita GDP, foreign trade deficit (import-export), population, total housing sales, and total bank deposit accounts. The limitation of this study is that the most up-to-date values of statistics collected by provinces are 2019.

The fact that the provinces have quite different levels of economic development inevitably made it necessary to consider the effect of outlying observations in the data. For this reason, since the TOPSIS-M method is based on the classical covariance estimator and this estimator is a low breakdown estimator, the covariance matrix was made resistant to outliers using the robust MM estimator. In addition, provinces were classified using the robust clustering method.

According to the Robust Cluster Analysis, Istanbul, Ankara, and Izmir, which are obtained as outliers were found to be the top 3 provinces with the Robust TOPSIS-M method. Antalya and Bursa, which are in the first cluster, are ranked as the fourth and fifth provinces in the ranking. Gaziantep, Kocaeli, Konya, Adana, and Denizli, which are in the second cluster, were ranked from 6 to 10 in the Robust TOPSIS-M ranking, again producing consistent results. The last 3 provinces in the ranking for economic development are Ardahan, Tunceli, and Bayburt.

The top provinces in the robust TOPSIS-M ranking and observations in clusters number three and four (including outliers) correspond to important industrial and trade centers. Likewise, it is seen that the population density is concentrated in these provinces. For this reason, housing sales are also high in these provinces. When the provinces that are the last in the ranking are examined, it is known that these provinces have some disadvantages such as natural disasters and terrorism due to their geographical location, and therefore economic development is lower. This situation both accelerates migration and prevents investment in these regions.

According to our findings, obtained robust clusters and homogenous groups that are based on MM estimator based TOPSIS-M and the actual situation seem compatible. This research presents that robust MM estimator based TOPSIS-M performs correct rankings and partitions homogeneous groups in case of variables with outliers. The ranking of the provinces taking into account the socio-economic indicators are included in various studies. However, while ranking in these studies, the dependency between indicators and the potential effects of outliers were not taken into account. The TOPSIS approach based on robust Mahalanobis distance, which is resistant to outliers, was used because the data used in this study consisted of provinces with different development levels and correlated variables. To make Mahalanobis distances resistant to outliers, a robust covariance matrix was used. The covariance matrix employed in this study is based on the MM estimator. The Findings obtained in this study are consistent with the real situation. For this reason, we recommend using robust MM estimator based TOPSIS-M for the evaluation of the economic development of provinces described by variables with outliers.

In this study, the importance of the criteria was accepted as equal and the ranking was made accordingly. The importance of criteria can also be determined by subjective methods such as AHP, ANP, DEMATEL or objective weighting methods such as CRITIC and Entropy-based on expert opinion. In addition, the results can be compared by considering the VIKOR, ARAS, COPRAS methods. Another suggestion is that Robust estimators can be used when analyzing data sets containing outliers.

Acknowledgement: The authors would like to thank the editor and two anonymous referees who kindly reviewed the earlier version of this manuscript and provided valuable suggestions and comments.

Appendix

Appendix 1. Initial Decision Matrix

opt. direction	*max*	*max*	*max*	*min*	*max*
Provinces	C1	C2	C3	C4	C5
Adana	55967796.32	28014.82016	1877332.698	-311514.1	2250.26969
Adıyaman	1863197.32	2070.82016	251073.698	-31357.12	-12116.15031
Afyonkarahisar	6888921.32	4691.82016	355526.698	234945.9	1539.61969
Ağrı	-2645137.68	-2840.17984	154049.698	-87890.12	-17843.02031
Aksaray	713663.32	1693.82016	41625.698	19646.88	2482.87969
Amasya	-295349.68	150.82016	-45891.302	427.8769	1172.38969
Ankara	492294499.3	151783.8202	5281936.698	-3483295	36456.87969
Antalya	132877245.3	58586.82016	2166922.698	780921.9	26061.19969
Ardahan	-5284044.68	-5119.17984	-285224.302	-49309.12	74.52969
Artvin	-3411236.68	-3236.17984	-211884.302	-15058.12	16262.21969
Aydın	23029583.32	28466.82016	737698.698	511716.9	3318.19969
Balıkesir	25442739.32	26952.82016	858899.698	149926.9	9731.58969
Bartın	-3302268.68	-2577.17984	-182406.302	-31205.12	-2380.33031
Batman	-675291.68	-32.17984	238892.698	-58419.12	-11171.71031
Bayburt	-5952091.68	-4568.17984	-299475.302	-52799.12	-588.14031
Bilecik	24778.32	-1558.17984	-162668.302	2948.877	22498.06969
Bingöl	-4503701.68	-2761.17984	-99617.302	-50850.12	-7248.06031
Bitlis	-3181196.68	-3062.17984	-30391.302	-49285.12	-12390.60031
Bolu	203256.32	1250.82016	-66583.302	-106321.1	19585.19969
Burdur	-950198.68	-1557.17984	-114293.302	144657.9	7718.20969
Bursa	103889557.3	49910.82016	2720447.698	1892625	24386.28969
Çanakkale	5925653.32	7541.82016	160162.698	7834.877	19109.07969
Çankırı	-2747841.68	-2633.17984	-188957.302	46700.88	3018.99969
Çorum	6674460.32	3493.82016	148740.698	-1790497	-2984.09031

opt. direction	*max*	*max*	*max*	*min*	*max*
Provinces	C1	C2	C3	C4	C5
Denizli	53935630.32	12770.82016	659529.698	1355305	11958.85969
Diyarbakır	15438764.32	14021.82016	1402045.698	97005.88	-10925.07031
Düzce	1390404.32	2540.82016	14293.698	37837.88	9178.98969
Edirne	3728462.32	2354.82016	26377.698	-93268.12	9517.71969
Elazığ	7909597.32	5613.82016	206574.698	69351.88	-2341.99031
Erzincan	-3181739.68	-2104.17984	-146954.302	-33907.12	12717.06969
Erzurum	8618759.32	4625.82016	376893.698	-73632.12	-4335.33031
Eskişehir	18079022.32	16869.82016	507442.698	96372.88	21037.71969
Gaziantep	85062990.32	30046.82016	1719771.698	2837014	3062.58969
Giresun	1361999.32	2313.82016	67335.698	183646.9	-3347.60031
Gümüşhane	-4913512.68	-3789.17984	-239683.302	-17616.12	-5486.51031
Hakkari	-4193366.68	-5115.17984	-100871.302	-51723.12	-4378.33031
Hatay	35258735.32	19863.82016	1277934.698	-1128064	-3548.01031
Iğdır	-4458034.68	-3356.17984	-180071.302	20415.88	-3832.76031
Isparta	1270343.32	1548.82016	58918.698	115079.9	6658.64969
İstanbul	1461674123	259786.8202	15081066.7	-44100660	52227.99969
İzmir	184423821.3	88145.82016	4013308.698	3085818	25983.10969
Kahramanmaraş	22580684.32	10205.82016	786777.698	-173798.1	-464.72031
Karabük	206223.32	-727.17984	-137771.302	-253143.1	4144.99969
Karaman	-772106.68	-2061.17984	-126466.302	102636.9	12431.04969
Kars	-3063130.68	-2282.17984	-96462.302	-52533.12	-8298.62031
Kastamonu	1818376.32	1564.82016	-5008.302	98800.88	4187.53969
Kayseri	30238897.32	24721.82016	1040069.698	1343356	9640.35969
Kırıkkale	-1904612.68	1071.82016	-102682.302	-52676.12	4675.43969
Kırklareli	2668193.32	3197.82016	-19648.302	-25132.12	22464.03969
Kırşehir	-311130.68	-763.17984	-138343.302	-100793.1	-798.78031
Kilis	-5406827.68	-2276.17984	-238593.302	-35270.12	-5464.94031
Kocaeli	86408382.32	31458.82016	1615872.698	-1863656	46657.65969
Konya	60562975.32	31884.82016	1868634.698	1237525	6322.18969
Kütahya	3786265.32	2929.82016	195302.698	50603.88	7249.71969
Malatya	6182146.32	7375.82016	424770.698	120705.9	-4147.51031
Manisa	31011819.32	20323.82016	1069230.698	-208845.1	14896.21969
Mardin	4259936.32	3300.82016	473330.698	582686.9	-5707.20031
Mersin	37674319.32	38184.82016	1487371.698	317713.9	2502.11969
Muğla	33571393.32	16931.82016	619387.698	276033.9	21892.43969
Muş	-3682386.68	-2947.17984	29731.698	-29532.12	-11243.22031
Nevşehir	-435112.68	-1773.17984	-76423.302	-24949.12	2160.34969
Niğde	-370740.68	1959.82016	-19314.302	-50039.12	1344.10969
Ordu	6967854.32	6100.82016	380014.698	159544.9	-4303.13031
Osmaniye	3450177.32	1594.82016	167170.698	-342117.1	-4603.69031
Rize	4066309.32	-1308.17984	-37026.302	78696.88	6147.14969
Sakarya	16619602.32	17106.82016	661263.698	1655493	15186.54969
Samsun	22123112.32	20644.82016	974693.698	-115775.1	229.80969
Siirt	531142.32	-2521.17984	-50315.302	8529.877	-7978.65031
Sinop	-3238326.68	-1697.17984	-164925.302	-30873.12	-3016.23031
Sivas	4712271.32	4699.82016	254503.698	2109.877	418.87969
Şanlıurfa	13184870.32	20959.82016	1733870.698	-130692.1	-17105.90031
Şırnak	-2774068.68	-4059.17984	156376.698	528624.9	-7290.49031
Tekirdağ	23358321.32	29306.82016	699679.698	256729.9	36217.16969
Tokat	2076276.32	1249.82016	216475.698	-31300.12	-7668.86031
Trabzon	15582031.32	6753.82016	430515.698	909257.9	2743.69969
Tunceli	-5448571.68	-4318.17984	-297942.302	-52940.12	13259.17969
Uşak	1847229.32	680.82016	-11952.302	8509.877	9212.63969

opt. direction	max	max	max	min	max
Provinces	C1	C2	C3	C4	C5
Van	4106565.32	2366.82016	767956.698	-45450.12	-15861.99031
Yalova	1351893.32	6788.82016	-105335.302	-173924.1	20458.87969
Yozgat	409397.32	136.82016	37709.698	-58432.12	-5858.70031
Zonguldak	4575397.32	1537.82016	209818.698	-818261.1	2122.10969

Appendix 2. Normalize Decision Matrix

Provinces	C1	C2	C3	C4	C5
Adana	0.036	0.082	0.106	-0.007	0.017
Adıyaman	0.001	0.006	0.014	-0.001	-0.093
Afyonkarahisar	0.004	0.014	0.020	0.005	0.012
Ağrı	-0.002	-0.008	0.009	-0.002	-0.137
Aksaray	0.000	0.005	0.002	0.000	0.019
Amasya	0.000	0.000	-0.003	0.000	0.009
Ankara	0.313	0.446	0.298	-0.078	0.281
Antalya	0.084	0.172	0.122	0.017	0.201
Ardahan	-0.003	-0.015	-0.016	-0.001	0.001
Artvin	-0.002	-0.010	-0.012	0.000	0.125
Aydın	0.015	0.084	0.042	0.011	0.026
Balıkesir	0.016	0.079	0.048	0.003	0.075
Bartın	-0.002	-0.008	-0.010	-0.001	-0.018
Batman	0.000	0.000	0.013	-0.001	-0.086
Bayburt	-0.004	-0.013	-0.017	-0.001	-0.005
Bilecik	0.000	-0.005	-0.009	0.000	0.173
Bingöl	-0.003	-0.008	-0.006	-0.001	-0.056
Bitlis	-0.002	-0.009	-0.002	-0.001	-0.095
Bolu	0.000	0.004	-0.004	-0.002	0.151
Burdur	-0.001	-0.005	-0.006	0.003	0.059
Bursa	0.066	0.147	0.153	0.042	0.188
Çanakkale	0.004	0.022	0.009	0.000	0.147
Çankırı	-0.002	-0.008	-0.011	0.001	0.023
Çorum	0.004	0.010	0.008	-0.040	-0.023
Denizli	0.034	0.037	0.037	0.030	0.092
Diyarbakır	0.010	0.041	0.079	0.002	-0.084
Düzce	0.001	0.007	0.001	0.001	0.071
Edirne	0.002	0.007	0.001	-0.002	0.073
Elazığ	0.005	0.016	0.012	0.002	-0.018
Erzincan	-0.002	-0.006	-0.008	-0.001	0.098
Erzurum	0.005	0.014	0.021	-0.002	-0.033
Eskişehir	0.011	0.050	0.029	0.002	0.162
Gaziantep	0.054	0.088	0.097	0.063	0.024
Giresun	0.001	0.007	0.004	0.004	-0.026
Gümüşhane	-0.003	-0.011	-0.014	0.000	-0.042
Hakkari	-0.003	-0.015	-0.006	-0.001	-0.034
Hatay	0.022	0.058	0.072	-0.025	-0.027
Iğdır	-0.003	-0.010	-0.010	0.000	-0.030
Isparta	0.001	0.005	0.003	0.003	0.051
İstanbul	0.929	0.763	0.850	-0.987	0.402
İzmir	0.117	0.259	0.226	0.069	0.200
Kahramanmaraş	0.014	0.030	0.044	-0.004	-0.004
Karabük	0.000	-0.002	-0.008	-0.006	0.032
Karaman	0.000	-0.006	-0.007	0.002	0.096

Provinces	C1	C2	C3	C4	C5
Kars	-0.002	-0.007	-0.005	-0.001	-0.064
Kastamonu	0.001	0.005	0.000	0.002	0.032
Kayseri	0.019	0.073	0.059	0.030	0.074
Kırıkkale	-0.001	0.003	-0.006	-0.001	0.036
Kırklareli	0.002	0.009	-0.001	-0.001	0.173
Kırşehir	0.000	-0.002	-0.008	-0.002	-0.006
Kilis	-0.003	-0.007	-0.013	-0.001	-0.042
Kocaeli	0.055	0.092	0.091	-0.042	0.359
Konya	0.038	0.094	0.105	0.028	0.049
Kütahya	0.002	0.009	0.011	0.001	0.056
Malatya	0.004	0.022	0.024	0.003	-0.032
Manisa	0.020	0.060	0.060	-0.005	0.115
Mardin	0.003	0.010	0.027	0.013	-0.044
Mersin	0.024	0.112	0.084	0.007	0.019
Muğla	0.021	0.050	0.035	0.006	0.169
Muş	-0.002	-0.009	0.002	-0.001	-0.087
Nevşehir	0.000	-0.005	-0.004	-0.001	0.017
Niğde	0.000	0.006	-0.001	-0.001	0.010
Ordu	0.004	0.018	0.021	0.004	-0.033
Osmaniye	0.002	0.005	0.009	-0.008	-0.035
Rize	0.003	-0.004	-0.002	0.002	0.047
Sakarya	0.011	0.050	0.037	0.037	0.117
Samsun	0.014	0.061	0.055	-0.003	0.002
Siirt	0.000	-0.007	-0.003	0.000	-0.061
Sinop	-0.002	-0.005	-0.009	-0.001	-0.023
Sivas	0.003	0.014	0.014	0.000	0.003
Şanlıurfa	0.008	0.062	0.098	-0.003	-0.132
Şırnak	-0.002	-0.012	0.009	0.012	-0.056
Tekirdağ	0.015	0.086	0.039	0.006	0.279
Tokat	0.001	0.004	0.012	-0.001	-0.059
Trabzon	0.010	0.020	0.024	0.020	0.021
Tunceli	-0.003	-0.013	-0.017	-0.001	0.102
Uşak	0.001	0.002	-0.001	0.000	0.071
Van	0.003	0.007	0.043	-0.001	-0.122
Yalova	0.001	0.020	-0.006	-0.004	0.157
Yozgat	0.000	0.000	0.002	-0.001	-0.045
Zonguldak	0.003	0.005	0.012	-0.018	0.016

Appendix 3. Covariance Matrix

	C1	C2	C3	C4	C5
C1	7.76E+13	71414896520	2.90942E+12	3.62346E+11	30383494618
C2	7.14E+10	71756333	2661769030	374774730	34537249
C3	2.91E+12	2661769030	1.33093E+11	18567394308	-212823424
C4	3.62E+11	374774730	18567394308	32006766617	107912881
C5	3.04E+10	34537249	-212823424	107912881	165872410

Appendix 4. Robust TOPSIS-M results and Robust Clusters

Provinces	S-	S*	C*	Rank	Robust Cluster
İstanbul	3806970.55	0.00	1.0000	1	0
Ankara	1315344.95	2494550.68	0.3452	2	0
İzmir	540509.74	3274118.34	0.1417	3	0
Antalya	396058.35	3419752.48	0.1038	4	4
Bursa	330753.25	3487381.04	0.0866	5	4
Gaziantep	277507.93	3542972.56	0.0726	6	3
Kocaeli	276162.66	3541735.68	0.0723	7	3
Konya	219392.06	3603602.94	0.0574	8	3
Adana	207115.82	3615707.45	0.0542	9	3
Denizli	194374.17	3630396.97	0.0508	10	3
Mersin	163408.66	3664411.81	0.0427	11	2
Hatay	154532.08	3673023.35	0.0404	12	2
Muğla	147826.70	3681960.66	0.0386	13	2
Kayseri	145282.08	3686437.22	0.0379	14	2
Manisa	145128.76	3684833.95	0.0379	15	2
Balıkesir	132516.62	3700386.28	0.0346	16	2
Tekirdağ	127596.18	3706567.06	0.0333	17	2
Aydın	127282.54	3707360.65	0.0332	18	2
Samsun	126212.93	3708004.87	0.0329	19	2
Kahramanmaraş	125600.94	3708571.90	0.0328	20	2
Diyarbakır	116569.03	3721282.25	0.0304	21	2
Sakarya	116280.49	3723596.74	0.0303	22	2
Eskişehir	115656.03	3721757.37	0.0301	23	2
Şanlıurfa	114373.51	3724234.47	0.0298	24	2
Trabzon	111612.58	3728659.48	0.0291	25	2
Erzurum	98085.95	3747016.37	0.0255	26	1
Elazığ	96291.94	3750128.47	0.0250	27	1
Ordu	96003.68	3751018.17	0.0250	28	1
Afyonkarahisar	95901.64	3751339.97	0.0249	29	1
Malatya	95048.94	3752610.14	0.0247	30	1
Van	93597.31	3755186.68	0.0243	31	1
Mardin	93352.18	3756901.33	0.0242	32	1
Çanakkale	93207.95	3755240.61	0.0242	33	1
Sivas	91889.38	3757735.11	0.0239	34	1
Çorum	91063.00	3754443.44	0.0237	35	1
Kütahya	90466.14	3760470.56	0.0235	36	1
Zonguldak	90079.02	3758778.28	0.0234	37	1
Rize	89697.81	3761760.02	0.0233	38	1
Edirne	89321.95	3762063.33	0.0232	39	1
Osmaniye	89151.99	3761846.64	0.0232	40	1
Tokat	88192.13	3764793.87	0.0229	41	1
Adıyaman	88081.94	3765080.11	0.0229	42	1
Kırklareli	87977.97	3764919.61	0.0228	43	1
Kastamonu	87144.59	3767103.59	0.0226	44	1
Giresun	87058.94	3767686.80	0.0226	45	1
Uşak	87010.94	3767075.77	0.0226	46	1
Isparta	86840.86	3767906.40	0.0225	47	1
Düzce	86662.16	3767969.21	0.0225	48	1
Aksaray	85953.20	3769527.17	0.0223	49	1
Yalova	85801.86	3768973.01	0.0223	50	1

Provinces	S-	S*	C*	Rank	Robust Cluster
Yozgat	85421.17	3770463.34	0.0222	51	1
Siirt	85271.04	3770921.94	0.0221	52	1
Batman	85096.64	3771558.44	0.0221	53	1
Bolu	84797.12	3771567.26	0.0220	54	1
Amasya	84458.37	3772823.86	0.0219	55	1
Niğde	84410.23	3772788.28	0.0219	56	1
Bilecik	84407.81	3772772.88	0.0219	57	1
Karabük	84164.54	3772408.90	0.0218	58	1
Nevşehir	84142.10	3773447.97	0.0218	59	1
Kırşehir	83876.31	3773707.63	0.0217	60	1
Karaman	83874.45	3774547.24	0.0217	61	1
Burdur	83803.32	3774923.73	0.0217	62	1
Şırnak	83736.19	3777277.36	0.0217	63	1
Ağrı	82723.75	3777316.70	0.0214	64	1
Kırıkkale	82594.90	3777297.79	0.0214	65	1
Çankırı	81699.87	3780150.88	0.0212	66	1
Bitlis	81664.43	3780126.62	0.0211	67	1
Kars	81542.53	3780329.88	0.0211	68	1
Muş	81497.20	3780856.44	0.0211	69	1
Erzincan	81377.80	3780799.86	0.0211	70	1
Sinop	81221.97	3781266.28	0.0210	71	1
Bartın	81109.97	3781574.80	0.0210	72	1
Artvin	81017.96	3781881.92	0.0210	73	1
Hakkari	80631.68	3783181.03	0.0209	74	1
Bingöl	80405.97	3783954.88	0.0208	75	1
Iğdır	80323.38	3784453.71	0.0208	76	1
Gümüşhane	79753.45	3786130.63	0.0206	77	1
Kilis	79407.02	3787346.82	0.0205	78	1
Ardahan	79335.75	3787401.81	0.0205	79	1
Tunceli	79231.01	3787762.23	0.0205	80	1
Bayburt	78884.23	3789196.40	0.0204	81	1

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