International Journal of Human Sciences
ISSN:1303-5134

Volume: 8 Issue: 2 Year: 2011

Relationship between hierarchic - spatial differentiation of social structure and population size of municipalities in Turkey: Evidence from the election case of local administration in 2004

Murat Çiftçi[1]

Abstract

Turkey, whose population is young and dynamic, is a country where social change has a high acceleration. This circumstance has led to a spatial heterogeneity of social structure in the scale of campuses. Almost all the municipalities differ significantly from each other. In results of statistical applications, it was possible to conclude that there is a relationship between spatial differentiation of social structure indicators (PDI, PIDI) and population sizes in municipalities. This relationship also supports that there was a differentiation of graded spatial social structure among municipalities in the Turkey of 2004. It is possible to make contact with this to the spatial differentiation that moves in parallel with population size and is in transition degree from a community to a society.

Keywords: Political demography; political indecision; social disintegration; social structure; social policy; regional science; statistics.

[1] * Yrd. Doç. Dr. Trakya Üniversitesi İİBF Öğretim Üyesi
İletişim: Balkan Yerleşkesi İİBF, Edirne.
Email: muratciftci77@yahoo.com

Çiftçi, M. (2011). Relationship between hierarchic - spatial differentiation of social structure and population size of municipalities in Turkey: Evidence from the election case of local administration in 2004. *International Journal of Human Sciences* [Online]. 8:2. Available: http://www.InsanBilimleri.com/En

Türkiye'de mekansal-kademeli sosyal yapı farklılaşması ve yerleşim birimlerinin nüfus büyüklükleri ilişkisi: 2004 yerel seçimlerinden bir kanıt

Özet

Genç ve dinamik bir nüfusa sahip olan Türkiye, sosyal değişmenin yüksek ivmeli olduğu bir ülkedir. Bu durum, yerleşkelerin kademesinde sosyal yapının mekansal heterojenliğine yol açmaktadır. Türkiye, genç ve dinamik nüfusa sahip bir ülke olarak sosyal değişimin yüksek ivmeli olduğu bir ülkedir. Bu durum ise, nüfusun sosyal yapısının yerleşkeler ölçeğinde mekânsal heterojenliğine yol açmaktadır. Hemen her yerleşim birimi, bir diğerinden ciddi farklılıklar göstermektedir. Yapılan istatistiksel uygulamalar sonucunda mekansal-kademeli sosyal yapı farklılaşması göstergeleri (siyasal ilgisizlik ve siyasal çözülme endeksleri) ile yerleşim birimlerinin nüfus hacimleri arasında ilişki olduğu sonucuna varılmıştır. Bu ilişki ise 2004 Türkiyesinde yerleşim birimleri arasında kademeli bir mekâna dayalı sosyal yapı faklılaşmasının yaşandığını desteklemektedir. Bunu nüfus büyüklüğüyle paralel olarak hareket eden cemaatten cemiyete geçiş derecesindeki mekana dayalı farklılaşmayla ilişkilendirmek mümkündür.

Anahtar kelimeler: Siyasal demografi, siyasal kararsızlık, sosyal çözülme, sosyal yapı, sosyal politika, istatistik.

1. Introduction

Behaviors of human who is a social being change according to size of places where he or she lives. It is possible to meet frequently communal relationships among people living in the places thinly populated. Intrinsic connections among members are very high in these communities. There is a sharp sense of belonging (Erkal, 1995; Gezgin, 1996). This social structure causes individuals to be mostly more sensitive against the social events than those living in the overpopulated areas. Population growth of settlement places we can label as urbanization lead mostly to weaken the ties among individuals. We can determine this circumstance as transition from community to society.

Although Occupational stratification becomes dominant in the societies dominated in the overpopulated settlements in opposition to communities, becoming compatriot stays at the back. Thus, we encounters with anomie as social problem of societies, showing itself as aimless, purposelessness and individualism (Erkal, 1995). This circumstance comes together with social disintegration.

It is extremely difficult to determine the fact of the anomie and of the social disintegration, which increase with the transition to becoming a society, with statistical applications. Indicative representations of measurements based on poll works are also quite limited. For, both the number of municipalities is limited to make comparison in these works and it is encountered with representatives problems that stemm from taking the possibility of effect-the desired reactions as basis instead of the measurement of effect-reaction. However, rather than desires of the test subjects it is necessary to measure the attitudes of individuals against reel events. We can only follow the spatial differentiation of the personal behaviors when we leave desires. Thus, it is possible to reveal concretely the relationship between the social disintegration and campus scale.

It is necessary to examine the relationship according to the kinds of socializations with the exception of the relationship of social disintegration and of community-society. It is possible to find mostly the differentiation between a municipality whose population is 10,000 and the other whose population is 100,000. The intensity of social disintegration can increase when municipalities overpopulate. Therefore, it can be argued that there is a relationship between the social disintegration and the population of settlement. The aim of this work is also to reveal the relationship between the population growth of campus and the level of social disintegration with statistical applications.

The behaviors of voters are extremely representative indicator in determining the relationship between the population size in municipalities and the individuals' sensitiveness against the social events. Election of municipal council members has an exceptional importance in election of local administration among election kinds because most of countries apply a country barrage in general elections. There is also a 10 % national barrage in Turkey. Furthermore, the party administrations determine the most of candidates for becoming mayors. However, the base of a party determines the most of municipal council members. Furthermore, it is expected that election of municipal council members' political participation rate will be high.

In the statistical applications in this work, the elections' results constituted the main body for 3209 municipalities in the Election of Municipal Council Members on March 28, 2004 in Turkey. A three- value variable for everyone was calculated. In the second level, whether or not variables provide hypotheses of multivariate normal distribution were tested. In the third level, the K-means cluster analysis was realized. The procedure was repeated by dividing the main body into cluster between 2 and 10. In the fourth level, the discriminant function analysis by taking the results of K – means cluster was realized. In the fifth level, the relationship among the average lines of variables in the group with the coefficients of Spearman rank correlation was tested.

The writer of this work used SPSS 14 statistical packet program for K – means cluster and discriminant function analysis and calculated Gini coefficients, multivariate normal distribution and Spearman rank correlation applications in the Excel.

2. Methods and Data

2.1. Data

The data used in this work were compiled from a book known as "The Election of Local Administrations 28.03.2004" published by DIE "State Institute of Statistics" (DIE, 2005). Three variables in the applications were used. The variables are originated in political indecision index "PINDI", political disintegration index "PDI", and natural logarithmic form of voter number. PIDI and PDI variables represent spatial differentiation of social structure in Turkey when the last variable symbolizes the population size in level of municipality. The number of registered voters for the population size in the level of municipality was taken because it is impossible to reach the census made in 2000. At the same time, the number of registered voters constituted the population above 18 ages. To diminish the scale we used the natural logarithmic form of voter number in the applications.

2.2. Gini Coefficient For Political Indecision Index "PIDI"

Gini coefficient used in the measurement of dispersive inequality among observations (individual or regional disparity) is expressed as index of odd inequality (Laporte, 2002). The coefficient is the most commonly referred and the best known to measure of inequality (Ravallion, 2001, 6; Fedorov, 2002, 447; Moran 2003, 353). Certainly, that Gini index is the oldest methods effects to this commonly using. In 1912, Gini created firstly this number used intensively in the inequality measurement (Sen, 1973). However, there are many other indices (Dahl' s Index, Nagel' s Index like Gini index that those based on devitions (from a standard such as the mean, or from other shares) or coefficient of variation, logarithmic variance, Theil index that it is based on entropy or information theory or Atkinson index that it is based on normative social welfare models), too (Chakravorty,1996).

These indices are used for many different subjects and disciplines such as measurement of regional inequality in productivity and GDP per capita (Duro, Esteban, 1998; Benito, Ezcurra, 2005; Ezcurra, et al. 2005; Ezcurra, & Rapún, 2006; Ezcurra, Pascual, 2007; Escurra, Pascual, Rapún, 2007; Gezici, 2007), in agricultural yield fertility (Sadras, Bongiovanni, 2004), in inter-regional human capital and education inequalities (Siew, Lim, Tang, 2008) and in capital stock per capita (Lu, 2008) for economics, in distribution of assets, debts for finance (Marks, Headey, Wooden, 2005), in occupational segregation by gender or nationality for sociology (Chagravarty, Silber, 2007), in decomposition of migration flow for demography (Sweeney, Goldstein, 2005), in nationalism for political parties (Johns, Mainwaring, 2003), in a centralization measurement (Dawkins, 2006) and regional distribution of workforce (Carlino, Chatterjee, 2002; Heindenreich, 2003) for urban and regional planning, in energy-intensity inequalities across countries (Alcantara, Duro, 2004) and in air, water, land, underground pollution per capita across states (Millimet, Slottjet, 2002) for environment science, in pitfall for competitive balance (Utt, Fort, 2002) and attendance (Schmidt, Berri, 2001) in Major League Baseball for sports, in offenders distribution for criminology (Oberwittler, 2004), to test of goodness for statistics (Jammalamadaka, Goria, 2004), even in body lengths of helminth parasites for helminthology (Poulin, Latham, 2002)).

There are discussions about indicator capability of disparity indices. For instance, Harvey (2005) claims that the NRSI hypothesis is robust to the approximate relationship between the Gini coefficient and the Atkinson index. As an opposite thesis, according to Garcia and Molina (2001, 2418), the best indicator is the Atkinson index. Each of disparity indicators (Gini index, coefficient of variation, logarithmic variance, average relative deviation, Theil and Atkinson indices) satisfies different theoretical ordinal properties that are desired, namely, the s-convexity, which is necessary in order to guarantee that the inequality index is consistent with the Lorenz criterion; the relative decrease in the impact of regressive transfers; the distributive homotheticity which implies that, as inequality increases, so the index gives more importance to the poorest individuals; and, finally, the limited variation of the magnitude between zero and one, in order to facilitate the economic interpretation of the index. These properties defined the advantages of each index with respect to the others. In particular, only the Atkinson indexes family satisfies the four desired properties. According to Salas (1997), Atkinson index in one of the standard welfare-consisted inequality indices satisfies to perform, too. Hence, there does not go to the fore any index and every index satisfy for applications.

The Gini coefficient takes a value among [0, 1]. If its coefficient was 1, the value accumulated in only one observation by looking at its distribution. The total value distributed equally in the whole values if it was zero. To calculate Gini coefficient we benefit from different methods. Gini coefficient in the method, which has been rather popular in the last years, is calculated with

$$G = \frac{2Co\,\mathrm{var}(Y, R_y)}{N\bar{Y}} \qquad [1]$$

formula. According to this, “G” represents Gini coefficient. “Y” represents value of observation when “$\bar{Y}$” symbolizes average value of whole observations. “N” represents the number of observations and, “R_y” symbolizes the line of observations from the smallest to the biggest one (Lerman, Lerman, 1986: 325; Milanovic, 1997: 45).

In this calculation method, the maximum gini value is always smaller than one. This Gini-coefficient ranges between 0 and (N-1)/N. Hence, the standardized Gini-coefficient G*N/(N-1), referred to as the Lorenz-Münzner coefficient, is used in the estimates. (Stirböck, 2002: 6)

$$G_{st} = \left(\frac{2Co\,\mathrm{var}(Y, R_y)}{N\bar{Y}}\right) \times \left(\frac{N}{N-1}\right) \Rightarrow \qquad [2]$$

$$G_{st} = \left(\frac{2Co\,\mathrm{var}(Y, R_y)}{(N-1) \times \bar{Y}}\right) \qquad [3]$$

In this work, the distribution of ballot numbers in the Election of Municipal Council Members was calculated among twenty-one political parties participated in 2004 local administration. However, the ballot distribution of the first nine parties having the highest ballot rates was calculated as median with Gini coefficient because the numbers of political parties taking ballot were among 1-16. For the application with nine observations, standardized gini coefficient was formulated as

$$G_{st} = \left(\frac{2Co\,\text{var}(Y, R_y)}{(9-1) \times \overline{Y}} \right) = \left(\frac{Co\,\text{var}(Y, R_y)}{4\overline{Y}} \right) \quad [4]$$

To constitute Political indecision index was benefited from Gini coefficients. To increase indecision when the value of index increases;

$$PIDI = 1 - G_{st} \Rightarrow \quad [5]$$

$$PIDI_i = 1 - \left(\frac{Co\,\text{var}(Y_i, R_{y_i})}{4\overline{Y}_i} \right) \quad [6]$$

was calculated because the equal ballot distribution to the parties increases if it approaches zero in gini coefficient. Therefore, it is necessary to take the opposite of the coefficient. Thus, 1 "G_{min}: equalitive distribution" represents the most undecided voter when 0 "G_{max}: inequalitive distribution" symbolizes the most determined voter.

2.3. Political Disintegration Index "PDI"

The rate of unconcern increases in a region as much as the participation rate decreases in elections. Therefore, a political disintegration index based on the participation rate of elections was constituted to make a spatial comparison. This index was formulated as

$$PDI_i = \left(\frac{\text{Nu. of registered voters}_i - \text{Nu. of actual voters}_i}{\text{Nu. of registered voters}_i} \right) \quad [7]$$

Çiftçi, M. (2011). Relationship between hierarchic - spatial differentiation of social structure and population size of municipalities in Turkey: Evidence from the election case of local administration in 2004. *International Journal of Human Sciences* [Online]. 8:2. Available: http://www.InsanBilimleri.com/En

2.4. Multivariate Normal Distribution

In statistical applications, many real – word problems fall naturally within the framework of normal theory. The importance of the normal distribution rests on its dual role both as population models for the certain natural phenomena and as approximate sampling distribution for many statistics. (Johnson, Wichern, 1988) Hence, many unvariate tests and confidence intervals are based on the unvariate normal distribution. Similarly, the majority of multivariate procedures have the multivariate normal distribution as their underpinning. (Rencher, 2002)

Multivariate normality (the combination of two or more variables) means that the individual variables are normal in a univariate sense and that their combinations are normal. Thus, if a variable is multivariate normal, it is also univariate normal. However, reverse is not necessarily true (two or more univariate normal variables are not necessarily multivariate normal). Thus, a situation in which all variables exhibit univariate normality will help gain, although not guarantee, multivariate normality. Multivariate normality is more difficult to test, but some tests are available for situations in which the multivariate technique is particularly affected by a violation of this assumption. (Hair, etc, 1998: 70 -71)

Both and Mahalonobis distance and chi – squared measurement are used together to test the multivariate normal distribution. In this test procedure:

The set of multivariate outcomes x such that

$$(\mathbf{x}_i - \boldsymbol{\mu})' \sum^{-1} (\mathbf{x}_i - \boldsymbol{\mu}) = D_i^2 \qquad [8]$$

$$(\mathbf{x}_i - \boldsymbol{\mu})' \sum^{-1} (\mathbf{x}_i - \boldsymbol{\mu}) \leq \chi_p^2(0.5) \qquad [9]$$

has probability 0.5. Thus, we should expect roughly the same percentage, 50%, of sample observation to lie in the ellipse. This formulation is transformed for samples:

$$(\mathbf{x}_i - \bar{\mathbf{x}})' S^{-1} (\mathbf{x}_i - \bar{\mathbf{x}}) \leq \chi_p^2(0.5) \qquad [10]$$

(Johnson, Wichern, 1988: 151)

2.5. K – Means Cluster Analyses

Cluster analysis is a generic term for a wide range of numerical methods for examining multivariate data with a view to uncovering or discovering groups or clusters of observations that are homogeneous and separated from other groups. (Everitt 2005: 115) This method is one of the explanatory multivariate statistical methods like factor analysis. (Timm, 533: 2002; Harris, 2001: 409 – 410; Venables, Riplay, 2002: 301 – 330) Cluster analysis differs fundamentally from classification analysis. In the classification analysis, we allocate the observations to a known number of predefined groups or populations. In cluster analysis, neither the number of groups nor the groups themselves are known in advance. (Rencher, 2002: 451) Nevertheless, there were works showing this analysis with discriminant function analysis among classification techniques (Johnson, Wichern, 1988: 470 – 589).

Cluster analysis divides into two: Hierarchic and non-hierarchic. K – Means cluster analysis is also a non-hierarchic statistical approach. Researcher gives number of heaps in the K – means cluster analysis. Consequently, this application provides a large option for the researcher. The centers of groups are calculated and, the procedure functions when observations cluster around the centers. It is possible to test the application with anova analysis in SPSS. We go to the application by taking variables one by one in the anova analysis used a kind of K – means cluster analysis test in order to determine the clusters. However, there is not a test process considering totally the whole variables.

2.6. Discriminant Function Analyses

The aim of discriminant function analysis is to classify an observation, or several observations into these known groups (Hardle, Hlavka, 2007: 227). The anova is used for an only variable to test whether the classification rightly was made. Manova “multivariate analysis of variance” can be used for two or more variables. If the number of independent variable is more than one in the application, in the first attention it seems possible to argue that the manova analysis functions like the discriminant function analysis. The main difference from manova is that Discriminant function analysis uses the continuous (discriminating) variables as predictors of the categorical group membership dependent variable. Hence, the focus in discriminant function analysis is reversed between "independent" and "dependent" variables compared with MANOVA (Harlow, 2005: 129). Accordingly, the discriminant function analysis not only tests whether observations remained in the right group or not but also redistributes them to the ideal groups where they necessarily remain.

The application procedure in the discriminant function analysis can be summarized like that:

Firstly, it is possible to begin with the discriminant factor of the linear discriminant functions by revealing maximum group differentiations. The number of discriminant factors is one less than the number of groups. To determine these factors it is necessary to calculate a discriminating factor criterion and Wilks' lambda. Meaningfulness of factors is statistically tested with the values of χ^2 calculated by utilizing Wilks' lambda and percentages of the variance explanation are found for every one of the discriminant factors. Thus, we determine which canonical correlation discriminant function is a weighted explanatory in the discriminant function analysis. Furthermore, we find the relationship among the linear discriminant functions "discriminating factor: canonical discriminant factor" by calculating canonical correlation coefficients gotten with variables (Bolch, Huang, 1974: 229 - 238; Saraçoğlu, 1992; Amstrong, 2000: 294 – 297.). Additionally, the second procedure, which makes the discriminant function analysis more different and more important than manova analysis, starts after discriminating factors are found and are tested. In addition, the possibilities of inclusion were determined for the observations in the groups by testing whether or not the observations were rightly classified (Klecka, 45 – 47).

3. Results

We tested whether or not three variables fitted with the assumption of the multivariate normal distribution before starting multivariate statistic applications. In the end of the calculation, it was observed that 36 % of calculated χ^2 value is bigger than critic χ^2 value. We began applications after reaching a conclusion that three variables fit with the assumption of the multivariate normal distribution because this proportion is less than 50 %. We realized the applications with K – means cluster analysis and bi – variate and multivariate discriminant function analysis. The number of clusters was given in [2, 10] in orderly applications.

It was determined that every one of three variables has also discriminating power among the groups (table 1).

Table 1: Tests of Equality of Group Means

	PIDI				PDI				LV			
Nu. Of Cluster	Wilks' Lambda	F stat.	df	Sig.	Wilks' Lambda	F stat.	df	Sig.	Wilks' Lambda	F stat.	df	Sig.
First	0.854	548.6	3,207	0.000	0.859	525.7	3,207	0.000	0.329	6,539.3	3,207	0.000
Second	0.817	358.8	3,206	0.000	0.842	300.2	3,206	0.000	0.169	7,905.9	3,206	0.000
Third	0.810	251.3	3,205	0.000	0.832	215.5	3,205	0.000	0.102	9,424.8	3,205	0.000
Fourth	0.800	200.7	3,204	0.000	0.831	162.8	3,204	0.000	0.066	11,313.7	3,204	0.000
Fifth	0.801	158.8	3,203	0.000	0.830	131.3	3,203	0.000	0.049	12,488.3	3,203	0.000
Sixth	0.799	134.5	3,202	0.000	0.827	111.9	3,202	0.000	0.038	13,652.3	3,202	0.000
Seventh	0.798	115.9	3,201	0.000	0.823	98.0	3,201	0.000	0.031	14,110.8	3,201	0.000
Eighth	0.793	104.2	3,200	0.000	0.826	84.0	3,200	0.000	0.024	16,206.2	3,200	0.000
Ninth	0.791	93.8	3,199	0.000	0.823	76.2	3,199	0.000	0.020	17,138.7	3,199	0.000

Hypothesis of equal population covariance matrices was obtained in the discriminant function analyses (table 2). s

Table 2: Tests null Hypothesis of Equal Population Covariance Matrices

		Applications (Rank of Clusters)								
		First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth
Box's M		733.36	618.21	634.77	424.67	452.83	428.61	387.98	516.24	530.15
F	Approx.	122.00	51.38	35.14	17.61	15.01	11.81	9.14	10.63	9.70
	df1	6	12	18	24	30	36	42	48	54
	df2	7,102,870	2,765,546	1,530,195	922,085	783,719	380,245	178,584	165,099	176,035
	Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

In the end of the meaningfulness test based on the Wilks' Lambda and Chi-square values, it was concluded that the discriminant factors are statistically meaningfulness (table 3).

Table 3: Test of Meaningfulness for Discriminant Factors

		Applications (Rank of Clusters)								
Test of Function(s)		First	Second	*Third	*Fourth	*Fifth	*Sixth	*Seventh	*Eighth	*Ninth
First	Wilks' Lambda	0.3261	0.1648	0.0988	0.0640	0.0472	0.0364	0.0303	0.0232	0.0195
	Chi-square	3,591.7	5,779.4	7,416.1	8,807.1	9,780.7	10,609.3	11,198.7	12,048.4	12,606.6
	degree of fredom	3	6	9	12	15	18	21	24	27
	Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Second	Wilks' Lambda	…	0.9834	0.9744	0.9705	0.9681	0.9700	0.9673	0.9647	0.9611
	Chi-square	…	53.6	83.1	95.9	103.8	97.5	106.6	115.0	127.1
	degree of fredom	…	2	4	6	8	10	12	14	16
	Sig.	…	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Third	Wilks' Lambda	…	…	0.9991	0.9978	0.9976	0.9977	0.9980	0.9966	0.9949
	Chi-square	…	…	2.9	7.1	7.6	7.5	6.4	10.8	16.4
	degree of fredom	…	…	1	2	3	4	5	6	7
	Sig.	…	…	0.089	0.029	0.055	0.111	0.265	0.095	0.022

* First: 1 through 3, for test of fuction(s)
* First: 1 through 2, for test of fuction(s)
* Second: 2 through 3, for test of fuction(s)

Çiftçi, M. (2011). Relationship between hierarchic - spatial differentiation of social structure and population size of municipalities in Turkey: Evidence from the election case of local administration in 2004. *International Journal of Human Sciences* [Online]. 8:2. Available: http://www.InsanBilimleri.com/En

It was seen that the variant explanation proportion of the first discriminant factor in every one of the nine applications changes between 99.6 % and 100 % (table 4).

Table 4: Eigenvalues for Canonical Discriminant Functions

Function		Applications (Rank of Clusters)								
		First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth
1	Eigenvalue	2.066	4.969	8.859	14.16	19.506	25.625	30.931	40.549	48.304
	% of Variance	100.0	99.66	99.71	99.79	99.832	99.880	99.891	99.910	99.917
	Cumulative %	100.0	99.66	99.71	99.79	99.832	99.880	99.891	99.910	99.917
	Canonical Correlation	0.821	0.912	0.948	0.966	0.975	0.981	0.984	0.988	0.990
2	Eigenvalue	…	0.017	0.025	0.028	0.030	0.028	0.032	0.033	0.035
	% of Variance	…	0.338	0.285	0.198	0.156	0.111	0.103	0.081	0.073
	Cumulative %	…	100.0	99.99	99.98	99.988	99.991	99.993	99.992	99.989
	Canonical Correlation	…	0.129	0.157	0.165	0.172	0.166	0.175	0.179	0.184
3	Eigenvalue	…	…	0.001	0.002	0.002	0.002	0.002	0.003	0.005
	% of Variance	…	…	0.010	0.016	0.012	0.009	0.007	0.008	0.011
	Cumulative %	…	…	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Canonical Correlation	…	…	0.030	0.047	0.049	0.048	0.045	0.058	0.072

In this work, it is possible to undervalue the other discriminant factors by taking the first functions as principles because of these high proportions. That in the first canonical discriminant function, all three variables have a positive effect shows that political indecision, disintegration and population size move together at the same direct in the municipalities (table 5).

Table 5: First Canonical Discriminant Function Coefficients

Unstandardized coefficients	Applications (Rank of Clusters)								
	First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth
PIDI	0.7836	0.6946	0.3361	0.4862	0.0781	0.3236	0.2181	0.2911	0.4844
PDI	1.1909	0.8130	0.7345	0.4262	0.2934	0.3963	0.5691	0.2049	0.1434
LV	1.4419	2.0562	2.6734	3.3283	3.8944	4.4262	4.8471	5.5410	6.0315
(Constant)	-11.955	-16.800	-21.669	-26.902	-31.330	-35.679	-39.069	-44.589	-48.556

It is possible to observe that the groups divided with K – means cluster analyses are rightly separated in all the discriminant function analyses, generally (table 6).

Table 6: Classification Results

Cluster Number of Case		Applications (Rank of Clusters)								
		First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth
1	Cluster	610	275	159	102	81	53	30	26	25
	Discriminant	497	257	153	100	81	53	30	26	25
	%	81.5	93.5	96.2	98.0	100.0	100.0	100.0	100.0	100.0
2	Cluster	2599	2063	1521	229	587	350	739	837	132
	Discriminant	2599	2062	1515	221	534	335	682	828	131
	%	100.0	100.0	99.6	96.5	91.0	95.7	92.3	98.9	99.2
3	Cluster	…	871	1074	498	1181	715	386	360	337
	Discriminant	…	726	984	463	1178	659	373	306	327
	%	…	83.4	91.6	93.0	99.7	92.2	96.6	85.0	97.0
4	Cluster	…	…	455	1197	151	76	69	60	49
	Discriminant	…	…	429	1187	149	72	69	60	49
	%	…	…	94.3	99.2	98.7	94.7	100.0	100.0	100.0
5	Cluster	…	…	…	1183	306	1142	129	320	66
	Discriminant	…	…	…	1173	299	1142	128	314	65
	%	…	…	…	99.2	97.7	100	99.2	98.1	98.5
6	Cluster	…	…	…	…	903	681	1066	159	600
	Discriminant	…	…	…	…	851	623	1066	156	567
	%	…	…	…	…	94.2	91.5	100.0	98.1	94.5
7	Cluster	…	…	…	…	…	192	204	87	193
	Discriminant	…	…	…	…	…	187	196	87	192
	%	…	…	…	…	…	97.4	96.1	100.0	99.5
8	Cluster	…	…	…	…	…	…	586	818	677
	Discriminant	…	…	…	…	…	…	519	817	660
	%	…	…	…	…	…	…	88.6	99.9	97.5
9	Cluster	…	…	…	…	…	…	…	542	286
	Discriminant	…	…	…	…	…	…	…	502	249
	%	…	…	…	…	…	…	…	92.6	87.1
10	Cluster	…	…	…	…	…	…	…	…	844
	Discriminant	…	…	…	…	…	…	…	…	842
	%	…	…	…	…	…	…	…	…	99.8
total	%	96.5	94.9	96.0	98.0	96.4	95.7	95.5	96.5	96.8

It is possible to observe the similar movement among the averages of variables when the group statistics are examined. The averages of variables among the groups increased together or decreased together in every one of three.

Table 7: Group Statistics

Cluster Number of Case				Rank of Applications First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth
1	PIDI	Mean	Value	0.281	0.298	0.298	0.301	0.297	0.304	0.306	0.314	0.311
			Rank	1	1	1	1	2	1	1	1	1
		Std. Deviation		0.091	0.086	0.078	0.076	0.070	0.063	0.056	0.053	0.053
	PDI	Mean	Value	0.252	0.273	0.281	0.288	0.291	0.295	0.295	0.292	0.293
			Rank	1	1	1	1	1	1	1	1	1
		Std. Deviation		0.080	0.074	0.068	0.063	0.059	0.053	0.051	0.045	0.046
	LV	Mean	Value	9.988	10.945	11.531	11.964	12.152	12.414	12.688	12.755	12.771
			Rank	1	1	1	1	1	1	1	1	1
		Std. Deviation		1.079	0.900	0.748	0.575	0.492	0.396	0.315	0.283	0.275
2	PIDI	Mean	Value	0.187	0.176	0.168	0.295	0.233	0.258	0.208	0.191	0.292
			Rank	2	3	4	2	4	4	6	7	3
		Std. Deviation		0.089	0.084	0.081	0.092	0.095	0.089	0.092	0.085	0.095
	PDI	Mean	Value	0.166	0.158	0.154	0.258	0.199	0.230	0.179	0.165	0.267
			Rank	2	3	4	2	4	4	6	7	4
		Std. Deviation		0.084	0.084	0.087	0.078	0.079	0.082	0.075	0.074	0.081
	LV	Mean	Value	7.570	7.373	7.214	10.184	8.404	9.046	8.006	7.705	10.212
			Rank	2	3	4	2	4	4	6	7	4
		Std. Deviation		0.522	0.378	0.305	0.413	0.256	0.257	0.185	0.143	0.233
3	PIDI	Mean	Value	…	0.244	0.212	0.254	0.187	0.219	0.250	0.155	0.247
			Rank	…	2	3	3	5	5	5	9	6
		Std. Deviation		…	0.096	0.093	0.093	0.084	0.096	0.094	0.081	0.092
	PDI	Mean	Value	…	0.210	0.183	0.221	0.163	0.188	0.219	0.151	0.217
			Rank	…	2	3	3	5		5	9	6
		Std. Deviation		…	0.082	0.078	0.081	0.079	0.079	0.080	0.092	0.077
	LV	Mean	Value	…	8.664	8.070	8.858	7.654	8.162	8.746	6.776	8.725
			Rank	…	2	3	3	5	5	5	9	6
		Std. Deviation		…	0.490	0.302	0.327	0.196	0.220	0.235	0.191	0.206
4	PIDI	Mean	Value	…	…	0.275	0.199	0.302	0.304	0.301	0.290	0.291
			Rank	…	…	2	4	1	2	2	4	4
		Std. Deviation		…	…	0.094	0.089	0.092	0.086	0.083	0.076	0.080
	PDI	Mean	Value	…	…	0.241	0.171	0.270	0.276	0.284	0.289	0.292
			Rank	…	…	2	4	2	2	2	2	2
		Std. Deviation		…	…	0.081	0.076	0.079	0.071	0.064	0.067	0.067
	LV	Mean	Value	…	…	9.438	7.843	10.588	11.272	11.687	11.826	11.935
			Rank	…	…	2	4	2	2	2	2	2
		Std. Deviation		…	…	0.494	0.246	0.373	0.346	0.328	0.278	0.219
5	PIDI	Mean	Value	…	…	…	0.164	0.272	0.180	0.299	0.260	0.309
			Rank	…	…	…	5	3	6	3	5	2
		Std. Deviation		…	…	…	0.081	0.093	0.084	0.092	0.089	0.083
	PDI	Mean	Value	…	…	…	0.153	0.236	0.159	0.270	0.230	0.268
			Rank	…	…	…	5	3	6	3	5	3
		Std. Deviation		…	…	…	0.091	0.081	0.081	0.082	0.082	0.068
	LV	Mean	Value	…	…	…	7.113	9.385	7.516	10.510	9.053	11.037
			Rank	…	…	…	5	3	6	3	5	3
		Std. Deviation		…	…	…	0.271	0.325	0.170	0.287	0.231	0.254

Çiftçi, M. (2011). Relationship between hierarchic - spatial differentiation of social structure and population size of municipalities in Turkey: Evidence from the election case of local administration in 2004. *International Journal of Human Sciences* [Online]. 8:2. Available: http://www.InsanBilimleri.com/En

Table 7 (continue): Group Statistics

Cluster Number of Case				Number of Cluster: First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth
6	PIDI	Mean	Value	…	…	…	…	0.163	0.159	0.176	0.292	0.213
			Rank	…	…	…	…	6	7	7	3	7
		Std. Deviation		…	…	…	…	0.082	0.078	0.083	0.098	0.093
	PDI	Mean	Value	…	…	…	…	0.153	0.151	0.156	0.251	0.184
			Rank	…	…	…	…	6	7	7	4	7
		Std. Deviation		…	…	…	…	0.091	0.09	0.083	0.079	0.079
	LV	Mean	Value	…	…	…	…	7.021	6.937	7.446	9.952	8.078
			Rank	…	…	…	…	6	7	7	4	7
		Std. Deviation		…	…	…	…	0.245	0.224	0.157	0.248	0.163
7	PIDI	Mean	Value	…	…	…	…	…	0.295	0.278	0.304	0.280
			Rank	…	…	…	…	…	3	4	2	5
		Std. Deviation		…	…	…	…	…	0.093	0.089	0.085	0.091
	PDI	Mean	Value	…	…	…	…	…	0.255	0.239	0.274	0.235
			Rank	…	…	…	…	…	3	4	3	5
		Std. Deviation		…	…	…	…	…	0.078	0.079	0.074	0.081
	LV	Mean	Value	…	…	…	…	…	10.116	9.574	10.787	9.413
			Rank	…	…	…	…	…	3	4	3	5
		Std. Deviation		…	…	…	…	…	0.323	0.264	0.263	0.220
8	PIDI	Mean	Value	…	…	…	…	…	…	0.159	0.168	0.167
			Rank	…	…	…	…	…	…	8	8	9
		Std. Deviation		…	…	…	…	…	…	0.079	0.081	0.082
	PDI	Mean	Value	…	…	…	…	…	…	0.150	0.154	0.154
			Rank	…	…	…	…	…	…	8	8	9
		Std. Deviation		…	…	…	…	…	…	0.092	0.090	0.093
	LV	Mean	Value	…	…	…	…	…	…	6.896	7.260	7.177
			Rank	…	…	…	…	…	…	8	8	9
		Std. Deviation		…	…	…	…	…	…	0.215	0.133	0.121
9	PIDI	Mean	Value	…	…	…	…	…	…	…	0.225	0.152
			Rank	…	…	…	…	…	…	…	6	10
		Std. Deviation		…	…	…	…	…	…	…	0.097	0.081
	PDI	Mean	Value	…	…	…	…	…	…	…	0.192	0.153
			Rank	…	…	…	…	…	…	…	6	10
		Std. Deviation		…	…	…	…	…	…	…	0.078	0.095
	LV	Mean	Value	…	…	…	…	…	…	…	8.269	6.723
			Rank	…	…	…	…	…	…	…	6	10
		Std. Deviation		…	…	…	…	…	…	…	0.192	0.180
10	PIDI	Mean	Value	…	…	…	…	…	…	…	…	0.183
			Rank	…	…	…	…	…	…	…	…	8
		Std. Deviation		…	…	…	…	…	…	…	…	0.082
	PDI	Mean	Value	…	…	…	…	…	…	…	…	0.157
			Rank	…	…	…	…	…	…	…	…	8
		Std. Deviation		…	…	…	…	…	…	…	…	0.073
	LV	Mean	Value	…	…	…	…	…	…	…	…	7.584
			Rank	…	…	…	…	…	…	…	…	8
		Std. Deviation		…	…	…	…	…	…	…	…	0.127
Total	PIDI	Mean		0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205
		Std. Deviation		0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097
	PDI	Mean		0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182
		Std. Deviation		0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090
	LV	Mean		8.030	8.030	8.030	8.030	8.030	8.030	8.030	8.030	8.030
		Std. Deviation		1.158	1.158	1.158	1.158	1.158	1.158	1.158	1.158	1.158

To measure the together moving levels according to the inside-group averages of variables, it was determined that there were relationships, whose lowest one reaches 94 %, in the end of the Spearman rank correlation analysis made by taking inside-group lines as principle. There is an absolute correlation in the outside of six coefficients (table 8).

Table 8: Results of Spearman Rank Correlation Coefficients

Applications	Nu. of obs.	PIDI-PDI	PDI-LV	PIDI-LV
*First	2	1.00	1.00	1.00
*Second	3	1.00	1.00	1.00
*Third	4	1.00	1.00	1.00
*Fourth	5	1.00	1.00	1.00
Fifth	6	0.94	*1.00	0.94
*Sixth	7	1.00	1.00	1.00
*Seventh	8	1.00	1.00	1.00
Eighth	9	0.95	*1.00	0.95
Ninth	10	0.99	*1.00	0.99

* Absolute inter-variables movement

4. Discussion and Conclusion

Turkey, which has dynamic and young population, has hierarchic-spatial differentiation in the perspective of social structure. Distinctive dominated in the every part of the country. It was observed that when the structure of community continued in some places, the structure of society in which individualism and anomie are observed ossified in the other places. However, it is possible to observe the process from community to society, which has a dynamic and spatial variety, instead of the differentiation of hard society or of hard community in the important part of the country. There is also this multi-dimensional circumstance not only in Turkey but also in most of countries having young and dynamic population.

The applications show that the spatial differentiation of social structure has a close relationship to the population size in the municipality. The together movement of three variables used in the applications supports that political indecision and disintegration increases when the population increases. If it is thought that political indecision and disintegration represents spatial differentiation of social structure, it can be concluded that there is an opposite directed-relationship between population size in municipality and spatial differentiation of social structure in Turkey of 2004. In other words, although the community structure, which is more sensitive against the social events, increases in less populated places, the social structure, which is less sensitive against the social events, improved in the overpopulated areas. In addition to this, it is necessary to express that the anomaly of community-society is not divided clearly and there is a graded distribution. In other words, neither one part of the country has one type community structure nor its other part has one type society structure. Municipalities as balanced with their population sizes differentiate in the component of community and society with the weightiness of their distinctive components.

References

Alcantara, V. and Duro, J. A. (2004). "Inequality of energy intensities across OECD countries: a note," *Energy Policy,* 32: 1257–1260.

Amstrong, H. W. and Read, R. (2000). "Comparing the economic performance of dependent territories and sovereign microstates," *Economic Development and Cultural Change*, 48 (2): 285 – 306.

Benito, J. M. and Ezcurra, R. (2005). "Spatial Disparities in Productivity and Industry Mix: The Case of the European Regions," *European Urban and Regional Studies*, 12: 177-194.

Bolch, B. W. and Huan, C. J. (1974). *Multivariate statistical methods for business and economics***.** New Jersey: Prentice Hall.

Carlino, G. and Chatterjee, S. (2002). "Employment Deconcentration: A New Perspective of America's Postwar Urban Evolution," *Journal of Regional Science*, 42(2): 455-475.

Chakravarty, S. (1996). "A Measurement of Spatial Disparity: The Case of Income Inequality," *Urban Studies*, 33(9): 1671–1686.

Chakravarty, S.R. and Silber, J. (2007). "A Generalized Index of Employment Segregation, Mathematical Social Sciences," 53: 185–195

Dawkins, C. (2006). "The Spatial Pattern of Black–White Segregation in US Metropolitan Areas: An Exploratory Analysis," *Urban Studies,* 43(11): 1943–1969.

DIE. (2005). *The Election of Local Administrations 28. 03. 2004,* Ankara: State Institute of Statistics Prime Ministry Republic of Turkey.

Duro, J. A. and Esteban, J. (1998). "Factor Decomposition of Cross-Country Income Inequality, 1960–1990," *Economics Letters,* 60: 269–275.

Erkal, M. (1995). *Sosyoloji*, 6th ed. Istanbul: Der publishing.

Everitt, B. S. (2005). *An R and S-PLUS® Companion to Multivariate Analysis*, London: Springer – Verlag.

Ezcurra, R. and Pascual, P. (2007). "Regional Polarisation and National Development in the European Union," *Urban Studies,* 44(1): 99–122.

Ezcurra, R. and Rapún, M. (2006). "Regional Disparities and National Development Revisited: The Case of Western Europe," *European Urban and Regional Studies,* 13(4): 355–369.

Ezcurra, R., Carlos G., Pascual, P. and Rapún, M. (2005). "Inequality, Polarisation and Regional Mobility in the European Union," *Urban Studies* 42 (7): 1057-1076.

Ezcurra, R., Pascual, P. and Rapún, M. (2007). "Spatial Inequality In Productivity In The European Union: Sectoral And Regional Factors," *International Regional Science Review*, 30(4): 384–407.

Fedorov, L. (2002). "Regional Inequality and Regional Polarization in Russia, 1990–99," *World Development,* 30(3): 443-456.

Garcia, I. and Molina, J. A. (2001). "The Effects of Region on the Welfare and Monetary Income of Spanish Families," *Urban Studies,* 38(13): 2415-2424.

Gezgin, M. F. (1997). *Genel Sosyoloji – Köy Sosyolojisi İlişkileri*. Istanbul: Istanbul University, Faculty of Economics, Nu: 3925 / 552.

Gezici, F. (2007). "Türkiye' nin Bölgelerarası Gelişmişlik Farkları ve Bölgesel Politikalarının Yeni Yaklaşımlar Çerçevesinde Değerlendirilmesi," *Bölge Biliminde Yeni Yaklaşımlar – Bildiriler Kitabı*, Istanbul: 12th National Regional Science / Congress of Regional Planning, Bölge Bilim Türk Milli Komitesi, Istanbul Technical University and Government Planning Association, pp. 269-278.

Hair, J., Anderson, R. E., Tatham, R. I. and Black, W. C. (1998). *Multivariate Data Analysis.* 5th ed. New Jersey: Prentice Hall International Inc.

Hardle, W. and Hlavka, Z. (2007). *Multivariate Statistics: Exercises and Solutions.* Berlin: Springer – Verlag.

Harlow, L. L. (2005). *The Essence of Multivariate Thinking – Basic Themes and Methods.* Mawhal, New Jersey, London: Lawrance Erlbaum Associates, Publishers.

Harris, R. J. (2001). *A Primer of Multivariate Statistics.* 3rd ed. Mawhal, New Jersey, London: Lawrance Erlbaum Associates, Publishers.

Harvey, J. (2005). "A Note on the 'Natural Rate of Subjective Inequality' Hypothesis and the Approximate Relationship between the Gini Coefficient and the Atkinson Index," *Journal of Public Economics,* 89: 1021–1025.

Heindenreich, M. (2003). "Regional Inequalities in the Enlarged Europe," Journal of *European Social Policy,* 13: 313-333.

Jammalamadaka, S. R. and Goria, M. N. (2004). "A Test of Goodness-of- t Based on Gini's Index of Spacings," *Statistics & Probability Letters,* 68: 177–187.

Johnson, R. A. and Wicherin D. W. (1988). *Applied Multivariate Statistical Analysis*. New Jersey: Prentice Hall.

Jones, M. P. and Mainwaring, S. (2003). "The Nationalization of Parties and Party Systems: An Empirical Measure and an Application to the Americas," Party Politics, 9: 139-166.

Klecka, W. R. (1980). *Discriminant Function Analysis*. Newbury Park, London, New Delhi: SAGE Publications.

Laporte, A. (2002). "A Note on the use of a single inequality index in testing the effect of income distribution on mortality," *Social Science & Medicine,* 55: 1561–1570.

Lerman, D. L. and Lerman, R. I. (1986). "Imputed Income from owner-occupied housing and income inequality," *Urban Studies*, 23: 323-331

Lu, D. (2008). "China's Regional Income Disparity - An Alternative Way to Think of the Sources and Causes," *Economics of Transition,* 16(1): 31–58.

Marks, G. N., Headey, B. and Wooden, M. (2005). "Household Wealth in Australia: Its Components, Distribution and Correlates," *Journal of Sociology,* 41(1): 47–68.

Milanovic, B. (1997). "A Simple Way to Calculate the Gini Goefficient, and Some Implications," *Economic Letters*, 56: 45 – 49.

Millimet, D. M. and Slottje, D. (2002). "Environmental compliance costs and the distribution of emissions in the U.S.," *Journal of Regional Science,* 42 (1): 87 - 105.

Moran, T. P. (2003). "On the Theoretical and Methodological Context of Cross-National Inequality Data," *International Sociology,* 18(2): 351-378.

Oberwittler, D. (2004). "A Multilevel Analysis of Neighbourhood Contextual Effects on Serious Juvenile Offending: The Role of Subcultural Values and Social Disorganization," *European Journal of Criminology,* 1: 201-235.

Poulin, R. and Latham, A. D. M. (2002). "Inequalities in Size and Intensity Dependent Growth in a Mermithid Nematode Parasitic in Beach Hoppers," *Journal of Helminthology,* 76: 65–70.

Ravallion, M. (2001). *Growth, Inequality and Poverty: Looking Beyond the Averages.* Washington, DC: World Bank Policy Research Working Paper. No. 2558.

Rencher, A. C. (2002). *Methods of Multivariate Analysis.* 2nd ed. New York: Wiley – Interscience.

Sadras, V. and Bongiovanni, R. (2004). "Use of Lorenz curves and Gini Coefficients to Assess Yield Inequality within Paddocks," *Field Crops Research,* 90: 303–310.

Salas, R. (1997). "Welfare-Consistent Inequality Indices in Changing Populations: The Marginal Population Replication Axiom A Note," *Journal of Public Economics*, 67: 145–150.

Saraçoğlu, B. (1992). “Ülkelerin Ekonomik Kalkınmışlık Düzeyleri Açısından İncelenmesi,” *Hacettepe Üniversitesi İİBF Dergisi*, 10: 17 – 54.

Schmidt, M. B. and Berri, D. J. (2001). “Competitive Balance and Attendance: The Case of Major League Baseball,” *Journal of Sports Economics* 2 (2): 145–167.

Sen, A. K. (1973). *On Economic Inequality*, Oxford, etc: Oxford University Press.

Siew, A., Lim,K. and Tang, K.K. (2008). “Human Capital Inequality and the Kuznets Curve,” *The Developing Economies*, XLVI-1: 26–51

Stirböck, C (2002). *Relative Specialization of EU Regions: An Econometric Analysis of Sectoral Gross Fixed Capital Formation*. Germany: Centre for European Economic Research.

Sweeney, S. H. and Goldstein, H. (2005). “Accounting for Migration in Regional Occupational Employment Projections,” *The Annals of Regional Science*, 39: 297–316.

Timm, N. H. (2002). *Applied Multivariate Analysis*. New York, etc.: Springer Verlag.

Utt, J. and Fort, R. (2002). “Pitfalls to Measuring Competitive Balance With Gini Coefficients,” *Journal of Sports Economics*, 3: 367-373.

Venables, B. and B. Riplay. (2002). *Modern Applied Statistics with S. Plus*. 4th ed. ?: Springer.