Research and Monetary Policy Department
Working Paper No:06/09

Convergence Across Provinces of Turkey: A Spatial Analysis

Altan ALDAN
Esma GAYGISIZ

December 2006

The Central Bank of the Republic of Turkey

CONVERGENCE ACROSS PROVINCES OF TURKEY: A SPATIAL ANALYSIS

Altan ALDAN[*]

Central Bank of the Republic of Turkey
Research and Monetary Policy Department
Ankara, Turkey
altan.aldan@tcmb.gov.tr
Phone: +90-312-324-1645

Esma GAYGISIZ

Middle East Technical University
Department of Economics
Ankara, Turkey
esma@metu.edu.tr
Phone: +90-312-210-2043

ABSTRACT

The aim of this study is to analyze regional disparities and to test the convergence hypothesis across the provinces in Turkey. The study also attempts to analyze the spatial spillovers in the growth process of the provinces. The analyses cover the 1987-2001 period. Two alternative methodologies are used in the analyses. First, the methodology of β-convergence based on cross-sectional regressions is used and the effects of spatial dependence are analyzed by using spatial econometric techniques. Second, Markov chain analysis is employed and spatial dependence is integrated using spatial Markov chains. Results from both methodologies signal non-existence of convergence and the existence of spatial spillovers in the growth process of provinces.

Key Words: Regional Disparities, β-convergence, Markov Chains, Spatial Econometrics.

JEL Classification: R11, R12

[*] The corresponding author. The views and opinions expressed in the paper are those of the authors and do not reflect those of the Central Bank of the Republic of Turkey, or its staff.

I. INTRODUCTION

Reducing gaps in income and standard of living between rich West and poor East is an important issue in politics and economic policy making. Since 1970s, five-year development plans have adopted a regional perspective. Some regional development programs like Southeastern Anatolia Project (GAP), Eastern Anatolia Project (DAP) and Eastern Black Sea Project (DOKAP) have been developed and implemented to improve the socio-economic conditions in the lagging provinces in these regions. Additionally, investment incentives have been used to promote private investment and economic development in the least developed provinces.

Reducing income gaps has also been an important policy issue in the European Union (EU) as well as in Turkey. The objective of reducing disparities across regions in the EU is laid down in the preamble to the Treaty of Rome (1957). After inclusion of Greece, Spain and Portugal, this objective has been further emphasized and annual spending on regional policy has increased (Neven and Gouyette, 1995). Regional Development Fund comprises almost half of the structural funds in EU (DPT 2000).

In line with the increasing importance in politics and economic policy making, whether countries and regions converge in terms of per capita income or output has become one of the prominent issues in the literature starting the pioneering paper of Baumol (1986) and several papers of Barro and Sala-i Martin.

The objective of this study is to investigate whether the convergence process has occurred across provinces of Turkey in the period from 1987 to 2001. The study uses two different methodologies: *traditional* and *distribution dynamics* approaches. The traditional approach examines whether initially poor regions grow faster than the initially richer ones. Distribution dynamics approach examines the changes in cross section distributions of per capita income over time.

The main focus of the study is to analyze the effects of spatial dependence between provinces of Turkey in the growth and the convergence process. Since, it is unrealistic to assume regions within a country as independent of each other, recent studies on convergence issues take spatial dependence into account. Spillover effects between provinces are calculated and spatial dependence is integrated both in traditional approach and distribution dynamics approach.

The study is organized as follows: The next section reviews the empirical models that analyze convergence, tests the spatial dependence and integrates it in the convergence analysis. Section III applies the alternative methodologies to test convergence in Turkey and integrates spatial dependence in the analysis. Finally, Section IV concludes the paper.

II. METHODOLOGY[1]

Convergence Concepts

After the seminal works by Baumol (1986) and Barro and Sala-i Martin (1991), convergence in per capita income across countries and within countries has become one of the most prominent issues in empirical economics. Following these papers, a large number of studies tended to uncover whether there is convergence among or within countries. The theoretical background for the first empirical studies of income convergence was the neoclassical growth theory formulated by Solow (1956), which implies that all economies will converge to balanced growth paths with constant capital per effective labor, regardless of their initial conditions. Barro and Sala-i Martin (1991) show that, under certain conditions, the process of convergence will also apply in per capita incomes and economies with initially lower per capita incomes will grow faster. Therefore, if a significant negative relationship between initial per capita incomes and growth rates of economies are found, it is argued that convergence exist and neoclassical growth theory is valid in explaining the growth process. Many empirical studies used the methodology suggested by Barro and Sala-i Martin (1991) utilizing cross-section and panel data regression techniques, which we call the traditional approach.[2]

The convergence concept in the traditional methodology is called *β-convergence*. Two types of β-convergence are used in the literature: absolute and conditional. In absolute β-convergence, all economies converge to the same steady state. In conditional β-convergence, on the other hand, steady states of the economies can differ and control variables are added to the regression of income growth on initial incomes. In this study, the absolute β-convergence is tested for two reasons. First, although differences in technology and preferences do exist across regions within a country, these differences are likely to be smaller than those across countries since regions within a country share a common central government, institutional and legal system. Second and more important, as a policy issue, conditional β-convergence is

[1] See Magrini (2004) for a detailed analysis of convergence concepts and literature survey.
[2] Magrini (2004) calls this approach as regressions approach.

irrelevant. One cannot argue that there is convergence and policies to reduce regional disparities are successful using conditional β-convergence framework.

Another convergence concept commonly used in the traditional literature is σ-convergence developed by Baumol (1986). Although it has nothing to do with the neoclassical growth model, it has generally been used by researchers in traditional approach as a complement to β-convergence. There is σ-convergence if the dispersion of per capita income across the weighted-mean declines over time. In this framework, standard deviation or coefficient of variation are used as measures of dispersion. Concepts of β-convergence and σ-convergence are not identical, though related. The former relates to the mobility of per capita income within the same distribution whereas the latter relates to the evolution of the distribution of per capita income over time. Unconditional β-convergence is a necessary but not a sufficient condition for σ-convergence (Barro and Sala-i Martin, 1991).

The use of regression-based techniques to test the convergence hypothesis was severely criticized. It is pointed out that regressions concentrate on the behavior of the representative economy that can give information on the transition of the economy towards its own steady state whilst giving no information on the dynamics of the entire cross-sectional distribution of income. After Quah (1993), many studies used his methodology to analyze the convergence process, which led to distribution dynamics approach. Distribution dynamics approach deals with the cross sectional distributions of per capita incomes and the evolution of these distributions over time.

Let F_t denote the cross-sectional distribution of per capita incomes at time t. Then the evolution of this distribution over time can be described by the following equation

$$F_{t+1} = T(F_t) \qquad (1)$$

where *T* is an operator that describes the transition from one distribution into the other.

Two ways of analyzing convergence in the framework of equation (1) is possible. The first one is to treat F_t as continuous. Then, a probability distribution is estimated for F_t and the operator becomes *T* can be interpreted as a stochastic kernel (Quah, 1996a). The second way to analyze convergence is to treat income space as discrete. Then, F_t can be represented by probability vectors and the operator *T* becomes a probability transition matrix, *P*. In that case, equation (1) can be rewritten as

$$F_{t+1} = P.F_t \qquad (2)$$

and the system is treated as a first-order Markov process. Using stochastic kernels has advantage over using discrete Markov chains in the sense that there is some arbitrariness in discretization. On the other hand, while stochastic kernels allow characterizing the evolution of global distribution they do not provide any information about the movements of the regions within this distribution (Le Gallo, 2004). Therefore, while stochastic kernels are not as restrictive as discrete Markov chains, they are not as informative as discrete Markov chains as well. In this study, discrete Markov chains will be used to analyze convergence.

The analysis of Markov chains starts with defining a set C of K income classes (or states). F_t becomes the probability vector of these classes at time t, that is $F_t = (F_{1t}, F_{2t}, \ldots. F_{Kt})'$. Then P can be interpreted as a transition probability matrix: for any two income classes i and j ($i, j \in$ C), the element p_{ij} of P define the probability of moving from class i to class j between time t and $t+1$ (Magrini, 2004). In that case, a (first-order, discrete) Markov chain is defined as a stochastic process such that, for any variable x of a region r, the probability p_{ij} of being in a state j at any point of time $t+1$ depends only on the state i it has been at t, but not on the states at previous points of time, that is (Bickenbach and Bode, 2003)

$$P\{x_{r,t+1} = j | x_{r,t} = i, x_{r,t-1} = i_{-1}, \ldots, x_{r,0} = i_0\} = P\{x_{r,t+1} = j | x_{r,t} = i\} = p_{ij} \quad (3)$$

for any region r and for any $i, j \in$ C. Equation (3) is usually referred to as Markov property. If the process is time independent, the Markov chain is completely determined by the Markov transition matrix P with $p_{ij} \geq 0$ and $\sum_j p_{ij} = 1$ which summarizes all K^2 transition probabilities and an initial distribution $h_0 = (h_{1,0}, h_{2,0}, \ldots. h_{K,0})$, $\sum_i h_{i,0} = 1$ describing the starting probabilities of the various states.

It is also informative to find the limiting probabilities of states in the long run, p_i, $i \in$ C. However not all Markov chains have limiting probabilities. If a Markov chain is ergodic it has a limiting (stationary, ergodic) distribution.

The transition matrix can be estimated by a Maximum Likelihood approach (Bickenbach and Bode, 2003). Assume that there is only one transition period, with the initial distribution $h_i = n_i/n$ being given and let n_{ij} denote the empirically observed absolute number of transitions from i to j. Then, maximizing

$$\ln L = \sum_{i,j=1}^{K} n_{ij} \ln p_{ij} \qquad \text{s.t.} \sum_{\mathrm{j}} p_{ij} = 1, \; p_{ij} \geq 0 \qquad (3)$$

with respect to p_{ij} gives

$$\hat{p}_{ij} = \frac{n_{ij}}{\sum_{j} n_{ij}} \tag{4}$$

as the asymptotically unbiased and normally distributed Maximum Likelihood estimator of p_{ij}.

The reliability of the Markov transition probabilities depends on the assumption of homogeneity over time, i.e. the transition probabilities do not change over time. In order to test time homogeneity, whole period is divided into sub periods and the hypothesis that transition probabilities estimated for sub periods do not differ than those estimated for the entire period. In order to test the hypothesis, the following test statistic is utilized (Bickenbach and Bode, 2003)

$$Q^{(T)} = \sum_{t=1}^{T} \sum_{i=1}^{K} \sum_{j=1}^{K} n_i(t) \frac{(\hat{p}_{ij}(t) - \hat{p}_{ij})^2}{\hat{p}_{ij}} \tag{5}$$

where $\hat{p}_{ij}$ is the probability of transition from class i to class j estimated from the whole period, $\hat{p}_{ij}(t)$ is the corresponding transition probability estimated from sub period t and $n_i(t)$ is the number of observations in class i in sub period t. T is the number of sub periods and K is the number of classes. The statistic is distributed as χ^2 with degrees of freedom of $\sum_{i=1}^{K}(a_i - 1)(b_i - 1)$ where a_i is the number of sub periods in which observations for the *i-th* row are available and b_i is the number of positive entries in the *i-th* row of the matrix for the entire sample.

Analysis of convergence is carried out by examining the probabilities p_{ij} and the ergodic distribution. If the probability of moving to richer classes is high in the poor income classes, then convergence is said to occur since a region starting from a poor income class have the chance to become richer. If the probability of middle-income classes is higher than the probabilities of classes in the tails of the distribution in the ergodic distribution compared with the initial distribution, again convergence is concluded. On the other hand, if the ergodic distribution is concentrated around two distinct classes, then formation of convergence clubs or bimodality in the income distribution is concluded.

Spatial Dependence

Spatial dependence in a sample refers to the fact that one observation associated with a location *i* depends on other observations at location $j\ (j \neq i)$ That is,

$$x_i = f(x_j) \qquad i = 1,.........N \qquad j \neq i \tag{6}$$

where x is the variable under consideration. Two broad sources of spatial dependence are generally pointed out. First, it is a result of spatial interaction effects such as technological spillovers and factor mobility. Second, it may be due to the measurement problems resulting from the fact that administrative borders may not coincide with the borders of economic activity (Anselin, 1988).

The most common statistic used for detecting the spatial dependence is the Moran's I statistic which is formulated as (Upton and Fingleton, 1985)

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{7}$$

where *n* is the number of regions, S_0 is the sum of the elements in the spatial weight matrix *W* which summarizes the spatial effects between regions, w_{ij} are the elements of the spatial weight matrix *W* corresponding to the regions *i* and *j*. Moran's I statistic can take values between –1 and 1. Positive values of Moran's I indicate positive spatial autocorrelation in which similar values are more likely than dissimilar values between neighbors and vice versa. If x_is are normally distributed, then *I* can be also assumed as normally distributed function.

Spatial weight matrix is the fundamental tool to model and detect spatial dependence. Several forms of spatial weight matrices are suggested in the literature. In this study, contiguity weight matrix, having value of 1 if two regions i and j are neighbors and 0 for other entries of the matrix, is used. The matrix is row standardized, that is sum of elements in a row add to 1.

Spatial Dependence and Convergence Analysis

The empirical methodology of traditional approach to test convergence is based on cross-section regressions. In order to have correct results in these regressions, residuals must satisfy the standard Gauss-Markov assumptions. One of these assumptions is the independence of error terms. However, if there is spatial autocorrelation in the regional data, then the residuals of the regression may be spatially autocorrelated, which violates the Gauss

Markov assumptions. A number of test statistics are suggested in the literature to test spatial autocorrelation in the residuals of OLS regression, namely Moran's I, likelihood ratio, Wald test, and a Lagrange Multiplier test.[3]

Several specifications are suggested in the existence of spatial autocorrelation in the error terms of an OLS regression. The easiest model used in the presence of spatial autocorrelation is the spatial cross-regressive model, which can be written as

$$Y = X\beta + WX\theta + u \tag{8}$$

where Y contains an $nx1$ vector of dependent variables, X represents the nxk matrix of independent variables, WX is the spatial lag of the independent variable and u is the disturbance term satisfying usual Gauss-Markov properties. Since the spatial lag of the independent variable is exogenous, the model can be estimated via OLS. In order to test spatial autocorrelation in the residuals of the model, test statistics based on OLS residuals can be used as the model is estimated via OLS.

Another model is the spatial lag model (spatial autoregressive model) where spatial dependence is filtered out by the inclusion of spatial lag of dependent variable. The spatial lag model can be defined as

$$Y = X\beta + WY\rho + u \tag{9}$$

where WY denotes the spatial lag of the dependent variable and the error terms u satisfy the Gauss Markov assumptions. Estimation of spatial lag model via OLS gives biased and inconsistent estimates. Consequently, maximum likelihood method is used to estimate the spatial lag model (Anselin, 1988). In order to examine whether the spatial lag model eliminates spatial autocorrelation, a Lagrange multiplier test based on spatial lag model (LMLAG) is used.

Spatial cross-regressive and spatial lag models are suitable to filter out spatial dependence that originates from spatial spillovers. On the other hand, if spatial dependence originates also from measurement problems, i.e. mismatch between borders of economic activity and administrative units, these models may be inappropriate (Magrini, 2004). In such a case, the error term in the cross-section regression becomes non-spherical and spatial errors model is used, which can be defined as

$$Y = X\beta + u$$

[3] See Le Sage (2002) for details of test statistics of spatial autocorrelation.

$$u = \lambda Wu + \varepsilon \quad (10)$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2 I_n)$$

OLS estimate of β is unbiased but is inconsistent. Therefore, as in spatial lag model this model is also estimated via maximum likelihood method (Anselin, 1988).

Effects of spatial dependence have recently been included in the Markov chain analysis for convergence. In spatial Markov chain analysis suggested by Rey (2001), traditional Markov chain is modified in such a way that the transition probabilities of a province are conditioned on the class of its spatial lag for the beginning of the year. This procedure results in a transition matrix, which is a traditional *KxK* matrix decomposed into *K* conditional matrices of dimension *KxK*. Then an element in the *k-th* conditional matrix $\hat{p}_{ij}(k)$ gives the probability that a region in class *i* at time *t* moves to class *j* at *t+1*, given that its spatial lag is in class *k* at time *t*. To test existence of spatial dependence formally, a test statistic, $Q^{(R)}$ is developed by Bickenbach and Bode (2003) using spatial Markov chains.

III. CONVERGENCE ANALYSIS FOR TURKEY

Traditional Approach

In this study, GDP per capita is used as the measure of income to investigate convergence and spatial spillovers in the period from 1987 to 2001. Data for provincial GDP are taken from Turkish Statistics Institute (TURKSTAT) in 1987 constant prices. Population data are taken from official census done by TURKSTAT for the years 1985, 1990, 1997 and 2000. Population data for the years between the census years are interpolated. From 1989 to 1999 number of provinces in Turkey increased from 67 to 81. In this study, values related to 14 provinces established after 1989 were added to the values of the provinces from which they were separated for the sake of simplicity.

We start with the unconditional β-convergence model via OLS. It reveals that, there is no evidence of convergence throughout the period. The convergence rate is 0.3 % and statistically insignificant.[4] Then, we turn to the detection of spatial autocorrelation in the OLS residuals. Gezici and Hewings (2002) find significant spatial autocorrelation for the years

---

[4] In this study, we use the linear specification $g = \alpha + b\log(\hat{y}_0)$ with g denoting the growth rate and $\hat{y}_0$ denoting the initial level of per capita income. The rate of convergence β is calculated as $\beta = -\ln(1+Tb)/T$. The half life, that is the time necessary to fill half of the variation to the steady-state is calculated as $\tau = -\ln 2/\ln(1+b)$.

1980 and 1997. We also find significant spatial autocorrelation in per capita GDP of 1987 using Moran's I statistics. In case of growth rate of per capita GDP, we find positive but not strongly significant spatial autocorrelation (Moran's I statistic is 0.11 with p-value of 0.12).

Finding spatial dependence in the data, we estimate three basic models that deal with spatial autocorrelation. Table 1 summarizes the results of OLS and different spatial models. Use of goodness of fit measures may be misleading in spatial econometrics especially when the error term structure is non-spherical. An R^2 measure calculated in the usual manner is meaningless and may yield nonsensical values (Anselin, 1988). Therefore, information based criteria, namely Akaike (AIC), Schwarz (SC) and Hannah-Quinn (HQ) are used in the table.

Spatial cross-regressive model does not improve the model in terms of information criteria and there seems to remain significant spatial autocorrelation in the model. Spatial lag model improves in terms of information criteria but there is still spatial autocorrelation. Therefore, there seems to be significant spatial autocorrelation in the errors structure. The term λ is large and strongly significant in the spatial errors model. Therefore, there is positive spatial autocorrelation in the disturbances of the OLS model and a shock to a specific province will affect the growth rate of all provinces. In all three models, the coefficient of initial per capita income is negative and the p-values decline with respect to OLS estimates. However, the implied convergence is quite low, 0.7% (half life is 108 years) in spatial cross-regressive model and 0.6 % in the spatial errors model (half life is 122 years). Therefore, it seems that there is no strong evidence of income convergence even after filtering out spatial dependence.

Table 1: Results of Different Models

Dep. Var.	OLS	Spatial Cross-Regressive	Spatial Lag	Spatial Errors
Constant	0.045 (0.23)	-0.041 (0.45)	0.055 (0.13)	0.089 (0.02)
$\ln y_0$	-0.003 (0.36)	-0.006 (0.05)	-0.003 (0.20)	-0.005 (0.06)
$W\ln y_0$		0.010 (0.03)		
Wg			0.338 (0.03)	
λ				0.417 (0.00)
AIC	-5.98	-6.02	-6.70	-6.72
SIC	-5.91	-5.93	-6.60	-6.62
HQ	-5.95	-5.98	-6.62	-6.68
Moran's I	0.18 (0.01)	0.15 (0.03)		
LR	5.67 (0.02)	3.59 (0.06)		
Wald	7.75 (0.01)	3.37 (0.07)		
LMERR	4.95 (0.03)	3.50 (0.06)		
LMLAG			19.2 (0.00)	
β (Percent)	0.3	0.7	0.3	0.6

Note: p-values in parenthesis.

Distribution Dynamics Approach

The first task to investigate the distribution dynamics of GDP per capita of provinces in Turkey is to form classes in which per capita income for each province will be placed. In order to form classes, GDP per capita of all provinces are normalized by national average for all years in the period, that is

$$\tilde{y}_{it} = \frac{\hat{y}_{it}}{\bar{\hat{y}}_t} \tag{11}$$

where $\tilde{y}_{it}$ is the nationally normalized per capita income of province *i* in year t, $\hat{y}_{it}$ is the per capita income of province i in year t and $\bar{\hat{y}}_t$ is the per capita income of Turkey in year t.

Forming classes is somewhat arbitrary since there is no commonly accepted definition of being poor or rich within a country. In order to check whether the number of classes affect the results, the analysis is done by dividing the sample into four and five classes. The entire sample (total number of observations is 1005 since there are 67 provinces and 15 years) is divided into four and five income classes with equal frequencies and the values of observations in the boundaries of the quintiles form the gridlines for classes. The bounds of the classes are fixed across the entire period under consideration.[5] The gridlines for the classes are 51%, 72% and 105% of national per capita income in the 4-class transition matrix. That is, poorest provinces whose GDP per capita are below 51 per cent of national GDP per capita form class 1, provinces with GDP per capita between 51 per cent and 72 per cent form class 2, provinces with GDP per capita between 72 per cent and 105 per cent form class 3 and the richest provinces with GDP per capita higher than 105 per cent form class 4.

After forming classes, transitions of provinces between classes throughout the 14-year transition period are found, the transition probabilities are calculated and the transition probability matrix is formed. Estimated transition probability matrix is given in Table 2.

Table 2: Transition Probability Matrix

Classes	1	2	3	4	N
1	0.94	0.06	0	0	236
2	0.06	0.90	0.04	0	233
3	0	0.05	0.87	0.09	234
4	0	0	0.08	0.92	235
Initial	0.27	0.22	0.27	0.23	
Ergodic	0.23	0.27	0.24	0.26	

In Table 2, classes in the first column denote the initial classes and the classes in the first row denote the final classes after one-year transition period. Last column shows the number of transitions for each class throughout the whole period. The entries inside the tables show the corresponding transition probabilities. For example, there are 236 transitions whose initial class is 1 and a province initially at class 1 in year t will be in class 1 in year $t+1$ with a probability of 0.94 and in state 2 with a probability of 0.06. The eigen-values of the matrix are smaller than or equal to 1. Therefore, the matrix is ergodic and ergodic distribution is also given as well as the initial distribution (distribution in 1987).

The transition probabilities show high degree of persistence especially in the poorest and richest states. In the middle classes there is more mobility in both upward and downward directions. However, these states are also immobile since the diagonal entries are not less than 0.87. Therefore, there seems to be very low interclass mobility and the probability of poor provinces catching the richer ones and jump up to a richer class is very low.

[5] We present the results with the 4-class Markov chain. Similar results are obtained using 5-class Markov chains.

The degree of mobility of states can also be analyzed using mobility indices, which summarize the information about mobility from the transition matrix into a single statistic. Two mobility indices are used. The first one is the Prais index which is formulated as

$$M_1 = \frac{K - tr(P)}{K - 1} \tag{12}$$

where K is the number of classes and $tr(P)$ denotes the trace of transition matrix P. The second index can be written as

$$M_2 = 1 - |\lambda_2| \tag{13}$$

where $|\lambda_2|$ is the absolute value of the second largest eigen-value of the transition matrix P. For both statistics, values near 1 reveal high interclass mobility and values near 0 show low interclass mobility. The values of M_1 and M_2 are 0.12 and 0.03, respectively, which are close to 0. Therefore the finding that there is no interclass mobility is also verified by the mobility indices.

The ergodic distribution can be interpreted as the long-run equilibrium distribution given that there is no policy change or external shock. If there is convergence, the frequencies of middle-income classes - especially class 3 which include national average-, should be higher than the frequencies of rich and poor classes in the ergodic distribution. Concentration of the frequencies in two different classes, on the other hand, can be considered as formation of clubs, where two groups of provinces converge within each other but the groups do not converge.

Ergodic distribution reveals no sign of tendency to converge. There is no tendency of concentration of frequencies in middle-income classes in the ergodic distribution. Indeed, the probability of class 3 declines in ergodic distribution compared with the initial distribution. On the other hand, there seems to be no sign of club convergence since frequencies of all classes are similar. Therefore, the divergent situation will remain in the long run in the absence of policy shocks.

In order to test time homogeneity, the $Q^{(T)}$ statistic derived in section III is used. Two $Q^{(T)}$ statistics are calculated. In the first one the whole sample is divided into two sub samples. The first sub sample covers the years between 1987 and 1994 and the second sub sample covers the years between 1994 and 2001. In the second Q statistic, all of the yearly transitions are thought to be different sub samples. Therefore, there are 14 sub periods in the second test statistic. The value of the first statistic is 4.5 and the second statistic is 76.7, which are lower than the critical values of chi-squared distribution at 5 per cent significance level with 6 and 78 degrees of freedom, respectively, resulting non-rejection of the null hypothesis of equality of transition probabilities for different periods.

To sum up, neither of the Markov chains reveal tendency of provinces to converge. Low mobility in the transition matrices indicates that provinces tend to stay in their initial states. Ergodic distributions also reveal that the divergent situation will continue in the long run and there is no tendency of convergence club formation.

Traditional approach shows that spatial autocorrelation exists in convergence process of provinces. Thus, spatial dependence should also be included in Markov chain analysis. We use spatial Markov chains introduced by Rey (2001) to show the effects of spatial dependence.

Table 3 shows the results of spatial Markov chain analysis. In the table, first column gives the classes of spatial lag that is the classes which average per capita income of neighbors of a province belong to. Second column gives the corresponding initial classes and the first row the final classes. Total numbers of transitions are given in the last column. The entries in the matrix are the corresponding transition probabilities. For example, figure in the second column and third row, 0.97 gives the probability of a province initially in class 1 to stay in class 1, given that its neighbors are in class 1 on average.

Total number of observations in each class reveals that neighboring provinces tend to have similar per capita incomes. Among provinces with poorest neighbors (spatial lag 1) total number of observations initially in class 1 is 148 whereas total number of observations in all other states is 54. Therefore, provinces surrounded by poor regions tend to be poor. The same situation is valid for all classes. For all of the spatial lags, the observations are concentrated on the class of spatial lag. On the other hand, as the difference between initial class and the class of the spatial lag increases, number of observations declines. There is even no observation in classes 1 and 2 with spatial lag of class 1. Therefore, per capita income of a province is affected by its neighbors' per capita incomes.

Table 3: Spatial Markov Chain (4 states)

Spatial Lag	Class	1	2	3	4	N
1	1	0.97	0.03	0	0	148
	2	0.16	0.81	0.03	0	37
	3	0	0.18	0.73	0.09	11
	4	0	0	0.17	0.83	6
2	1	0.90	0.10	0	0	70
	2	0.04	0.91	0.05	0	105
	3	0	0.05	0.92	0.03	65
	4	0	0	0.17	0.83	18
3	1	0.83	0.17	0	0	18
	2	0.03	0.92	0.04	0	91
	3	0	0.06	0.83	0.11	99
	4	0	0	0.10	0.90	82
4	1	-	-	-	-	0
	2	-	-	-	-	0
	3	0	0	0.90	0.10	59
	4	0	0	0.05	0.95	129

Notes: The first column of the table gives the classes of the spatial lag. The second column gives the initial classes, the first row gives the final classes and the entries inside give the corresponding probabilities. Finally, the last row column gives the number of transitions. For example, there were 148 instances in which initial class was 1 with spatial lag of 1 (first entry in the last row) and the probability of a province initially at class 1 with spatial lag of 1 is estimated as 0.97 (first entry in the third column).

Transition probabilities in spatial Markov chain significantly differ from the traditional Markov chain. The probability of a province in class 1 whose neighbors' average per capita income is in class 1 to jump up to a higher income group is 3 percent whereas in the entire sample it is 6 percent and in the sample with spatial lag of 2 it is 10 percent. Conversely, the probability of a province in class 2 to move down to class 1 declines from 6 percent to 3 percent if the spatial lag is 3 and 4 percent if the spatial lag is 2 and increases to 16 percent if spatial lag is 1. For almost all cases, the probability of moving up increases and the probability of moving down decreases as class of spatial lag increases. Therefore, there is positive spatial autocorrelation and the evolution of per capita income of a province is affected by its' neighbors per capita incomes.

Spatial Markov chain confirms the presence of spatial autocorrelation. To test the hypothesis formally, the $Q^{(R)}$ of Bickenbach and Bode (2003) is used. The value of test statistics is 31.9, higher than the critical value of chi-squared distribution with corresponding degrees of freedom of 15 at 5 percent significance level. Therefore, the null hypothesis of equality of transition probabilities is rejected and there is spatial dependence in transition probabilities.

IV. CONCLUSION

In this study, we analyzed regional income convergence in Turkey taking into account spatial dependence. Regional disparities have been one of the most important problems in Turkey, which is also recognized by the policy makers. Policies to reduce regional disparities and enable income convergence have been implemented since 1960's. Therefore, the study also tested the success of the regional policies for the period of 1987-2001.

Two alternative approaches used frequently in the literature to test convergence , namely traditional approach and distribution dynamics approach are applied to analyze income convergence across provinces in Turkey. In both of the methodologies, no convergence was revealed, in line with the other studies related to Turkey.[6]

Second, spatial dependence were integrated into the analysis of convergence. In the traditional approach, it is shown that residuals of cross-section regression to test convergence suffer from spatial dependence. In addition, an external shock to a province will influence its neighbors positively. In the distribution dynamics approach, the analysis of spatial dependence showed that the probability of a province to move up to richer classes increases, as the neighbor provinces get richer. Therefore, spatial dependence affects the convergence process of provinces. However, there is no strong evidence of convergence even after controlling for spatial dependence.

The finding of spatial dependence among provinces in terms of per capita income has important implications for regional studies. In econometric studies using regional data, one should investigate the existence of spatial dependence of variables under interest. If there is spatial dependence, an appropriate model that filters out spatial dependence should be used. Use of spatial econometrics will avoid autocorrelation in the error terms and thus misleading results.

In sum, the finding of no tendency to converge suggests that regional development policies have not been successful in Turkey. Some new policy measures should be taken. The finding of significant spatial dependence in convergence of provinces suggests that taking spatial dependence into consideration may be useful in constructing regional development programs.

[6] Some examples of other studies related to income convergence in Turkey are Erk et al. (2000), Gezici and Hewings (2001), Tansel and Güngör (1998) and Temel et al. (1999).

An important issue for further research may be to detect local spatial spillovers. This study showed that there is spatial dependence in the provinces of Turkey, globally. Further research should focus on local spatial spillovers and find which provinces affect each other most positively. This research will give the chance to the policy makers to simulate the effects of regional development programs and regional development funds will be distributed more effectively.

References

Anselin, L. (1988), *Spatial Econometrics: Methods and Models*, Dordrecht, Kluwer Academic Publishers,.

Barro, R.J. (1991), "Economic Growth in a Cross Section of Countries", *Quarterly Journal of Economics,* 106, 407-444.

Barro R.J. and X. Sala-i Martin (1991), "Convergence Across States and Regions", *Brooking Papers on Economic Activity*, 1,107-182.

Barro, R.J. and X. Sala-i Martin (1992), "Convergence", *Journal of Political Economy*, 100, 223-252.

Barro, R.J. and X. Sala-i Martin (1995), *Economic Growth*, New York, Mc Graw-Hill.

Baumol, W.J. (1986), "Productivity Growth, Convergence and Welfare: What the Long-Run Data Show", *American Economic Review* 76,1072-1085.

Baumont C., C. Ertur and J. Le Gallo (2002), "The European Regional Convergence Process,1980-1995: Do Spatial Regimes and Spatial Dependence Matter?", *Regional Economics Applications Laboratory (REAL) Working Paper* No. 02-T-10 (forthcoming in *International Regional Science Review* 2005).

Bickenbach, F. and E. Bode (2003), "Evaluating the Markov Property in Studies of Economic Convergence", *International Regional Science Review*, 26, 363-392.

DPT [State Planning Organization](2000), Uzun Vadeli Strateji ve Sekizinci Beş Yıllık Kalkınma Planı [Long Term Stategy and Five Year Development Plan no. 8], Ankara, DPT.

Erk N., Ş. Ateş and T. Direkçi (2000), "Convergence and Growth within GAP Region (South Eastern Anatolia Project) and Overall Turkey's Regions", International Conference in Economics IV, METU.

Gezici F. and J.D. Hewings(2001), "Regional Convergence and Economic Performance of Peripheral Areas in Turkey", *REAL Working Paper* No: 01-T-13.

Gezici, F. and J.D. Hewings (2002), "Spatial Analysis of Regional Inequalities in Turkey", *REAL Working Paper* No. 02-T-11.

Karaca O. (2004), " Türkiye'de Bölgeler Arası Gelir Farklılıkları: Yakınsama Var mı?", *Turkish Economic Association Discussion Paper* No. 2004/7.

Le Gallo, J. (2004), "Space Time Analysis of GDP Disparities Among European Regions: A Markov Chains Approach", *International Regional Science Review*, 27,138-163.

LeSage, J.P. (2002), *The Theory and Practice of Spatial Econometrics,* Retrieved June 15, 2005 from http://www.spatial.econometrics.com/html/sbook.pdf.

Magrini, S. (2004), "Regional (di)Convergence", in *Handbook of Regional and Economics Volume 4* (*eds. Vernon Henderson and Jacques-Francois Thisse)*, North Holland, Amsterdam.

Neven, D. and C. Gouyette (1995), "Regional Convergence in the European Community", *Journal of Common Market Studies*, 33, 47-65.

Quah, D. (1993a), "Galton's Fallacy and Tests of the Convergence Hypothesis", *Scandinavian Journal of Economics*, 95, 427-443.

Quah, D.T. (1993b), "Empirical Cross-Section Dynamics in Economic Growth", *European Economic Review*, 37, 426-434.

Quah, D.T. (1996a), "Regional Convergence Clusters Across Europe", *European Economic Review*, 40, 951-58.

Quah, D.T. (1996b), "Empirics for Economic Growth and Convergence", *European Economic Review*, 40, 1353-1375.

Rey, S.J. (2001), "Spatial Empirics for Economic Growth and Convergence", *Geographical Analysis*, 33, 195-214.

Sala-i Martin, X. (1996), "The Classical Approach to Convergence Analysis", *The Economic Journal*, 106, 1019-1036.

Solow, R.M. (1956), "A Contribution to the Theory of Economic Growth", *Quarterly Journal of Economics*, 70, 65-94.

Tansel A. and N.D. Güngör(1998), "Economic Growth and Convergence: An Application to the Provinces of Turkey, 1975-1995", METU ERC *Working Paper* No. 98/9.

Temel T., A Tansel and P.J. Albersen (1999), "Convergence and spatial patterns in labor productivity: non-parametric estimations for Turkey", *Journal of Regional Analysis and Policy*, 29, 3-19.

Upton, J.G. and B. Fingleton (1985), *Spatial Data Analysis by Example*. Wiley, New York.