SPATIAL ECONOMETRIC ANALYSIS OF REGIONAL GROWTH AND EMPLOYMENT CONVERGENCE IN TURKEY

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ABSTRACT

SPATIAL ECONOMETRIC ANALYSIS OF REGIONAL GROWTH AND EMPLOYMENT CONVERGENCE IN TURKEY

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The main objective of this thesis is to investigate how spatial interactions across the provinces and regions may affect the regional growth and employment convergence in Turkey. The overall outcomes suggest not only the validity but also the superiority of the spatial econometric models. First, a comprehensive set of spatial cross-sectional models is employed to reveal the provincial growth convergence from 1991 to 2009. The results suggest evidences of absolute and conditional convergence across provinces with main driving forces being employment and human capital described by the high school graduates. Second, a methodological departure is provided by the spatial dynamic panel data models. The outcomes disclose structural differences in the 2002-2007 period in which the initially ineffective public and private investments turn out to be growth-promoting. On the other hand, the employment and human capital as measured by the university graduates could not mark significant differences in determining provincial growth. Third, the employment convergence that exhibits both regional and sectoral variations is estimated by spatial panel seemingly unrelated regression models. Throughout the 2004-2011 period, the growth rate of employment rates display divergence in the agriculture and convergence in the services sector. The industry sector shows divergent pattern in static models which becomes insignificant in dynamic setting. The agriculture sector loses its significance and regional competition for labor arises among neighbors. On the contrary, the employment rates in the industry and services sectors signify positive feedbacks across adjacent regions. The estimation results validate the employment shifts from agriculture to services sector.

Keywords: Regional growth convergence, Sectoral employment, Turkey, Spatial dynamic panel data, Spatial panel seemingly unrelated regression model

ÖZ

TÜRKİYEDE BÖLGESEL BÜYÜME VE İSTİHDAM
YAKINSAMASININ MEKANSAL EKONOMETRİK ANALİZİ

Akçagün, Pelin
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Bu tezin ana amacı Türkiye'de iller ve bölgeler arası mekânsal etkileşimlerin bölgesel büyüme ve istihdam yakınsamasını nasıl etkilediği araştırmaktır. Elde edilen bulgular uygulanan mekânsal ekonometrik yöntemlerin yalnızca geçerliliğini değil, aynı zamanda üstünlüğünü de göstermektedir. İlk olarak, 1991-2009 yılları arası il bazında büyüme yakınsamasını ortaya koymak amacıyla kesit düzeyinde kapsamlı bir mekânsal ekonometrik model seti kullanılmaktadır. Sonuçlar iller arasında mutlak ve koşullu yakınsamanın varlığına işaret etmekte, il bazında büyümede itici gücün istihdam ve lise mezunları ile ölçülen beşeri sermaye olduğunu ortaya koymaktadır. İkinci olarak, mekânsal dinamik panel veri modelleri kullanılarak metodolojik bir ayrışma sağlanmaktadır. Bulgular 2002-2007 döneminde yapısal bir değişiklik olduğunu göstermekte, başlangıçta anlamlı etkisi olmayan kamu ve özel yatırımların bu dönemde büyümeye katkı sağladığı ortaya çıkmaktadır. Diğer yandan, istihdam ve üniversite mezunları ile ölçülen beşeri sermaye illerin büyümesi üzerinde baz döneme kıyasla fark yaratamamış görünmektedir. Üçüncü olarak, sektörel ve bölgesel düzeyde değişim sergileyen istihdam yakınsaması mekânsal panel görünürde ilişkisiz regresyon modelleri ile tahmin edilmektedir. 2004-2011 dönemi boyunca, istihdam oranlarındaki büyüme tarım sektöründe ıraksama, hizmet sektöründe ise yakınsama göstermektedir. Sanayi sektörü için statik modelde ıraksama bulunurken dinamik modelde bu bulgu ortadan kalkmaktadır. Tarım sektörü giderek önemini yitirmekte ve komşu iller arasında tarımsal işgücü için rekabet doğmaktadır. Buna karşılık, sanayi ve hizmet sektörlerindeki istihdam oranları komşu bölgelerde pozitif geri bildirimlere işaret etmektedir. Tahmin sonuçları tarımdan hizmet sektörüne istihdam geçişleri olduğunu doğrulamaktadır.

Anahtar Kelimeler: Bölgesel büyüme yakınsaması, Sektörel istihdam, Türkiye, Mekânsal dinamik panel veri, Mekânsal panel görünürde ilişkisiz regresyon modeli

To my mother, Hafize Akçagün

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LIST OF ABBREVIATIONS

BACE	Bayesian Averaging of Classical Estimates
BC-LSDV	Bias-corrected Least Squares dummy variable
CD	Cross-section Dependence
DAP	Eastern Anatolia Project
DOKAP	Eastern Black Sea Project
EMU	European Economic and Monetary Union
ESDA	Exploratory Spatial Data Analysis
EU	European Union
FGS3SLS	Feasible Generalized Spatial Three Stage Least Squares
GAP	Southeastern Anatolia Project
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
GWR	Geographically Weighted Regression
HDI	Human Development Index
İŞKUR	Turkish Employment Agency
IV	Instrumental Variables
KOP	Konya Plain Project
LISA	Local Indicators of Spatial Association
LM	Lagrange Multiplier

LR	Likelihood Ratio
LSDV	Least Squares Dummy Variable
MCMC	Markov Chain Monte Carlo
MDG	Millennium Development Goals
ML	Maximum Likelihood
NEG	New Economic Geography
NUTS	Nomenclature of Territorial Units for Statistics
OLS	Ordinary Least Squares
PEP	Pre-Accession Economic Programme
PPD	Priority Provinces in Development
QML	Quasi-maximum likelihood
RLM	Robust Lagrange Multiplier
SDPD	Spatial Dynamic Panel Data
SUR	Seemingly Unrelated Regression
TBB	The Banks Association of Turkey
TFP	Total Factor Productivity
TurkStat	Turkish Statistical Institute
UNDP	United Nations Development Program
VAR	Vector Autoregressive Model
YHGP	Yeşilırmak Basin Development Project
ZBK	Zonguldak-Bartın-Karabük Project

CHAPTER 1

INTRODUCTION

Regional development has been a major objective and one of the biggest challenges of policy-makers in all countries. The main focus has been to eliminate the regional disparities with appropriate economic and policy tools. Empirical researchers have investigated not only the size and reasons but also the evolvement of these disparities both across and within the countries. This has resulted in a continuous interest in the convergence model which remains to be one of the most novel contributions to the economic growth theory. A vast literature came out following a discussion of almost half a century and the level of analysis has recently shifted away from cross-country studies to within country units. Given that the regions within the same country borders share common economic and social background, it has been argued that convergence is a more likely phenomenon at the regional level. As a natural consequence of the emphasis on regional interactions, a closer look to these models has become necessary in the light of spatial proximity.

In this thesis, we tackle the question of how spatial interactions across the provinces and regions may affect the regional growth and employment convergence dynamics in Turkey. The aim of this thesis is to reconsider the standard Solow-Swan convergence hypothesis in the light of the well-stated first law of geography: *"Everything is related to everything else, but near things are more related than distant things*" (Tobler, 1970). An analytical approach is pursued relying on the most recent theoretical contributions to the spatial econometric literature as well as the most up-to-date and available data employed in the empirical analysis. The thesis mainly consists of three stand-alone chapters all being the first empirical examples as long as the data set and the scope of the models are concerned. Although the focus is on Turkish economy, the methodological discussions are kept as general as possible to highlight the potential of techniques in examining convergence and growth issues empirically.

Incorporating spatiality into the regional convergence models has both economic and methodological grounds. In economic terms, five main reasons constitute our point of departure. First, social, economic and even political conjunctures are more alike in the neighboring regions as compared to the non-neighbors. This factor amplifies the interactions among neighbors and has a direct influence on the regional growth and employment processes. Moreover, the policy tools such as regional development projects, the priority provinces in development and the regional development agencies are region-specific in nature. These specified regions may go through their own phases of development unlike the regions that are not subject to the same programs.

Second, most of the indicators that determine the growth and the labor market potentials of an economy are highly mobile across the regions. Specifically, human capital, labor, private investment and population move from one region to the other. Among the adjacent regions, labor and capital are highly mobile due to low transfer costs and ease of transportation. Hence, the income and employment dynamics in one region would have a direct impact on the nearby regions.

Third, input-output linkages are likely to be more pronounced across the neighbors. Most regions use the output of other regions in the economy as intermediate goods, as frequently observed at sectoral level. Since those interlinkages are stronger for the immediate neighbors, the inefficiency in production processes in one region would have a direct influence on the other. This also have consequences in the labor market and affect the employment convergence dynamics alongside the growth convergence.

Fourth, the proximity strengthens the spillover effects across the regions. The diffusion of knowledge that promotes economic growth is largely a spatial phenomenon. As a matter of fact, the positive externalities arising via knowledge spillovers are more effective among the regions in close proximity.

Fifth, any possible shock that affects a particular region has more severe and quick reflections on the adjacent regions. More specifically, as the regional economies are hit by unexpected events such as natural disaster, terror, changes in climatic or soil structure, they have instantaneous impacts on the neighbors. The political resolutions in a country may possibly alter the regional compositions. Immigration may have effects on the regional development dynamics in particular regions as opposed to the others. The underlined circumstances that strike the regional output and the employment patterns undoubtedly have spatial aspects.

The rationale for the spatial analysis has also methodological bases. As a natural consequence of the economic reasons, the spatiality can arise in various forms in the econometric specifications. It may appear in the dependent variables, independent variables as well as in the error terms of the regressions. Their combinations in different forms yield a family of spatial econometric models. If the true data generating process has in fact at least one of these spatial structures, ignorance in the estimation would give rise to severe problems in the estimated parameters. The estimates may become biased and inconsistent in the case of omitted spatiality in the dependent variables or may turn out to be inefficient in the case of discarded spatiality in the error terms. In order to tackle with these problems, this thesis considers a comprehensive set of various specifications and estimation procedures some of which were not considered for the data set employed here before.

The following chapter focuses on the provincial growth convergence in Turkey from 1991 to 2009 period. Entire set of spatial econometric models proposed for cross-section analysis are employed to uncover the true form of spatial structure in the regional convergence of Turkish provinces. The model selection procedure discloses evidence of spatial heterogeneity represented by the spatial error models. Accordingly, any economic shock that affects the output structure of a particular province has an impact on the neighboring provinces in the same direction. The maximum likelihood estimation results indicate the presence of absolute and conditional growth convergence with human capital and employment being the main driving forces of provincial income growth. On the contrary, the public and private investments seem to be insufficient for the output creation mechanism.

In the third chapter, the level of analysis is extended by integrating the time effects into the provincial growth convergence. The spatial dynamic panel data models are employed in alternative forms and a detailed discussion on the estimation methods are provided. In forming the regressions, the structural changes in 2002 and the crises in 1994, 1999, 2001 and 2009 are taken into consideration. The methodological analysis and the corresponding test statistics imply that the dynamic fixed effects spatial lag models represent the growth convergence dynamics of Turkey better than the alternatives. The positive spatial lag parameters reported by the generalized method of moments estimations indicate that growth in one province have a direct impact on the growth in the neighboring provinces. The provincial growth is determined in varying degrees by human capital, employment, real public investment, real private investment and population.

The last chapter is devoted to the regional employment convergence in 26 NUTS-2 level regions of Turkey throughout the 2004-2011 period. In doing this, both regional and sectoral aspects are under consideration in a unified modelling framework. For agriculture, industry and services sectors, separate spatial panel data models are estimated. Subsequently, the sectoral employment regressions are estimated together in spatial panel seemingly unrelated regression framework. The feasible generalized spatial three stage least squares estimations reveal sector-specific outcomes. There is evidence of employment shifts away from agriculture to services sectors. This is accompanied by regional divergence in the agriculture and convergence in the services sectors. The industry sector has peculiar characteristics as the results are dependent on whether the models are constructed as static and dynamic. The signs of the spatial error parameters in the estimations also have sector-specific implications, being negative in agriculture and positive in industry as well as services. Thus, for the agricultural employment, a shock experienced in a province has repercussions in the opposite direction due to possible competition for human resources. On the other hand, for the industry and services sectors positive feedback effects are observed such that any unexpected event taking place in one region has similar impacts on the neighbors.

Overall, the results revealed in this thesis suggest not only the validity but also the superiority of the spatial econometric methods in modelling the regional growth and convergence problem of Turkey. More specifically, the outcomes are very important in showing that neglecting spatiality may cause not only disguised economic linkages among the regions but also biased, inconsistent and/or inefficient parameter estimates leading to misleading inferences. Furthermore, considering comprehensive set of spatial econometric specifications here also indicate that adhering to a few forms of spatial models may not be sufficient to uncover the true nature of spatial relations among the regions.

CHAPTER 2

SPATIAL CROSS-SECTIONAL ANALYSIS OF REGIONAL GROWTH CONVERGENCE IN TURKEY

Regional convergence has long been one of the main concerns of scientists from various disciplines seeking to understand regional dynamics and enhancing suitable policy tools to decrease spatial disparities. Neoclassical growth models serving as a benchmark for convergence analysis have been extended to various forms such as the ones with technological spillovers and geographical clustering analysis. These progressions in the field have led to the growing need for more sophisticated methodologies. The spatial econometric models, in particular, have become more popular in examining the regional convergence problem in the last two decades.

Further research on regional convergence with an emphasis on spatiality needs to be carried out to fill two major gaps in the empirical literature. First, the spatial cross-sectional regional convergence models applied in the literature do not fully cover more sophisticated models which include spatiality in alternative forms. Second, the applied spatial regional growth models are mostly based on the evidences from core countries. However, regional disparities are more of a developing country problem and disclosing the empirical aspects of convergence dynamics in these countries could be more illuminating.

The aim of this chapter is to employ a comprehensive set of spatial econometric specifications to reveal regional convergence dynamics in Turkey. The absolute and conditional convergence hypotheses are analyzed at provincial level over 1991-2009 period. Particularly, spatially augmented Solow-Swan models are exploited to show whether per capita income differentials and hence regional discrepancies decrease over time. Comparative analysis of the results from various specifications is crucial not only for revealing different convergence dynamics of the Turkish economy at regional level, but also for uncovering the true nature of the spatiality that characterizes the regional data. For this purpose, general-to-specific model selection procedure is applied to find the most appropriate model and implications of all models are evaluated. Empirical findings show that spatial error model outperforms all other specifications and suggest the presence of both absolute and conditional convergence[1] among Turkish provinces for 1991-2009 period.

The chapter is composed of six sections. The first section presents the growth convergence literature. The second section provides a general outlook to the regional development in Turkey. The data and basic regional indicators are introduced in the third section. The fourth section discusses the exploratory spatial data analysis, empirical models, and methodology used in the estimation of all models. Section five introduces results of the estimations and the final section concludes by evaluating the analytical results and discussing policy recommendations.

2.1. Regional Growth Convergence Literature

2.1.1. Neoclassical Convergence Model

This chapter takes the supply-side neoclassical growth model as the point of departure in order to explain the convergence among provinces. The growth models developed by Solow (1956) and Swan (1956) are the main pillars of neoclassical growth theory. The

[1] Although the outcomes document absolute convergence, we further look for the presence of conditional convergence. These regressions are employed not only for handling the possible omitted variables problem in the absolute convergence models, but also to estimate the determinants of provincial growth. Sala-i-Martin states that "*the conditional convergence and the absolute convergence hypotheses coincide, only if all the economies have the same steady state (…) Hence, we may want to look for absolute convergence within the sets of 'more similar' economies*" (Sala-i-Martin, 1996b: 1027). If regions differ according to their characteristics, the constant term appearing in the absolute convergence models becomes region-specific and may be a function of regional features. The conditional convergence model approximates this constant by a vector of variables, which also depict the determinants of growth.

standard Solow-Swan model considers technology as an exogenous variable and the driving force of the economic growth. The model assumes constant returns to scale, positive but diminishing marginal returns to each input, constant saving rates and lies upon the Cobb-Douglas production function with labor-augmenting technological process:

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha} \qquad 0<\alpha<1 \tag{2.1}$$

where Y_t is output, K_t is capital, L_t is labor and A_t denotes total factor productivity (TFP) indicating the level of technology. Labor and TFP grows exogenously at constant rates n and g such that,

$$\begin{aligned} L_t &= L_0 e^{nt} \\ A_t &= A_0 e^{gt} \end{aligned} \tag{2.2}$$

Defining k as capital per effective labor such that $k=\dfrac{K}{AL}$ and y as output per effective labor such that $y=\dfrac{Y}{AL}$ the law of motion per effective labor is governed by:

$$\dot{k} = sk^{\alpha} - k(n+\delta+g) \tag{2.3}$$

where δ is the depreciation rate. Due to diminishing marginal returns to capital, regions with lower levels of national income at the initial year tend to grow faster than regions with higher initial incomes and the so-called absolute convergence takes place. This basic version of the convergence model proposes single steady state in a cross-country analysis.

Subsequently, some extensions to the standard Solow model as well as new estimation techniques appeared in the growth literature. Following the work of Ramsey (1928) on consumer optimization problem, Cass (1965) and Koopmans (1963) revise the Solow growth model with endogenous determination of saving rates. This extension retains the convergence hypothesis and the steady state due to the exogenous technology. Barro and Sala-i Martin (1992) introduce the conditional convergence model which allows different countries converging to different steady states. In their model, a set of parameters such as human capital is controlled in the estimation. Mankiw, Romer and Weil (1992) propose an augmented Solow model incorporating human capital as well as physical capital inside the production function. Based on Summers and Heston (1988) data set including real income, government consumption, private consumption, investment and population series of almost all countries except the centrally planned economies over the period 1960-1985, they find half-life[2] of 35 years which is predicted to be 17 years by standard textbook Solow model.

Quah (1993) argues that the standard cross-section convergence tests suffer from Galton's fallacy[3] and that coefficient of initial observations in the cross-sectional convergence equation does not say anything as to the existence of convergence or divergence, a negative coefficient can still prevail in the absence of convergence. Bliss (1999), on the other hand, states that if the data generating process is a unit root process or if it contains correlated error terms with the independent variables and serial correlated shocks, the estimates from the cross-sectional convergence model can be biased. Yet, these econometric issues are not due to Galton's fallacy and hence cannot be treated merely by the comparison of variances of log incomes.

One should note that, apart from the neoclassical theory, some other approaches to regional convergence appeared in the growth literature. In fact, before the neoclassical upsurge of the growth models based on supply-side analysis, the demand-side Keynesian models address the issue of convergence. Harrod (1939) and Domar (1946)

[2] The calculation of half-life in the empirical models will be provided in section (3.4.1).

[3] Galton (1885) examines the heights of 930 children and their respective 205 parents and argues that the height of children from very short or very tall parents move towards the average. This fallacy based on the misleading regression to the mean, or "regression towards mediocrity" in Galton's words, is then referred in the literature as "regression fallacy" or "Galton's fallacy". The heights tending to regress towards the mean does not imply that the dispersion of heights is narrowing.

models indicate that growth rate of output is determined by the marginal propensity to save and the capital-output ratio. Intuitively, level of savings matters since higher savings enable higher investment and capital-output ratio is indicative of the efficiency of investment. Another major post-Keynesian line of argument known as Kaldor-Dixon-Thirlwall (KDT) models, suggest that regional growth is driven by export growth. Thus, following the earlier work of Kaldor (1970), Dixon and Thirlwall (1975) incorporate balance-of-payments constraint into the convergence model.

Along with the supply-side approach, some critiques to the neo-classical convergence model have also emerged. Endogenous growth theory pioneered by Romer (1986, 1990) removes the assumption of diminishing returns to capital and hence does not predict absolute or conditional convergence. Instead, as in the AK model as a benchmark example for endogenous growth theory, the economies grow at the same per capita rate regardless of their initial conditions. The so-called MAR spillovers named after Marshall (1890), Arrow (1962) and Romer (1986) imply that the proximity of firms within an industry affects the diffusion of knowledge and facilitates innovation and growth. New Economic Geography (NEG) models based on Krugman (1991) provide an explanation for the geographic clustering of the economies. In line with these advancements, new estimation techniques have also emerged to overcome the shortcomings of the standard Solow-Swan model. Among those, the spatial econometric literature provides excellent tools to extend the neoclassical model by considering the spillover effects as well as the geographical locations in the convergence analysis.

2.1.2. Spatial Cross-Sectional Extensions of the Convergence Model

According to Tobler's first law of geography "*Everything is related to everything else, but near things are more related than distant things*" (Tobler, 1970). This idea, manifesting that spatial proximity escalates the interaction among units, has provided a new outlook to the regional development problem. It has become more outspoken that neighboring units share common economic, social and cultural values which in turn increase mutual relations and affect regional convergence. In consequence, incorporation of spatial relations in the regional convergence models has substantially increased in the last two decades.

The earlier empirical literature on convergence relies upon the spatial statistical tools which can be classified under the title of exploratory spatial data analysis (ESDA). Particularly, they allow for the initial assessment of spatiality based on the tests for spatial dependence and heterogeneity. In the regional growth literature, global and local Moran I, Getis-Ord G_i statistics, and the LM tests are extensively used for these purposes. Lopez-Bazo et al.(1999) is one of the first studies to conduct Moran I and Getis-Ord tests for spatial autocorrelation for European Union dataset. Arbia (2001) utilizes spatial statistics for analyzing the employment of manufacturing industry in Italian provinces at 1991 and shows that neglecting the spatial features of data produces serious biases in the measurement of industrial agglomeration. Le Gallo and Ertur (2003) also exploit ESDA techniques such as global and local Moran I and Getis-Ord G_i statistic to examine the spatial distribution of regional GDP per capita in Europe over 1980-1995. The results reveal significant positive global spatial autocorrelation and two distinct spatial regimes with clustering of high and low values. DeDominicis et al.(2007) analyze 23 manufacturing industries and 17 services sectors in Italy by means of exploratory spatial tools and conclude that concentration declines in the manufacturing industry whereas services sector become more concentrated over 1991-2001.

Following the outcomes of the statistical methods in the empirical growth literature in favor of spatiality, a growing need for handling spatial dependence has become more evident in the econometric estimations. Most commonly used models in the cross-sectional regional convergence analysis have been spatial lag and spatial error models as they integrate the basic forms of spatial dependence and heterogeneity. Rey and Montouri (1999) is a leading example to reveal that standard analysis of regional income convergence may be misspecified due to the ignorance of spatial error dependence. Their estimation results for U.S. states over 1929-1994 period suggest strong empirical evidence that shocks originating in one state can cause spillover effects on the surrounding states. Baumont et al. (2000) analyze the consequences of spatial dependence on regional growth and convergence for European regions over 1980-1995. The authors estimate spatial lag, spatial error and spatial cross-regressive models[4] and find strong evidence of spatial autocorrelation in the unconditional beta-convergence model. Fingleton (2001a) considers a model that assumes increasing returns to capital in line with the endogenous growth theory and spatially varying technical progress which is linked to new economic geography literature. Results of the simulations and spatial lag model estimation for a dataset containing 178 NUTS-2 level European Union regions over 1975-1995 indicate that productivity levels and growth rates are higher in all regions when the financially assisted regions have faster output growth, which also reduces inequalities in levels of technology. Fischer and Stirböck (2004, 2006) reveal that spatial error specification for the two-club convergence model implied by the Getis-Ord statistics is the most appropriate to represent the data for 256 regional economies in Europe over 1995-2000. Egger and Pfaffermayr (2006) use a simulation experiment to disclose the role of spatial dependence for beta and sigma convergence dynamics of European regions over 1980-2002 period. They find that regional location and spillovers have considerable effects on the convergence rates while their influences are minor for sigma convergence. Ertur et al. (2006) investigate spatial dependence and spatial heterogeneity in the estimation of beta convergence of 138 European regions over 1980-1995. The results of exploratory spatial data analysis and estimation of spatial error models reveal that convergence process is different across diverse spatial regimes in the core and periphery, verifying North-South polarization in Europe. Ertur and Koch (2007) employ an augmented Solow model that includes both physical capital externalities and spatial externalities in knowledge and estimate a locally linear spatial autoregressive model to observe the impact of spillovers in a sample of 91 countries over the period 1960–1995. Garrett et al. (2007)

[4] Spatial cross-regressive models (or SLX models) presumes spatial dependence only in the explanatory variables.

construct spatial lag and error models with two different weights matrices to analyze the evidence of spatial correlation in income growth of U.S. states throughout 1977-2002. Dall’erba and LeGallo (2008) examine the impact of structural funds on the convergence process across 145 European regions over 1989-1999. They make use of spatial lag models under four different specifications which combine structural funds and group-wise heteroscedasticity and find that significant convergence takes place but funds have no effect on it.

Recently, in line with the progress in theoretical spatial econometric literature, regional growth models have confronted a need for adapting more sophisticated and extensive specifications in order to tackle with the complications in the convergence processes. To meet this increased demand for handling alternative forms of spatial dependence, particularly for the variables that determine growth, spatial Durbin models have become quite popular in the empirical literature. Basile (2008) explores the growth behavior of European regions over 1988-2000 via semi-parametric spatial Durbin model. The results indicate the presence of nonlinearities as well as global and local spatial spillovers. LeSage and Fischer (2008) provide a theoretical motivation for using spatial Durbin model and by means of Bayesian methods they compare the estimated empirical models with different spatial weight matrix specifications and set of explanatory variables. For EU dataset and 1995-2003 period, their empirical findings show that indirect effects caused by spatial spillovers are essential in determining regional income. Arbia et al. (2010) construct spatial Durbin models based on geographical and institutional distances to examine the productivity convergence across European regions for 1991-2004 period and verify the impacts of institutional framework and spatial spillovers on the output growth. Fischer (2011) applies a spatial Durbin model specification for the growth model extending Mankiw-Romer-Weil framework by introducing technological interdependence among regions. The evidence from 198 European regions over 1995-2004 suggests the presence of externalities through physical capital rather than human capital.

Together with innovative specifications, new estimation techniques have also been introduced. In particular non-parametric estimation methods have become more popular not only in the standard econometric theory, but also in the spatial econometric literature. Arbia et al. (2005) propose a nonparametric kernel density estimator to describe regional per capita income convergence in Europe. Ertur et al. (2007) explain the global and local beta convergences of European regions over 1980-1995 using Bayesian spatial autoregressive locally linear estimation approaches. Chapman et al. (2010) construct transition matrices and stochastic kernels in order to test whether the north-south spatial pattern of Europe should be replaced by an east-west pattern after the enlargement of EU to 27 countries. To reveal the convergence across European regions from 1995 to 2005, Cuaresma and Feldkircher (2013) propose a Bayesian moving average method that deals with the presence of spatial autocorrelation in unknown form and show that neglecting uncertainty in type of spatial weights matrix may have effects on the parameter estimates. Their empirical findings for European regions over 1995-2005 period assert that geographical location plays an important role in explaining the income convergence process.

Two immediate observations can be derived from the empirical regional convergence literature utilizing spatial cross-sectional models. First, to understand the complicated nature of convergence dynamics, there is still room for assessing more sophisticated models which can include spatiality in various structural forms. In order to keep pace with the substantial rise of regional interactions in the modern world, we believe the modelling framework can be extended to more inclusive models such as spatial Durbin error, SAC and SAC Durbin models. The information obtained from these models and model selection procedures can be exploited to attain the most suitable spatial structure inherent in the data.

Second, a good deal of papers in the applied spatial literature on regional growth considers the core countries such as U.S. and members of European Union. In fact, Abreu et al.(2004) state that 68% of the studies use European data and it seems legitimate to anticipate an increase in this rate through the last decade. There is still need for further study in the developing countries despite the data limitations, a constraint which also holds for Turkey. The regional development literature in Turkey is extensively based on the traditional econometric methods, with some exceptions.

2.1.3. Regional Convergence Literature in Turkey

In spite of the recent developments in theoretical spatial econometrics literature and the rising interest in empirical modeling, studies on regional development of Turkey generally ignored spatial dynamics and applied different techniques coming up with mixed results. Doğruel and Doğruel (2003) use panel data methods for 1987-1999 period and conclude that all provinces experience beta convergence, though sigma convergence is observed only in high-income provinces. In another panel data study, for 1975-1995 period, Tansel and Güngör (1998) show that there exist absolute and conditional convergences in the labor productivity of provinces. Erlat and Özkan (2006) conduct tests for unit root and structural shift across regions where they find absolute convergence in 14 provinces and conditional convergence in 13 provinces over 1975-2000. For the same time period, Karaca's (2004) results indicate divergence using ordinary least squares; Kırdar and Saraçoğlu (2008) reveal absolute divergence and conditional convergence using two stage least squares; Temel et al.(1999, 2005) employ Markov chain models and find polarization between low-productivity and high-productivity provinces. For 1979-1998 time period, Sarı and Güven (2007) consider generalized entropy decomposition to analyze Theil index and reveal that there exists income divergence where Priority Provinces in Development (PPD) and non-PPD provinces depart from each other.

The regional convergence literature that takes spatial aspects into account is quite limited for Turkey. Gezici and Hewings (2004) utilize Moran I statistic and estimations with spatial dependence in the explanatory variables to analyze regional convergence and core-periphery relations in Turkey over 1980-1997 period. The authors find no evidence of convergence and show that PPDs do not grow faster as compared to the other provinces. For the same time period, Gezici and Hewings (2007) examine Theil index using exploratory spatial data analysis and present that inequalities increase among the regions whereas they decline within them.

More complicated spatial methods have been utilized in a very few studies. For the 1987-2001 period, Aldan and Gaygısız (2006) do not find convergence using spatial lag, spatial error and spatial cross-regressive models as well as the spatial Markov chains. Yıldırım and Öcal (2006) discuss regional convergence via estimating spatial lag, spatial error and spatial cross-regressive models for Turkish provinces over 1979-2001 period. The estimation results reveal that Theil index increases during expansionary and diminishes during recessionary periods, and at the overall level there exists beta convergence. For the 1987-2001 period, Yıldırım et al. (2009) provide an in-depth analysis of regional convergence via spatial error, spatial lag and geographically weighted regression (GWR)[5] methods. Their results suggest that there is considerable variation in speed of convergence of provinces which can be captured through GWR estimation. Empirical findings display faster growth in eastern and southeastern provinces showing the evidence of convergence.

2.2. Regional Development in Turkey

2.2.1. General Outlook of the Economy

In this chapter, Turkey's regional development problem is analyzed over 1991-2009 period at provincial level. Throughout this period, the economy experienced significant structural changes as well as major economic and financial crises. Following the shift towards the export-promoting growth policies since the beginning of 1980s, flexing the import regime and finally the capital account liberalization in 1989, Turkish economy started 1990s as a highly outward-oriented country. Along with the financial

[5] Geographically weighted regression models allow obtaining local coefficients as opposed to the global beta convergence parameters. For another application on regional convergence, see Eckey et al. (2007) where the authors derive local speeds of convergence for the labor productivity of German regions.

liberalization, the economy became fragile to the speculative capital flows, domestic currency got overvalued, the interest rates increased and the domestic demand expanded[6]. In the wake of the devaluation and economic crisis in 1994, Decisions of April 5 was announced; the wages were suppressed to shrink domestic demand and to get over the crisis. In 1996, Customs Union agreement with the European Union was put in order. After a short period of recovery, Turkish economy was shocked again by the 1997 Asian, 1998 Russian crises and the 1999 earthquake. In 2001, a great depression occurred in the economy; real GDP fell by 7.4 per cent, inflation in consumer prices increased up to 54.9 per cent and the Turkish lira lost 51 per cent of its value against foreign currencies. As a result of this significant shock, the unemployment rate rose above 10 per cent and real wages fell by 20 per cent (Yeldan, 2011). The recovery from this crisis faced with no major obstacles until the 2008-09 global recession.

As a result of this turbulence in the economy in the post-1990 period, the development indicators were not very promising and some measures had to be taken in accordance with the decisions of the international organizations. The most striking one is United Nations millennium development goals (MDGs) adopted in 2000 composed of a number of objectives to globally improve income distribution, poverty, education, health and gender indicators in the twenty-first century. Following this summit that Turkey was also a participant, State Planning Organization[7] prepared two MDG reports in 2005 and 2010 which can be formulated around eight key elements targeting national and regional development. The primary objective of 2010 MDG report was to "*eradicate extreme poverty and hunger*" (SPO, 2010). According to the report, the

[6] Yeldan (2005), Boratav (2012) and Yentürk (2003) present a detailed research on the evolution of Turkish economy since the beginning of 1990s.

[7] In June 3, 2011 the authority and duties of State Planning Organization was delegated to the Ministry of Development, established by decree of the Council of Ministers.

population ratio with daily income less than 1 dollar[8] was 1.1 per cent in 1994, 0.2 per cent in 2002 and set to zero in 2006. On the other hand, 2010 Income and Living Conditions Survey (TurkStat, 2011) reported that according to the poverty threshold determined by considering the 50 per cent of household disposable median income, 16.9 per cent of the population was at-risk-of-poverty; this ratio was 14.3 per cent for urban and 16.6 per cent for rural areas. Moreover, at-persistent-risk-of-poverty rate was 18.5 per cent, material deprivation rate was 66.6 per cent in 2010[9]. Gini coefficient, as one of the income inequality criteria, was estimated as 0.402. Considering the quintiles constituted by the household disposable income, the share of the fifth quintile which has the highest income was 46.4 per cent whereas the share of the first quintile which has the lowest income was 5.8 per cent.

After adopting the concept of Human Development Index (HDI) by the United Nations Development Program (UNDP, 1990), the education and health targets have also gained importance besides the pure economic objectives. In 2010, Turkey ranked 83 out of 169 countries in HDI values, calculated by using various indicators such as life expectancy at birth, expected years of schooling, mean years of schooling as well as gross national income per capita (UNDP, 2010). Although Turkey was in a comparatively better ranking in per capita income measures (57th out of 169 countries), the education and health indicators were quite unsatisfactory at the end of target period. Turkey ranked 84th in life expectancy at birth, 112th in mean years of schooling and 96th in the expected years of schooling rates in 2010 (Şeker, 2011).

[8] This criterion for absolute poverty was designated by 1990 World Development Report and calculated using the poverty figures of Bangladesh, Egypt, India, Indonesia, Kenya, Morocco and Tanzania and found to be 370 dollars per capita in 1985 prices (approximately 1 dollar per day) (Şenses, 2001).

[9] "At-persistent-risk-of-poverty-rate" shows the percentage of the population living in households where the disposable income was below the "at-risk-of-poverty threshold" for the current year and at least 2 out of the preceding 3 years. 60% of household disposable median income is taken into account in calculating at-persistent-risk-of-poverty-rate. Material deprivation rate is defined as the percentage of population with an enforced lack of at least four out of nine material deprivation items in the "economic strain and durables" dimension (TurkStat, 2011).

2.2.2. Regional Development Policies in Turkey

The First Development Plan introduced in 1963 was the initial step to execute certain programs based on regional assessments. Since then, the implementation of the Development Plans has been a major resolution towards diminishing regional disparities in Turkey although their influences have relatively weakened after the intensified liberalization policies in the post-1980 period. The motivation has shifted towards more outward oriented policies which went hand in hand with the candidacy in the European Union. The Sixth Five-Year Development Plan published in 1990 was mirroring the regional development perception of European Union in Turkey. After the Helsinki summit held in 1999, in which Turkey gained the candidate status, the emphasis on reducing the regional disparities in line with the EU policies has become more critical. In 2002, the Nomenclature of Territorial Units for Statistics (NUTS) system was adopted from European Union. The NUTS levels were defined for three stages: 81 provinces in NUTS-3, 26 sub-regions in NUTS-2 which are grouped according to their economic, social, cultural and geographical properties, 12 regions in NUTS-1 which are re-grouped considering the same criteria. E.U. dominance was more apparent in the Ninth Development Plan which was prepared with a vision of "*Turkey, a country of information society, growing in stability, sharing more equitably, globally competitive and fully completed her coherence with the European Union*" (SPO, 2006). Although Tenth Development Plan published for 2014-2018 period does not have a direct reference to E.U. in terms of its visions and missions, the Pre-Accession Economic Programme[10] 2014-2016 still gives a wide coverage to the regional development agenda (Ministry of Development, 2014).

In this quest of diminishing regional disparities in Turkey, three major steps were taken through time: the establishment of Priority Provinces in Development in 1968, constructing certain regional development projects starting from 1989 and the foundation of regional development agencies in 2006.

[10] Turkey has been submitting Pre-Accession Economic Programme (PEP) to the European Commission since 2001.

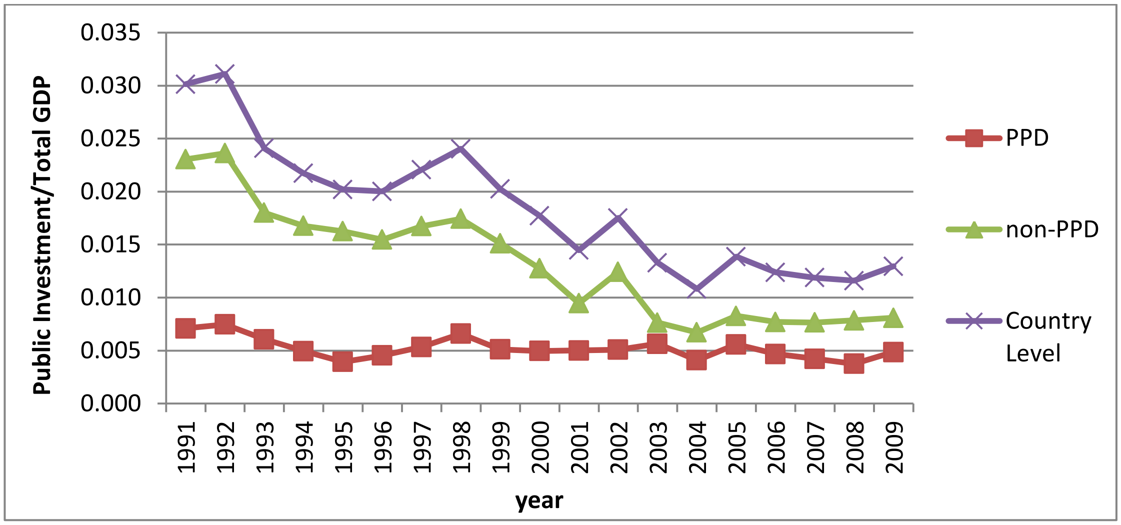
2.2.2.1. Priority Provinces in Development (PPDs)

Priority Provinces in Development (PPDs) were defined for 22 Eastern and Southeastern provinces in accordance with the decree[11] in 1968. In 1980, there were 40 provinces defined as PPDs. In 1981, paying regard to their different levels of development, 1st degree PPDs (20 provinces) and 2nd degree PPDs (5 provinces) distinction was introduced and the incentive schemes were discriminated. The number of provinces defined as PPD has changed over time; in 1996, 2nd degree PPDs were removed and all PPDs (38 provinces) were declared as 1st degree. From 1998 onwards, there have been 49 provinces and 2 districts designated as PPDs[12]. Common characteristics of the PPDs have been high growth of population, high rates of outward migration, low urbanization rate, relatively low GDP per capita and high rates of informal labor. Main policies towards the development of these PPDs have included increasing public investment with special emphasis on infrastructure and providing investment incentives to the private sector. By this means, an improvement in productivity as well as a decline in informality has been expected.

For a discussion regarding the effectiveness of the Priority Provinces in Development Programs, the following figures present the public resources allocated to PPD and non-PPD provinces. Figure 1 indicates that although public investment as a ratio of GDP decreased over the 1991-2009 period at the country level as well as in the non-PPD provinces, it remained in a certain range without a major decline in the PPDs. It seems that although the central government aimed at shrinking the public sector in these two decades, this was not possible in the underdeveloped provinces given the already insufficient infrastructure of these regions. However, the public investments in non-PPD provinces have always been higher than those in PPDs throughout 1991-2009.

[11] In February 28, 1968 the notion of "Priority Provinces in Development" emerged due to Legislation no 202.

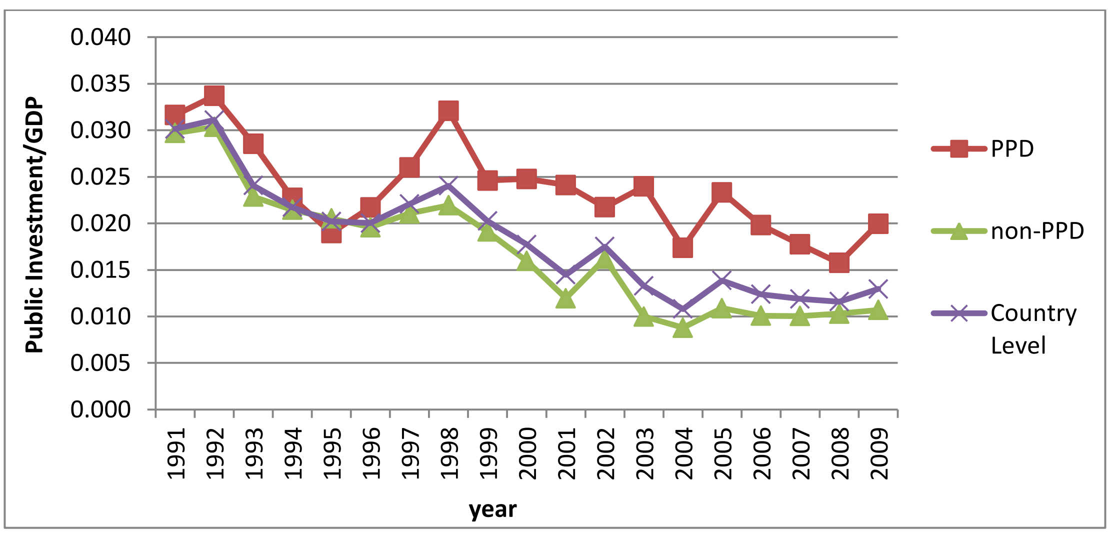
[12] An up-to-date list of Priority Provinces in Development as of 1998 can be found in the Appendix.



Notes: From 1998 onwards there are 49 provinces and 2 districts designated as PPDs. Here, PPD figures are aggregated in line with the number of provinces in 1991. Accordingly, the figure represents 44 PPD and 29 non-PPD provinces out of 73 in total. The values are calculated as follows: PPD = (Public Investment in PPDs/Total GDP); Non-PPD = (Public Investment in non-PPDs/Total GDP); Country Level = (Total Public Investment/Total GDP)

Source: Authors' calculations from public investment (Ministry of Development) and GDP (Turkstat) data.

Figure 1: Public Investment as a ratio of Total GDP



Notes: From 1998 onwards there are 49 provinces and 2 districts designated as PPDs. Here, PPD figures are aggregated in line with the number of provinces in 1991. Accordingly, the figure represents 44 PPD and 29 non-PPD provinces out of 73 in total. The values are calculated as follows: PPD = (Public Investment in PPDs/GDP in PPDs); Non-PPD = (Public Investment in non-PPDs/GDP in non-PPDs); Country Level = (Total Public Investment/Total GDP)

Source: Authors' calculations from public investment (Ministry of Development) and GDP (Turkstat) data.

Figure 2: Public Investment as a ratio of Regional GDP

Figure 2 shows that the dependency of PPD provinces on public resources prevailed through time. Despite major declines during 1990s, overall, the ratio of public investment to regional income has been higher in PPDs compared to non-PPD provinces.

2.2.2.2. Regional Development Projects

Following the initiation of Southeastern Anatolia Project (GAP), project-based approaches have gained importance as a policy tool to enhance regional development. In 1970s, the main objective of GAP was to improve irrigation facilities in the highly rural area of Southeastern Anatolia. As of 1989, with Decree Law No. 1989/388, GAP Regional Development Administration was officially founded including the provinces Adıyaman, Batman, Diyarbakır, Gaziantep, Kilis, Mardin, Siirt, Şanlıurfa and Şırnak where the objectives were extended to integrate the infrastructure investments in agriculture, industry, transportation, education and health. Although it has been the largest project in Turkey, under the unstable economic environment of 1990s this project was far from being efficient enough (TÜSİAD, 2008).

In the 7th Development Plan Period (1996-2000), within the framework of Reconstruction Law No. 3194 and Decree Law No. 540 on "The Establishment, Organization and the Tasks of the State Planning Organization", the basis for Zonguldak-Bartın-Karabük Project (ZBK), Eastern Anatolia Project (DAP) and Eastern Black Sea Project (DOKAP) were initiated. Main objective of ZBK has been to improve the investment opportunities in coal mining as an abundant natural resource of the region. The master plan for DAP published in 2000 consisted of 16 provinces: Ağrı, Bingöl, Bitlis, Elazığ, Erzincan, Erzurum, Gümüşhane, Hakkari, Kars, Malatya, Muş, Tunceli, Van, Ardahan, Bayburt and Iğdır. The aim of this project has been to constitute economic, social and cultural unity as well as to ensure the region's sustainable development. DOKAP was prepared with the technical cooperation with Japanese International Cooperation Agency (JICA) for seven provinces in Black Sea: Ordu, Giresun, Trabzon, Rize, Artvin, Gümüşhane and Bayburt. The aim is to realize sustainable development and reducing disparities by improving transportation, telecommunication and urban infrastructure and enhancing soil productivity as well as environmental quality. In the same 7th Development period Yeşilırmak Basin Development Project (YHGP), which included Amasya, Çorum, Samsun and Tokat provinces, was undertaken for "*monitoring and management of natural resources, prevention of erosion in this scope, determination of water pollution and improvement of pasture*" in the region (SPO, 2001).

In 2011, Regional Development Administrations for Eastern Anatolia Project (DAP), Konya Plain Project (KOP) and Eastern Black Sea Project (DOKAP) were established (Ministry of Development, 2014). KOP region consists of Aksaray, Karaman, Konya and Niğde provinces and similar to GAP it is mainly based on enhancing the irrigation facilities.

2.2.2.3. Regional Development Agencies

In accordance with the Legislation number 5449, Regional Development Agencies (RDAs) were established in the beginning of 2006 in 26 NUTS-2 level regions in Turkey. The Tenth Development Plan (SPO, 2014) states that during 2014-2018 period, "*Regional Development Agencies will place emphasis to attracting foreign and domestic capital investments in order to exploit regional potentials and will assume a complementary role at the regional level for the Investment Support and Promotion Agency*" which performs under Prime Ministry of Turkey. Hence, the role of central government on carrying out regional growth policies is quite extensive. The Regional Development Agencies have taken the role of being a follower of the development projects with regard to the assigned regions rather than being in a position of taking decisions.

2.3. Data and Basic Regional Indicators

The variables that have been used so far in the cross-country growth analysis are quite diverse. In fact, Durlauf et al. (2005) provide a comprehensive survey of the empirical growth models and collect all possible determinants of growth applied in the cross-country convergence literature and end up with a list of 145 regressors. Gennaioli et al. (2013) utilize development accounting for examining the regional development determinants of 110 countries and consider variables such as temperature, distance to ocean, natural resource endowments, institutional quality, trust, ethnic heterogeneity and average education. On the other hand, for the within-country studies, it is quite difficult to work with large datasets given the data limitations especially for the developing countries.

The variables that we utilize in this chapter are also constrained by the availability of the data. Although we collect the most recent data at hand, variable set can be defined by the basic determinants of growth. For the variables that are not directly observed such as human capital and private investment, we make use of proxy variables. As to the human capital variable, two alternative measures are utilized: rate of high school and university graduates. This distinction is in line with Gennaioli et al. (2013) measuring the skilled labor as the share of population with a college degree and the others as the share of population with high school degree. Similarly, for the private investment variables, three different proxies are utilized for which the data is available from 1991: total deposits, specialized loans and total loans.

On the whole, the descriptive analysis of this chapter makes use of provincial real gross domestic product (GDP); number of high school and university graduates as proxies for human capital; population; employment; real public investment; total deposits, specialized loans and total loans as proxies for real private investment. The data are collected for 1991-2009 period and all real indicators are expressed in 1998 prices.

Real GDP series are derived from the Turkish Statistical Institute (TurkStat) database for 1991-2001 period and from the Ministry of Development for 2002-2009 period. The numbers of high schools and university graduates as well as the population series are compiled using the census data declared by TurkStat and data for the non-census years are obtained via interpolation. Employment variable represents the number of employees working as registered with any of the three social security institutions in Turkey[13]. Real public investment data are collected from the Ministry of Development. The figures for total deposits obtained from The Banks Association of Turkey (TBB) include public sector deposits, commercial deposits, interbank deposits, saving deposits and other institutions' deposits. The data for total loans, also obtained from TBB database, are considered in two different ways as their particular effects on productivity are concerned. First, specialized loans (agriculture, real estate, vocational, maritime, tourism and other); then total loans which also include non-specialized loans (consumer credits, credit cards, etc.) are investigated[14]. The sources and data descriptions are summarized in Table 1. The descriptive statistics of the variables are presented in Appendix A.1.

[13] The social security system in Turkey includes three main institutions, namely the Social Insurance Institution (SSK), the Retirement Fund (RF) and the Social Security Institution of Craftsmen, Tradesmen and other Self- Employed (Bag-Kur). The three institutions were unified under the name "Social Security Institution" in 2006. This study makes use of formal labor figures published by these institutions. It does not include the unregistered informal labor as reliable data does not exist at the provincial level.

[14] TBB (2010) reports that, by the end of 2009, total loan stock worth of 379.4 million TL was composed of 93 per cent non-specialized loans whereas the specialized loans constituted 7 per cent. The specialized loans were distributed as 44.2 per cent in agriculture, 17.2 per cent in vocational and 37.6 per cent in the other subcategories. The shares of real estate, maritime and tourism were less than 1 per cent.

Table 1: Data Description

Variable	Entitlement	Explanation	Unit	Source
Real GDP	gdp	Real GDP in 1998 year prices	million TL	Turkish Statistical Institute (1991-2001), T.R. Ministry of Development (2002-2009)
Human Capital	hc1	Number of high school graduates*	thousand person	Turkish Statistical Institute
	hc2	Number of university graduates*	thousand person	Turkish Statistical Institute
Population	pop	Total population at provincial level*	thousand person	Turkish Statistical Institute
Level of employment	emp	Number of employees registered to a social security institution	thousand person	T.R. Social Security Institution
Real Public Investment	pinv	Real public investment in 1998 prices	million TL	T.R. Ministry of Development
Real Private Investment	depos	Total deposits in 1998 prices (Commercial deposits, Public sector deposits, Interbank deposits, Saving deposits, Other Inst. deposits)	million TL	The Banks Association of Turkey
	slen	Specialized loans in 1998 prices(agriculture, real estate, vocational, maritime, tourism, other)	million TL	The Banks Association of Turkey
	loan	Total loans in 1998 prices (specialized and non-specialized)	million TL	The Banks Association of Turkey

* Data for the non-census years are obtained via interpolation

Using the collected series, provincial per capita GDP, growth, the ratio of high school and university graduates in provincial population, employment rate, per capita public investment, per capita deposits, per capita specialized loans and per capita total loans are calculated and embedded in the digital map of Turkey. In 1991, there were 73 provinces in Turkey whereas in 2009 the number of provinces went up to 81. The newly defined provinces and their original correlatives are as follows: in 1991 Bartın separated from Zonguldak; in 1992 Ardahan and Iğdır from Kars; in 1995 Yalova from İstanbul, Karabük from Zonguldak, Kilis from Gaziantep; in 1996 Osmaniye from Adana and in 1999 Düzce from Bolu province. In accordance with the objective of this study, to conceive the regional development of Turkey after 1991 and arrive at comparable results, the data are aggregated to the 73 provinces of the starting year[15].

Main regional indicators in 1991 and 2009 are presented in Figure 3. In both years, per capita GDP figures were quite dissimilar in the Eastern and Western parts of the country. The values in 2009 show that in western regions and along the coastal provinces in particular, welfare levels seem to have increased. On the other hand, there was a decline in per capita incomes of the two big cities, İstanbul and Ankara which received quite a large amount of immigrants. The ratios of high school and university graduates in the population show that Ankara has been a leading province in the education and hence human capital figures. Southeast Anatolia, on the other hand, has been the most underdeveloped region in this sense. In the population series, İstanbul has always been a significant outlier; as of year 2009, 17.8 per cent of the country population was residing in İstanbul[16]. This was followed by Ankara, İzmir, Bursa and Adana.

[15] The aggregated 73 provinces as of 1991 and the corresponding NUTS codes are provided in the Appendix.

[16] OECD (2012) defines functional urban areas and divides them into four categories according to the population size: small urban areas, medium-sized urban areas, metropolitan areas, large metropolitan areas. Large metropolitan areas are described as the provinces with a population of 1.5 million or more. In case of Turkey, İstanbul has been the most striking model of these metro areas with increasing population density through time. The literature on urban studies has been dwelling upon the characteristics of these cities. Remarkably, Ingram (1998) anticipates that as the developing countries urbanize, the large metropolitan areas will continue to grow and the employment structures will be evolving, with decentralization in manufacturing and centralization in services.

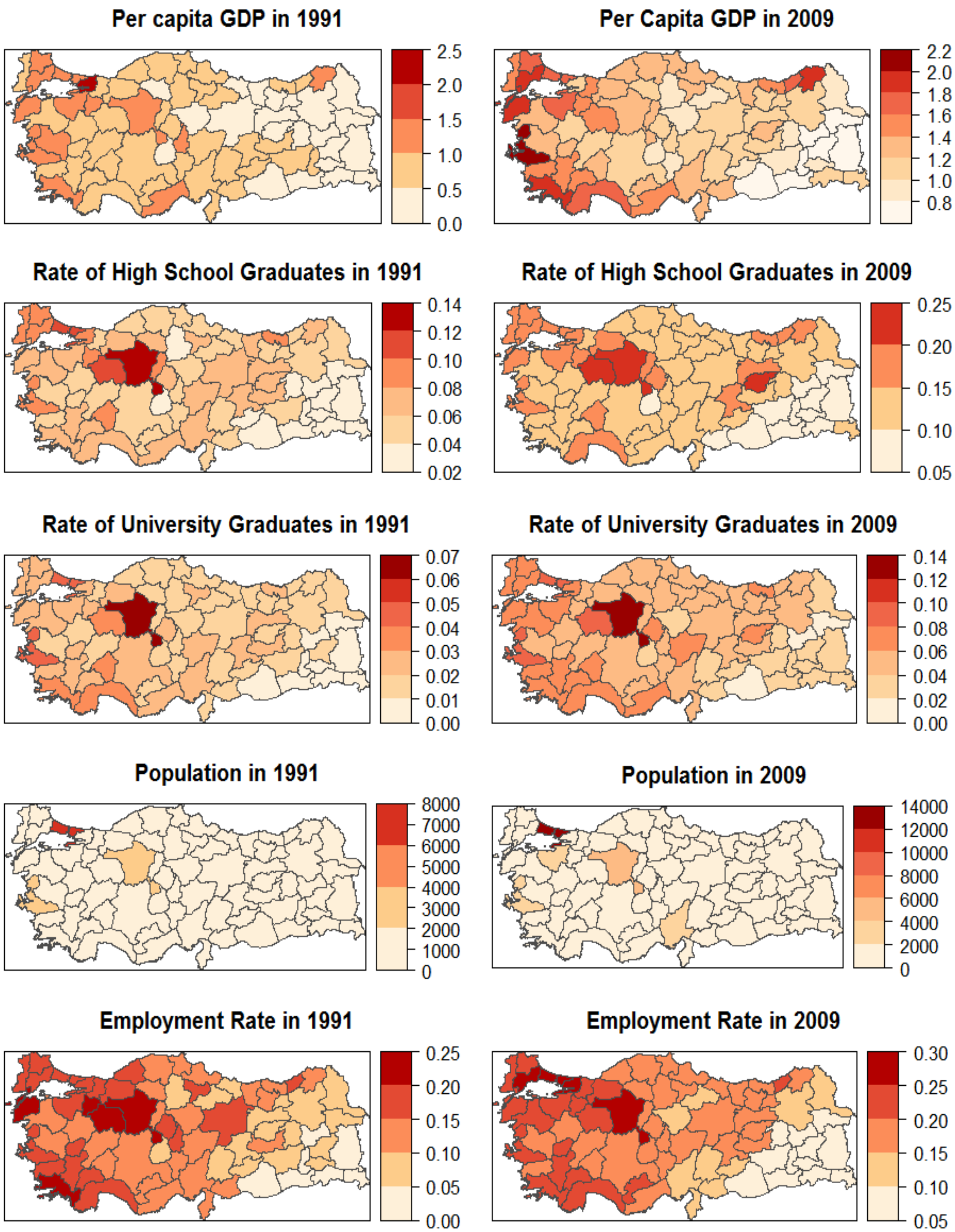
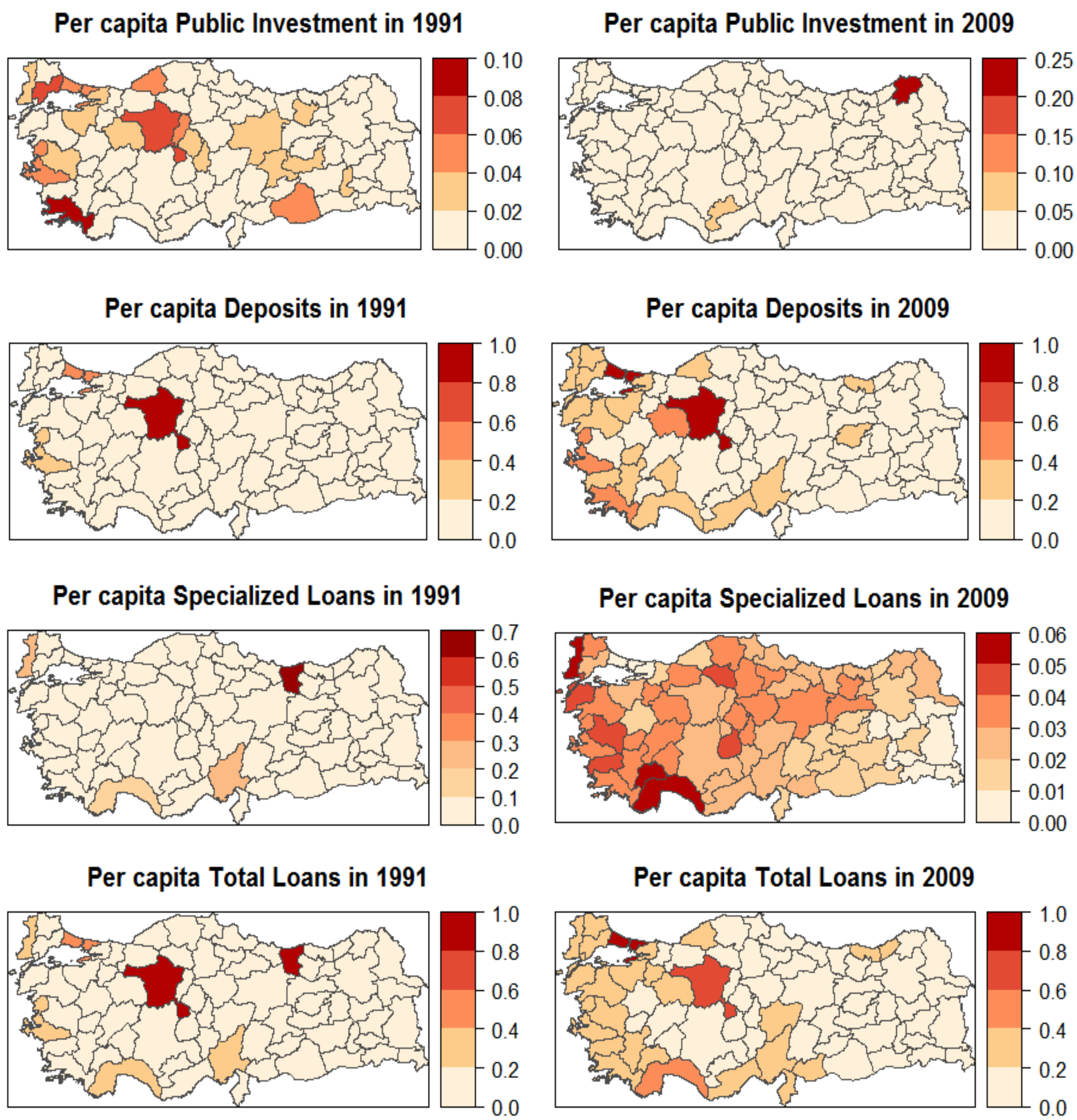


Figure 3: Main Regional Indicators in Turkey for 1991-2009 Period



Notes: Population, high school/university graduates and number of employed people are expressed in *thousand person*. Gross Domestic Product, public investment, deposits, specialized loans and total loans are presented in *million TL*. The corresponding ratios are calculated based on these units.

Figure 3 (cont'd): Main Regional Indicators in Turkey for 1991-2009 Period

As to the employment rates, high discrepancies in 1991 have been compensated for some Eastern provinces in 2009; but still existed particularly in Southeastern Anatolia. This may be caused by high rates of informal labor, unpaid family work especially in the agriculture sector, high rates of increase in population and hence comparably high density of non-working-age population under age 15.

Per capita public investment data show that Muğla, Ankara and Tekirdağ have somewhat lost their significance from 1991 to 2009. It is observed that public investments in proportion to population have stayed in a certain range for all provinces, with the exception of Artvin and Karaman. As for the private investments, western regions have experienced an increase whereas no major changes have taken place in the eastern provinces. In the per capita deposits indicators, initially only a few metropolises such as İstanbul, Ankara and İzmir were above the average. In 2009, although the shares of Aegean and Mediterranean coastal cities became higher, they could not catch up with rates in İstanbul and Ankara. Eskişehir and Muğla seemed to catch up with İzmir when the ratio of deposit holdings is concerned. The specialized loans, in which agriculture has a particular importance, have been concentrated mostly in the mid-Anatolian regions. On the other hand, total loans including the credit card holdings and consumer credits have shown a pattern analogous to the level of development. In the western provinces which have been more prone to consumption and notably in İstanbul, Ankara and Antalya; the loan holding rates were quite high. By the end of 2009, the highest average per capita loans were observed in İstanbul with 10,395 TL which was followed by Ankara with 8,240 TL and Antalya with 5,624 TL. The country-level average was 4,336 TL and Muş province was at minimum with 377 TL per person (TBB, 2010).

The descriptive analysis shows that since the beginning of 1990s, although there seems to be an improvement in terms of declining regional discrepancies in general, some clustering have persisted in particular regions. This clustering in regional indicators makes the consideration of spatiality essential given that variables affecting provincial income levels such as employment, human capital and private investment move from one region to another as a result of labor and capital mobility. With increasing ease of mobility due to low transfer costs and transportation facilities, income in one province would likely to affect that of neighboring provinces. The input-output linkages among the provinces would further strengthen the spatial dependency. Moreover, any possible shock that affects a region, such as terror, natural disaster, sudden changes in the climatic and soil structure, would affect the adjacent regions sooner and deeper as compared to the non-neighbors. Therefore, one can expect that spatial relations may have an influence on regional growth rates, which will be tested in the next section.

2.4. A Spatial Extension to Regional Growth Convergence in Turkey

2.4.1. Empirical Results of Standard Solow Swan Growth Model

In the Solow-Swan regional convergence model, growth rates are linked to the initial incomes and as long as the provinces with initially lower levels of GDP catch higher growth rates compared to high-income provinces, there exists absolute convergence. Conditional convergence, on the other hand, takes into account the structural differences among regions by including certain control variables in the model. In that sense, regional convergence can be explained not only by the initial income levels but also by other explanatory variables that may affect growth rates.

Throughout the estimations and testing of the conditional convergence, the rate of high school graduates is selected as a proxy for human capital. This is consistent with the previous literature (Barro, 2001) and provides a better representation at regional level as this variable reflects higher variability across provinces. For the private investment variable, this study makes use of total loans as a proxy, which is comparatively more reliable[17]. Employing these variables, standard Solow-Swan growth model characterizing the absolute and conditional convergence are presented in equations (2.4) and (2.5) respectively:

[17] The specialized loans, which have a particular productive effect through agriculture, constitute less than 5 per cent of total loans, hence is not a very good representative of the private investment in sectors other than agriculture. The deposits are not very descriptive either, since they reflect the private consumption figures and their contribution to the creation of value-added is quite limited.

$$\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right)=\alpha+\beta\log(gdppc91)+\varepsilon \tag{2.4}$$

$$\begin{aligned}\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right)=\alpha+\beta\log(gdppc91)+\gamma_1\log(hc1pc91)+\gamma_2\log(emppc91)\\+\gamma_3\log(pinvpc91)+\gamma_4\log(loanpc91)+\varepsilon\end{aligned} \tag{2.5}$$

where $\log\left(\frac{gdppc09}{gdppc91}\right)$ is the growth of per capita GDP over 1991-2009 period, $\log(gdppc91)$ is the per capita GDP in the initial year, $\log(hc1pc91)$ is the per capita high school graduates in the initial year representing a proxy for human capital, $\log(emppc91)$ is the per capita employment in the initial year, $\log(pinvpc91)$ is the per capita public investments in the initial year and $\log(loanpc91)$ is the per capita loans in the initial year as a proxy for private investment. β is the convergence parameter, negative and significant values of it imply the existence of convergence. γ represents the coefficients of the control variables in the conditional convergence model and α is the intercept term. ε is independent and identically distributed error term with mean 0 and variance σ^2.

In accordance with cross-sectional convergence analysis, equations (2.4) and (2.5) reflect the average growth rate over the time interval of T=18, considering the two observations at the beginning and at the end of the time period. In these logarithmic empirical functions, the slope coefficient of initial income variable becomes $\beta=-\frac{1-e^{bT}}{T}$ where T is the number of years and b is the convergence rate[18]. Straightforward arithmetic manipulations give the convergence rate as follows:

[18] The Taylor series approximation from the structural Solow growth model to the empirical model and the derivations can be found in Barro and Sala-i Martin (2004).

Convergence Rate: $b = -\frac{\ln(1+\beta T)}{T}$ (2.6)

Half-life, as a measure representing half-way between the initial value and the steady state value, is expressed as:

Half-life: $\tau = -\frac{\ln(2)}{\ln(1+\beta)}$ (2.7)

OLS outcomes for the standard Solow convergence models are presented in Table 2. The results indicate that the coefficient of initial GDP variable, $\log(gdppc91)$, is found to be negative and significant, suggesting the presence of absolute convergence. Under the conditional convergence framework; it is observed that including human capital, employment, public investments and private investments cause an increase in the rate of convergence.

Table 2: OLS Estimation Results of the Convergence Models

	Absolute Convergence	***Conditional Convergence***
Intercept	0.0177***	0.0811***
	(0.0000)	(0.0000)
log(gdppc91)	-0.0373***	-0.0499***
	(0.0000)	(0.0000)
log(hc1pc91)		0.0231***
		(0.0000)
log(emppc91)		0.0105***
		(0.0096)
log(pinvpc91)		-0.0028*
		(0.0930)
log(loanpc91)		-0.0029
		(0.1245)
Convergence Rate	0.0618	0.1273
Half-Life	18.25	13.53
Jarque-Bera normality test	2.3372	2.1524
	(0.3108)	(0.3409)
Breusch-Pagan Heteroscedasticity Test	0.0355	12.5235**
	(0.8505)	(0.0283)
RESET test	4.8579**	4.4626***
	(0.0106)	(0.0001)
F-statistic	247.20***	88.03***
	(0.0000)	(0.0000)
Residual standard error	0.0113	0.0090
Multiple R-squared	0.7769	0.8679
Adjusted R-squared	0.7737	0.8580
Degrees of Freedom	71	67

Notes: The dependent variable is the provincial per capita GDP growth. The values in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

To have reliable coefficients, the estimated OLS model should satisfy the assumptions of independent and identically distributed residuals and there should not be any specification error. The latter is checked by RESET test[19] which imply that there is misspecification in both the absolute and conditional convergence models. For the former, the residuals of OLS model should be checked whether they are NID~$(0,\sigma^2)$.

[19] This test mainly captures the misspecification caused by nonlinearity in the model.

The following regression diagnostics reveal that the standard Solow growth models estimated by OLS do not fulfill this condition.

i) Normality

Jarque-Bera normality test results in Table 2 indicate that the residuals are normally distributed. To observe this pattern graphically, quantile-quantile plots (Figure 4) and residual distribution plots (Figure 5) for absolute and conditional convergence are also presented. The figures point out a very light-tailed distribution for both models.

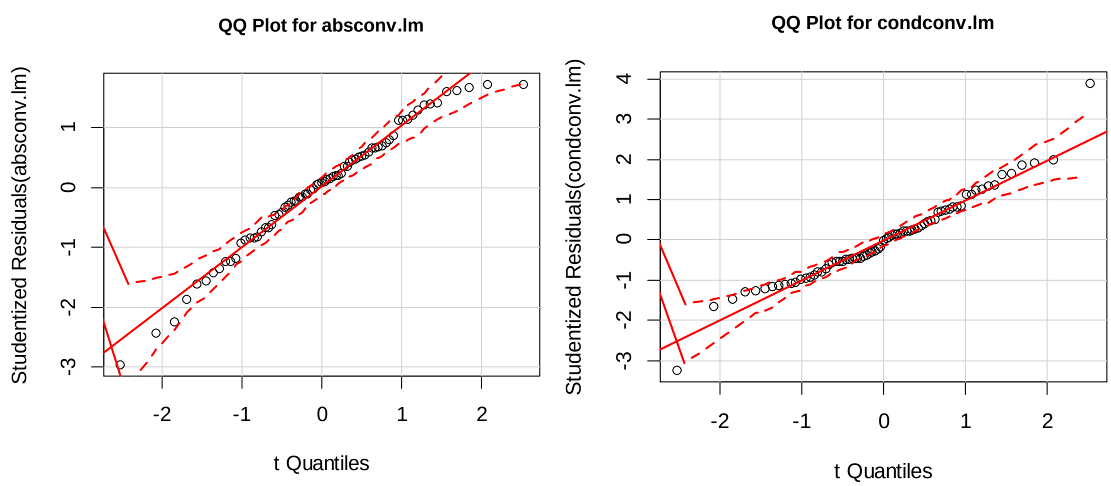


Figure 4: Quantile-Quantile Plots for the OLS Estimated Models

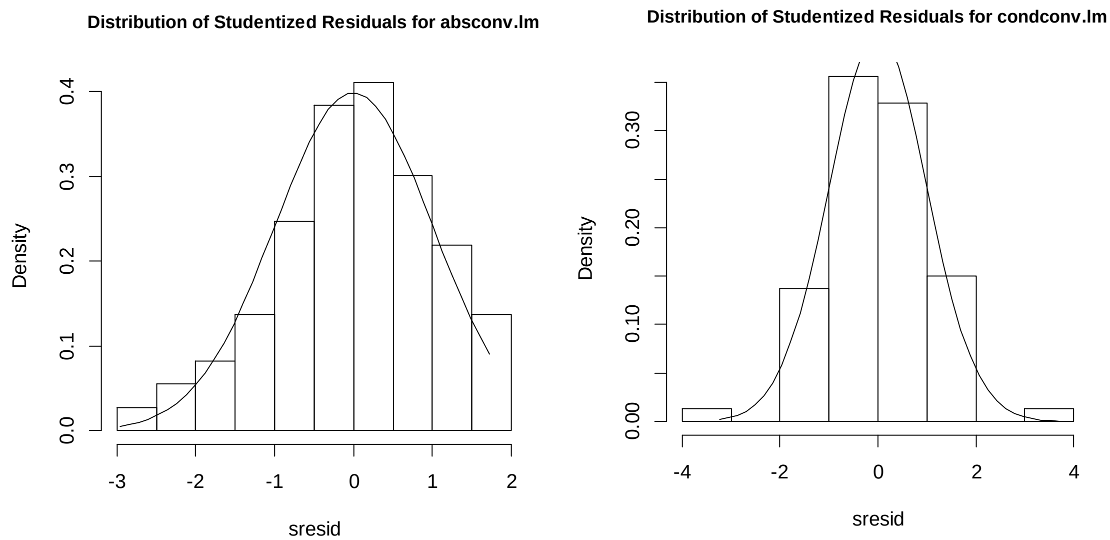


Figure 5: Residual Distribution for the OLS Estimated Models

Observing that the Q-Q plots are almost on the 45-degree line and that the residuals have nearly a bell-shaped density with mean zero, one may claim that the residuals are normally distributed. In effect, we carry out a maximum likelihood estimation method based on the assumption of normal distribution in section (3.5.1) and in the appendix we show for the selected model that the outcomes are better as compared to that of generalized method of moments.

ii) Heteroscedasticity

Breusch-Pagan test results in Table 2 indicate the presence of heteroscedasticity in the conditional convergence model. Figure 6 reveals that mean residuals slightly increase for both the absolute and conditional convergence models as indicated by the red line in the plots. Moreover, the spread of the residuals slightly increase for the fitted values of the conditional convergence model. As the non-constant spreads are considered as a sign of heteroscedasticity, we cannot claim that the conditional convergence model is satisfying the homoscedasticity criterion.

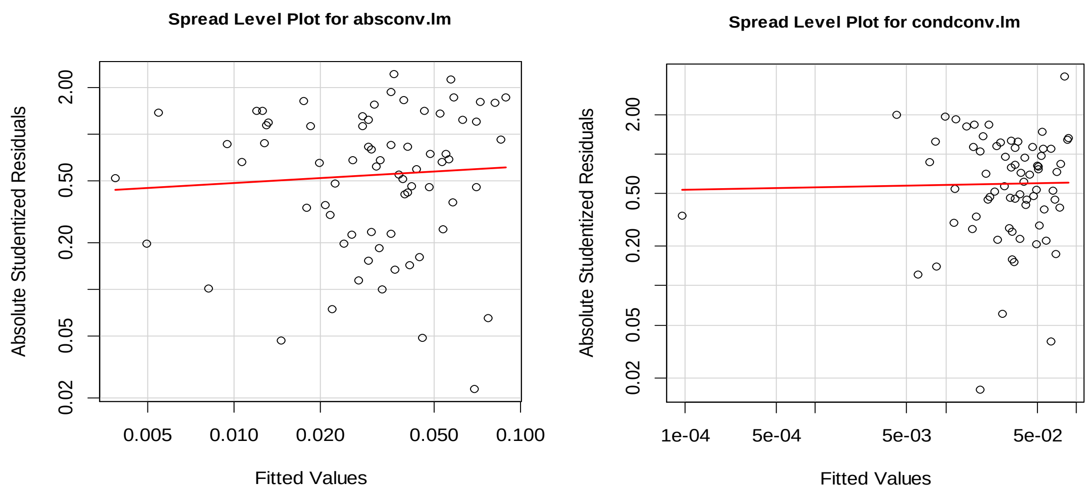


Figure 6: Spread Level Plots for the OLS Estimated Models

The heteroscedasticity inherent in the data can be attributed to various reasons, one of which is the possible spatial dependence in the error terms.

iii) Spatial Autocorrelation

It is apparent from Figure 7 that OLS residuals show concentration among the adjacent regions as they tend to have the same colors. This residual clustering may be associated with possible omitted spatiality in the base model.

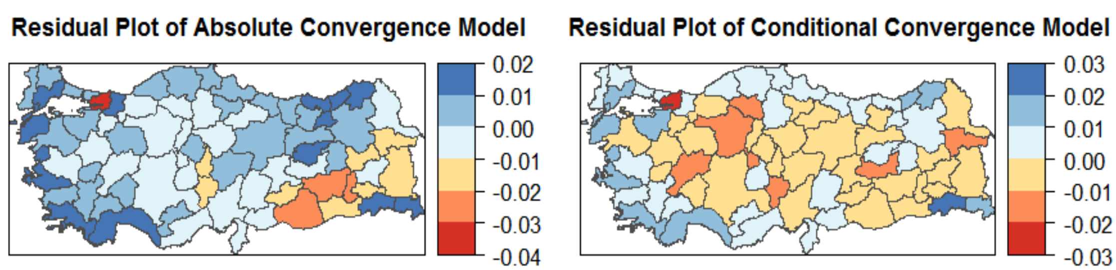


Figure 7: Residual Plots of the Models Estimated by Ordinary Least Squares

The diagnostics reveal that apart from the possible nonlinearity that may exist in the model, the results for heteroscedasticity seem to be problematic. Yet, the most important shortcoming of the standard model remains to be possible spatial autocorrelation which may also be the cause of heteroscedasticity in the model. It is feasible to conduct detailed tests for residual spatial autocorrelation after a neighborhood matrix is introduced in the model.

2.4.2. Introducing Neighborhood Definition and Spatial Weights Matrix

To account for spatial proximity in the regression, neighborhood relations should be defined in a mathematical structure. Suppose, we denote the spatial weights matrix as W_{NxN} where N is the number of cross-sections. We end up with a 73x73 matrix whose cells represent the degree of proximity in accordance with well-defined weights for the neighborhood. In this chapter, the matrix is based on the binary contiguity weights, which implies that provinces sharing a common border are considered as neighbors taking a value of 1 on the matrix. Non-neighboring regions, on the other hand, take a value of zero and the elements on the diagonal are zero by definition, since a province cannot be a neighbor of itself. Hence the elements of the matrix are as follows:

$$w_{ij} = \begin{cases} 1 \ , & j \in N(i) \\ 0 \ , & j \notin N(i) \end{cases} \tag{2.8}$$

where $N(i)$ is the set of all neighbors, w_{ij} correspond to the elements of the weights matrix. Given this definition, the neighborhood relations can be observed as in Figure 8. In the figure, the provinces sharing common borders are connected with a line. Here, we make use of first order binary contiguity definition, i.e. the effects of immediate neighbors are analyzed such that the provinces connected with a single line are at stake.

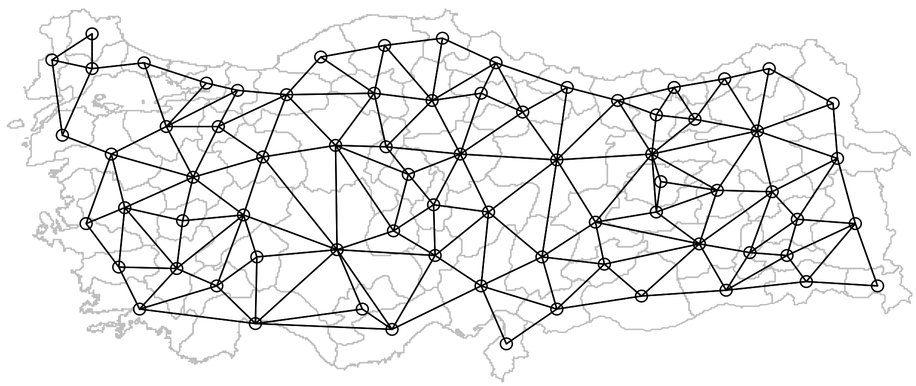


Figure 8: Neighborhood in Turkey according to binary contiguity weights

This weights matrix is row-standardized so that sum of the row elements adds up to one. Define $\eta_i = \sum_j w_{ij}$ where η_i corresponds to the row-sum and standardize the matrix as follows:

$$w_{ij}^* = \frac{w_{ij}}{\sum_j w_{ij}} = \frac{w_{ij}}{\eta_i} \qquad \sum_j w_{ij}^* = 1 \tag{2.9}$$

The rows in the matrix denote the effect of all the other provinces on any specified province and the columns correspond to the converse, i.e. the effect of any specified province on all the other provinces. Hence, row-standardization implies that for any specified province, the impacts of neighboring provinces are equalized (Elhorst, 2010a).

2.4.3. Exploratory Spatial Data Analysis

For an elaborate testing of spatiality in the data, the spatial weights matrix is employed in the exploratory spatial data analysis and tests are performed both at the global and local level for the detection of any possible spatial autocorrelation in the OLS estimated model. The results are crucial to have reliable coefficients in the regression since disregarding spatial relations that need to be included in effect may cause serious estimation problems. Global and local spatial autocorrelation tests will be further employed for the GDP per capita figures, as conventional in the related literature (see LeGallo and Ertur (2003); Gezici and Hewings (2007) for ESDA on regional growth convergence).

i) Testing for Spatial Autocorrelation in the OLS Estimated Models

For both convergence models, clustering observed in the disturbance terms of the OLS estimation, as indicated in Figure 7, may be caused by neglecting possible spatial autocorrelation. First, Moran I statistic introduced by Cliff and Ord (1972) is computed for the residuals of the OLS estimated model and tested against the null hypothesis of no spatial autocorrelation. Under the null hypothesis there is no spatial autocorrelation, Moran I equals to zero. By definition, the index values range between -1 and +1; negative and significant values imply negative spatial correlation whereas positive and significant values denote positive spatial correlation. Positive spatial autocorrelation can be interpreted as a signal of clustering, whereas negative spatial autocorrelation renders dispersion.

Table 3: Tests for Spatial Autocorrelation in the OLS Estimated Model

	Absolute Convergence	***Conditional Convergence***
Moran-I	0.3182***	0.1955***
	(0.0000)	(0.0008)
LMerr	17.1321***	6.4648**
	(0.0000)	(0.0110)
LMlag	0.9488	0.4344
	(0.3300)	(0.5098)
RLMerr	19.0920***	6.3556**
	(0.0000)	(0.0117)
RLMlag	2.9086*	0.3252
	(0.0881)	(0.5685)

Note: The values in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

The results for Moran I tests presented in Table 3 indicate the evidence of positive spatial autocorrelation for both absolute and conditional convergence models estimated by OLS. The scatterplot of Moran I index presented in Figure 9 also exhibits the positive association between disturbance terms of the OLS model and their spatial lagged counterparts. The slope of the graph shows the values of Moran I statistic; the values on the upper-right (left) and lower-left (right) corners signify positive (negative) spatial autocorrelation.

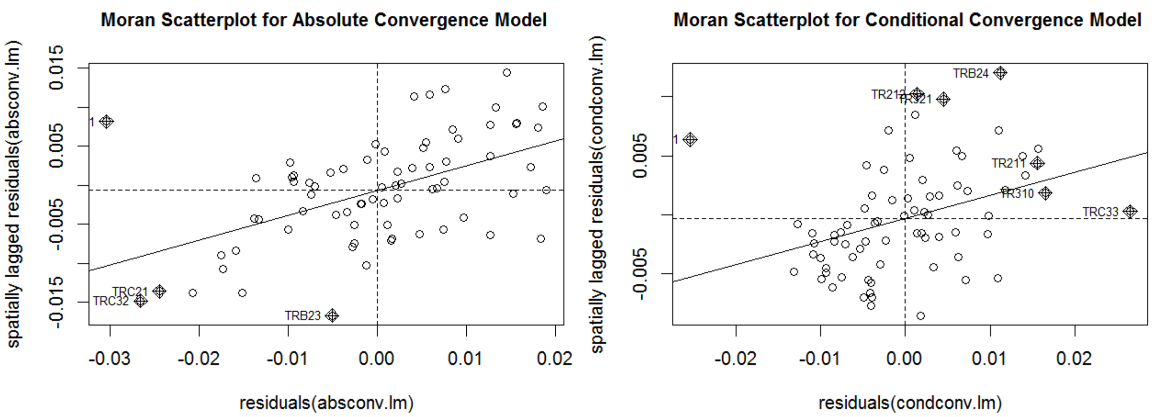


Figure 9: Moran Scatterplots for OLS Residuals

Local Moran I statistic allows a further clarification whether there exists clustering or dispersion among the OLS residuals. Figure 10 confirms positive spatial autocorrelation as the number of provinces taking a positive local Moran I value is larger than those with a negative value.

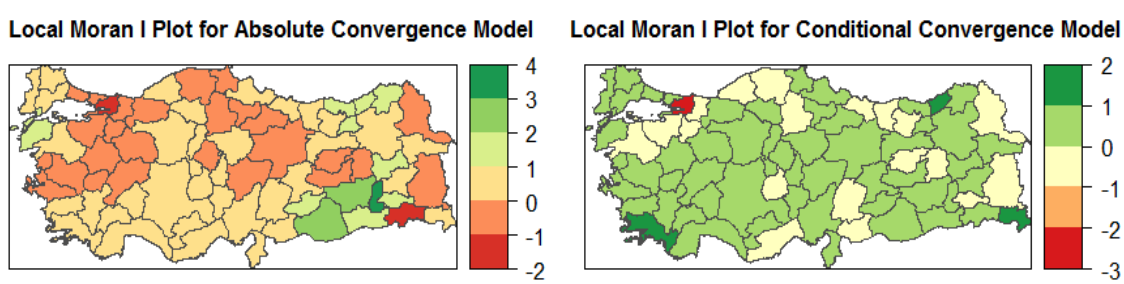


Figure 10: Local Moran I Plots for OLS Residuals

Global and local Moran I statistics presume that the positive spatial autocorrelation reflects itself as clustering in the OLS residuals whereas the cause of this correlation is an important question that remains to be answered. Moran I statistic is not sufficient to answer which spatial structure in particular leads to the apparent spatial autocorrelation since it does not have an explicit alternative hypothesis in terms of the spatial structure; rather it is formulated as a "spatial independence versus spatial dependence" problem. There may be spatial dependence which reflects itself as an autocorrelation because of omitted spatial lag causing positive spillovers among neighbors. For the convergence models, this can be observed when a rise in growth rates of one region triggers a rise in the growth rates of the neighboring regions. If the model suffers from omitted spatially lagged dependent variable problem, OLS estimates would be biased and inconsistent. Moreover, there may be spatial heterogeneity in the model such that a shock in one region is transmitted to the neighboring regions in a similar vein. This would be considered as a sign of spatiality in the error terms leading to heteroscedastic innovations and inefficient estimates in the OLS model.

In order to uncover the form of spatial relation, Lagrange multiplier (LM) tests are proposed by Burridge (1980). Under the null hypothesis that there is no spatial correlation, LMlag and LMerr statistics correspond to testing the spatial lag and spatial errors, respectively. Anselin et al.(1996) suggests the robust versions of these test statistics under local misspecification. Accordingly, RLMlag statistic is used to test for spatial lag model robust to the presence of spatial error and RLMerr statistic is employed for testing spatial error model robust to the presence of spatial lag. Based on the LM statistics and their robust counterparts, the decision rule would be as follows: If the LMlag (LMerr) statistic provides lower p-value compared to the LMerr (LMlag) and RLMlag (RLMerr) is significant whereas RLMerr (RLMlag) is not, the true from of the spatial correlation is spatial lag (spatial error).

For the estimated absolute and conditional convergence models, the spatial error specification seems to be more appropriate to characterize the data given that LMerr and RLMerr are significant whereas the LMlag and RLMlag statistics are not (Table 3). One should bear in mind that these initial results are useful for testing the presence of spatial autocorrelation but they are not sufficient to arrive at a definitive conclusion that the convergence models should be specified as a spatial error model. These statistics are very helpful for testing the initial two forms of spatiality; yet more complicated spatial structures nesting spatial error model may also persist in the data which motivates us to estimate several functional forms as in section (3.5.1).

The overall analysis of standard models reveals that the regional data at hand is subject to spatial heterogeneity and the standard OLS estimated models bring out inefficient estimates at best. The positive spatial autocorrelation shows itself as a clustering in the data which may lead to different spatial regimes in which low and high values cluster in their own neighborhood.

ii) Testing for Spatial Autocorrelation in GDP per capita

Following the literature on regional growth convergence carrying out exploratory spatial data analysis (LeGallo and Ertur, 2003; Gezici and Hewings, 2007) we present tests for spatial autocorrelation in GDP per capita variable.

Table 4: Tests for Global Spatial Autocorrelation for Log GDP per capita

Statistic	Log GDPPC 1991	Log GDPPC 2009
Global Moran I	0.5897***	0.5730***
	(0.0000)	(0.0000)
Geary's C	0.3757***	0.4131***
	(0.0000)	(0.0000)
Getis-Ord Global G	0.0732*	0.0673
	(0.0803)	(0.8714)

Notes: Moran I and Geary's C statistics are computed for log GDP per capita using row-standardized binary contiguity weights matrix. For the calculation of Getis-Ord Global G statistic, due to the nature of the test, GDP per capita variables are considered without logarithmic transformation (as they should be non-negative) and the spatial matrix is based on non-standardized binary contiguity weights. The values in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

Global Moran I tests are carried out for the log GDP per capita variables for the initial and final year, whose interpretation are similar to that of OLS residuals. Table 4 and Figure 11 reveal that the values are showing positive spatial autocorrelation, i.e. similar values display a statistically significant clustering. These clusters may be observed in different clubs where high and low values are concentrated in their close vicinity.

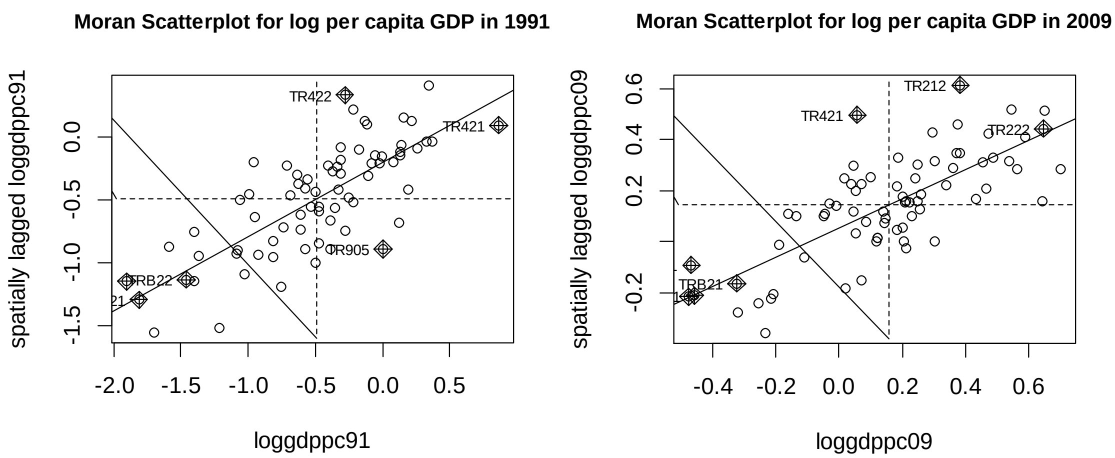


Figure 11: Moran Scatterplots for Log GDP per capita in 1991 and 2009

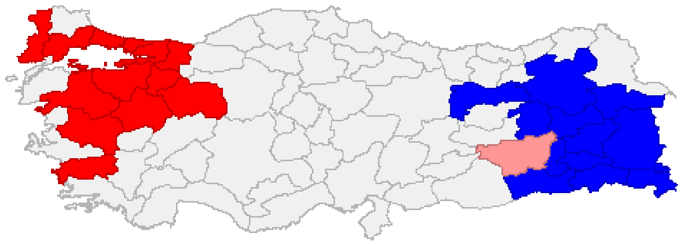
For the Geary's C test, the values of statistic vary from 0 to 2 where 0 indicates perfect positive autocorrelation, 2 indicates perfect negative autocorrelation and 1 implies no autocorrelation. Hence the interpretation of Geary's C is opposite to that of Moran I as the lower values are now indicative of positive autocorrelation. The results for Geary's C tests also confirm clustering in the log GDP per capita in the initial and final year since the values of the statistics lie between 0 and 1 and significant (Table 4).

Getis-Ord Global G test, on the other hand, mainly measures the concentration under the alternative hypothesis of positive spatial autocorrelation. Significant positive values of the test implies concentration of high values of the variables (*hot spots*) whereas significant negative values show concentration of the low values of the variable (*cold spots*), in either case there exists positive spatial autocorrelation. The test results suggest GDP per capita figures in 1991 are clustered such that the high values are concentrated in their own neighborhood at 10% significance level (Table 4). On the other hand, for 2009, the concentration in GDP per capita cannot be described as hot or low spots globally and more elaborate discussion at local level is crucial to determine the character of clustering.

To identify the structure of the clusters, the analysis is extended to Local Indicators of Spatial Association (LISA) as in Figure 12. Local Moran I cluster maps for GDP per capita in 1991 and 2009 convey mainly two regions of concentration in Turkey. High-high and low-low regions exhibit positive spatial autocorrelation in log GDP per capita figures showing that high values cluster mostly in the Marmara and Aegean regions whereas low values are concentrated in Southeastern Anatolia. The mid-Anatolian provinces, on the other hand, are not described by significant positive or negative spatial autocorrelation.

Local Gi statistics without taking the log of GDP per capita also confirm the results of local Moran I. Broadly speaking; the hot spots prevail in the Marmara and Aegean regions in the initial and final year. Cold spots, on the other hand are detected in Eastern and Southeastern Anatolia whereas the surface area for these clustered regions with low GDP per capita has diminished over 1991-2009.

LISA Local Moran I Cluster Map for logGDPPC91



Red: High-High (12 provinces)
Blue: Low-Low (12 provinces)
Purple: Low-High (0)
Pink: High-Low (1 province)
Not significant (48 provinces)

LISA Local Moran I Cluster Map for logGDPPC09

Red: High-High (10 provinces)
Blue: Low-Low (11 provinces)
Purple: Low-High (1 province)
Pink: High-Low (0)
Not significant (51 provinces)

Gi cluster map for GDPPC91

Red: High (9 provinces)
Blue: Low (14 provinces)
Not significant (50 provinces)

Gi cluster map for GDPPC09

Red: High (10 provinces)
Blue: Low (11 provinces)
Not significant (52 provinces)

Notes: Local Moran I maps are obtained under randomization (5000 permutations) for log GDP per capita using row-standardized binary contiguity weights. Getis-Ord local Gi maps are obtained under normality for GDP per capita using non-standardized binary contiguity weights.

Figure 12: Cluster Analysis of GDP per capita

Overall, explanatory spatial data analysis suggests that there is positive spatial autocorrelation in values of the GDP per capita over 1991-2009 period in Turkey. This also reflects itself as a clustering in the OLS residuals which induces inefficient coefficients at best. If the data structure is incorporating more complicated forms of spatiality such as spatial dependence in the regressand and regressors, then OLS estimates may even turn out to be biased and inconsistent. This motivates us to introduce spatial econometric extensions to the standard regional convergence models by discussing several possible forms of spatial dependence that may be inherent in the data.

2.4.4. Spatial Econometric Modelling

Elhorst (2010a) discusses different spatial econometric models proposed in the literature and suggests that one should consider all alternative forms to arrive at the most appropriate specification. In this chapter, a similar procedure is carried out running six different spatial econometric regressions for both absolute and conditional convergence models and a general-to-specific approach in model selection.

(i) SAC Durbin Model

Most generic model, SAC Durbin, includes all forms of spatiality by means of spatial lags in the dependent and independent variables, and spatial error components. The extended absolute convergence model using a SAC Durbin model implies that income growth in a particular province can be explained by its own initial income per capita, growth and income per capita in the neighboring regions as well as the spatial heterogeneity induced by the disturbance terms in the regression:

$$\begin{aligned} \frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right) &= \alpha + \beta\log(gdppc91) + \rho W\log\left(\frac{gdppc09}{gdppc91}\right) \\ &\quad + \theta_1 W\log(gdppc91) + u \qquad (2.10) \\ u &= \lambda W u + \varepsilon \end{aligned}$$

where ρ is the coefficient of spatial lag in the dependent variable, θ_i is the coefficient of spatial lag in the independent variable, λ is the coefficient of the spatial error term, the other parameters and variables are as defined before. The conditional convergence model, on the other hand, incorporates control variables human capital, employment, public investment and private investment and their spatially lagged counterparts.

$$
\begin{aligned}
\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right) = \alpha + \beta\log(gdppc91) + \gamma_1\log(hc1pc91) + \gamma_2\log(emppc91) \\
+ \gamma_3\log(pinvpc91) + \gamma_4\log(loanpc91) + \rho W\log\left(\frac{gdppc09}{gdppc91}\right) \\
+ \theta_1 W\log(gdppc91) + \theta_2 W\log(hc1pc91) + \theta_3 W\log(emppc91) \\
+ \theta_4 W\log(pinvpc91) + \theta_5 W\log(loanpc91) + u
\end{aligned}
\tag{2.11}
$$

$$u = \lambda Wu + \varepsilon$$

The conditional convergence model in equation (2.11) describes the average growth rate in any province by using the initial income and other control variables of itself and its neighbors as well as the growth rate of the neighbors. Moreover, this growth rate is subject to spatial heterogeneity via first order spatial autoregressive structure in the error terms.

(ii) SAC Model

SAC model[20] named by LeSage and Pace (2009) corresponds to the first order spatial autoregressive model with spatial autoregressive disturbances, including the spatial lag in the dependent variable and the spatial error term. The specifications for absolute and conditional convergence models are presented in equations (2.12) and (2.13) respectively:

[20] It corresponds to the SARAR(1,1) model, which is the spatial autoregressive model (of order one) with autoregressive disturbances (of order one). Kelejian and Prucha (1998) call it also as Cliff-Ord type spatial model.

$$
\begin{aligned}
&\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right) = \alpha + \beta\log(gdppc91) + \rho W\log\left(\frac{gdppc09}{gdppc91}\right) + u \qquad (2.12)\\
&u = \lambda Wu + \varepsilon
\end{aligned}
$$

$$
\begin{aligned}
\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right) &= \alpha + \beta\log(gdppc91) + \gamma_1\log(hc1pc91) + \gamma_2\log(emppc91)\\
&+ \gamma_3\log(pinvpc91) + \gamma_4\log(loanpc91) + \rho W\log\left(\frac{gdppc09}{gdppc91}\right) + u \qquad (2.13)\\
u &= \lambda Wu + \varepsilon
\end{aligned}
$$

These models are nested in SAC Durbin models where it only excludes the spatially lagged independent variables. In this case, the average growth rate in any province is explained by the initial incomes of that province and other control variables, the growth rate of the neighboring provinces and the spatial heterogeneity described by the error terms.

(iii) Spatial Durbin Model

Spatial Durbin model allows for spatiality in the dependent variable and the independent variables. Yet, it does not cover the spillover effects of stochastic shocks in the adjacent regions. The absolute convergence model under the spatial Durbin specification can be identified as follows:

$$
\begin{aligned}
\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right) &= \alpha + \beta\log(gdppc91) + \rho W\log\left(\frac{gdppc09}{gdppc91}\right)\\
&+ \theta_1 W\log(gdppc91) + \varepsilon \qquad (2.14)
\end{aligned}
$$

Conditional convergence model, on the other hand, incorporates other explanatory variables, and their spatially lagged correspondents:

$$
\begin{aligned}
\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right) &= \alpha + \beta\log(gdppc91) + \gamma_1\log(hc1pc91) + \gamma_2\log(emppc91) \\
&+ \gamma_3\log(pinvpc91) + \gamma_4\log(loanpc91) + \rho W\log\left(\frac{gdppc09}{gdppc91}\right) \\
&+ \theta_1 W\log(gdppc91) + \theta_2 W\log(hc1pc91) + \theta_3 W\log(emppc91) \\
&+ \theta_4 W\log(pinvpc91) + \theta_5 W\log(loanpc91) + \varepsilon
\end{aligned}
\tag{2.15}
$$

Spatial Durbin model is also nested by the SAC Durbin model in the sense that it only excludes the spatial error term. Spatial dependence in all forms is incorporated in the model whereas the spatial heterogeneity is left out in the analysis.

(iv) Spatial Durbin Error Model

Spatial Durbin error model allows for spatial dependence through the independent variables and spatial heterogeneity via the disturbance terms. Hence, with regard to absolute convergence model, the average growth rate of any province is explained by its own initial income, neighbors' initial income as well as the spillover effects of a shock experienced by the neighbors:

$$
\begin{aligned}
&\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right) = \alpha + \beta\log(gdppc91) + \theta_1 W\log(gdppc91) + u \\
&u = \lambda Wu + \varepsilon
\end{aligned}
\tag{2.16}
$$

The conditional convergence model includes also the conditioning variables and their spatial lags as the variables to determine the average growth rate of the province at hand, as shown in equation (2.17):

$$\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right)=\alpha+\beta\log(gdppc91)+\gamma_1\log(hc1pc91)+\gamma_2\log(emppc91)$$
$$+\gamma_3\log(pinvpc91)+\gamma_4\log(loanpc91)+\theta_1 W\log(gdppc91)$$
$$+\theta_2 W\log(hc1pc91)+\theta_3 W\log(emppc91)+\theta_4 W\log(pinvpc91) \quad (2.17)$$
$$+\theta_5 W\log(loanpc91)+u$$
$$u=\lambda Wu+\varepsilon$$

Spatial Durbin error model is also nested in SAC Durbin model under the restriction that the spatial lag in the dependent variable is dropped in the equation.

(v) Spatial Lag Model

Spatial lag model[21] indicates spatial interaction via the spatially lagged dependent variable. The absolute convergence model becomes:

$$\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right)=\alpha+\beta\log(gdppc91)+\rho W\log\left(\frac{gdppc09}{gdppc91}\right)+\varepsilon \quad (2.18)$$

The conditional convergence model includes the additional covariates, all other factors remaining the same:

$$\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right)=\alpha+\beta\log(gdppc91)+\gamma_1\log(hc1pc91)+\gamma_2\log(emppc91)$$
$$+\gamma_3\log(pinvpc91)+\gamma_4\log(loanpc91)+\rho W\log\left(\frac{gdppc09}{gdppc91}\right)+\varepsilon \quad (2.19)$$

(vi) Spatial Error Model

The spatial error model reveals spatial heterogeneity through the disturbance terms. Hence as additional elements to the standard OLS models, we include first order spatial

[21] Also known as SAR (spatial autoregressive) model.

autoregressive disturbances in the absolute and conditional convergence models, as shown in equations (2.20) and (2.21).

$$\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right)=\alpha+\beta\log(gdppc91)+u \\ u=\lambda Wu+\varepsilon \tag{2.20}$$

$$\frac{1}{T}\log\left(\frac{gdppc09}{gdppc91}\right)=\alpha+\beta\log(gdppc91)+\gamma_1\log(hc1pc91)+\gamma_2\log(emppc91) \\ +\gamma_3\log(pinvpc91)+\gamma_4\log(loanpc91)+u \\ u=\lambda Wu+\varepsilon \tag{2.21}$$

Note that SAC model encompasses the spatial lag and spatial error models as it reflects both spatial dependence and spatial heterogeneity.

Given that the six spatial econometric specifications are related to each other under certain restrictions, one can make use of the likelihood ratio (LR) tests to compare these models as long as log-likelihood functions of both restricted and unrestricted models are available. Following Elhorst (2010a) we describe the model selection using a somewhat general-to-specific approach. SAC Durbin, specified in model 1, is the most generic model nesting all the other regressions. The following restrictions apply for SAC Durbin as the unrestricted model:

LR test 1: $H_0:\theta=0$ Restricted model: SAC (model 2)

LR test 2: $H_0:\lambda=0$ Restricted model: spatial Durbin (model 3)

LR test 3: $H_0:\rho=0$ Restricted model: spatial Durbin error (model 4)

Similarly, SAC model (model 2) including the spatial lag in the dependent variable and the spatial error term is encompassing the spatial lag and error models as designated by the following restrictions, where SAC is the unrestricted model:

LR test 4: $H_0 : \lambda = 0$ Restricted model: spatial lag (model 5)

LR test 5: $H_0 : \rho = 0$ Restricted model: spatial error (model 6)

Spatial Durbin model (model 3) which allows for the presence of spatially lagged terms of not only the dependent variable but also the covariates is nesting the spatial lag and spatial error models. Consider the following restrictions, where spatial Durbin is the unrestricted model:

LR test 6: $H_0 : \theta = 0$ Restricted model: spatial lag (model 5)

LR test 7: $H_0 : \theta = -\rho\beta$ Restricted model: spatial error (model 6)

Finally, spatial Durbin error model which includes spatial dependence in the independent variables and spatial heterogeneity in the disturbance terms encompasses the spatial error model. The likelihood ratio test is based on the following restriction where spatial Durbin error is the unrestricted model:

LR test 8: $H_0 : \theta = 0$ Restricted model: spatial error (model 6)

Starting from the most generic SAC Durbin model and using these eight LR tests based on a sequential testing approach, it is possible to obtain the most suitable spatial econometric specification to explain the absolute and conditional convergence across provinces.

2.5. Outcomes of the Spatial Econometric Regional Convergence Model

In spatial econometric modeling, spatial lagged components added as a covariate in the regression violates the assumption of orthogonality with the disturbance terms, and hence causes endogeneity. Under these circumstances, consistent estimation of parameters is possible either by using Maximum Likelihood (ML) as in LeSage &

Fischer (2008) and Elhorst (2010a); or by Generalized Method of Moments (GMM) as suggested by Kelejian and Prucha (1999). The advantage of GMM approach is that it does not necessitate any assumptions concerning the distribution of population, hence providing robust estimates. ML estimation relies on normality assumption, yet provides more efficient outcomes as compared to the GMM counterparts. In this chapter the spatial econometric models are estimated via maximum likelihood as the normality assumption holds for the given data set (section 2.4.1) and robust measures can be attained. Moreover, ML estimation provides better estimates compared to that of GMM, as suggested by the contour plots provided in the Appendix.

2.5.1. Maximum Likelihood Estimation Results

The ML estimation results of the six spatial econometric regressions to test the absolute convergence hypothesis are presented in Table 5. For all of the estimated models, beta coefficients that show the effect of initial per capita income on growth are found to be negative and significant, supporting the absolute convergence hypothesis. Depending on the type of the specification, the convergence rates vary from 5.67 to 8.54 per cent. Spatial error parameter λ is found to be significant in all of the estimated models, which confirms the presence of spatial heterogeneity revealed in the exploratory spatial data analysis. The parameter ρ indicating the spatial lag of the dependent variable and the coefficient for the spatial lag of the independent variable W*log(gdppc91) are significant only in the spatial Durbin model.

Table 5: Spatial Models Estimated for Absolute Convergence Hypothesis

	Model 1	***Model 2***	***Model 3***	***Model 4***	***Model 5***	***Model 6***
	SAC Durbin Model	SAC Model	Spatial Durbin Model	Spatial Durbin Error Model	Spatial Lag Model	Spatial Error Model
Intercept	0.0228**	0.0236***	0.0087***	0.0198***	0.0153***	0.0164***
	(0.0134)	(0.0002)	(0.0020)	(0.0000)	(0.0000)	(0.0000)
log(gdppc91)	-0.0425***	-0.0424***	-0.0436***	-0.0428***	-0.0355***	-0.0421***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
W*log(gdppc91)	0.0020		0.0287***	0.0079		
	(0.9126)		(0.0000)	(0.1194)		
ρ	-0.1508	-0.1960	0.5662***		0.0927	
	(0.7311)	(0.1471)	(0.0000)		(0.3489)	
λ	0.6649***	0.6877***		0.5770***		0.6097***
	(0.0052)	(0.0000)		(0.0000)		(0.0000)
Convergence rate	0.0805	0.0801	0.0854	0.0818	0.0567	0.0788
Half-life	15.95	15.99	15.55	15.84	19.15	16.11
AIC	-456.22	-458.21	-457.67	-458.14	-441.84	-457.82
Log likelihood	234.1115	234.1057	233.8358	234.0677	224.9205	232.9111
ML Residual Variance (σ^2)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Number of observations	73	73	73	73	73	73
Number of parameters estimated	6	5	5	5	4	4
LM test for residual autocorrelation			0.0131		17.3660***	
			(0.9089)		(0.0000)	
Hausman test for spatial error				8.9972**		6.9888**
				(0.0293)		(0.0304)

Notes: The dependent variable is the provincial per capita GDP growth. The values in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively. AIC=Akaike Information Criterion.

The performances of the spatially augmented absolute convergence models can be illustrated by two important diagnostics. First, residual autocorrelation is tested for the models which contain the spatial lag of the dependent variables but not the spatial error component (models 3 and 5). The LM test results indicate that there exists remaining autocorrelation in the spatial lag model which purports the need for including spatiality in the disturbance terms in order to get rid of spatial autocorrelation. Second, for the models which includes spatiality in the error terms but not in the dependent variables (models 4 and 6), Hausman test statistic is adapted to test the difference between OLS and spatial error estimates. In the Hausman test, OLS estimates are consistent but inefficient whereas those of spatial error model are efficient. Under the null hypothesis, there is no significant difference between the estimated parameters of these two models, which can be interpreted as "*the omitted variables do not represent a serious problem or are not correlated with the explanatory variables*" (LeSage and Pace, 2009). The significant test statistics suggest that for both spatial Durbin error model and spatial error model, the spatial structure in the error terms are indispensable.

As for the conditional convergence hypothesis, the results in Table 6 show that for all of the estimated spatial regressions, statistically significant and negative beta coefficients imply the existence of conditional convergence. In all specifications, the inclusion of human capital, employment, public and private investment variables causes an increase in the rate of convergence varying from 11.87 to 14.19 per cent. The effects of human capital and employment are statistically significant and positive, as expected. On the other hand, initial per capita public investments and loans do not have significant effects on growth at 5% significance level. Spatial error parameter λ is found to be significant in all models, except SAC Durbin specification. The parameter ρ reflecting spatial dependence in growth and the coefficient for W*log(gdppc91) reflecting spatial dependence in the initial incomes are significant only in the spatial Durbin specification.

Table 6: Spatial Models Estimated for Conditional Convergence Hypothesis

	Model 1	***Model 2***	***Model 3***	***Model 4***	***Model 5***	***Model 6***
	SAC Durbin Model	SAC Model	Spatial Durbin Model	Spatial Durbin Error Model	Spatial Lag Model	Spatial Error Model
Intercept	0.0611	0.0802***	0.0444*	0.0759***	0.0787***	0.0786***
	(0.6124)	(0.0000)	(0.0517)	(0.0046)	(0.0000)	(0.0000)
log(gdppc91)	-0.0509***	-0.0512***	-0.0509***	-0.0508***	-0.0490***	-0.0509***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc91)	0.0238***	0.0219***	0.0234***	0.0240***	0.0225***	0.0218***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(emppc91)	0.0080*	0.0084**	0.0078*	0.0082**	0.0108***	0.0093**
	(0.0691)	(0.0293)	(0.0537)	(0.0430)	(0.0045)	(0.0147)
log(pinvpc91)	-0.0029	-0.0020	-0.0028*	-0.0031*	-0.0027*	-0.0021
	(0.1382)	(0.1317)	(0.0672)	(0.0664)	(0.0786)	(0.1247)
log(loanpc91)	-0.0033*	-0.0023	-0.0031*	-0.0034*	-0.0028	-0.0023
	(0.0995)	(0.1256)	(0.0640)	(0.0680)	(0.1150)	(0.1349)
W*log(gdppc91)	0.0156		0.0257***	0.0064		
	(0.8285)		(0.0031)	(0.3186)		
W*log(hc1pc91)	0.0031		-0.0013	0.0070		
	(0.9335)		(0.9086)	(0.5660)		
W*log(emppc91)	0.0007		-0.0016	0.0026		
	(0.9636)		(0.8382)	(0.7811)		
W*log(pinvpc91)	-0.0038		-0.0033	-0.0043		
	(0.5216)		(0.3666)	(0.3043)		
W*log(loanpc91)	-0.0030		-0.0023	-0.0036		
	(0.6345)		(0.5454)	(0.4122)		
ρ	0.1950	-0.0817	0.4111***		0.0519	
	(0.8942)	(0.4125)	(0.0031)		(0.5169)	
λ	0.2589	0.4992***		0.4218***		0.4340***
	(0.8554)	(0.0005)		(0.0023)		(0.0015)
Convergence rate	0.1380	0.1419	0.1379	0.1361	0.1187	0.1379
Half-life	13.26	13.18	13.26	13.30	13.80	13.27
AIC	-468.96	-476.53	-470.68	-470.80	-471.63	-477.86
Log likelihood	248.4807	247.2635	248.3389	248.4014	243.8152	246.9320
ML residual variance (σ^2)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Number of observations	73	73	73	73	73	73
Number of parameters estimated	14	9	13	13	8	8
LM test for residual autocorrelation			0.8295		6.0014**	
			(0.3624)		(0.0143)	
Hausman test for spatial error				11.0410		6.1287
				(0.4398)		(0.4089)

Notes: The dependent variable is the provincial per capita GDP growth. The values in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively. AIC=Akaike Information Criterion.

The diagnostics of the spatially augmented conditional convergence models disclose somewhat similar results to that of the absolute convergence models. LM tests show that there exists residual autocorrelation in the spatial lag model, once again providing evidence in favor of specifications containing spatial error terms. For the spatial Durbin error and spatial error models, Hausman test statistic is employed and the results do not find a significant difference between the OLS and SEM estimates. This may indicate that the spatial error term in SEM captures the effects of omitted variables, but they are not correlated with the included variables (LeSage and Pace, 2009). If the true data generating process is spatial error, which is reasonable given the positive spatial autocorrelation pointed out by the ESDA and the significant spatial error terms in the estimated models, then the variance-covariance matrix of the usual OLS would be inconsistent (Pace and LeSage, 2008). It follows that the OLS estimates would still yield inefficient estimates.

Under these circumstances, one can immediately say that the spatial lag models are inappropriate to represent the characteristics of the data and spatial error terms should be included in the model, which are consistent with the initial LM and RLM test results. A more detailed discussion on model selection can only be possible through the general-to-specific LR testing approach outlined in section (2.4.4).

2.5.2. Model Selection

Both for absolute and conditional convergence models, although beta convergence coefficients seem to be close to each other in different specifications, there are notable differences in the convergence rates. Hence, prior to an elaborate discussion on the estimated parameters, model comparison is essential to choose the best specification. The likelihood ratio test results for the restrictions stated in section (2.4.4) are presented in Table 7.

Table 7: Likelihood Ratio Test Results

Test	Unrestricted model	Restricted model	Rest.	Absolute Convergence LR	Absolute Convergence p-value	Conditional Convergence LR	Conditional Convergence p-value
(1)	SAC Durbin	SAC	$\theta = 0$	0.0116	0.9141	2.4344	0.7863
(2)	SAC Durbin	Spatial Durbin	$\lambda = 0$	0.5513	0.4578	0.2836	0.5944
(3)	SAC Durbin	Spatial Durbin Error	$\rho = 0$	0.0876	0.7673	0.1586	0.6905
(4)	SAC	Spatial Lag	$\lambda = 0$	18.3703	0.0000	6.8966	0.0086
(5)	SAC	Spatial Error	$\rho = 0$	2.3892	0.1222	0.6631	0.4155
(6)	Spatial Durbin	Spatial Lag	$\theta = 0$	17.8306	0.0000	9.0475	0.1072
(7)	Spatial Durbin	Spatial Error	$\theta = -\rho\beta$	1.8495	0.1738	2.8139	0.7286
(8)	Spatial Durbin Error	Spatial Error	$\theta = 0$	2.3132	0.1283	2.9389	0.7094

For the absolute convergence model, SAC Durbin specification is eliminated as the null hypothesis of LR tests (1), (2) and (3) cannot be rejected. The model is over-specified and the spatial dependence parameters for dependent and independent variables are insignificant as shown in Table 5. SAC model is also excluded as suggested by LR test (5) and the insignificant spatial lag parameter ρ in this model. Spatial Durbin model is invalid as we cannot reject the null hypothesis of LR test (7) implying that the common factor restriction $\theta = -\rho\beta$ holds. Lastly, spatial Durbin model is eliminated since we cannot reject the null hypothesis of LR test (8) and the parameter for spatially lagged independent variable is insignificant. The two left-out models spatial lag and spatial error models are not nested in each other and therefore cannot be compared by LR tests. Spatial lag specification can also be rejected based on three facts: First, the null hypothesis of LR test (6) is rejected meaning that the eliminated spatial Durbin model is already better than the spatial lag model. Second, there exists remaining residual autocorrelation as suggested by the LM tests in Table 5. Third, based on the comparison of spatial lag and error specifications, the LM tests of Burridge (1980) and RLM tests of Anselin et al. (1996) have already pointed out the superiority of the error model. In consequence, spatial error specification is chosen as the most appropriate model to represent our absolute convergence hypothesis.

For the conditional convergence model, SAC Durbin specification is eliminated as the null hypothesis of LR tests (1), (2) and (3) cannot be rejected. The model is over-parametrized as the coefficients corresponding to the spatiality in the dependent variable and the independent variables as well as the spatial heterogeneity in the error terms are insignificant. SAC model is also excluded as suggested by LR test (5) and considering the insignificance of the spatial lag parameter. According to the LR tests (6) and (7) spatial Durbin model is outperformed by the spatial lag and error models and therefore excluded. Spatial Durbin error is not preferred to spatial error model as a result of LR test (8) since it includes irrelevant spatially lagged independent variables. Comparing the two left-out models spatial lag and spatial error, one can say that a similar line of reasoning in selecting suitable absolute convergence models also holds for the conditional convergence model. Given that the null hypothesis of LR test (4) is rejected in favor of SAC model, the existence of remaining residual autocorrelation in the spatial lag model as well as the LM and RLM test results given in section (3.4.3), spatial lag model is rejected and the spatial error specification is chosen as the most appropriate model to represent the conditional convergence.

2.5.3. Results and Discussion

As noted earlier positive spatial autocorrelation causes a clustering in the OLS residuals and hence the standard estimation methods are insufficient. In particular, as long as the data generating process is a spatial error, the OLS estimated coefficients will be inefficient since their variance-covariance matrices are inconsistent. Observing such clustering in the data may be due to the fact that a shock that affects growth rates in any province also penetrates to the neighboring provinces similarly and significantly as compared to the non-neighboring counterparts. Indeed, model selection procedure confirms this case, suggesting that spatial error models better represent the absolute and conditional convergence dynamics of Turkey over 1991-2009.

The spatial error model indicates the evidence of absolute convergence across provinces of Turkey over 1991-2009 period with a 7.88 per cent convergence rate. Beta coefficient is negative and statistically significant revealing that the underdeveloped provinces starting with a lower level of initial per capita GDP catch up with the others by experiencing a faster growth. The half-life from the initial year to the steady state value is 16.11 years. The spatial error terms are positive and statistically significant and the Hausman statistic to test the difference between OLS and spatial error is significant.

The spatial error model extended by additional covariates confirms the evidence of conditional convergence as shown by the negative and statistically significant beta coefficients. The convergence rate increases up to 13.79 per cent and the half-life to the steady state becomes 13.27 years. The provincial growth rate in GDP per capita is affected positively by human capital and employment whereas no significant impacts of public investment and loans are apparent. The insignificance of public investment may be due to wrong policy instruments such that the distribution and operation mechanism is not governed well enough to create necessary value added causing income growth. As for the insignificance of private investment, it is likely that incentives provided to private sector may have been insufficient for convincing them to invest in PPDs due to geographical locations, ethnic disputes and low skilled labor in these regions. In a nutshell, one can say that the public and private investments were not sufficient to serve the purposes of income growth in the underdeveloped provinces.

The main driving forces of provincial convergence remain to be human capital and employment in Turkey over 1991-2009. Clusters in the GDP per capita variables can also be rationalized based on this observation. The high spots suggested by the local indicators of spatiality observed in the Marmara and Aegean regions may be attributed to the qualified labor force operating mainly in the services sector. Similarly, the cold spots of Southeastern Anatolia may be due to the unregistered labor force and unproductive employment in the region. More in-depth examination of employment dynamics at sectoral level will be provided in Chapter 4.

2.6. Conclusion

This chapter explores the regional convergence problem in Turkey over 1991-2009 time period based on an extension of neoclassical Solow-Swan growth model. Following the awakening interest in the regional growth and the recent developments in the econometric literature, we question the validity of the standard estimation approaches. The descriptive analysis as well as several test results indicates that the standard OLS estimation is insufficient to explain the cross-sectional convergence as it neglects spatial features. The a-spatial models estimated via OLS suffer from spatial autocorrelation which reflects itself as clustering of residuals in the adjacent regions.

The spatial matrix assigning binary contiguity weights helps us to account for the spillovers in growth, human capital, employment, public and private investment variables together with the transmission of shocks. Using this predefined weight matrix, six different spatial econometric specifications are estimated via maximum likelihood. The general-to-specific testing procedure for model selection leads us to the spatial error model for both absolute and conditional convergence hypotheses. This brings us to the conclusion that any economic shock a particular province goes through is also transmitted to the neighboring provinces in a similar vein. The significant beta coefficients in the models display the existence of absolute and conditional convergence among provinces. The estimation results disclose the fact that human capital and employment are the main driving forces of provincial income growth. On the other hand, public and private investments have been insufficient to serve the purposes of productive value-added creation.

Despite the high convergence rates across provinces, the outcomes should be interpreted in caution given that regional discrepancies still persist. The per capita GDP measures are clustered such that Marmara and Aegean regions constitute a club in which high values are concentrated both in the initial and final year. On the other hand, the regions comprising Eastern and Southeastern Anatolian provinces in the initial year can be described as cold spots embodying lower values of per capita GDP. In 2009, the surface area of cold spots somewhat diminished to include merely the Southeastern provinces. This progression may be attributed to the advancements in the human capital and employment in the Eastern Anatolia. In fact, rate of high school graduates and the employment have shown substantial rises in the Eastern Anatolia whereas they lagged behind in the Southeastern provinces. Various regional development policies implemented during this period including the establishment of priority provinces in development and regional development projects have been targeting these underdeveloped provinces particularly in the Southeastern Anatolia. However, lack of sufficient incentives for private sector, low public investment, poor human capital, lack of innovation, technology and physical infrastructure have been the main reasons of not having new job opportunities and required levels of economic growth in these regions.

The overall analysis depicts a further need to take additional regional development measures. In forming the provincial policies, the spatial interactions should not be ignored in the first place. The regional development agencies, as a major step towards decreasing disparities, would better function as long as they carry out policies at provincial level with a special attention on unobserved effects that may transmit through the provinces. Moreover, the public and private investment strategies focusing on the enhancement of qualified labor and more efficient labor markets as well as the improved physical infrastructure seem to be essential to have the desired results on regional development.

CHAPTER 3

SPATIAL DYNAMIC PANEL DATA ANALYSIS OF REGIONAL GROWTH CONVERGENCE IN TURKEY

Convergence studies are mostly based on cross-sectional models which explore output growth rates given the national income measures of an initial and final year. Nevertheless, these models need reconsiderations mainly because of two reasons. First, they do not display the dynamic structure of each region in the given time span and fail to reflect the heterogeneity within these regions. Empirical models based on panel data modelling offer a solution to this type of heterogeneity. Second, the original models for convergence do not consider the specific effect of adjacency between regions. This problem, which may possibly be powerful in the presence of large spillovers in the neighboring regions, can be circumvented by means of spatial econometric specifications. On the other hand, if the true data generating process incorporates dynamics both at temporal and spatial level, ignorance of either effect may result in biased and inconsistent estimates. To characterize both spatial correlation and heterogeneity, spatial panel and spatial dynamic panel data models (SDPD) are proposed in the empirical regional convergence literature.

SDPD models as a recent contribution to the spatial econometric literature offer many novelties to the neoclassical regional convergence problem. Apart from the incorporation of space and time effects into the model, the dynamic panel framework allows the initial GDP variable to be time-varying unlike the usual static panel data alternatives. This feature is especially important for the fixed effects estimation as the time-invariant variables are wiped out during the within transformation. Therefore the modelling structure provides a comprehensive framework robust to various sorts of heterogeneity and flexible to different methods of estimation.

This chapter employs spatial dynamic panel data models to examine the provincial growth and convergence dynamics in Turkey over the 1991-2009 period. The SDPD models are quite recent in the literature with limited applications and have not been employed for the regional convergence analysis of Turkey yet. Thus, the main contribution of this chapter is a methodological departure from the existing empirical studies for Turkey. In line with the expectations, the corresponding test results imply the superiority of SDPD models over the classical cross sectional and panel data counterparts. The dynamic fixed effects spatial lag, dynamic random effects spatial lag, dynamic fixed effects spatial error and dynamic random effects spatial error models are estimated via generalized method of moments. Various tests are then utilized to make a comparison between these four types of specifications. The empirical findings show that the fixed effects spatial lag specification is the preferred model to represent the convergence dynamics in Turkey for the given time period. The estimation results point out the evidence of conditional convergence among the provinces of Turkey in which human capital, employment, real public investment and real private investment significantly affect provincial growth. Besides, it is found that the structural change in the post-2002 period had significant effects on the convergence dynamics. The overall outcome reveals that growth dynamics are subject to spatial dependence in which the growth in the proximate regions causes a positive effect on the growth rate of any province over the 1991-2009 period with post-2002 period being more pronounced.

The chapter is composed of five sections. Section one presents the literature on growth convergence models with a special emphasis on empirical spatial econometric modelling. Section two introduces the data and basic regional indicators in a panel framework. Section three provides the evidence of spatial dependence in the panel data structure and presents the empirical models for a spatial panel data extension to the growth convergence problem in Turkey. Section four reports the results of the estimations and section five concludes.

3.1. Panel Data Literature on Regional Growth Convergence

Baltagi (2010: 6-7) summarizes the superiority of the panel data models over the cross-sectional alternatives as "*controlling for individual heterogeneity, providing more informative data, more variability, less collinearity among the variables, more degrees of freedom, more efficiency and presenting dynamics of adjustment*". The two widely used models proposed in the empirical literature have been the fixed effects and the random effects models which can be applied both in a static and a dynamic framework. This section presents the empirical literature on regional growth and convergence using standard aspatial panel data models, spatial panel data models and the recent methods on spatial dynamic panel data models.

3.1.1. Standard Panel Data Approaches to the Convergence Model

Dynamic panel data modelling have become prevalent in cross-country convergence studies and the underlying motivations have been widely discussed in the empirical growth models context. Temple (1999) favors the usage of panel data techniques while annotating that dynamic panel data methods introduce additional complexities. As to the advantages of using panel data, the author argues that it controls for unobserved heterogeneity and eliminates endogeneity biases when the lagged regressors are used as instruments, which is somewhat routinized in GMM procedure. Durlauf et al. (2005) also argue that the fixed effects model, as the most commonly addressed method in the empirical growth studies, is powerful because it handles the unobserved heterogeneity.

In a dynamic panel setting, the fixed effects models have become the predominant way of describing the convergence hypothesis. Handling the country fixed effects, the earlier studies relied on the within estimation. One of the most influential papers was put forward by Islam (1995) who follows Mankiw, Romer and Weil (1992) (henceforth

MRW) augmented Solow framework[22]. Based on Summers-Heston data set for the 1960-1985 period, Islam (1995) estimates the fixed effects dynamic panel data model using Least Squares Dummy Variable (LSDV) method and compares the results with the minimum distance estimation with correlated effects. He concludes that adoption of panel data approach leads to higher rates of convergence and empirically more plausible estimates.

On the other hand, some regressors which are fixed within the country by nature, such as the geographic characteristics, are not well represented in these models as they only vary between the countries. As the usual fixed effects procedure rules out the between variation, it may cause inefficient estimates. To eliminate the disadvantages of the standard within estimation and for the dynamic models in particular, GMM and IV methods may be preferred (Durlauf et al., 2005).

Barro (1996) utilizes country fixed effects and an instrumental variable technique in which the lagged values of the regressors are introduced as instruments. Estimations for a panel of 100 countries over the 1960-1990 period display the existence of cross-country conditional convergence. The control variables used in the study include schooling, life expectancy, fertility rate, government consumption, rule-of-law index, terms of trade, democracy index, inflation rate and regional dummies. Among those, the author sheds light on the importance of human capital in determining economic growth. Barro (2001) reveals that growth is positively related to the secondary and higher schooling of adult males. On the other hand, secondary and higher schooling of females are found to be insignificant, implying that the labor markets cannot fully benefit from the highly educated women.

Caselli et al. (1996) (henceforth CEL) argue that the existing cross-country convergence literature provides inconsistent estimates because of the mistreatment of

[22] Indeed, MRW model provided a benchmark for a number of scholars who motivated a panel data approach to conditional convergence model. These studies mostly exploit Summers and Heston (1988) data set also known later as Penn World tables.

country-fixed effects and the endogenous explanatory variables. Instead, they suggest a two-step procedure with differencing in the first stage and instrumenting via lagged values of the regressors in the second stage. Empirical results for 97 countries over the period 1960-1985 based on the Summers-Heston data set reveal that the convergence rates are about 10%, which is quite above the rates found in the previous literature. This study has started an important discussion on the use of GMM method in dynamic panel growth models. Bond et al. (2001) revisit the CEL procedure and argue that when time series are persistent, the first-differenced GMM can be unsatisfactory as the lagged levels of the series become weak instruments[23]. The authors suggest two solutions for their empirical Solow growth model, either using the system GMM estimator or strengthening the instrument set by using other variables that are not included in the model. Estimation results of both procedures provide much slower speeds of convergence as compared to CEL model. Dowrick and Rogers (2002) propose an alternative to MRW model via replacing the investment variable with capital stock data. By this means, they estimate output-capital elasticity and identify the factors of conditional convergence as technological catch-up (due to the technology transfer) and capital convergence (due to the diminishing returns to capital). As for the estimation, the authors follow the CEL method using dynamic panel data model with country fixed effects. Empirical analysis based on 57 countries and five year periods over 1965-1990 reveals a convergence rate of around 8% per year.

Hoeffler (2002) analyzes Africa’s growth performance by using a two-step procedure. In step one, the author estimates the dynamic panel data model by system GMM and obtain the residuals. In step two, she regresses the residuals on Africa dummy and estimates by OLS. Unbalanced panel data for 85 countries over 1960-1990 with 10-year averages reveal that there is no significant difference between African and non-African countries.

[23] See Section 3.3 for more information on the diff-GMM and system-GMM estimators.

As a matter of fact, these studies based on the standard GMM and IV methods to estimate the dynamic fixed effects models must tackle with certain issues inherent in the modelling practice. There are at least two potential problems that need to be emphasized. First, the assumption of parameter heterogeneity across different countries may create problems especially in the presence of serial correlation in the explanatory variables. In that case, the model may not satisfy the necessary condition of GMM, which is the absence of serial correlation in the disturbances. Second, if the variables are persistent in time, then the instruments based on the lagged values of these variables may be weak. To handle these two issues, scholars usually test for serial correlation in the residuals (see Barro, 1994 among others) and check for instrument validity using Sargan and Difference Sargan tests for overidentifying restrictions (Hoeffler, 2002).

Alternative methods to the GMM and IV approaches have also been proposed in the empirical growth literature. Lee et al. (1997) criticize the standard Barro-type cross-section convergence approach and employ a stochastic Solow growth model. Evidence from 102 countries from 1960 to 1989 implies that common technological growth rate is rejected across countries and growth rate heterogeneity causes the variance of output to rise. Interestingly, when the homogeneity assumption is relaxed, convergence rate rises up to 30% per year. This is in contrast with the so-called "iron law of convergence" of Barro (2012) stating that the speed of convergence lies in the range of 2% per year (see also Sala-i-Martin, 1996a). In fact, as noted before, the rates of convergence in panel data models are quite above those in cross-section models.

Another noteworthy practice is to use model averaging methods in estimating the growth regressions. Sala-i-Martin et al. (2004) propose Bayesian Averaging of Classical Estimates (BACE) based on the idea of Bayesian model averaging and conducted by taking the averages of the OLS estimates of different models. By this means, the authors decide upon which variables are indeed determining the growth in a cross-country framework. For a sample of 88 countries, 18 out of 67 variables are found to be correlated with the growth rate over 1960-1996 period. Durlauf et al. (2008) consider cross-country growth associated with seven different growth theories for an unbalanced panel dataset comprising 53 to 57 countries over three sub-periods from 1965 to 1994. Applying model averaging methods, the authors find that variations in growth rates across countries are mainly determined by macroeconomic policies and regional heterogeneity through fixed effects.

Last but not least, in estimating the panel data models for convergence analysis, cross-section dependence may be prevalent in the data when for instance "*countries that are geographically close together, or trading partners, may experience common shocks*" (Durlauf et al., 2005). The authors suggest that this problem may be dealt with spatial correlation in errors, yet the spatial proximity should be analyzed in caution and in some instances not only the geographical location but also some other measures for socio-economic and political proximity may be adopted. In the light of these observations, a remarkable literature on spatial panel data models has appeared in the empirical convergence context.

3.1.2. Spatial Panel Data Extensions of the Convergence Model

The spatial panel data models have gained importance due to the need for incorporating the effects of both time and space heterogeneity into the empirical growth convergence specifications. For these purposes, scholars have used various extensions ranging from standard static models estimated by LSDV, GMM and ML methods as well as dynamic regressions handled mostly by using the GMM or ML estimations.

3.1.2.1. Empirical Literature on Static Spatial Panel Data

As for the non-dynamic spatial panel data counterparts, the earlier studies relied on the LSDV estimation methods in analogy to the standard dynamic panel data literature. Lall and Yilmaz (2001) examine the effects of human capital and public capital in the convergence of U.S. states over the period 1969-1995 by using least squares dummy variable models. The spatially lagged independent variable is found to be positive and significant indicating that regional per capita incomes are positively affected by human capital in the neighbors. The speed of convergence from this spatial specification is quite high with an annual estimate of 17.9 per cent.

For those studies that consider the maximum likelihood estimation of the static spatial panel data models, the most commonly referred specifications have been spatial lag and spatial error under a fixed effects framework. Arbia and Piras (2005) consider maximum likelihood estimation of spatial lag and spatial error models to analyze the long-run convergence of 125 NUTS-2 regions of European Union over 1977-2002. The results show that spatial lag model is more appropriate to represent the convergence dynamics of EU regions as compared to the spatial error model. Piras and Arbia (2007) discuss the convergence of per-capita GDP of 125 EU regions throughout the period 1977-2002 by using spatial lag and spatial error extensions of the fixed effects and estimate the models via maximum likelihood. They conclude that the inclusion of spatiality in the form of spatially lagged dependent variable causes an increase in the speed of convergence.

Ramos et al. (2010) analyze the impact of human capital on the regional convergence of Spanish provinces between 1980 and 2007. The maximum likelihood estimation results of the spatial panel data models indicate the positive impact of physical and human capital on regional productivity and growth whereas the effects of geographical spillovers are negative. The authors argue that this outcome may possibly be due to the competition between the neighboring regions. Peng and Hong (2013) examine the impact of sectoral linkages on productivities in Chinese provinces over 1996-2007. The results indicate that spatial Durbin model is superior to spatial lag and spatial error specifications. The estimation outcomes reveal that sectoral productivity is linked to other sectors, public capital investment creates positive spillover effects on per capita income levels and growth rates and the agglomeration diseconomies are reflected in the low coefficients of agglomeration spillover. Benos et al. (2015) consider two different types of growth models[24] to analyze the growth spillovers for 1273 NUTS-3 regions in seven EU countries for 1990-2005 period. The authors make use of two definitions for neighborhood: spatial proximity based on geographic distance as well as economic and technological proximity based on the measures of GDP per capita and R&D output. The maximum likelihood estimation results indicate that externalities across regions are crucial for European regions regardless of the definition of the neighborhood.

Although the GMM estimation methods are mostly encountered in the dynamic panel data context, it can also be preferred in a static framework as long as the appropriate set of instruments is employed. Mohl and Hagen (2010) investigate the effects of Objective 1, 2 and 3 structural funds on the economic growth of European regions over the 1995-2005 time period. For this purpose, the authors employ a system GMM estimator in a panel framework and to account for spatial spillovers they also include a spatially lagged dependent variable into the fixed effects model. The estimation results reveal that EU regional policy funds for the less-developed regions have a positive effect on regional per capita GDP.

Last but not least, Bayesian methods are also exploited as a means of estimating the static spatial panel data models. Feldkircher and Polasek (2006) estimate a spatial fixed effects model to analyze the income convergence of 238 NUTS-2 regions in Europe over 1995-2003. Bayesian Markov Chain Monte Carlo (MCMC) estimation results for the unconditional convergence model yield a convergence rate of 2.16 % per year. Arbia et al. (2008) investigate the impact of estimation strategy on the implied convergence rates of European regions throughout 1977-2002. The empirical results for two samples with 129 and 183 regions indicate that spatial panel error model displays greater values for the beta coefficient as compared to the spatial panel lag model, fixed effects panel data model, spatial cross-section models and their Bayesian counterparts.

[24] Namely, they refer to the Mankiw, Romer &Weil (1992) and Benhabib & Spiegel (1994) studies in their analysis. The latter one is taken into consideration particularly because it allows for externalities across regions.

3.1.2.2. Empirical Literature on Dynamic Spatial Panel Data

In a spatial dynamic panel data context, scholars mostly consider the diff-GMM or system-GMM methods in estimating the regional convergence models. Badinger et al. (2004) estimate the income convergence of 196 European regions for the 1985-1999 period. For this purpose, the authors first eliminate the spatial dependence by means of spatial filtering methods based on the Getis-Ord G_i statistic and then they apply system GMM for the obtained dynamic panel data model. The results suggest that the correctly specified model takes account of spatial autocorrelation and yields a convergence rate around 7% and the elasticity of output with respect to capital is found to be 0.43. Madariaga et al. (2005) apply Badinger et al. (2004) technique to analyze the per capita income convergence of 23 Argentinian provinces for the 1983-2002 period. Accordingly, the dynamic panel data models obtained by spatial filtering at the first stage are estimated by difference-GMM and system-GMM at the second step. The authors conclude that the system-GMM estimators are preferred over the diff-GMM and that the ignorance of spatial proximity causes underestimated speed of convergence.

For analyzing the convergence of European regions, Bouayad-Agha and Vedrine (2010) employ GMM estimator in a two-step procedure following Arellano and Bond's (1991) methodology. Initially, the individual effects are eliminated taking the first-differences and then the moment conditions are constructed so that the lagged values of the dependent variable are used as instruments. Empirical results for 191 regions in EU over 1980-2005 using five-year periods reveal that the convergence process is engaged not only in temporal, but also in spatial dynamics. Bouayad-Agha et al. (2013) consider an SDPD model to analyze the impact of cohesion policy on the development of European economies. Estimations for a dataset of 143 European regions over 1980-2005 period indicate that funding the Objective 1 regions have an effect on growth rates whereas the Structural Fund policies do not have a direct impact.

Elhorst et al. (2010) estimate growth model for 193 regions of the European Union over 1977-2002 time period via fixed effects spatial panel data models. The estimation is based on Arellano and Bond's (1991) GMM method, taking the first differences and eliminating the intercept and spatial fixed effects and using a set of instruments later on. The outcomes from the unconstrained spatial Durbin model reveal that including fixed effects reduces the bias in the speed of convergence caused by the ignorance of spatiality.

Atems (2013) analyzes 3109 U.S. counties for the period 1970-2007 over 10-year intervals using a dynamic spatial Durbin model. The examination of direct, indirect and total effects suggests that inequality measured by Gini coefficient has significant negative influence on growth and the spillover effects are even larger than the own-country effects. Ho et al. (2013) examine the growth spillovers through bilateral trade for a sample of 26 OECD countries over the period 1971-2005. For this purpose, the authors consider a spatial dynamic panel data regression with time-varying spatial weights for a Solowian growth model. The estimation results with country and year fixed effects indicate that positive growth spillovers occur from one country to the other by way of trade linkages rather than the geographical proximity.

As for the maximum likelihood alternative, we should remind that by construction, this method requires normality in the disturbances. In a spatial dynamic panel data framework, Yu et al. (2008) weaken this assumption by considering the quasi-maximum likelihood (QML) estimator in which the error terms no longer need to be normal. Based on this estimation setting, Yu and Lee (2012) employ spatial dynamic panel data models with fixed effects to study the regional growth convergence of 48 states in the U.S. over the period 1930-2006. The quasi-maximum likelihood outcomes suggest that the convergence rate is higher in the SDPD due to the effect of technological spillovers. Alternatively, consistent estimates in a maximum likelihood context can also be obtained by conditioning on the initial values. For 211 European regions over the 1980-2005 period, Pfaffermayr (2012) shows that the estimated convergence speeds in various models with spatial spillovers are considerably higher than the 2 percent rate prescribed by the cross-section studies. In doing this, the author prefers using the maximum likelihood approach arguing that the instruments used in GMM estimations may be weak if the process is highly persistent.

In the light of the previous literature, this chapter employs GMM methods to estimate the SDPD models for analyzing the provincial income convergence of Turkey over the 1991-2009 period. The chapter extends the previous spatial econometric structure presented in Chapter 2 by adding time dimension. In the next sections, following a reminder on the data set in a panel data context, the econometric models are discussed in detail.

3.2. Data and Basic Regional Indicators in a Panel Framework

The data and basic regional indicators have been presented in Chapter 2 to investigate the provincial growth convergence in Turkey over the 1991-2009 period. Unlike the previous cross-section analysis, the time heterogeneity is also included alongside the spatial heterogeneity to analyze the data in a dynamic fashion. The GDP per capita and growth variations among the 73 provinces over time can be seen in the Data Appendix B.1.

To account for the observed variations in both time and space, the chapter employs alternative SDPD specifications with different combinations of the variables provided in Table 1. The descriptive statistics of the variables are presented in Appendix B.1. The real GDP per capita variable is used in a dynamic form; in particular for a model specified at time t, the lagged GDP per capita (*laggdppc*) levels for time t-1 are used as regressors to observe the existence of convergence dynamics. As proxy for human capital variable, the rates of high school (*hc1pc*) and university graduates (*hc2pc*) are employed in different specifications. The rates of employment (*emppc*) and real public investment (*pinvpc*) are used in all models. For the real private investment variable, the rates of total deposits (*depospc*) and total loans (*loanpc*) are used as proxies in different specifications. Lastly, the population (*pop*) is included as an added regressor to control for the high variations over the given period. The variables are logarithmically transformed and all real variables are expressed in 1998 prices.

In this panel structure, as the data are now reflecting the observations in the whole time period, the structural changes and the outliers are also of concern. As mentioned before in Chapter 2, the economy suffered from a depression in 2001 followed by a recovery in 2002 which continued until the global recession in 2008. This conjuncture also somewhat coincided with the one-party government which was elected in November 2002 and has stayed in power from then on. Thus, to account for this structural change in the economy, we introduce a dummy variable (*dum*) for the 2002-2007 time period[25]. Moreover, we control for the crises in 1994, 1999, 2001 and 2009 by using dummy variables *D94*, *D99*, *D01* and *D09* respectively. As the estimation outcomes in section (3.4) show, these years are indeed significant outliers and it is indispensable to include the corresponding dummy variables into the model.

The incorporation of time dimension in conjunction with the additional information in the data set introduces certain complication to the models. Thus, prior to the discussion on the tests and the estimation outcomes, the econometric modelling framework is described in the next section.

3.3. A Spatial Panel Data Extension to Regional Growth Convergence in Turkey

3.3.1. Spatial Panel Data Model Specifications

Spatial panel data models are proposed in the literature as a means to characterize both spatial dependence and heterogeneity problem. The estimation of the error component models that incorporate both space and time dynamics is first considered in the early work of Anselin (1988). Extensive surveys of literature and the estimation of different

[25] Acemoglu and Ucer (2015) also discuss the distinct character of this period with growth-enhancing reforms under the guidance of European Union and emphasize the turnaround in the post-2007 period with lower-paced growth influenced by the political dynamics.

spatial panel data specifications are provided in Elhorst (2003a), Anselin et al. (2008), Elhorst (2010c) and Baltagi (2011).

A number of specifications have been proposed under the static and dynamic spatial panel data model frameworks. The ongoing debate about whether the problem should be specified as fixed or random effects can be discussed in two respects. First, the validity of either model can be outlined based on the rationale and the underlying assumptions. In doing this, the advantages and disadvantages of each specification should be discussed. Second, a statistical argument can be provided via the corresponding test statistics.

First of all, to clarify the rationale for specifying the spatial panel data as fixed effects model one should present the potential disadvantages inherent in the specification. One potential shortcoming of the fixed effects specification is the so-called *incidental parameters problem* that can arise in short panels. This problem is first discussed by Neyman and Scott (1948) and then by Lancaster (2000). The main argument is that the number of unknown parameters increases as N increases. Thus, it is suggested that the spatial fixed effects can be estimated only when T is sufficiently large (Elhorst, 2003a, 2012). If LSDV method is used in the fixed effects estimation, any variable that does not change over time cannot be estimated because it is wiped out by the demeaning transformation (Elhorst, 2012); and the introduced dummy variables cause a great loss of degrees of freedom. These last two points have essentially led researchers to choose random effects rather than the fixed effect models in empirical studies.

Nevertheless, the random effects specifications have even greater problems especially in the context of regional convergence models. The random effects model is an appropriate specification if N individual items from a large population are drawn randomly, to make these individual items representative of the population. The assumption is that there is no correlation between the random effects and the explanatory variables. Regional growth models, in nature, are based on studying all the regions or provinces of a country. In this case, the sample becomes the population itself, rather than representing a randomly selected part of it (Beck, 2001; Beenstock and Felsenstein, 2007). This violates the random effects conjecture as long as the spatial units are fixed. Hereby, the assumption of the random effects model stating that the units of observation should be representative of a larger population does not seem to hold for most of the datasets utilized in examining the regional convergence hypotheses.

On the other hand, comparison between the fixed and random effects specifications can also be carried out by the Hausman test statistic for the standard panel data models. In a spatial panel data model, Hausman type test statistics are suggested by Mutl and Pfaffermayr (2008, 2011), Sen et al. (2012), Baltagi and Liu (2014).

In this chapter, we discuss both fixed and random effects specifications with both spatial lag and spatial error components. Although it is sensible to believe that the fixed effects model is more appropriate in nature, we do not want to impose the structure in advance but prefer to leave the discussion on model selection after carrying out the estimation and the relevant tests. Hence four different types of spatial dynamic panel data models, namely dynamic fixed effects spatial error, dynamic random effects spatial error, dynamic fixed effects spatial lag and dynamic random effects spatial lag can be specified. The spatial weight matrices used in all specifications are based on row-standardized binary contiguity weights as introduced in Chapter 2.

(i) Dynamic Fixed Effects Spatial Error Model

The fixed effects specification assumes that the unobservable individual specific effect is non-random and possibly correlated with the independent variables. For the sake of notational and computational simplicity, a one-way error component model with individual effects is taken into account. Given that a dynamic panel data is at stake, the growth rates are regressed on the lagged GDP per capita variable. The corresponding empirical specification for the absolute convergence model is provided in equation (3.1).

$$\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)=\alpha+\beta\log(gdppc_{i,t-1})+u_{i,t}$$
$$u_{i,t}=\mu+v_{i,t} \tag{3.1}$$
$$v_{i,t}=\lambda\sum_{j=1}^{N}w_{i,j}\mathrm{v}_{i,t}+\varepsilon_{i,t} \qquad t=1,\dots,T \qquad i=1,\dots,N$$

Negative and significant β parameters indicate the existence of convergence. α is the intercept term and $u_{i,t}$ implies the fixed effects specification with μ showing the individual effects. $v_{i,t}$ follows a spatial autoregressive process of order one where λ is the spatial error parameter and $w_{i,j}$ represents the individual items in the spatial weights matrix showing whether two spatial units i and j are neighbors or not. $\varepsilon_{i,t}$ is the independent and identically distributed error term.

In a conditional convergence context, additional regressors are inserted into the regression. Furthermore, the interactions with the structural change dummy variable are taken into consideration and the outlier dummies are also controlled. Hence, the model can be specified as in equation (3.2).

$$\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)=\alpha+\beta\log(gdppc_{i,t-1})+\gamma\log(\mathrm{X}_{it})+\xi*dum+\delta\log(X_{it})*dum$$
$$+\tau_1 D94+\tau_2 D99+\tau_3 D01+\tau_4 D09+u_{i,t} \tag{3.2}$$
$$u_{i,t}=\mu+v_{i,t}$$
$$v_{i,t}=\lambda\sum_{j=1}^{N}w_{i,j}\mathrm{v}_{i,t}+\varepsilon_{i,t} \qquad t=1,\dots,T \qquad i=1,\dots,N$$

where X_{it} is a vector of control variables such that

$$X_{it}=\left(hc1pc \quad hc2pc \quad emppc \quad pinvpc \quad depospc \quad loanpc \quad pop\right)'$$

with $hc1pc$: the rate of high school graduates

$hc2pc$: the rate of university graduates

$emppc$:	the rate of employees registered to a social security institution
$pinvpc$:	the rate of real public investment
$depospc$:	the rate of real total deposits
$loanpc$:	the rate of real total loans
pop:	the population

In different specifications we choose one variable from the pair ($hc1pc \quad hc2pc$) and one from ($depospc \; loanpc$) and end up with four different combinations each using different proxy variables. The dummy variables in model (3.2) are defined as

$$dum = \begin{cases} 1 & if \quad 2002 \leq t \leq 2007 \\ 0 & otherwise \end{cases}$$

$$D94 = \begin{cases} 1 & if \quad t = 1994 \\ 0 & otherwise \end{cases} \qquad D99 = \begin{cases} 1 & if \quad t = 1999 \\ 0 & otherwise \end{cases}$$

$$D01 = \begin{cases} 1 & if \quad t = 2001 \\ 0 & otherwise \end{cases} \qquad D09 = \begin{cases} 1 & if \quad t = 2009 \\ 0 & otherwise \end{cases}$$

The parameter γ indicates the effect of the control variables in the base period 1991-2001. The coefficient ξ is the differential intercept term describing the regressors' additional effect in 2002-2007 period as compared to the base period 1991-2001. Similarly, δ coefficient is the differential slope term which shows the additional effect of a one percent change in the regressors in the 2002-2007 period as compared to the base period. The parameters τ_1, τ_2, τ_3 and τ_4 correspond to the coefficients of the crisis dummies.

(ii) Dynamic Random Effects Spatial Error Model

In a random effects setting, the model relies on the assumption that the individual effects are random and hence uncorrelated with the error terms. The spatial error terms are again specified as a first order autoregressive process reflecting the effects of any shock transmitting through the immediate neighbors. Accordingly, the absolute convergence model can be modified as follows:

$$
\begin{aligned}
&\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right) = \alpha + \beta\log(gdppc_{i,t-1}) + u_{i,t} \\
&u_{i,t} = \mu_i + v_{i,t} \\
&v_{i,t} = \lambda\sum_{j=1}^{N} w_{i,j}\mathrm{v}_{i,t} + \varepsilon_{i,t} \qquad\qquad t = 1,\ldots,T \qquad i = 1,\ldots,N
\end{aligned}
\tag{3.3}
$$

with the variables and parameters defined as before. Nevertheless, unlike the fixed effects specification, this time the individual effects are allowed to vary and denoted by a subscript for the cross-sections (μ_i instead of μ).

For the conditional convergence model, the specification will again be analogous to (3.2) with the exception that the individual effects are now expressed by μ_i. Hence, the model becomes,

$$
\begin{aligned}
&\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right) = \alpha + \beta\log(gdppc_{i,t-1}) + \gamma\log(\mathrm{X}_{it}) + \xi * dum + \delta\log(X_{it}) * dum \\
&\qquad\qquad\qquad + \tau_1 D94 + \tau_2 D99 + \tau_3 D01 + \tau_4 D09 + u_{i,t} \\
&u_{i,t} = \mu_i + v_{i,t} \\
&v_{i,t} = \lambda\sum_{j=1}^{N} w_{i,j}\mathrm{v}_{i,t} + \varepsilon_{i,t} \qquad\qquad t = 1,\ldots,T \qquad i = 1,\ldots,N
\end{aligned}
\tag{3.4}
$$

The variables and the coefficients are as described before.

(iii) Dynamic Fixed Effects Spatial Lag Model

In a dynamic panel data context, the spatial dependence can also be observed through the spatially lagged dependent variable. For these dynamic spatial lag models, the endogeneity is caused not only by the lagged dependent variable but also by the spatially lagged dependent variables. Hence, the absolute convergence model is described as follows:

$$\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)=\alpha+\beta\log(gdppc_{i,t-1})+\rho\sum_{j=1}^{N}w_{i,j}\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)+u_{i,t} \qquad (3.5)$$
$$u_{i,t}=\mu+v_{i,t} \qquad t=1,\ldots,T \qquad i=1,\ldots,N$$

The coefficient ρ represents the spatial lag parameter and implies that the income growth in a province is affected by the income growth in the neighboring provinces. This dynamic fixed effects regression can be further extended by additional regressors and the conditional convergence can now be expressed as in (3.6).

$$\begin{aligned}\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)&=\alpha+\beta\log(gdppc_{i,t-1})+\rho\sum_{j=1}^{N}w_{i,j}\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)\\&+\gamma\log(\mathrm{X}_{it})+\xi*dum+\delta\log(X_{it})*dum\\&+\tau_1D94+\tau_2D99+\tau_3D01+\tau_4D09+u_{i,t}\end{aligned} \qquad (3.6)$$
$$u_{i,t}=\mu+v_{i,t} \qquad t=1,\ldots,T \qquad i=1,\ldots,N$$

where the variables and parameters are as described before.

(iv) Dynamic Random Effects Spatial Lag Model

As a last form of specification, the SDPD models can be constructed such that the individual effects are random and the spatial dependence is realized via the growth rates of the spatially proximate regions. The absolute convergence model in this case becomes as in (3.7) given below.

$$\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)=\alpha+\beta\log(gdppc_{i,t-1})+\rho\sum_{j=1}^{N}w_{i,j}\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right)+u_{i,t} \qquad (3.7)$$
$$u_{i,t}=\mu_i+v_{i,t} \qquad t=1,\ldots,T \qquad i=1,\ldots,N$$

Similarly, the conditional convergence specification with random effects would be,

$$
\begin{aligned}
\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right) &= \alpha + \beta\log(gdppc_{i,t-1}) + \rho\sum_{j=1}^{N} w_{i,j}\log\left(\frac{gdppc_{i,t}}{gdppc_{i,t-1}}\right) \\
&+ \gamma\log(X_{it}) + \xi * dum + \delta\log(X_{it}) * dum \\
&+ \tau_1 D94 + \tau_2 D99 + \tau_3 D01 + \tau_4 D09 + u_{i,t} \\
u_{i,t} &= \mu_i + v_{i,t} \qquad t = 1,\dots,T \qquad i = 1,\dots,N
\end{aligned} \tag{3.8}
$$

The interpretation of the model is parallel to the fixed effects case except the individual specific effects μ_i and the underlying assumptions.

3.3.2. Testing for Spatiality in Panel Data Models

To start with testing for the specified models, one needs to determine whether the pooled OLS results are sufficient or the model should be specified as a panel data. For this purpose, Lagrange Multiplier tests of individual effects are carried out based on the results of the pooling model. Breusch and Pagan (1980) test results presented in Table 8 show that individual effects are significant as compared to the pooled model. As shown by Honda (1985) Breusch-Pagan test statistic is robust also under non-normal disturbances. Honda (1985) also proposes a more reliable test statistic in the absence of time effects in the model. The results of this test also point out the need for the consideration of individual effects in the given data set (Table 8).

Given that the panel data models rule out the pooled OLS alternatives, in the second stage, one should figure out whether these models are subject to any spatial association. Identifying spatial correlation is linked to detecting the cross-section dependence, though there is no one-to-one correspondence between the two. The presence of cross-section dependence may be associated with the spatial correlation as well as the contemporaneous correlation in a seemingly unrelated regression type model.

Table 8: Diagnostic Tests for Panel Data

	Test Statistic	Alternative Hypothesis	Abs. Conv.	Conditional Convergence			
			Model 0	**Model 1**	**Model 2**	**Model 3**	**Model 4**
LM tests for individual effects compared to the pooled model	Breusch-Pagan (1980)	Significant effects	17.4770*** (0.0000)	5.3313** (0.0210)	6.0856** (0.0136)	5.1557** (0.0232)	5.9752** (0.0145)
	Honda (1985)	Significant effects	-4.1806*** (0.0000)	2.3090** (0.0210)	2.4669** (0.0136)	2.2706** (0.0232)	2.4444** (0.0145)
Cross-Section Dependence (CD) Test	Pesaran (2004)	CD in individual effects	59.0610*** (0.0000)	1.8871* (0.0591)	1.6941* (0.0903)	2.0595** (0.0394)	2.3412** (0.0192)

However, in the case of panel data, the presence of cross-section correlation would be indicative of spatial relationship. Pesaran (2004) suggests a cross-section dependence test in panel data models based on the pairwise correlation coefficients of the OLS residuals. The test statistic is provided in Appendix B.2 and the results for our data set are presented in Table 8. The results reveal the presence of cross-section dependence in individual effects for all specified models. This calls for the need to incorporate the spatial effects into the analysis. Further tests for spatiality are left to post-estimation where the form of the spatial dependence is discussed together with the model selection.

3.3.3. Estimation of Spatial Dynamic Panel Data Models

While the dynamic panel data estimation takes temporal dependence into account through the lagged dependent variable and the unobserved heterogeneity through the fixed effects (or possibly random effects), it does not provide an explanation for the spatial dependence at each point in time. The spatial dynamic panel data models fill this gap by incorporating possible spatiality in the dependent and independent variables as well as in the error components of the model[26]. Nevertheless, the sophistication of these models introduces certain complexities to the estimation and testing. In this section, we discuss the relevance of some estimation procedures for the dynamic panel and spatial dynamic panel data models. Throughout the discussion, we rule out the details of the nonparametric methods which are also applicable under proper circumstances[27].

3.3.3.1. Bias Corrected Least Squares Dummy Variable

In the static panel data case, the least squares dummy variables (LSDV) method is based on introducing dummy variables for each observation in individual and/or time effects, demeaning the model to eliminate the fixed effects and then running OLS estimation afterwards. The LSDV estimator used in the static panel data literature is no longer consistent in the presence of dynamic dependent variable in the regression. In particular, given the lagged dependent variable Y_{t-1}, the estimators become inconsistent as the orthogonality condition with the error terms is no longer satisfied. Moreover, when T is fixed, the demeaning procedure in the fixed effects estimation causes a correlation between the demeaned lagged dependent variable y_{it-1} and the demeaned error terms, which is known as the *Nickell bias* (Nickell, 1981). Therefore, a correction procedure is introduced to handle this bias in the dynamic panel data models, which is known as the bias-corrected Least Squares dummy variable (BC-LSDV).

For a dynamic panel data setting with spatial fixed effects, Korniotis (2010) uses a bias corrected LSDV estimator. Specifically, he introduces a new hybrid estimator which demeans the data as in the LSDV and modifies this procedure by instrumenting the endogenous control variables. Lastly, he applies a bias correction procedure to eliminate the resultant asymptotic bias.

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[26] Note that in the estimation of the spatial panel data models, the data are sorted first by time and then by spatial units whereas the classic panel data literature sort the data first by spatial units, then by time.

[27] For a well-studied example, the readers may refer to Parent and LeSage (2012) who consider a spatial dynamic panel data model with random effects and propose a space-time filter accompanied by a Bayesian MCMC procedure.

3.3.3.2. Maximum Likelihood

The maximum likelihood method used to estimate the dynamic panel data model can be built upon both conditional and unconditional likelihood function. The former ones are usually constructed conditional on the initial values, i.e. the first observations. Elhorst (2010b) suggests using ML estimators derived from the initial conditions, which provide consistent estimators. Alternatively, the unconditional likelihood function can also be utilized. By construction, this procedure necessitates pre-defined continuous probability density function which is mostly taken to be the normal distribution. The issue that requires attention at this point is that for the dynamic fixed effects model, the demeaning procedure causes the previously mentioned Nickell bias and hence inconsistency in the estimators of unconditional likelihood. To overcome the incidental parameters and initial conditions problem while avoiding Nickell bias, Hsiao et al. (2002) suggest first-differencing the model -rather than demeaning- and utilizing the unconditional likelihood thereafter. Given that the fixed effects are eliminated in the first step via differencing, the resultant estimators now become consistent. In a similar vein, Elhorst (2005) suggests using the unconditional likelihood function after taking the first-difference of the model for a panel of fixed T and large N.

In the case of spatial dynamic panel data, Yu et al. (2008) and Lee &Yu (2010) consider the bias-corrected quasi maximum likelihood (QML) estimator in which the error terms are not necessarily assumed to have a normal distribution. In this procedure, the model is first estimated by ML conditional on the initial observations of every spatial unit. Unlike Elhorst (2005), QML estimators are obtained after demeaning in the first stage rather than first-differencing. Then, they propose a bias corrected ML estimator when the number of cross section units N and time T tends to infinity. Su and Yang (2015) suggest a procedure for the QML estimation of spatial dynamic panel data with spatially autocorrelated error components when N is large and T is fixed. The authors show that under correctly specified initial conditions, the obtained estimators are consistent for both random effects and fixed effects models.

3.3.3.3. Generalized Method of Moments

The standard dynamic panel data models are basically estimated either using the first-differenced GMM of Arellano and Bond (1991) or the system-GMM proposed by Arellano and Bover (1995) and Blundell and Bond (1998). Diff-GMM method relies on eliminating the fixed effects by means of a first-difference transformation and then instrumenting the lagged difference of the endogenous variable by the previous lagged levels of that variable. In particular, the lagged dependent variable ΔY_{t-1} is instrumented by the variables $(Y_1 ... Y_{t-2})$ and $(X_1 ... X_{t-1})$ where $t \geq 3$. The consistency of this estimator necessitates the absence of serial correlation in the residuals of the transformed model (Arellano and Bond, 1991). This estimator is specifically appropriate for small T-large N panels. However if the time series is persistent, "*the lagged levels of variables tend to have only weak correlation with the first-differenced lagged dependent variable*" (Elhorst, 2014:100). This potentially weak instruments problem encountered in the diff-GMM is solved later on by the system-GMM extension. The system GMM method takes account of additional set of instruments and provides more efficient estimators by strengthening the instrument sets. In this case, the lagged first differences are used as instruments for the equations in levels and the lagged levels are used as instruments for the equations in first differences. The novelty of this procedure comes from the first part which is embedded as a solution to the weak instruments problem in diff-GMM. In addition to the instruments defined by the diff-GMM, Y_{t-1} is also instrumented by $(\Delta Y_1 ... \Delta Y_{t-2})$ and $(\Delta X_2 ... \Delta X_{t-1})$ where $t \geq 3$.

In a standard panel data context, the true implementation of the GMM procedure necessitates taking into consideration at least five main points. First, GMM procedure is implemented basically due to the existence of endogenous regressors. If indeed the variables are not endogenous, the estimator may be consistent but inefficient. For a dynamic panel data structure, Y_{t-1} is endogenous in nature, whereas in a static panel data model, conducting tests for endogeneity may become necessary. Second, the model is overidentified when there are more instruments than the endogenous regressors and by the help of these additional instruments, it is feasible to test for overidentifying restrictions using Sargan (1958) and Hansen (1982) methodology. Third, the main potential shortcoming of the GMM technique appears in the validity of instruments since the invalid instruments would cause biased and inconsistent estimates. The Sargan/Hansen test for overidentifying restrictions is in fact based on the assumption that the instruments are valid, which calls for checking the validity of the instruments. In the applied literature, by considering these two properties together, scholars employ Sargan/Hansen test to check for the overall validity of the moment conditions. Fourth, the weak instruments problem may appear when the instruments are weakly correlated with endogenous explanatory variable. The presence of weak instruments imply high variance and lead to small sample bias with biased parameter estimates and biased standard errors (Greene, 2003). Fifth, the residuals should be free of autocorrelation for the orthogonality conditions of GMM to hold. In order to test the presence of serial correlation in the residuals, Arellano and Bond (1991) check for second order serial correlation in the first differenced residuals. Intuitively, this corresponds to testing for serial correlation in the level equation (see also Elhorst, 2012).

As for the estimation of spatial dynamic panel data models, the aforementioned diff-GMM and system-GMM techniques can be applied with a proper set of instruments. Yet, this time not only the temporal lags but also the spatial lags of the variables should be considered. Baltagi et al. (2014) suggest a GMM estimator for SDPD models based on Kapoor et al. (2007) study that takes the static spatial panel data models into account. For a spatial autoregressive model with spatially correlated disturbances, the authors outline a two-step estimation procedure making use of both spatial and non-spatial instruments. Lee and Yu (2014) consider GMM estimation of fixed effects SDPD models with both individual and time effects when N is large and $T<N$. The moment conditions are constructed so that they are both linear and quadratic.

In estimating the spatial panel data models, this thesis prefers applying the GMM procedure over the ML counterpart as there are particular advantages of the GMM estimation. An overall comparison of the two methods for both static and dynamic panel data yields us five main points of departure. First and foremost, the GMM estimation does not necessitate an a priori specified density function, which is a methodological merit that simplifies and relaxes the constraints in the estimation. Second, during the estimation via maximum likelihood, a main obstacle is to compute the Jacobian determinant for panel data models. On the other hand, this computational burden is no longer a concern in the GMM estimation procedure (Lee and Yu, 2014). Third, as stated by Lee and Yu (2015), GMM methods can be applied for SDPD models with rather short time periods whereas the ML procedure necessitates large T for the asymptotic properties to hold. Fourth, GMM is applicable in SDPD models with time effects and the spatial weights matrices which are not row-normalized in advance (Lee and Yu, 2014). Fifth, in static spatial panel data models, GMM can be used to instrument endogenous explanatory variables whereas maximum likelihood cannot (Elhorst, 2012). Yet, in this case, we cannot use spatially lagged independent variables in GMM since these variables are used as instruments. For our estimation purposes, the first three points are of particular concern and constitute our main motivations to use GMM techniques for the spatial dynamic panel data model estimations.

3.4. Outcomes of the Dynamic Spatial Panel Regional Convergence Models

Based on the empirical models and the estimation methods discussed before, this section presents the GMM estimation outcomes of the four different SDPD models and provides a discussion on model selection. Thereafter, the coefficients of the selected model are interpreted in detail.

3.4.1. GMM Estimation Results

The estimation results of the dynamic fixed effects spatial error models in Table 9 display evidence of absolute and conditional convergence, given the negative and significant coefficients of the lagged GDP per capita variables. Spatial error parameters λ are found to be positive in all models, which implies that for a particular province economic shocks experienced by the neighboring provinces have impacts in the same direction. The spatial association works through the unobserved components and appear as a stochastic process in the disturbances.

In the conditional convergence models, the outlier dummy variables tend to be negative and significant suggesting that the economic crises in 1994, 1999, 2001 and 2009 indeed hurt the economy. As we have controlled for these effects in the estimation, the relatively stable economic conditions observed in the 2002-2007 period can be discussed in comparison to the base period. The structural change dummy that takes account of these different economic conjunctures is significant in all estimated models. The negative but small impacts of human capital variables on growth before 2002 seem to be compensated in the post-2002 period as verified by positive and significant coefficients corresponding to this period. The effects of employment rates in both periods are positive, with greater values in the initial period. Moreover, the impact of the public investment on growth is positive in both periods, with the sizes of the coefficients being greater and statistically significant for the period after 2002. This is consistent with Figure 1 presented in Chapter 2 revealing that the ratio of public investment in GDP has declined a great deal throughout 1990s while it tends to be relatively stable after 2001. With regard to the proxies for private investment, the effects of deposits are significant and higher in the first period whereas the reverse is true for the loans which tend to be more influential in the post-2002 period. The population variables have negative coefficients which may not be surprising given that the growth variables are calculated based on the per capita values of the GDP.

Table 10 shows that the estimations of dynamic random effects models with spatial error components also confirm the presence of absolute and conditional convergence but yield smaller coefficients in absolute value which in turn indicate smaller rates of convergence. For all the estimated regressions, the convergence is more rapid in the post-2002 as compared to the previous period. Once again, the spatial error parameters are positive disclosing the fact that the effects of the economic shocks turn out to be in the same direction.

Table 9: Estimation Results for Dynamic Fixed Effects Spatial Error Model

	Abs. Conv.	**Conditional Convergence**			
Coefficients	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
log(laggdppc)	-0.0783***	-0.1241***	-0.1272***	-0.1232***	-0.1256***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc)		-0.0298	-0.0344		
		(0.1965)	(0.1295)		
log(hc2pc)				-0.0468**	-0.0510**
				(0.0496)	(0.0287)
log(emppc)		0.1708***	0.1398***	0.1768***	0.1487***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(pinvpc)		0.0087	0.0056	0.0085	0.0062
		(0.1246)	(0.3222)	(0.1328)	(0.2759)
log(depospc)		0.0035		0.0054	
		(0.8082)		(0.7076)	
log(loanpc)			0.0165***		0.0177**
			(0.0404)		(0.0276)
log(pop)		-0.0746**	-0.0775**	-0.0771**	-0.0791**
		(0.0251)	(0.0200)	(0.0161)	(0.0140)
dum		0.5779***	0.5528***	0.6188***	0.7435***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(laggdppc)*dum		-0.3420***	-0.3357***	-0.3418***	-0.3378***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc)*dum		0.0406	0.0980***		
		(0.2254)	(0.0016)		
log(hc2pc)*dum				0.0332	0.1213***
				(0.3705)	(0.0001)
log(emppc)*dum		0.0167	0.0822***	0.0130	0.0389
		(0.5281)	(0.0010)	(0.6653)	(0.2028)
log(pinvpc)*dum		0.0363***	0.0403***	0.0369***	0.0402***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(depospc)*dum		0.0794***		0.0792***	
		(0.0000)		(0.0000)	
log(loanpc)*dum			0.0098		0.0107
			(0.3197)		(0.2724)
log(pop)*dum		-0.0068	0.0128*	-0.0101	0.0002
		(0.4124)	(0.0999)	(0.2173)	(0.9771)
D94		-0.0656***	-0.0602***	-0.0668***	-0.0607***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
D99		-0.0521***	-0.0467***	-0.0502***	-0.0443***
		(0.0000)	(0.0003)	(0.0001)	(0.0006)
D01		-0.0395***	-0.0247	-0.0362***	-0.0205
		(0.0033)	(0.1114)	(0.0071)	(0.1838)
D09		-0.0319**	-0.0334**	-0.0209	-0.0228
		(0.0389)	(0.0253)	(0.2175)	(0.1718)
λ	0.3699	0.0812	0.0741	0.0795	0.0753
σ_v^2	0.0129	0.0087	0.0087	0.0087	0.0087

Table 10: Estimation Results for Dynamic Random Effects Spatial Error Model

	Abs. Conv.	Conditional Convergence			
Coefficients	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	0.0259***	0.0968**	0.0973**	0.0217	0.0357
	(0.0000)	(0.0323)	(0.0349)	(0.7189)	(0.5553)
log(laggdppc)	-0.0418***	-0.0594***	-0.0578***	-0.0603***	-0.0574***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc)		-0.0349**	-0.0333**		
		(0.0261)	(0.0309)		
log(hc2pc)				-0.0480***	-0.0398**
				(0.0089)	(0.0188)
log(emppc)		0.0507***	0.0509***	0.0613***	0.0620***
		(0.0012)	(0.0013)	(0.0003)	(0.0004)
log(pinvpc)		0.0094**	0.0099**	0.0094*	0.0102**
		(0.0494)	(0.0367)	(0.0504)	(0.0305)
log(depospc)		0.0089		0.0138	
		(0.3466)		(0.1657)	
log(loanpc)			0.0061		0.0061
			(0.3599)		(0.3562)
log(pop)		-0.0005	-0.0007	0.0033	0.0033
		(0.9307)	(0.9069)	(0.5447)	(0.5597)
dum		0.5469***	0.5273***	0.6561***	0.7334***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(laggdppc)*dum		-0.3132***	-0.3066***	-0.3100***	-0.3082***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc)*dum		0.0645	0.1049***		
		(0.0459)	(0.0005)		
log(hc2pc)*dum				0.0787**	0.1314***
				(0.0303)	(0.0000)
log(emppc)*dum		0.0328	0.0699***	0.0148	0.0207
		(0.2091)	(0.0041)	(0.6154)	(0.4894)
log(pinvpc)*dum		0.0313***	0.0325***	0.0318***	0.0323***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(depospc)*dum		0.0536***		0.0459**	
		(0.0023)		(0.0165)	
log(loanpc)*dum			0.0108		0.0123
			(0.2685)		(0.2059)
log(pop)*dum		-0.0026	0.0097	-0.0089	-0.0043
		(0.7592)	(0.2127)	(0.2839)	(0.6034)
D94		-0.0697***	-0.0679***	-0.0688***	-0.0672***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
D99		-0.0544***	-0.0516***	-0.0538***	-0.0511***
		(0.0000)	(0.0001)	(0.0000)	(0.0001)
D01		-0.0409***	-0.0359**	-0.0389***	-0.0353**
		(0.0024)	(0.0171)	(0.0041)	(0.0185)
D09		-0.0367***	-0.0371***	-0.0305**	-0.0316**
		(0.0090)	(0.0092)	(0.0376)	(0.0338)
λ	0.3871	0.0792	0.0804	0.0814	0.0826
σ_v^2	0.0128	0.0090	0.0091	0.0090	0.0090
σ_1^2	0.0045	0.0127	0.0130	0.0126	0.0129

In the dynamic random effects spatial error model, the dummy variables for the crisis years are negative and significant as expected (Table 10). The differential intercept and slope coefficients for the 2002-2007 period provide evidence of structural change in 2002. Except for Model 1, the significantly positive coefficients for high school and university graduates surpass the negative effects observed in the first period. The employment has positive effects on growth with relatively more significant coefficients in the base period, 1991-2001. The public investments have positive and significant impacts on growth whereas the outcomes for private investment are mixed. Although for both deposits and loans the effects are positive, only the second period's deposits appear to be influential on the growth rates. The negative coefficients for the population variable are no longer significant in the random effects case as opposed to the fixed effects.

Spatial correlation may also exist because of the spatially lagged dependent variable. The estimation results for the dynamic fixed effects spatial lag models are presented in Table 11. In conditional convergence models 2, 3 and 4, the spatial lag parameters are found to be positive and significant implying that a particular province is positively affected by the growth in the neighboring provinces. This positive autocorrelation demonstrates that there are mutual relations among the provinces such that a positive economic environment in one of them transmits directly to the others.

Table 11: Estimation Results for Dynamic Fixed Effects Spatial Lag Model

	Abs. Conv.			Conditional Convergence	
Coefficients	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
log(laggdppc)	-0.0501***	-0.1215***	-0.1244***	-0.1201***	-0.1224***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc)		-0.0287	-0.0237		
		(0.2132)	(0.3014)		
log(hc2pc)				-0.0436*	-0.0413*
				(0.0667)	(0.0783)
log(emppc)		0.1745***	0.1409***	0.1812***	0.1509***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(pinvpc)		0.0084	0.0049	0.0080	0.0053
		(0.1509)	(0.4019)	(0.1692)	(0.3618)
log(depospc)		0.0048		0.0069	
		(0.7372)		(0.6350)	
log(loanpc)			0.0183**		0.0193**
			(0.0263)		(0.0191)
log(pop)		-0.0757**	-0.0803**	-0.0771**	-0.0789**
		(0.0291)	(0.0212)	(0.0207)	(0.0187)
dum		0.5756***	0.5436***	0.5977***	0.7264***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(laggdppc)*dum		-0.3374***	-0.3288***	-0.3356***	-0.3314***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc)*dum		0.0414	0.1009***		
		(0.2318)	(0.0017)		
log(hc2pc)*dum				0.0265	0.1178***
				(0.4867)	(0.0003)
log(emppc)*dum		0.0134	0.0754***	0.0118	0.0355
		(0.6226)	(0.0032)	(0.7018)	(0.2573)
log(pinvpc)*dum		0.0352***	0.0384***	0.0357***	0.0387***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(depospc)*dum		0.0821***		0.0838***	
		(0.0000)		(0.0000)	
log(loanpc)*dum			0.0144		0.0155
			(0.1528)		(0.1199)
log(pop)*dum		-0.0079	0.0110	-0.0112	-0.0015
		(0.3502)	(0.1685)	(0.1838)	(0.8627)
D94		-0.0582***	-0.0410***	-0.0566***	-0.0427***
		(0.0000)	(0.0037)	(0.0000)	(0.0024)
D99		-0.0468***	-0.0332**	-0.0431***	-0.0316**
		(0.0003)	(0.0116)	(0.0008)	(0.0159)
D01		-0.0350***	-0.0140	-0.0305**	-0.0104
		(0.0078)	(0.3662)	(0.0206)	(0.4991)
D09		-0.0302**	-0.0276*	-0.0192	-0.0192
		(0.0406)	(0.0564)	(0.2374)	(0.2306)
ρ	-0.6801	0.0940	0.2315***	0.1278*	0.2178***
	(0.1535)	(0.2220)	(0.0017)	(0.0871)	(0.0030)
σ^2	0.0204	0.0083	0.0084	0.0083	0.0084

Table 12: Estimation Results for Dynamic Random Effects Spatial Lag Model

	Abs. Conv.	Conditional Convergence			
Coefficients	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	0.0325***	0.0956***	0.0910***	0.0479	0.0833**
	(0.0000)	(0.0019)	(0.0039)	(0.2572)	(0.0481)
log(laggdppc)	-0.0392***	-0.0605***	-0.0527***	-0.0637***	-0.0549***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(hc1pc)		-0.0214*	-0.0080		
		(0.0773)	(0.4990)		
log(hc2pc)				-0.0310**	-0.0051
				(0.0229)	(0.6825)
log(emppc)		0.0184*	0.0339***	0.0266**	0.0363***
		(0.0741)	(0.0011)	(0.0165)	(0.0019)
log(pinvpc)		0.0011	0.0044	0.0013	0.0035
		(0.7413)	(0.1705)	(0.6767)	(0.2636)
log(depospc)		0.0267***		0.0306***	
		(0.0000)		(0.0000)	
log(loanpc)			0.0048		0.0041
			(0.2491)		(0.3147)
log(pop)		-0.0044	-0.0006	-0.0016	0.0007
		(0.2121)	(0.8798)	(0.6439)	(0.8539)
dum		0.1993**	0.2033***	0.3776***	0.3209***
		(0.0105)	(0.0093)	(0.0004)	(0.0027)
log(laggdppc)*dum		-0.0587***	-0.0706***	-0.0399**	-0.0596***
		(0.0027)	(0.0004)	(0.0375)	(0.0023)
log(hc1pc)*dum		0.0877***	0.0713**		
		(0.0095)	(0.0252)		
log(hc2pc)*dum				0.1343***	0.0847***
				(0.0003)	(0.0087)
log(emppc)*dum		-0.0046	-0.0313	-0.0420	-0.0684**
		(0.8657)	(0.1945)	(0.1566)	(0.0203)
log(pinvpc)*dum		0.0190***	0.0139**	0.0182***	0.0142**
		(0.0046)	(0.0382)	(0.0057)	(0.0321)
log(depospc)*dum		-0.0432**		-0.0673***	
		(0.0154)		(0.0004)	
log(loanpc)*dum			-0.0102		-0.0110
			(0.2842)		(0.2424)
log(pop)*dum		0.0013	-0.0044	-0.0076	-0.0142
		(0.8895)	(0.6072)	(0.4035)	(0.1177)
D94		-0.0504***	-0.0481***	-0.0510***	-0.0490***
		(0.0006)	(0.0012)	(0.0005)	(0.0009)
D99		-0.0455***	-0.0397***	-0.0461***	-0.0412***
		(0.0017)	(0.0064)	(0.0015)	(0.0046)
D01		-0.0344**	-0.0312**	-0.0336**	-0.0337**
		(0.0167)	(0.0358)	(0.0195)	(0.0235)
D09		-0.0333**	-0.0281*	-0.0294*	-0.0280*
		(0.0251)	(0.0594)	(0.0511)	(0.0653)
ρ	-0.1459	0.2275***	0.2595***	0.2110***	0.2464***
	(0.4015)	(0.0030)	(0.0008)	(0.0046)	(0.0012)
σ^2	0.7373	1.3668	1.3483	1.3786	1.3657

At the overall level, with some exceptions, it can be argued that the dummy variables for the outlying years and for the structural change are significant (Table 11). Similar to the spatial error models, the coefficient for the human capital variables are negative in the first period and become positive after 2002. Once again, the effects of employment rates on growth are positive in both periods with significant and higher values for the base years. This is in contrast with the patterns of public investment. The per capita public investments have a positive impact on growth in all years; but these effects are quite small and statistically insignificant before 2002. In terms of the private investments, it is observed that deposits (loans) have significantly positive effects on growth in the first (second) period. The population variable has significant negative impacts on the growth of per capita GDP only in the base period and is not effective over 2002-2007.

Lastly, Table 12 shows the estimation results of the dynamic spatial lag model with random effects. As in the spatial error case, the results of the spatial lag models reveal that the random effects models provide smaller coefficients for the lagged GDP per capita variables and hence smaller rates of convergence compared to the fixed effects. The spatial lag parameters are positive and significant in all conditional convergence models, showing that a particular province is positively affected by the growth in the neighboring provinces. This positive autocorrelation demonstrates that there are mutual relations among the provinces such that a positive economic environment in one of them transmits directly to the others.

Controlling for outliers and structural change is again found to be essential. Over the 2002-2007 period, the structural differences can be seen in the human capital, public investment and deposits. While these changes have been favorable for the growth effects of human capital and public investment, when it comes to deposits negative repercussions were observed. On the other hand, loans per capita and population have been overall ineffective on growth. As for the rates of employment, it is apparent that the structural transformations in the post-2002 period have not been successful in obtaining promising outcomes as long as the provincial growth is concerned.

3.4.2. Model Selection

Having estimated four SDPD models considering both fixed versus random effects and spatial lag versus spatial error specifications, it is now crucial to choose the correct form of the spatiality and the panel data structure. We discuss the specifications for spatial error and spatial lag models in turn.

3.4.2.1. Evaluation of Dynamic Panel Spatial Error Models

First of all, to compare random and fixed effects models for the spatial error specifications, one can make use of the Hausman type test statistic. As it is conventional in these test statistics, under the null hypothesis, the fixed effects model is consistent and random effects model is efficient. Table 13 shows that in all of the estimated convergence models with spatial error components, the random effects models are rejected in favor of the fixed effects models. Thus, the random effects spatial error model can be eliminated based on the Hausman[28] test statistic.

To elaborate on the spatiality in the error terms, LM tests for spatial autocorrelation proposed by Baltagi et al. (2003) and Baltagi et al. (2007) can be carried out, whose details are provided in the Appendix B.2[29]. However, one should keep in mind that these tests are designed for static models and no tests are available for the spatial dynamic panel data counterparts (see Bouayad-Agha 2010, 2013). Baltagi et al. (2003) study random effects model with spatial error correlation and consider joint,

[28] Here, Hausman-type test statistic follows the method of Mutl and Pfaffermayr (2011) who consider instrumental variable estimation of static panel data model with spatial lag and error components. Although the test statistic is not performed for dynamic spatial panel data models, we present the results here to provide background information. To the best of our knowledge, no dominating test procedure which also considers the SDPD specifications exists in the literature yet.

[29] Appendix B.2 provides all possible test statistics and is presented in the original notations used by the authors. In this section, we provide only the relevant test results that serve our purposes.

conditional and marginal tests for the presence of these two effects together. The results in Table 14 indicate that for the absolute convergence model as well as for different specifications of the conditional convergence model, the one-sided joint LM tests for random effects and spatial autocorrelation deliver statistically significant results. However, conditional on the possible presence of random or fixed effects such that $\sigma_{\mu}^{2} \geq 0$, the test results do not display evidence of spatial error correlation. This also rules out the fixed effects spatial error model as there is no apparent spatial association in the error terms.

Note that the elimination of spatial error models is not contradictory with the results of the cross-section dependence (CD) tests reported in Table 8 that reveal the presence of CD in individual effects. This is because Pesaran's (2004) CD test is devised for the non-spatial panel data models and any kind of omitted spatial effects may show up as dependence in the residuals. Hence, one can state that the observed cross-section dependence may be due to the omitted spatial lag terms rather than spatial error in the model.

Table 13: Hausman Specification test for Spatial Error Models

		Abs. Conv.	Conditional Convergence			
Test Statistic	**Alternative Hypothesis**	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Hausman test between random effects and individual effects	Random effects model is inconsistent	9.0453*** (0.0026)	294.3700*** (0.0000)	1082.7000*** (0.0000)	384.2100*** (0.0000)	738.6500*** (0.0000)

Table 14: Tests for Spatial Autocorrelation

			Abs. Conv.	Conditional Convergence			
	Test Statistic	**Alternative Hypothesis**	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
LM tests of Baltagi, Song&Koh (2003)	LM-H one-sided joint test	Random Regional Effects and Spatial autocorrelation	155.1500*** (0.0000)	9.2337*** (0.0037)	10.2230*** (0.0022)	9.3110*** (0.0035)	10.3750*** (0.0020)
	LM*-lambda conditional LM test (assuming $\sigma_{\mu}^{2} \geq 0$)	Spatial autocorrelation	2.3941** (0.0167)	1.3657 (0.1720)	1.3928 (0.1637)	1.2796 (0.2007)	1.2830 (0.1995)
LM tests of Baltagi, Song, Jung & Koh (2007)	C.2 conditional test	Serial correlation in error terms, under random effects and spatial dependence	0.1265 (0.7221)	2.1156 (0.1458)	1.3772 (0.2406)	2.0905 (0.1482)	1.5716 (0.2100)

Lastly, we check for the possible presence of serial correlation in the spatial error models. Baltagi et al. (2007) consider a more generalized form of the panel data models with spatial autocorrelation by also incorporating serial correlation in the disturbance terms as a first order autoregressive process. The results provided in Table 14 indicate that under random effects and spatial error correlation, there is no serial correlation in the error terms. Yet this time, the test can only be carried out for the random effect case and the possibility of fixed effects are ruled out in test statistic given that σ_{μ}^2 is assumed to be strictly greater than zero. The locally robust test statistics for a non-spatial panel data structure presented in Appendix B.3 also imply the absence of serial correlation.

3.4.2.2. Evaluation of Dynamic Panel Spatial Lag Models

For the SDPD model with spatially lagged dependent variables, the comparison between random versus fixed effects can be discussed in two aspects. First, as noted in section (3.3.1), the nature of the regional convergence models is more in line with the specification of the individual effects as fixed rather than random. This is because the sampled units are not selected from a population; instead they somewhat represent the population themselves. As argued before, this violates the orthogonality assumption between random individual effects and the regressors. Second, in the estimated models, it is observed that the residual variances for the fixed effects specification are noticeably lower than that of random effects. Based on these grounds, it is more meaningful to prefer the fixed effects pattern for the data set under consideration[30].

Both the estimated random and fixed effects spatial model specifications ascertain that the spatial lag parameters ρ are positive and significant. In the selected dynamic fixed effects spatial lag specification, spatial lag parameters are significant for

[30] Given that the rationale for the comparison of fixed versus random effects is provided for the SDPD models with spatial lag components, the question arises whether this could also be handled via statistical testing methods such as Hausman tests. Here, the usage of Hausman tests for the spatial lag case is not preferred as the proposed tests of Mutl and Pfaffermayr (2011) are designed for static panel data models in spatial autoregressive model with spatial autoregressive disturbance structure. For a dynamic panel data spatial lag setting, the results would not be binding but it could only provide background information.

Models 2, 3, and 4. For these models, one can argue that the dynamic panel data structure must include the spatiality in the lagged dependent variables and ignorance of these effects would result in unbiased and inconsistent estimates in accordance with the omitted variable problem.

3.4.3. Results and Discussion

The overall econometric analysis offers five main results in a nutshell. First, panel data specifications are preferred to the pooled OLS as the individual effects are found to be significant. Second, there is evidence of cross-section dependence in the panel data structure, which calls for the need for incorporating spatiality into the model. Third, random effects are rejected in favor of the fixed effects models. Fourth, no apparent spatial correlation can be found in the error terms. Fifth, the spatial lag terms are positive and significant in general. In the light of these results, one can conclude that the dynamic fixed effects spatial lag models may be better characterizing the regional convergence dynamics of Turkey throughout the 1991-2009 period.

The estimation results for dynamic fixed effects spatial lag models indicate that the conditional convergence Models 2, 3 and 4 provide more promising results since the spatial lag terms are significant. Model 2 utilizes the rate of high school graduates as proxy for human capital and loans as proxy for private investment. Thus, it is in fact an extension of the models considered in Chapter 2. The results indicate that the economic depression in 2001 followed by the recovery period that continues until 2008 have indeed significant effects on the provincial growth determinants. On the other hand, the crisis years expressed by the outlier dummies have somewhat unexpected coefficients in this model. The dummy defined for the 2001 crisis is found to be insignificant, which also holds for Model 4. In this respect, Model 3 can be a better characterization of the Turkish economy in the 2000s. We could argue that Turkey was less affected by the global crises in 2009 but more damaged by the 2001 domestic banking crisis. Hence, it is plausible to have insignificant coefficients for D09 as opposed to the significant values for D01.

In Table 11, taking Model 3 as a point of departure, we observe that the coefficients of the human capital variable measured by the university graduates are negative and statistically insignificant at 5% level in the base period and the overall period. These outcomes are not uncommon in growth regressions estimated by panel data. Islam (1995) reports the following:

> (…) such "anomalous" results regarding the role of human capital in the growth process are not new. Whenever researchers have attempted to incorporate the temporal dimension of human capital variables in the growth regressions, outcomes of either statistical insignificance or negative sign have surfaced. So far, there have been two kinds of responses to these types of results. One is to point out the discrepancy between the theoretical variable *H* in the production function and the actual variable used in the regressions. (…) The second response is to think of richer specification of the production function with respect to human capital.
>
> (Islam, 1995: 1153)

In the light of these observations we keep our results based on practical grounds. The potential issue of inadequacy of the available variables as measures of human capital may be caused by the possible persistence in the series. Yet, this problem is hard to solve straightaway, given the data limitations. Furthermore, this panel data analysis aims to extend the previous cross-section framework in a comparative manner by incorporating the time effects and alternative sets of variables. In doing this, the differentiation of skilled and unskilled labor is essential to comprehend the diverse effects of different measures of human capital on the provincial growth. In fact, in Chapter 2, the rate of high school graduates as an indicator of human capital was found to be one of the main driving forces of the provincial convergence. For the SDPD setting, the analogous specification represented by Model 2 has similar characteristics. This model reveals that during 2002-2007 period, the rate of high school graduates has contributed much to the provincial output growth such that it compensated for the insignificance in the base period.

Another growth determinant which was found to be contributing a lot to the growth in the previous cross-sectional analysis was the employment rate. In Model 2, this variable again happens to be highly significant and positive in both periods. On the other hand, for the more plausible Model 3, it is discovered that in the post-2002 period up until the global recession, the employment policies did not have a significant contribution. In effect, during this period the employment creation has been one of the weak spots of the economy. We leave the further discussion on the so-called "jobless growth" and the employment creation problem to Chapter 4 in which we discuss the issue with a scope of analysis at both regional and sectoral level.

A further interesting observation from the SDPD estimation analysis is that public investments which have been insufficient to serve for the purposes of provincial growth in the base year have evolved after 2002 such that they yielded affirmative results. Evaluating the results of the cross-section analysis in Chapter 2, it was argued that the insignificance of public investment variables in the entire period may be observed due to the wrong policy instruments put into practice. As the shares of the public investment have recovered after 2002, this conjuncture may have been reversed (Figure 1). The estimation results for Model 3 reflects that the private investment measured by rate of deposits follow a similar path to that of public investment. The insignificant coefficients in the base year have been recovered by the highly significant and positive differential slope terms in the 2002-2007 period.

3.4. Conclusion

This chapter employs spatial dynamic panel data models to explore the provincial output growth in Turkey throughout the 1991-2009 period. By means of the SDPD models, it becomes possible to take both time and spatial effects into consideration. Moreover, thanks to the dynamic structure of the SDPD models, the initial GDP variables are allowed to be time-varying. This feature basically helps us to track the progress of the GDP on a yearly basis and obtain more reliable estimates for the convergence parameters.

The results of various specification tests imply that the pooled OLS models as well as the standard panel data counterparts are insufficient to explain the underlying true data generating process. Thus, four different SDPD models, namely dynamic fixed effects spatial error, dynamic random effects spatial error, dynamic fixed effects spatial lag and dynamic random effects spatial lag models are estimated. Following a discussion on both the rationale of the regional convergence analysis and employing the relevant tests statistics for determining the form of the panel data and the spatiality, the dynamic fixed effects spatial lag model appears as the most appropriate model. The results of the generalized method of moments estimations together with the corresponding tests confirm not only the validity but also the superiority of the SDPD specifications. The selected model has significantly positive spatial lag terms indicating that the growth in one province is directly linked to the growth in the neighboring provinces. The inclusion of time effects has introduced some alterations in the estimation outcomes as compared to the previous spatial cross section analysis carried out in Chapter 2.

Overall, there is evidence of absolute and conditional convergence among the provinces of Turkey throughout the 1991-2009 period. The provincial growth is determined by human capital, employment, real public investment, real private investment and population. Furthermore, 2002-2007 expansion period is recorded as a period of structural change and the crises experienced in 1994, 1999, 2001 and 2009 are found to be significant outliers that are controlled in the econometric analysis.

In conclusion, there are at least four main observations which can be followed by certain policy implications. First, the contribution of the university graduates to the output growth is found to be relatively limited. The output creation mechanism may still be relying on human capital at the level of secondary school. Further policy actions should be taken to benefit from the more qualified labor force. Second, it is observed that the employment policies carried out over the 2002-2007 period did not add much on the existing policies and hence has not been able to contribute to provincial output growth. The economic expansion in this period may not have created job opportunities. In fact, taking correct policy incentives for the employment creation would have resulted in feedback effects which also enhance the output growth. Third, base year public investments insufficient to produce output growth have turn out be more effective in the post-2002 period. These results are promising in the sense that the governance of public investments has recently got better. Fourth, the private investments measured by the rate of deposits have positively affected provincial output growth in the 2002-2007 period as compared to the base period.

CHAPTER 4

SPATIAL PANEL SEEMINGLY UNRELATED REGRESSION ANALYSIS OF SECTORAL REGIONAL EMPLOYMENT CONVERGENCE IN TURKEY[31]

The enhancement of employment vis-à-vis growth is the optimal strategy for any country and the regional growth would be fully comprehended only if the interactions with employment creation are taken into consideration. On the other hand, the economies rarely attain these two goals together. In reality, the growth may take place without creating job opportunities or conversely the increase in employment may not help promoting growth because of the low growth elasticity of employment or poorly qualified labor force. Thus, the analysis of employment convergence alongside the growth convergence becomes crucial for the assessment of the regional development dynamics.

Turkey as a developing country has long been suffering from regional disparities in employment, not to mention wages especially in the private sector. This unequal pattern has been going hand in hand with the employment shifts across the main sectors of the economy. Having been a highly agricultural economy up until the beginning of the 1980s, the economy has experienced some changes in the labor market and became more labor abundant in the services sector. Thus the evolvement of employment dynamics throughout the last three decades has been attached not only to regional but also to sectoral differentiations in the labor market. Even though regional employment has been a highly debated issue in the literature, these sectoral interactions in employment have mostly been neglected. This last observation has constituted the main motivation for a further study on employment

[31] A previous version of this chapter was presented before in The VII World Conference of the Spatial Econometrics Association, Washington DC, U.S.A., 10-12 July 2013.

dynamics in Turkey, aiming to fill this gap with a comprehensive empirical framework.

This chapter discusses the employment convergence problem in 26 NUTS-2 level regions of Turkey throughout the 2004-2011 period. Separate sectoral equations for agriculture, industry and services are constructed such that the neighborhood and time effects are considered via spatial panel data framework. For each sectoral equation, the random effects panel data models with spatial error components are estimated by feasible generalized spatial three stage least squares (FGS3SLS). Subsequently, we further allow for the existence of correlation between the estimated spatial panel data models and employ a spatial panel seemingly unrelated regression (SUR) model, in which the sectoral employment convergence equations are related through the contemporaneous correlation in the disturbances. The estimation results point out a divergent pattern in the agriculture sector and a convergent trend in the services sector, which is in line with the preliminary data analysis and the expectations. Moreover, the interaction model estimated in a spatial panel seemingly unrelated regression framework posits that lower levels of agricultural employment in the initial year has ended up with higher levels of employment in services sector as observed in the economy through time.

The chapter is composed of six sections. Section one presents regional employment convergence literature. Section two summarizes the general outlook of the labor market and regional employment policies in Turkey. Section three introduces the data and basic labor market indicators at both sectoral and regional level. Section four discusses the evidence of spatial effects in the baseline models and provides the methodological basis for handling the three dimensions -time, space and sectors- in a generalized modelling framework. Section five displays the outcomes of the empirical models for sectoral regional employment convergence in Turkey. Section six summarizes and concludes.

4.1. Regional Employment Convergence Literature

4.1.1. Regional Employment Convergence Model

Analogous to the growth convergence model that has been considered in the previous two chapters, the employment convergence model discussed in this chapter is based on the Solow-Swan beta convergence hypothesis. In accordance with the neoclassical structure that has been under consideration, the convergence models rely upon the assumptions of constant returns to scale with diminishing returns to inputs. The principle of diminishing marginal returns to labor asserts that as the number of workers increases, the marginal product of each additional worker will be less than the previous one. Given this setup together with inter-regional mobility, the regions with lower employment rates tend to have higher employment growth and this process continues until a state of convergence is achieved.

The differentiations in the employment have been investigated by researchers especially when the mergers of different economic formations or diverse labor market structures are of concern. Funkhouser (2000) discusses the convergence in employment rates of immigrants relative to natives in US. Using the census data from 1980 and 1990, the author concludes that during the initial years following the immigration, there is a large increase in employment rates. The subsequent change in the employment rates is larger for more skilled immigrants who have disadvantageous positions initially. Boeri and Terrel (2002) investigate the asymmetric patterns of GDP, employment and labor reallocation for the transition countries that moved from planned to market-oriented economy. For this purpose the authors compare Central and Eastern European countries with former Soviet Union countries by means of calculating the transition probabilities of some indicators such as employment, unemployment and labor force. They argue that the so-called non-employment benefits have been operated more by the Central and Eastern European countries as compared to the former Soviet Union countries. This basically led to a differentiation between the two labor market adjustment processes and the paces of structural change.

The regional analysis of employment has also been discussed by some scholars together with an income convergence aspect. Glaeser et al. (1992) examine the employment growth of large industries in 170 US cities over the period 1956-1987. The authors employ standard cross-sectional conditional convergence regressions for city-industry employment growth and wage growth. They conclude that "*at the city-industry level, specialization hurts, competition helps, and city diversity helps employment growth*" (Glaeser et al., 1992:1150). Martin (2001) explores the regional productivity and employment growth of Economic and Monetary Union (EMU) over the 1975-1998 period. He argues that across the EU regions, worker productivity has shown weak convergence whereas the regional employment growth has been divergent. Perugini and Signorelli (2004) investigate the employment performance in conjunction with the convergence of 262 regions of the 27 European countries after 1997. In the empirical analysis, they utilize a standard neoclassical convergence model adapted for the rate of total employment of different country groups. The results reveal the presence of significant convergence in the total employment rates of EU-15 and EMU-12 countries for the 1999-2003 time period.

The labor market dynamics and convergence problem have been examined at sectoral level as well. Marelli (2004) analyzes the distribution of employment between agriculture, industry and services sectors of the 145 European Union regions over the 1983-1997 period. The author finds that the specialization in agriculture has overall been decreasing. For the industry, five regions have an increase in relative specialization and for the services sector employment shares increase in all regions with relatively low levels of specialization.

In general, the studies covering the labor market differentiation with a common consideration of regional and sectoral effects are quite rare. In this respect, the standard approaches to the employment convergence problem fall short of the expectations. One possibility to take account of this problem is to exploit the potentials of spatial econometric methods.

4.1.2. Spatial SUR Extensions of the Regional Employment Convergence Model

In the empirical literature, the idea of using seemingly unrelated regression models for discussing the regional employment can be found in some earlier studies. White and Hewings (1982) consider a model for 5 regions and 31 sectors in Illinois over the 1965-1977 period. The authors report the estimation results of SUR and OLS regressions for six sectors and compare the results of the two procedures.

On the other hand, the spatial dimension of the employment convergence problem has been discussed less often. The earlier research relied on the spatial economic discussions without spatial modelling of the problem. Desmet and Fafchamps (2005) investigate the sectoral employment growth equations for US counties over the period 1972-2000 for 13 sectors. They construct a cross-sectional convergence model extended by adding the effect of neighboring locations. The distance measures between the two counties are based on the latitude and longitude. Controlling for employment at different distances, the empirical analysis indicate that aggregate employment has become more concentrated in US counties mostly due to the clustering in the services sector. In a similar vein, Desmet and Fafchamps (2006) examine the spatial distribution of jobs across the counties of US over the period 1970-2000. Similar to the findings in their previous study, services sector is again shown to be more concentrated unlike the agriculture and industry sectors. Combes et al. (2008) study the spatial wage disparities across the local labor markets in France using a panel data set for the 1976-1996 period and argue that up to almost half of the spatial wage disparities has been due to the differences in skills of the workers.

Studies that make use of spatial econometric analyses have diversities in the construction of SUR models. By and large, these studies make use of Anselin (1988) type SUR models in which each equation correspond to a different time period. In this case, the model is two-dimensional with space-time structure. Fingleton (2001b) examines the manufacturing productivity growth of 178 EU regions for three periods 1975-1981, 1981-1989, 1989-1995. The author employs a three-equation SUR model in which each equation correspond to the predetermined time periods. The results show that there is a significant increase in the level of positive spatial autocorrelation of productivity growth. He argues that if this process persists, the productivity in manufacturing will remain spatially polarized, causing permanent disparities in welfare levels. Using the same data set, Fingleton (2007) extends this three equation model by allowing for a distinction of core and periphery as well as structural instability over time. He ends up with a spatial SUR model with 12 equations and concludes that the usual assumption of temporal and spatial parameter homogeneity is unrealistic. Kosfeld and Dreger (2006) study the disaggregated labor market data of unified Germany for the 1992-2000 period. By utilizing spatial SUR models, they find evidences of spatial dependence in the employment and unemployment. Moreover, as the output changes, the responses of employment and unemployment seem to be unstable even in the periods of high and low GDP growth.

A noteworthy practice in a spatial simultaneous-equations growth model framework is presented by Gebremariam et al. (2010) who analyze the median household income and employment growth rates in 417 Appalachian counties over the 1990-2000 period. Using generalized spatial two stage least squares and generalized spatial three stage least squares estimations, the authors find that employment growth rate (median household income growth rate) in one county is positively (negatively) affected by the employment growth rate and median household income growth rate in the neighboring counties.

The convergence analysis with sectoral, spatial and time dimension is almost inexistent in the literature. One exception is Angulo et al. (2011) who analyze the convergence of wages in 19 Spanish regions and five sectors throughout the period 1998-2009. The comparative analysis of various regressions reveal that the fixed effects SUR model with spatial error components should be the preferred model. In Lopez et al. (2014), the authors proceed with the same SUR framework with three pillars. Theoretically, they discuss the model selection in spatial SUR models by comparing the specific-to-general and general-to-specific strategies. The empirical analysis covers the regional productivity in six sectors and 171 NUTS-2 regions of EU-15 throughout the period 1980-2010. Using five-year intervals, they construct a model for 6 equations, 6 time periods and 171 spatial units. The results indicate that using different model selection algorithms, it is possible to select different specifications.

Overall, even though the convergence in the employment rates has long been a concern of the scholars, very few studies mention both the sectoral and the regional aspects of the problem. For those studies that consider both dimensions, the dynamic structure is often neglected. There is a considerable gap in the empirical literature and a lack of comprehensive analysis taking all these three dimensions into account.

4.1.3. Regional Employment Literature in Turkey

The regional discrepancies and the development of labor markets in Turkish economy have been widely investigated in the literature. Nevertheless, there is still limited empirical evidence on the common dynamics of regional and sectoral employment in Turkey. Considering the sectoral dynamics of labor market, scholars mostly focus on manufacturing sector as it is the driving force of the economy and more reliable data exist. Voyvoda and Yeldan (2001) discuss the wage cycles in relation to the productivity in manufacturing using Hodrick-Prescott filter. The results reveal that there is a fluctuating trend in wages whereas the labor productivity shows a secularly rising trend. Aydıner-Avsar and Onaran (2010) investigate the effects of openness, wages and demand on employment in the manufacturing sector and conclude that output elasticity of labor demand is higher than wage elasticity throughout the 1973-2001 period.

In a couple of studies, the patterns in labor market are discussed in a multi-sectoral framework. Temel et al. (2005) investigate the convergence in labor productivities across 67 provinces over the 1975-1990 period by using Markov chain models. The results show that in the long run convergence clubs are likely to occur in the agriculture and industry sectors whereas in the services sector global convergence is expected in Turkey. Saracoğlu (2008) presents a three-sector growth model with agricultural, formal and informal sectors in a dynamic general equilibrium framework extending the Ramsey growth model. The results indicate that reducing informal employment in the country can be possible by a reduction in the tax on formal sector employment. Berument et al. (2009) examine the responses of unemployment rates to various macroeconomic shocks in the economy by considering four main sectors and quarterly data for the period 1988-2004. Using a six variable vector autoregressive (VAR) model, they find that an income shock (a price shock) affects unemployment in all sectors in the short (long) run. Another noteworthy result is that unemployment in agriculture and manufacturing respond to macroeconomic shocks in different ways.

The studies that consider the regional dimensions in the Turkish labor market focus mostly on the disparities in wages or the dispersion of unemployment. Ilkkaracan and Selim (2003) investigate the role of regional unemployment rates in determining the individual wages in Turkey in 1994. The authors show the presence of a negative relationship between wages and unemployment. Considering the gender-specific characteristics, they find evidences of negative correlation only for male workers, which confirm the existence of segregated labor market in Turkey. Akgüngör (2006) examines the regional clusters in manufacturing industry with respect to various indicators including the number of establishments and employment. Based on the 1996 input-output table, the author identifies clusters by means of location quotients and compares the computed values with employment growth figures. Apart from the specific results for each region, the overall analysis reveals that the employment shares of newly developing industrial regions have increased over time.

The studies that make a significant contribution by integrating spatial modelling to the empirical analysis of Turkish regional labor market are essentially based on cross-section analysis. The beta convergence analysis of Öcal and Yıldırım (2008) show that there is divergence in the employment rates of 67 provinces over the 1985-2000 period. Performing a geographically weighted regression (GWR) model, the authors observe that well-known regional disparities exist also in the employment figures. In particular, compared to the eastern provinces, western provinces acquire higher employment levels. Filiztekin (2009) uses spatial and nonparametric techniques to analyze the regional unemployment disparities in

Turkey from 1980 to 2000. He finds that the gap between the provincial unemployment rates are widening over time. The spatial clusters exist and are mostly triggered by the alterations in human capital and demand.

4.2. Regional Employment in Turkey

4.2.1. General Outlook of the Labor Market

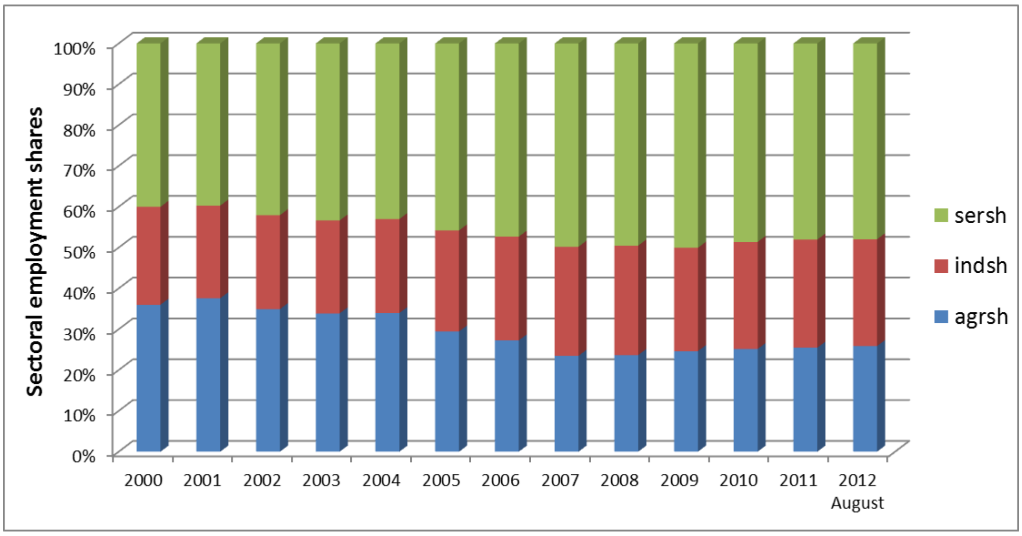
The labor market in Turkey has experienced major changes following the shifts in the political environment as well as the ups and downs in the macroeconomic conditions. Until 1980s, Turkey implemented an import substitution policy for economic growth which was replaced by the export-led growth regime following the structural adjustment program announced in January 24, 1980. During 1980s as a period of high population growth rate, the stabilization was achieved by means of imposing wage cuts. The export strategy was based on the idea that by lowering wages, lower inflation rates and real depreciation could be attained which would in turn trigger the export competitiveness in the economy (Taymaz, 1999). These labor market policies have been altered by the capital account liberalization in 1989 followed by a rise in real wages in 1990s. The structural changes in the macroeconomic conjuncture undoubtedly had major influences on the labor market:

> Our estimates of labor demand functions for Turkish manufacturing industries show that trade policy variables and macroeconomic variables are quite important for employment generation. These findings show that high real interest rates and the appreciation of the real exchange rate, which have played the key role to attract capital inflows after the liberalization of capital accounts in the late 1980s, and real wage hikes in the early 1990s have a very important effect on employment performance of the manufacturing industries.
>
> (Taymaz, 1999:26)

The positive macroeconomic atmosphere period in the early 1990s going hand in hand with appreciation in the domestic currency did not last long. As of 1994, a major financial crisis resulted in a sharp depreciation in the exchange rates along with rises in the interest rates. This conjuncture has reduced the real wage gains of post-1989 period (Yıldırım and Öcal, 2006).

During 2000s, the trend of high unemployment rates and low employment generation capacity persisted, even deteriorated further. The macroeconomic environment of the country had significantly worsened following the 2001 crisis. The unemployment rate rose to levels higher than 10 percent and real wages were reduced by 20 per cent (Yeldan, 2011). In the post-2001 crisis period, poor job creation, high interest rates, huge appreciation of TL and expanding current account deficits became the basic patterns of the economy. The employment elasticity showing the percentage gain in employment with respect to percentage change in GDP growth was relatively low. For the 1989-2008 period, the elasticity of employment was found to be 0.25. The values computed for two consecutive sub-periods have shown fluctuations before and after the 2001 crisis. During 1989-2000 the elasticity was 0.39 whereas between 2002 and 2008 it fell down to 0.14 (Yeldan, 2011).

The effects of these corrosions in the labor market were far from being homogeneous at the sectoral level. The structure of the labor force has been transforming together with movements out of rural areas to urban areas, resulting a decrease in agricultural employment and an increase in services employment. Since the beginning of 2000s, there has been a considerable increase in the employment share of services sector. Figure 13 shows that in 2000, almost half of the employed people were located in services sector and this climbed up until 2010.



Notes: sersh, indsh and agrsh stand for the employment rates in services sector, industry and agriculture respectively.
Source: Authors' calculations from Turkish Statistical Institute database.

Figure 13: Sectoral employment shares in Turkey (2000-2012)

The agriculture sector has been losing its significance especially after 2004, holding an employment share within the range of 23 to 30 per cent (Figure 13). Hence, it seems plausible to claim that unemployed labor in the agricultural sector might have found employment opportunities in the services sector during 2000s. On the other hand, the employment share of industry sector had a relatively smooth pattern varying from 23 to 27 per cent over 2004-2011. These labor market indicators may have been the corollary of not only the macroeconomic environment, but also the policies and regulations in the employment generation.

4.2.2. Employment Policies in Turkey

Regulations in the labor market have been one of the major concerns of policy-makers for many years. Only a few years after the establishment of the Republic, Turkey became a member of International Labor Organization in 1932. In 1936, with the Law No. 3008, first work law was officially put in action. Following the establishment of Ministry of Labor in 1945, first union law was enacted in 1947 by Law No. 5018. Starting with 1970s, the regulations in the labor market have accelerated. The Labor Law No. 1475 enacted in 1971 was covering a set of rules for most of the salary workers. In 1974, Ministry of Social Security which governs the Social Insurance Institution (SSK) and the Social Security Institution of Craftsmen, Tradesmen and other Self- Employed (Bağ-Kur) was founded.

In the aftermath of the military coup in 1980, major constitutional changes were put into practice. Some of the regulations were suggesting a short period of relief for the employees. Particularly, following a constitutional change in 1983, there had been some progressions in the work life. The amendments included freedom to work and contract, the right to form unions, the right for collective contract bargaining, the right to strike and lockout, and regulations in minimum wage (Tunalı, 2003). In 1983, the Ministry of Labor and Social Security was established. As of 1999, with Law No. 4447, the unemployment insurance was enacted. The law was put into force in 2002 and İŞKUR became in charge of administrating the payments. In 2002, the retirement ages were raised to 58 for women and 60 for men. In 2003, Turkish Labor Law 4857 was enacted[32] which replaced the former Labor Law No. 1475.

In line with the regulations in the labor market, employment policies covering the active and passive policies were built up. The aim of the active policies has been based on enhancing the employment opportunities and matching the right jobs with the right people. These include training programs, temporary public works programs and similar agenda based on consulting. On the other hand, the passive policies have been focusing on decreasing the negative outcomes of unemployment via unemployment insurance or related welfare benefits. Three passive labor market measures of utmost importance in Turkey have been the severance payments[33], unemployment insurance and job loss compensation (Tunalı, 2003). Other related measures for the labor market include the minimum wages and social security system.

[32] Taymaz and Özler (2005) compare the two Labor Laws and discuss the problems and prospects for labor market policies in Turkey.

[33] Severance payments include seniority payment and notice payment. The former one is calculated as 30 days salary for each year of service. The latter one covers the wages paid to the worker in case the employer fires the worker immediately.

Besides the specific measures for the labor market protection, National Employment Strategy was also announced by Ministry of Labor and Social Security for the 2014-2023 period. The strategy is based on four main pillars: strengthening the relation between education and employment, ensuring security and flexibility in the labor market, increasing employment for the groups necessitating specific policies, strengthening the relation between employment and social protection (MLSS, 2013). Main targets of this strategy for the year 2023 are three-fold: reducing the unemployment rate to 5%, increasing the employment rates up to 55% and decreasing the informal employment in the non-agricultural sector to the levels below 15%. It should be noted that no regional employment strategy is prescribed by this policy tool.

In fact, the regional employment strategies are mostly confined to the policy instruments such as the investment incentives and public expenditures. However, the investment incentive system in Turkey has been criticized for the insufficient consideration of the regional imbalances. Şahin et al. (2011) argue that in the East Anatolian and Black Sea regions, the incentives were given mostly to the energy sector instead of manufacturing or services sectors. They claim that neglecting the sector-specific dimensions in making regional policies would harm the long term development goals.

4.3. Data and Basic Labor Market Indicators

Inasmuch as the full comprehension of the labor market in Turkey requires a mutual analysis of regional and sectoral dynamics, the empirical part of this chapter considers the employment convergence dynamics in both dimensions. The data is collected for 26 NUTS-2 level regions in Turkey throughout the 2004-2011 period[34]. Data on the employment levels for the agriculture, industry, services sectors and non-institutional working age population are obtained from the Turkish

[34] Because of the limitations in data availability, the period under investigation is constrained to be 2004-2011. Before this period, there is lack of data both at regional and sectoral level.

Statistical Institute[35]. All variables are taken as thousand person and sectoral employment rates are calculated as the ratio of employed persons to the non-institutional working age population[36]. The empirical analysis incorporates the sectoral employment rates rather than levels, in order to control for the drastic changes in population. The descriptive statistics of the variables are provided in Appendix C.1.

Throughout the period under consideration, the employment rates at the sectoral level have been non-homogeneous across the regions[37]. Two immediate observations follow from Figure 14, which presents the regional sectoral employment rates in 2004 and 2011. First, in both years welfare disparities among regions of Turkey exhibit themselves in sectoral employment rates as well. Eastern regions and Central Anatolia have relatively high employment rates in agriculture, whereas Western regions have been more specialized in industry and services sectors both in 2004 and 2011. Second, services employment has become more intensive in the non-agricultural regions of Turkey.

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[35] The variables under consideration are limited by the data availability. Sectoral wages are inexistent at regional level. Average earnings, on the other hand, are not available at sectoral level.

[36] The non-institutional working age population includes the individuals with ages 15 and over and not residing in dormitories of universities, orphanage, rest homes for elderly persons, special hospitals, prisons and military barracks etc.

[37] The kernel density plots provided in Appendix C.3 confirms this observation. Particularly for the agriculture and the services sectors, the regional distribution of the employment variables tends to be skewed for all years.

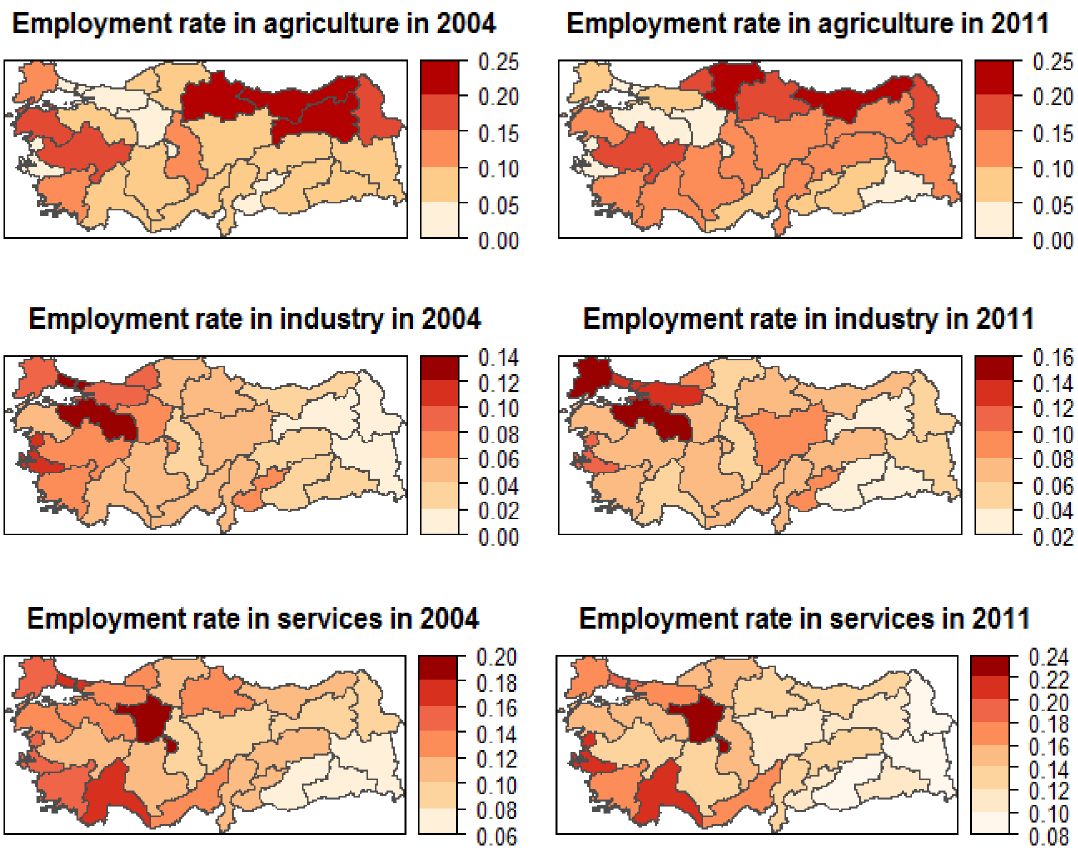
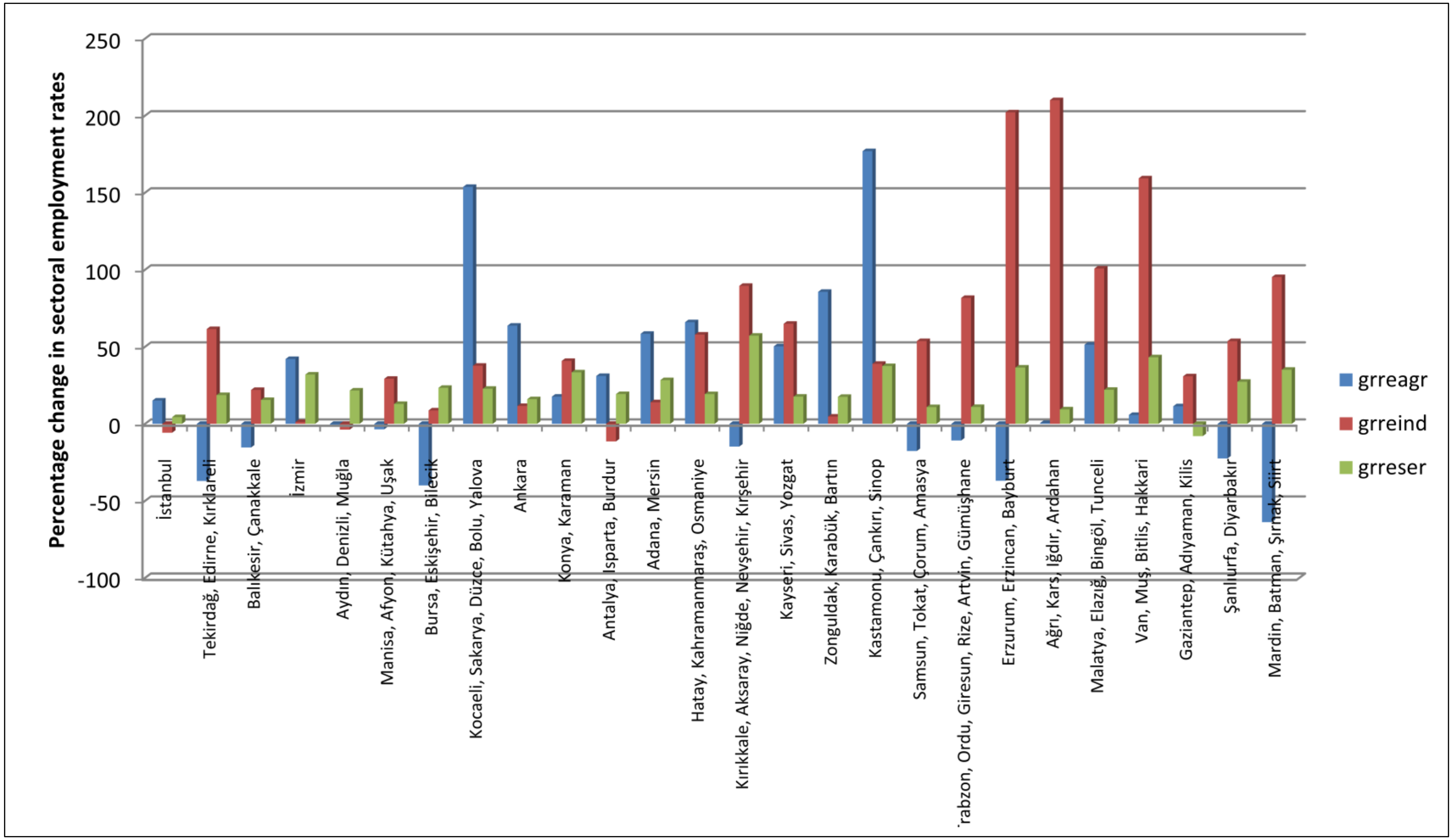


Figure 14: Sectoral Employment Rates in 2004 and 2011

From 2004 to 2011, the total number of employed people in agriculture increased by 7.54 per cent, whereas 30.54 per cent in industry and 28.26 per cent in services. Controlling for the drastic rise in the population growth and focusing on the employment in per capita terms, we observe that there is a 0.34 per cent fall in the agricultural employment rates, 20.98 per cent increase in the industrial employment rates and 18.86 per cent increase in the services sector employment rates[38]. At the regional level, negative growth in agriculture is recorded for nine regions in this period (Figure 15). Growth in industrial employment shows significant variability whereas growth in services sector employment rate has a relatively smooth positive pattern over the regions.

[38] Author's calculations using Turkish Statistical Institute database.



Notes: grreagr, grreind and grreser represent growth in agricultural employment rates, growth in industrial employment rates and growth in services sector employment rates respectively.
Source: Authors' calculations from Turkish Statistical Institute database.

Figure 15: Growth in sectoral employment rates in 26 regions (2004-2011)

4.4. A Spatial Extension to Regional Employment Convergence in Turkey

4.4.1. Empirical Results of Standard Employment Convergence Models

The standard convergence model postulates that negative and significant beta convergence parameters can be interpreted as evidence of convergence. As for the employment convergence, this is more meaningful within the scope of a multi-sector model. To put it simply, it is not likely that employment rates in agriculture would converge to that of the services sector. Although there are interactions among different sectors and the employees shift from one sector to the other, each sector has its own labor market dynamics. This calls for the need to specify a system of equations with three equations each representing the main sectors of the economy. Table 15 presents the estimated empirical models for the employment convergence problem under consideration. The variables EAGR, EIND and ESER denote employment rates in agriculture, industry and services sectors, respectively. Furthermore, in order to capture any interaction effects among the sectors, alternative models have also been considered for each of the specifications. In these interaction models, employment growth rates in a sector are conditioned not only on that sector's initial employment rate, but also on other sectors' initial employment rates.

Each sectoral convergence equation in Table 15 has its own dynamics and can be estimated separately. For comparison purposes, we first discuss the pooled OLS results as a benchmark regression. Subsequently, the systems estimation approach in a seemingly unrelated regression (SUR) framework is suggested on the grounds that error terms might be correlated across equations due to the omission of variables. SUR provides parameter estimates that are asymptotically more efficient than OLS estimates when there is contemporaneous correlation between disturbances of different equations (Zellner, 1962). As for the sectoral employment convergence, it is plausible to have such a correlation between the disturbances since the overall conjuncture in the labor market is likely to have consequences in the employment rates of each sector.

Moreover, any kind of shock experienced in the economy would have impacts on the sectoral employment in relation to the other sectors. Considering these factors, the subsequent analysis presents a three equation system estimated by SUR in which each equation represents one of the key sectors in the economy[39].

In this SUR model, the sectoral interactions may also be more straightforward such that the employment rates in one sector are directly affected by the employment rates of the other sectors. This direct impact can take place when the workers in one sector switch to new jobs in the other sectors. In this case, the employment growth in one sector is determined not only by its own initial employment rates but also by others'. This is more likely to occur from agriculture to services, given that becoming a more service sector oriented economy has been a general trend in most of the developing countries. The progress of industrial employment becomes crucial as it gives a clue about the development prospects of the country.

As a further exercise in this chapter, the dynamic models with lagged initial employment rates are also analyzed (Table 15). Accordingly, the modified base and interaction models have dynamic initial employment rates as regressors. In this case, the beta convergence parameters also reflect the short-run response of the employment growth to the employment rates given that the change in employment rates from one year to the next are considered.

[39] The corresponding contemporaneous correlations for the SUR estimations provided in Appendix C.2 also confirm the validity of systems of equations approach.

Table 15: Estimated Empirical Models

Static Models	
Base Model	Interaction Model
$\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i0} + u_{1i}$	$\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i0} + \beta_{12}\log EIND_{i0} + \beta_{13}\log ESER_{i0} + u_{1i}$
$\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EIND_{i0} + u_{2i}$	$\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EAGR_{i0} + \beta_{22}\log EIND_{i0} + \beta_{23}\log ESER_{i0} + u_{2i}$
$\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log ESER_{i0} + u_{3i}$	$\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log EAGR_{i0} + \beta_{32}\log EIND_{i0} + \beta_{33}\log ESER_{i0} + u_{3i}$
Dynamic Models	
Base Model	Interaction Model
$\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i,t-1} + u_{1i}$	$\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i,t-1} + \beta_{12}\log EIND_{i,t-1} + \beta_{13}\log ESER_{i,t-1} + u_{1i}$
$\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EIND_{i,t-1} + u_{2i}$	$\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EAGR_{i,t-1} + \beta_{22}\log EIND_{i,t-1} + \beta_{23}\log ESER_{i,t-1} + u_{2i}$
$\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log ESER_{i,t-1} + u_{3i}$	$\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log EAGR_{i,t-1} + \beta_{32}\log EIND_{i,t-1} + \beta_{33}\log ESER_{i,t-1} + u_{3i}$

Notes: The structures of the estimated empirical models are based on Yıldırım and Öcal (2006) and revised for a panel data setting. EAGR, EIND and ESER denote employment rates in agriculture, industry and services sectors, respectively.

For the model with static and dynamic initial employment rates, the pooled OLS estimation results of the base and interaction models are presented in Table 16. The static pooled OLS results indicate that in agriculture sector, the employment rates have been converging over the 2004-2011 period. However, when the sectoral interaction effects are taken into account, no significant convergence can be recorded. Considering the omitted variables, it is known that the exclusion of regional effects may cause a bias in the estimated parameters and hence in the estimated convergence rates (Barro, 2012). Therefore, it is not surprising to observe a high convergence in the base model in which no regional and no interaction effects are included. The static model specified for industry sector, on the other hand, reveals the presence of employment convergence both in the base model and in the interaction model. No convergence or divergence trends are observed for the services sector model estimated by pooled OLS.

The pooled OLS estimation results with dynamic initial employment rates have overall similar characteristics except for the services sector. In the services sector, the initially insignificant convergence parameters now turn out to be significant in both the base and interaction models. This may be because of the fact that with dynamic initial employment rates the recent variations in the labor market may be better represented in the modified models. Nevertheless, these models can only be considered as a benchmark analysis given that various dynamics at both space and time dimension are still neglected in this framework.

One interesting observation in the estimated pooled OLS regression follows from the interaction models. In these regressions, despite the direct inclusion of the other sectors' employment rates, the employment growth rate in each sector is explained only by its own initial employment rates. However, this pattern is not typical in the other estimation results, which will be presented later on.

Table 16: Pooled OLS estimation results of employment rate convergence models

Static Models						
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.0499	-0.0155	-0.1284***	-0.2717**	-0.0045	-0.0292
	(0.1457)	(0.9435)	(0.0009)	(0.0164)	(0.9278)	(0.6848)
log(eagr04)	-0.0244*	-0.0207		-0.0068		-0.0029
	(0.0831)	(0.2699)		(0.4808)		(0.6352)
log(eind04)		0.0159	-0.0654***	-0.0579***		-0.0009
		(0.6542)	(0.0000)	(0.0018)		(0.9357)
log(eser04)		-0.0089		-0.0845	-0.0125	-0.0215
		(0.9379)		(0.1530)	(0.6591)	(0.5680)
Residual standard error	0.2065	0.2075	0.1069	0.1069	0.0680	0.0684
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.6730	7.6641	2.0581	2.0343	0.8331	0.8320
MSE	0.0426	0.0431	0.0114	0.0114	0.0046	0.0047
RMSE	0.2065	0.2075	0.1069	0.1069	0.0680	0.0684
Multiple R-squared	0.0166	0.0177	0.1061	0.1164	0.0011	0.0024

Dynamic Models						
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.0616*	0.1130	-0.1558***	-0.2673***	-0.0905**	-0.1183*
	(0.0805)	(0.5453)	(0.0002)	(0.0057)	(0.0425)	(0.0528)
log(lageagr)	-0.0284**	-0.0196		-0.0036		-0.0040
	(0.0411)	(0.2478)		(0.6757)		(0.4740)
log(lageind)		0.0104	-0.0795***	-0.0698***		0.0006
		(0.7803)	(0.0000)	(0.0003)		(0.9630)
log(lageser)		0.0759		-0.0754	-0.0638**	-0.0758**
		(0.4333)		(0.1299)	(0.0151)	(0.0170)
Residual standard error	0.2058	0.2064	0.1059	0.1058	0.0670	0.0672
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.6233	7.5846	2.0202	1.9941	0.8070	0.8043
MSE	0.0424	0.0426	0.0112	0.0112	0.0045	0.0045
RMSE	0.2058	0.2064	0.1059	0.1058	0.0670	0.0672
Multiple R-squared	0.0230	0.0279	0.1226	0.1339	0.0324	0.0357

Notes: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. The values reported in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

Table 17: Pooled SUR estimation results of employment rate convergence models

Static Models						
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.0517	-0.0155	-0.1281***	-0.2717**	0.0080	-0.0292
	(0.1233)	(0.9429)	(0.0007)	(0.0153)	(0.8681)	(0.6814)
log(eagr04)	-0.0253*	-0.0207		-0.0068		-0.0029
	(0.0658)	(0.2646)		(0.4760)		(0.6314)
log(eind04)		0.0159	-0.0653***	-0.0579***		-0.0009
		(0.6506)	(0.0000)	(0.0016)		(0.9350)
log(eser04)		-0.0089		-0.0845	-0.0054	-0.0215
		(0.9372)		(0.1485)	(0.8413)	(0.5636)
Residual standard error	0.2065	0.2075	0.1069	0.1069	0.0680	0.0684
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.6732	7.6641	2.0581	2.0343	0.8334	0.8320
MSE	0.0426	0.0431	0.0114	0.0114	0.0046	0.0047
RMSE	0.2065	0.2075	0.1069	0.1069	0.0680	0.0684
Multiple R-squared	0.0166	0.0177	0.1061	0.1164	0.0007	0.0024

Dynamic Models						
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.0652*	0.1130	-0.1567***	-0.2673***	-0.0714*	-0.1183*
	(0.0585)	(0.5408)	(0.0001)	(0.0052)	(0.0934)	(0.0503)
log(lageagr)	-0.0300**	-0.0196		-0.0036		-0.0040
	(0.0269)	(0.2425)		(0.6723)		(0.4690)
log(lageind)		0.0104	-0.0798***	-0.0698***		0.0006
		(0.7779)	(0.0000)	(0.0003)		(0.9626)
log(lageser)		0.0759		-0.0754	-0.0526**	-0.0758**
		(0.4282)		(0.1257)	(0.0359)	(0.0159)
Residual standard error	0.2058	0.2064	0.1059	0.1058	0.0670	0.0672
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.6239	7.5846	2.0202	1.9941	0.8079	0.8043
MSE	0.0424	0.0426	0.0112	0.0112	0.0045	0.0045
RMSE	0.2058	0.2064	0.1059	0.1058	0.0670	0.0672
Multiple R-squared	0.0229	0.0279	0.1226	0.1339	0.0314	0.0357

Notes: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. The values reported in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

The pooled SUR estimation outcomes for the static and dynamic specifications are presented in Table 17. As expected, the results provide a similar tableau to that of pooled OLS but with smaller standard errors. In the presence of correlation among the disturbances of each equation, SUR is meant to offer more efficient results than OLS. However, these outcomes would still be insufficient as they ignore the time effects and possible spatial effects in the model.

4.4.2. Introducing Spatial Weights

The labor markets have regional characteristics and are likely to be affected by the neighbors due to similar reasons as in output growth problem. First and foremost, there are close economic linkages across the regions caused by the interdependencies through the access to the common markets. The spatially proximate regions often have similar industrial composition and production technologies. Hence, employment rates in any region may depend to some extent on the employment rates in the neighboring regions. Moreover, any possible shock that could affect the labor market in one region may possibly affect the other regions that produce similar goods at the common marketplace. Similarly, a shock to a producer in one region may affect suppliers of intermediate goods in the neighboring area (Glendon and Vigdor, 2003). Under these circumstances, if there is substantial spatial correlation among regions, its ignorance may result in biased and inconsistent estimates of the employment convergence rates. Thus, incorporating spatial effects into the analysis may lead to significant improvements in the estimated parameters.

To account for the possible spatial effects in the employment convergence problem, this chapter utilizes first-order binary contiguity weights described in Chapter 2. As the data set is composed of NUTS-2 level regions this time, we construct a spatial weight matrix W_{NxN} where number of columns and rows are equal to N=26. Note that this spatial weights matrix is row-standardized so as to equalize the impact of the neighboring provinces.

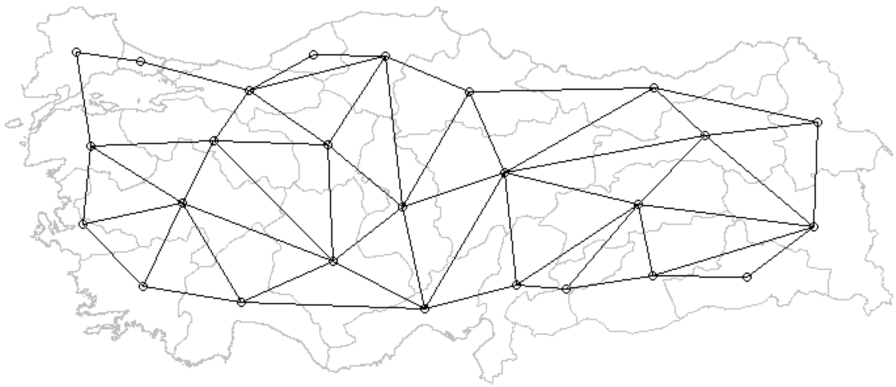


Figure 16: Neighborhood relations in 26 regions with binary contiguity weights

The neighborhood relations can be depicted as in Figure 16. Accordingly, the regions having common borders are linked with a line indicating the connections between them.

4.4.3. Spatial Econometric Methodology for Three Sector Model

In the literature the standard a-spatial SUR models have already been extended to a panel framework (Avery, 1997; Baltagi, 1980). These panel SUR models include both time and individual effects for each equation and further, a correlation between the error components of these SUR equations. Recently, some studies consider the spatial extensions of this panel SUR system. Baltagi and Pirotte (2011) make an important contribution by considering various estimators for panel SUR model with spatial error correlation. Baltagi and Bresson (2011) extend this work by incorporating spatially lagged dependent variable and proposing Lagrange multiplier tests.

The SUR analysis applied for the regional employment problem in this chapter has particular significance in terms of the modelling structure. Previous studies mostly follow the methodology of Anselin (1988) and handle the convergence problem by forming an SUR system in which each equation represents different time periods. Fingleton (2001b) employs this modelling framework in order to analyze the manufacturing productivity growth of European regions by constructing a three-equation SUR system for three sub-periods. Similarly, LeGallo & Dall'erba (2006) utilize a two-equation SUR model for European convergence problem in two consecutive periods. Hence, they build a space-time system with variations on time T and cross-section N. On the other hand, this chapter aims to constitute a framework which incorporates an additional dimension: the key sectors in the economy. In this sense it would be an (NTxG) system where G stands for the number of equations (sectors) in the system[40]. We construct a spatial panel SUR model with three sectoral equations separately estimated by spatial panel data method. Further, these regressions have contemporaneous correlation between the disturbances which will give an idea about the unobserved stochastic components that affect employment rates across different sectors.

The spatial panel data models estimated for each equation can be constructed in a number of ways. First, the panel data model can be specified either as fixed effects where the individual effects are constant, or random effects where the individual effects are allowed to vary. Either type of panel regression has its own advantages and shortcomings which have been presented in Chapter 3. In this chapter, following Wang and Kockelman (2007) and Baltagi and Bresson (2011) a random effects specification has been utilized. Thus we assume that the individual effects are independent of the explanatory variables.It is worth noting that in Chapter 3 we discussed fixed effects models may be more preferred in the regional growth convergence framework, because of the sample structure of the model. In that case, the sample became the population itself and the orthogonality assumption of random effects did not hold. Nevertheless, the sectoral labor market problem of this chapter has somewhat different characteristics than the previous regional growth problem. Here, the data utilized for the spatial panel data models are not representing the whole employment in the given region. As they are specified for each sector separately, they represent only part of the total regional

[40] In this sense, our approach is more like that of Angulo et al. (2011) and Lopez et al. (2014).

employment. The sample is no longer the population itself, which makes the random effects specification plausible.

The spatiality can also be introduced into the model in different ways. The two basic forms are spatial lag and spatial error specifications reflecting the spatial dependence and spatial heterogeneity. The spatial error model implies that spatial heterogeneity operates through the error processes. In this case, any random shock follows a spatial pattern leading to a correlation across adjacent regions. On the other hand, the spatial lag model suggests that employment growth rates in one region depend on those in the adjacent regions. For our purposes, the spatial dimension is introduced into the model by means of spatial error terms. Intuitively, this assumption is reasonable regarding the characteristics of the labor market. A shock to a producer in one region may affect suppliers of intermediate goods in the surrounding regions (Glendon and Vigdor, 2003). Further, in cases where regions produce similar goods for consumption in the global market and when the demand changes due to a shock, there will be consequences in the labor markets of the neighboring regions. Therefore, taking spatial dependence through the error components of the employment model is found to be convenient due to the nature of the employment problem.

Eventually, we construct a three equation spatial panel SUR model in which each equation is specified as random effects with spatial error components. We first present the modeling structure and the estimation of each sectoral equation and then discuss the extended system of equations.

4.4.3.1 Estimating Spatial Panel Models by FGS3SLS

The random effects spatial error model for employment convergence in each sector is specified as in equation (4.1)[41].

[41] Note that the notations used in this chapter are slightly different from those in Chapter 3. Here we prefer to employ the notations used in the original theoretical econometric models as described in the corresponding literature.

$$
\begin{aligned}
y_{i,t} &= \alpha + \beta X_{i,t} + u_{i,t} \\
u_{i,t} &= \rho \sum_{j=1}^{N} w_{i,j} u_{i,t} + \varepsilon_{i,t} \qquad i = 1,\ldots,N \qquad t = 1,\ldots,T \\
\varepsilon_{i,t} &= \mu_i + v_{i,t}
\end{aligned}
\tag{4.1}
$$

where $y_{i,t} = \ln\left(\frac{E_{i,t}}{E_{i,t-1}}\right)$ is the growth of employment rate and $X_{i,t} = \ln(E_{i,t-1})$ is the initial employment rate for the given sector. $\sum_{j=1}^{N} w_{i,j}$ corresponds to each element of the W_{NxN} spatial weights matrix, $u_{i,t}$ is the spatially autocorrelated error component, $\mu_i \sim i.i.d(0,\sigma_\mu^2)$ is the unobservable individual specific effect, $\varepsilon_{i,t} \sim i.i.d(0,\sigma_\varepsilon^2)$ is specified as a one-way error component model and $v_{i,t} \sim i.i.d(0,\sigma_v^2)$ corresponds to the independent and identically distributed error term. Note that the spatial autoregressive parameter ρ satisfies $|\rho| < 1$. In line with the random effects specification, we assume that the individual effects μ_i are uncorrelated with the explanatory variables.

It should be noted that the spatial autocorrelation can be identified in the error components in different ways. Baltagi et al. (2003) specify the random effects first and then apply a spatial autoregressive (SAR) process for the remaining $\varepsilon_{i,t}$ disturbances. On the other hand, Kapoor et al. (2007) first identify a SAR process for the $u_{i,t}$ terms and then specify random effects in the remainder error terms $\varepsilon_{i,t}$. In terms of the error component structure, this chapter follows the Kapoor et al. (2007) framework.

Recall that contrary to the usual panel data literature, in spatial panel data, the observations are sorted so that time t is the slow running index and cross-section i is the fast running index. In other words, the spatial panel data are stacked first by time period, and then by cross-section (Millo and Piras, 2012). After stacking the model in both cross-section and time, the model can be re-written as in equation (4.2).

$$
\begin{aligned}
&y = X\beta + u \\
&u = \rho(I_T \otimes W)u + \varepsilon \\
&\varepsilon = (\iota_T \otimes I_N)\mu + v
\end{aligned}
\tag{4.2}
$$

where y denotes the (NTx1) vector of dependent variable, X denotes the (NTxk) vector of independent variables including the constant term, W denotes the (NxN) spatial weight matrix, I_N and I_T correspond to the identity matrix of order (NxN) and (TxT) respectively; ι_T is the (Tx1) column matrix of ones and $\otimes$ denotes the usual Kronecker product. Hence, from (4.2) the disturbances of the model can be specified as,

$$
u = [I_T \otimes (I_N - \rho W)^{-1}]\varepsilon \tag{4.3}
$$

and the variance-covariance matrix of u is,

$$
\Omega_u = [I_T \otimes (I_N - \rho W)^{-1}]\Omega_\varepsilon [I_T \otimes (I_N - \rho W^T)^{-1}] \tag{4.4}
$$

where W^T is the transpose of the spatial weight matrix. The variance-covariance matrix of the one-way error component model is,

$$
\Omega_\varepsilon = \sigma_v^2 Q_0 + \sigma_1^2 Q_1 \qquad \text{where} \qquad \sigma_1^2 = \sigma_v^2 + T\sigma_\mu^2 \tag{4.5}
$$

Note that the usual variance transformation is applied by using the symmetric, idempotent matrices Q_0 and Q_1 which are orthogonal to each other[42] such that,

$$
\begin{aligned}
&Q_0 = (I_T - \frac{\iota_T \iota_T^T}{T}) \otimes I_N \\
&Q_1 = (\frac{\iota_T \iota_T^T}{T}) \otimes I_N
\end{aligned}
\tag{4.6}
$$

[42] See Kapoor et al. (2007) for further details.

The term $\iota_T \iota_T^T$ is referred to as J_T in the literature which is in fact a (TxT) matrix of ones.

In order to estimate this model based on the GMM framework, Kapoor et al. (2007) show that the following moment conditions can be employed for $T \geq 2$:

$$E\begin{bmatrix} \frac{1}{N(T-1)}\varepsilon^T Q_0 \varepsilon \\ \frac{1}{N(T-1)}\bar{\varepsilon}^T Q_0 \bar{\varepsilon} \\ \frac{1}{N(T-1)}\bar{\varepsilon}^T Q_0 \varepsilon \\ \frac{1}{N}\varepsilon^T Q_1 \varepsilon \\ \frac{1}{N}\bar{\varepsilon}^T Q_1 \bar{\varepsilon} \\ \frac{1}{N}\bar{\varepsilon}^T Q_1 \varepsilon \end{bmatrix} = \begin{bmatrix} \sigma_v^2 \\ \sigma_v^2 \frac{1}{N} tr(W^T W) \\ 0 \\ \sigma_1^2 \\ \sigma_1^2 \frac{1}{N} tr(W^T W) \\ 0 \end{bmatrix} \tag{4.7}$$

where $\bar{u} = (I_T \otimes W_N)u$; $\bar{\bar{u}} = (I_T \otimes W_N)\bar{u}$; $\varepsilon = u - \rho\bar{u}$ and $\bar{\varepsilon} = \bar{u} - \rho\bar{\bar{u}}$. The first three moment conditions can be used to compute the initial estimators $\tilde{\rho}$ and $\tilde{\sigma}_v^2$. Based on these initial estimators and the fourth moment condition, $\tilde{\sigma}_1^2$ is estimated. In the second step, by using the remaining three moment conditions, the parameters $\hat{\rho}$, $\hat{\sigma}_v^2$ and $\hat{\sigma}_1^2$ can be estimated. In the third step, the spatial feasible generalized least squares estimator for β can be obtained, after applying the following transformations to the model. Initially, the spatial Cochrane-Orcutt transformation is carried out such that,

$$\begin{aligned} y^*(\rho) &= [I_T \otimes (I_N - \rho W)^{-1}]y \\ X^*(\rho) &= [I_T \otimes (I_N - \rho W)^{-1}]X \end{aligned} \tag{4.8}$$

Then, the model in (4.8) is further transformed via pre-multiplying by $(I_{NT} - \theta Q_1)$ where $\theta = 1 - \frac{\sigma_v}{\sigma_1}$. Applying OLS to this transformed model yields the estimator of the parameter β.

In order to handle the complexity of the model with full set of moment conditions, simpler methods can be occupied in two alternative ways. First, the initial estimators based on the first three moment conditions can be employed. Second, the simplified weighting schemes in which each sample moment is given equal weights can be exploited. In this chapter, in order not to lose any information in the model, operating the full set of moment conditions is preferred although computationally it complicates the model. Based on this feasible generalized spatial three stage least squares estimation procedure, each employment equation is estimated separately for each sector. More specifically; for agriculture, industry and services sectors random effects spatial error models are estimated one by one using the described methodology.

Subsequently, these three estimated sectoral equations are further allowed to be related via contemporaneous correlation among disturbances in a spatial panel SUR setting. The estimation method proposed for this model is described in the following sub-section.

4.4.3.2. Estimating Spatial Panel SUR Models

Suppose that the estimated spatial panel data models for the sectors are further correlated with each other through their disturbance terms. Hence we have the following (NTxG) system of equations:

$$
\begin{aligned}
y_{g,it} &= \alpha_g + \beta_g X_{g,it} + u_{g,it} \\
u_{g,it} &= \rho_g \sum_{j=1}^{n} w_{ij} u_{g,it} + \varepsilon_{g,it} \qquad i = 1,...,N \qquad t = 1,...,T \qquad g = 1,...,G \qquad (4.9) \\
\varepsilon_{g,it} &= \mu_{g,i} + v_{g,it}
\end{aligned}
$$

where the variables and the parameters are described as before. The subscript g=1,…,G corresponds to the number of equations. G=3 as there exist three sectors in our empirical model, but we introduce the model in closed from and solve for the general case here.

For an SUR model, the correlations between the disturbances of equations should be specified. Accordingly, the variance-covariance matrices for the error components satisfy the following:

$$\begin{aligned} E[\mu_{g,i}\mu_{h,i}] &= \sigma_{\mu_{gh}} \quad \forall i \quad and \;\; g \neq h \\ E[v_{g,it}v_{h,it}] &= \sigma_{v_{gh}} \quad \forall i,t \;\; and \;\; g \neq h \end{aligned} \tag{4.10}$$

In order to have an analogous expression to model (4.2), we stack the observations over time and cross sections:

$$\begin{aligned} y &= X\beta + u \\ u_g &= \rho_g (I_{TG} \otimes W) u_g + \varepsilon_g \\ \varepsilon_g &= (\iota_T \otimes I_{NG}) \mu_g + v_g \end{aligned} \tag{4.11}$$

Note that the subscript "g" is not used for the weight matrix W since the neighborhood relation does not change over the equations. This can be generalized as W_g for different empirical problems, but for our specific purposes the assumption $W_g = W \quad for \;\; g = 1.,..,G$ holds since each regional employment equation has the same neighborhood pattern which is specified by the same weight matrix.

A similar spatial panel SUR modelling structure has been introduced before by Wang & Kockelman (2007). However, the model we describe in (4.9) has some different characteristics from their model in terms of the error structure. As the spatial autocorrelation exists in u_{it} rather than ε_{it} in our case, it is more like Kapoor et al.(2007) spatial panel model, but revised for an SUR setting. A similar error component structure has been considered by Baltagi & Bresson (2011) for spatial panel SUR. However, unlike the one specified here, their model includes a spatial lag term.

To arrive at an expression for the variance-covariance matrix of u, the spatially autocorrelated error component in (4.11) can be re-written as,

$$u_g = \underbrace{[I_{TG} \otimes (I_{NG} - \rho_g W)^{-1}]}_{B} \varepsilon_g \tag{4.12}$$

with $B = \begin{pmatrix} I_T \otimes B_1 & & & \\ & . & & \\ & & . & \\ & & & I_T \otimes B_G \end{pmatrix}$ and $B_g = I_N - \rho_g W$

Hence, the variance-covariance matrix of u would be as follows:

$$\Omega_u = B^{-1} \Omega_\varepsilon (B^T)^{-1} \tag{4.13}$$

And the variance-covariance matrix of the error component ε is

$$\Omega_\varepsilon = \Omega_v Q_0 + \Omega_1 Q_1 \qquad \text{where} \qquad \Omega_1 = \Omega_v + T\Omega_\mu \tag{4.14}$$

and $\Omega_\mu = \begin{pmatrix} \sigma^2_{\mu_1} & \sigma_{\mu_{12}} & \dots & \sigma_{\mu_{1G}} \\ \sigma_{\mu_{21}} & \sigma^2_{\mu_2} & \dots & \sigma_{\mu_{2G}} \\ . & . & . & . \\ . & . & . & . \\ \sigma_{\mu_{G1}} & \sigma_{\mu_{G2}} & \dots & \sigma^2_{\mu_G} \end{pmatrix}$ $\qquad \Omega_v = \begin{pmatrix} \sigma^2_{v_1} & \sigma_{v_{12}} & \dots & \sigma_{v_{1G}} \\ \sigma_{v_{21}} & \sigma^2_{v_2} & \dots & \sigma_{v_{2G}} \\ . & . & . & . \\ . & . & . & . \\ \sigma_{v_{G1}} & \sigma_{v_{G2}} & \dots & \sigma^2_{v_G} \end{pmatrix}$

The matrices Q_0 and Q_1 are specified as before:

$$
\begin{aligned}
Q_0 &= \left(I_T - \frac{\iota_T \iota_T^T}{T} \right) \otimes I_N \\
Q_1 &= \left(\frac{\iota_T \iota_T^T}{T} \right) \otimes I_N
\end{aligned}
\qquad (4.15)
$$

The estimation of this system requires the estimation of the spatial panel data model. For each equation in the system, the spatial panel data estimation described above will be separately applied. Subsequently, the residuals of these estimated equations will further have correlation in accordance with the SUR system.

The estimation procedure can be outlined as follows: In the first step, we apply feasible generalized spatial three stage least squares estimation for each and every spatial panel data regression. In the second step, we take the estimated disturbances and apply feasible generalized least squares to solve for the SUR structure. The resulting estimates will be more efficient as they possess all the information from a comprehensive model allowing for time, cross-section and sectoral heterogeneity at the same time.

4.5. Outcomes of the Spatial Panel SUR Models for Sectoral Regional Employment Convergence

4.5.1. Spatial Panel Data Estimation Results

The FGS3SLS estimation results of the random effects spatial error models for each sector's employment convergence regressions are presented in Table 18. The estimation results for the static models reveal the evidence of regional convergence in the agriculture sector's employment growth. Nonetheless, when the initial employment rates in the other sectors are taken into account, the model indicates neither convergence nor divergence in the agriculture sector. The effects of other sectors' initial employment on the agriculture sector are not significant either. For the industry sector, the static models show evidence of convergence both in the base and interaction models. As the regions that start over with lower levels of industrial employment show higher rates of growth in employment rates, the regions with smaller endowments of industrial labor are catching up the others. The interaction model shows that there is a negative relationship between the industrial employment growth rate and the initial employment rates of agriculture and services sectors. In the services sector no clear evidence of convergence or divergence can be reported as a result of the specified spatial panel data model estimation.

The dynamic random effects panel data model with spatial error components imply similar results as the static models. Although the sizes of the estimated parameters change a little, the signs and the significances of the resultant estimates stay the same. Accordingly, the results display the evidence of convergence in the base model of agriculture sector, convergence in the base and interaction models of the industry sector. For the services sector, no evidence of convergence or divergence pattern can be detected.

Table 18: Spatial panel estimation results of employment rate convergence models

			Static Models			
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.0477*	-0.0277	-0.1254***	-0.2776***	-0.0043	-0.0263
	(0.0630)	(0.8700)	(0.0000)	(0.0000)	(0.8600)	(0.4500)
log(eagr04)	-0.0232**	-0.0207		-0.0074		-0.0026
	(0.0310)	(0.1500)		(0.1734)		(0.3800)
log(eind04)		0.0131	-0.0644***	-0.0565***		-0.0005
		(0.6300)	(0.0000)	(0.0000)		(0.9300)
log(eser04)		-0.0114		-0.0894***	-0.0124	-0.0210
		(0.9000)		(0.0055)	(0.3700)	(0.2400)
Spatial error parameter (rho)	-0.1249	-0.1179	0.1225	0.1468	0.0933	0.0842
			Dynamic Models			
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.0489	0.1273	-0.1399***	-0.2602***	-0.0303	-0.0514
	(0.1000)	(0.4400)	(0.0000)	(0.0002)	(0.3600)	(0.2600)
log(lageagr)	-0.0227*	-0.0133		-0.0043		-0.0025
	(0.0580)	(0.3500)		(0.4873)		(0.5500)
log(lageind)		0.0123	-0.0734***	-0.0625***		-0.0019
		(0.7000)	(0.0000)	(0.0000)		(0.8400)
log(lageser)		0.0734		-0.0814**	-0.0283	-0.0346
		(0.3900)		(0.0217)	(0.1400)	(0.1500)
Spatial error parameter (rho)	-0.1150	-0.1108	0.1103	0.1147	0.0869	0.0809

Notes: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. Random effects model with spatial error components is estimated by feasible generalized spatial three stage least squares; full set of moments are used in the estimation. The values reported in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

The spatial error parameters are found to be negative in the regression for agricultural employment growth (Table 18). This negative spatial autocorrelation implies that the adjacent regions are adversely affecting each other. As the employment share of the agriculture sector has been diminishing over time, the existing labor in the agriculture has become more valuable. Thus the neighboring regions may be competing for the same human resources which in turn may cause negative spatial correlation.

On the other hand, positive spatial error parameters are found for the industry and services sectors. Especially in the industry, the sizes of the coefficients are quite large. The industrial production necessitates certain infrastructural facilities which are quite related with the regional development level. The provinces that are well-equipped in terms of industrial substructure are more likely to be close to the regions with similar configurations and are more likely to hold qualified labor. In fact, the qualifications of the workers in the industrial sector are highly related to that of the sector itself.

4.5.2. Spatial Panel SUR Estimation Results

Subsequently, we estimate a spatial panel SUR model as described in section (4.4.3.2). The SUR estimation outcomes with random effects and spatial error components are presented in Table 19. We observe substantial changes in the employment convergence model estimation results of each sector.

In the static models, base regressions do not provide any evidence of convergence or divergence in the sectoral employment rates. On the other hand, when the interactions among sectors are introduced, statistically significant coefficients are documented. In the agriculture sector, the regional employment rates follow a divergent pattern. The initial employment rates in industry and services sectors have positive impacts on the growth of agricultural employment rates. Also in the industry sector, the interaction model indicates regional divergence in the employment rates. Furthermore, the results indicate that initial employment rates in the agriculture (services) sector is positively (negatively) associated with the employment growth in the industry.

In the services sector, on the other hand, employment rates show evidence of convergence across the regions. The agricultural employment rate in the initial year has a negative effect on the growth in services sector employment rates. This implies that regions with lower rates of agricultural employment in the initial year has ended up with higher rates of employment in services over 2004-2011. The initial observations in Figure 14 have already suggested that the agriculture sector is more clustered in interior regions and the eastern provinces. The services employment, on the other hand, is increasing as a general trend in all regions, though with more concentration in the western parts of the country. Hence the agriculture and services sectors seem like being on different sides of the coin.

The spatial panel SUR estimation results of the dynamic models differ from those with time-invariant initial employment rates. Contrary to the previous case, now the base model estimations for all sectors imply convergence in the employment rates. However, keeping in mind that these models show only absolute convergence and disregard the presence of any conditional variable, they may still be suffering from omitted variable bias. The interaction models are expected to give more precise outcomes not only because of this reason, but also as they are capable of demonstrating the labor movements across sectors.

The estimated dynamic spatial panel SUR models with interaction effects display divergence in the agricultural employment and convergence in the services sector employment. In the industry sector, the modified model does not show a significant divergent pattern as before. Hence, industrial employment at the regional level may have diverged from its 2004 value, but this pattern is not obvious when yearly changes in the employment rates are accounted for. The lagged levels of services sector employment rates have significantly negative effects on the growth rate of industrial employment, and vice versa.

Table 19: Spatial panel SUR estimation results of employment rate convergence models

			Static Models			
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	0.0081	1.3264***	-0.0268	-0.1201	0.0378	-0.2498***
	(0.8200)	(0.0000)	(0.6600)	(0.4050)	(0.4400)	(0.0069)
log(eagr04)	0.0025	0.1036***		0.0350**		-0.0224**
	(0.8800)	(0.0001)		(0.0120)		(0.0114)
log(eind04)		0.2017*	-0.0270	0.3409***		-0.0190
		(0.0540)	(0.2400)	(0.0000)		(0.5747)
log(eser04)		0.3226*		-0.6486***	0.0116	-0.0960*
		(0.0650)		(0.0000)	(0.6800)	(0.0680)
Spatial error parameter (rho)	-0.1249	-0.1179	0.1225	0.1468	0.0933	0.0842
			Dynamic Models			
	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.0679*	1.0913***	-0.0718	-0.2517	-0.1532***	-0.7108***
	(0.0966)	(0.0011)	(0.2238)	(0.1510)	(0.0011)	(0.0000)
log(lageagr)	-0.0310*	0.0691**		0.0013		-0.0550***
	(0.0812)	(0.0317)		(0.9393)		(0.0000)
log(lageind)		0.0987	-0.0462**	0.0607		-0.0508*
		(0.2271)	(0.0489)	(0.1342)		(0.0510)
log(lageser)		0.4036***		-0.2669***	-0.1010***	-0.2809***
		(0.0075)		(0.0002)	(0.0003)	(0.0000)
Spatial error parameter (rho)	-0.1150	-0.1108	0.1103	0.1147	0.0869	0.0809

Notes: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. SUR model with random effects and spatial error components is estimated by feasible generalized spatial three stage least squares; full set of moments are used in the estimation. The values reported in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

The spatial error terms are found to be negative in the agricultural employment growth equation and positive in the industry and services sectors. Overall, for any region the feedback effects of the neighbors are negative in the agriculture sector whereas positive externalities exist in the industrial and services sector employment.

4.6. Conclusion

This chapter is an attempt to uncover the sectoral regional employment convergence in 26 regions of Turkey throughout the 2004-2011 period. The descriptive analysis shows that regional disparities in the employment rates have been substantial in this period. Furthermore, the differentiations in the labor market also prevail in the main sectors of the economy. Thus, an elaborate discussion of convergence in employment rates should pay attention to both types of labor market differentials in Turkey.

The econometric analysis utilized in this chapter has particular significance in terms of the modelling structure which incorporates time, space and sectoral heterogeneity. For comparison purposes, standard absolute convergence model as well as an interaction model which accounts for the sectoral connections is utilized. Furthermore, the employment convergence equations are specified using both static and dynamic initial employment rates. The model without any spatial, time and sectoral interaction effects displays convergence in the agriculture and industry sectors whereas no significant divergence or convergence are detected in the services sector. The spatiality introduced in the model has particular implications. Any possible shock that affects the labor market in one region would have consequences in the employment rates of the neighboring regions. The spatial correlation identified in the error terms of the model helps us to perceive this phenomenon.

From this point of view, each sectoral model is extended in order to capture the spatial aspects of employment dynamics. First, the effects of initial employment rates on the yearly growth in employment rates are estimated for each sector by using random effects models with spatial error components. Then, considering the possible contemporaneous correlation between these sectoral models, spatial panel seemingly unrelated regressions are employed. Feasible generalized spatial three stage least squares estimation results indicate that the results of the spatial panel SUR models are in line with the preliminary data analysis and the expectations.

In the agriculture sector, it appears that the growth of employment rates has beta-divergent trend across the regions. This observation is plausible and of particular importance considering the sectoral employment shares in Turkey. Over the 2004-2011 period, negative employment growth rates are observed in nine regions. The agriculture sector is losing its significance and the agricultural activities have remained restricted to particular regions, mostly in the Central and North-East Anatolia. The negative spatial error parameters found in the estimations imply the presence of regional competition for human resources. This result is consistent with the observation that the employment shares have decreased over time and the workers in the agriculture sector has become comparably scarcer than before.

As for the industry sector, mixed results are obtained in terms of convergence dynamics. The static spatial panel SUR model estimation results reveal the presence of divergence. On the other hand, when the initial employment rates are taken as dynamic, this divergent pattern is no more significant. The preliminary data analysis has already shown that the country-wide employment shares of the industry sector have a relatively smooth pattern throughout the last decade. More importantly, the patterns of regional disparities do not depict significant alterations from one year to the other. This may be due to the nature of the industry sector which is mostly dependent upon the infrastructural facilities. The production in this sector basically necessitates substantial investment which in turn limits the entrance and exit to the sector. This also holds true for the human resources when the investments in human capital are considered. The spatial error parameters of the industry sector employment growth model are found to be positive in the estimated spatial panel SUR models. As the regions with similar infrastructures tend to be close to each other, the positive externalities in the labor markets are more likely to occur. The industrial employment rates in the adjacent regions tend to be positively associated with each other and the shocks in one region would have similar consequences on the neighboring regions.

In the services sector, the results reveal the evidence of convergence, which is in line with the expectations. The descriptive analyses as well as the econometric estimations suggest that over the last decade Turkey has experienced a shift towards services sector, which positively affects the corresponding employment rates in all regions. In the estimated models, the spatial error parameters in the services sector's employment growth model are positive, indicating positive feedback effects across the regions.

Last but not least, the sectoral interaction models validate employment shifts from agriculture to the services sectors in both the static and dynamic models. The indicators at the aggregate level are also in line with this observation. Since the beginning of 2000s, the amount of decline in the agriculture sector's employment shares are almost equivalent to the amount of rise in the services sector's employment shares. It appears that the unemployed labor in the agriculture has switched to new jobs in the services sector.

CHAPTER 5

CONCLUSION

Even though regional convergence models have now been discussed for almost half a century, the spatiality in the convergence dynamics has only recently become a part of the analysis. The initial spatial econometric extensions mostly relied on two basic forms of the spatiality: spatial dependence in the spatial lag terms and spatial heterogeneity operating through the disturbances. The panel data analyses with spatial effects have mostly been static and the empirical literature with spatial dynamic panel data models has remained rather limited. On the other hand, panel seemingly unrelated regression model in a spatial framework in a regional growth context is almost inexistent.

All three chapters of this thesis have their own contributions. In the second chapter, the regional growth convergence of Turkey over the 1991-2009 period is analyzed by an entire set of spatial econometric specifications proposed in the literature and a model selection procedure is applied to arrive at the most appropriate specification. This analysis is crucial in at least two aspects. First, the empirical literature on Turkey mostly focuses on spatial lag and spatial error models in estimating the regional convergence problem and alternative combinations of spatiality have been disregarded. However, adhering to only a few forms of specifications may lead to incorrect inferences in the estimation as they may not be able to catch the true form of spatiality inherent in the data. This chapter is the first study to use a comprehensive set of models to uncover the real dynamics of the cross-sectional regional convergence problem in Turkey. Second, the data utilized in this chapter is based on the most recent data set available for Turkey. The empirical literature that examines the Turkish provincial growth convergence is mostly constrained by the data set up until 2001. The comprehensive analysis in this chapter is able to reveal the information provided by new data.

In the third chapter, the regional growth convergence analysis of Chapter 2 is extended by means of spatial dynamic panel data models estimated by generalized method of moments. The main contribution is a methodological departure from the existing empirical studies for Turkey. To the best of our knowledge, the spatial dynamic panel data models have not been investigated before in the context of Turkish provincial convergence. The results driven by such an extension are quite valuable as they are able to take account of heterogeneity in both time and space.

In the fourth chapter, we focus on the employment convergence in 26 NUTS-2 level regions of Turkey over the 2004-2011 period. The spatial panel SUR models employed in this chapter have been discussed quite recently and the empirical studies utilizing this framework is very limited. The consideration of both regional and sectoral dynamics in a unified modelling framework constitutes a major contribution not only for Turkish regional convergence problem but also for other similar countries and case studies.

In Turkey, regional disparities have been a major problem for many years. Policy makers have been conducting certain development projects to eliminate these inequalities. Major policy tools such as regional development agencies, regional development projects and priority provinces in development have been carried out to serve the purposes of enhancing growth in conjunction with creating employment opportunities and eliminating regional growth disparities. However, these policies conducted for ensuring the convergence across the regions of Turkey have not always been fruitful.

The descriptive analysis reveals quite striking results. Since the early 1990s, per capita GDP figures have remained quite dissimilar in the Eastern and Western parts of the country. Exploratory spatial data analysis shows that Marmara and Aegean regions have been *hot spots* with high GDP per capita values clustering together in both 1991 and 2009. These regions have been more abundant in qualified labor, especially in the services sector. On the other hand, Southeastern Anatolia appears as *low spot* region in which low per capita GDP values are concentrated. It has been the most underdeveloped region in terms of the human capital indicators measured by the high school and university graduates. The region is characterized by high rates of informal labor, unpaid family work especially in the agriculture sector, high population growth and relatively unproductive employment. Private investments follow a serious spatial pattern with uneven distribution across the regions. From 1991 to 2009, whereas Western regions have experienced an increase in the loan and deposit holdings, no major changes can be observed for Eastern provinces.

The employment indicators depict not only regional but also sectoral characteristics. Since the beginning of 2000s, there has been a substantial increase in the employment shares of services sector. Currently, about half of the employed people are located in the services sector. From 2004 to 2011, employment rates in services have risen by 18.86 per cent. On the other hand, the agriculture sector has been losing its significance especially after 2004. The employment share of agriculture has been declining from over 30 per cent down to 23 per cent. The employment rates in agriculture fell by 0.34 per cent over the 2004-2011 period and agricultural activities have stayed concentrated in particular regions, mostly in Central and North-East Anatolia. Negative growth in agriculture has been detected in nine regions. The shares of industrial employment, on the other hand, have remained relatively stable between ranges 23-27 per cent throughout the 2004-2011 period. The industrial sector employment rates have risen by 20.98 per cent. The sectoral employment rates have also been subject to regional disparities. Eastern regions and Central Anatolia have occupied high employment rates in agriculture whereas Western regions have been more specialized in industry and services sectors. Employment in the services sector has been more intensive in the non-agricultural regions.

The methodological discussion in the light of various diagnostics, tests and model selection procedures point out the importance of spatial factors to describe the regional growth and employment convergence in Turkey. In the cross-section analysis, it is shown that in explaining the growth convergence from 1991 to 2009, the standard Solow-Swan regressions are far from being sufficient. OLS estimated convergence models that neglect the spatial effects are shown to suffer from residual autocorrelation. The omitted spatiality induces clusters of residuals for the adjacent regions. In fact Moran I values for OLS estimated models confirm the presence of positive spatial autocorrelation which is a signal of clustering. The spatial error dependence is also revealed by the LM and robust LM test statistics. The symptoms of omitted spatial association necessitate considering a comprehensive analysis of convergence in the light of regional interactions. To analyze the provincial growth convergence over the 1991-2009 period, six different spatial cross-sectional models (SAC Durbin model, SAC model, spatial Durbin model, spatial Durbin error model, spatial lag model and spatial error model) are estimated by maximum likelihood. Following a general-to-specific procedure, model selection is carried out by means of likelihood ratio test statistics. In line with the initial diagnostics, it is found that spatial error models better characterize the provincial convergence of Turkey from 1991 to 2009. Accordingly, a shock that affects the growth rates has impacts on the neighboring provinces in the same direction.

The regional growth convergence models under a panel data structure also highlight the importance of spatial factors. Breusch-Pagan and Honda tests reveal that the individual effects are significant suggesting that the panel data models rule out the pooled OLS alternatives. Moreover, cross-section dependence is detected in the individual effects, indicating the presence of spatiality confirmed also by the post-estimation test statistics. Generalized method of moments estimation procedures are utilized to estimate four alternative spatial panel data models; namely dynamic fixed effects spatial error model, dynamic random effects spatial error model, dynamic fixed effects spatial lag model and dynamic random effects spatial lag model. Discussions on model selection in both economic and statistical terms lead to the dynamic fixed effects spatial lag model as the most appropriate specification. The positive and significant spatial lag parameters imply that growth in one province is directly related to the growth in neighboring provinces.

In a similar vein, the employment convergence models also disclose the fact that the labor market has its own spatial characteristics. For the main sectors of the economy, agriculture, industry and services, three equations are constructed as random effects spatial error model, each estimated separately by feasible generalized spatial three stage least squares. Further, considering the possible contemporaneous correlation among the disturbances of the equations, system of equations is constructed. The estimated parameters of this spatial panel SUR model are more convincing than the alternatives. There are sector-specific results in the signs and sizes of the spatial error parameters. This validates our hypothesis that the evolvement of employment dynamics can be described not only by regional but also by sectoral aspects.

The estimation results of the convergence analyses presented in three chapters have connections with each other. Chapter 2 reveals that over the 1991-2009 period, there is absolute convergence across provinces with a 7.88 per cent convergence rate and half-life of 16.11 years. When the additional covariates are incorporated, the rate of convergence increases up to 13.79 per cent and half-life to the steady state becomes 13.27 years. When the time effects are accounted for as in Chapter 3, it is found that 2002-2007 period marks significant differences in terms of the growth rates. Apart from this structural change, the crises in 1994, 1999, 2001 and 2009 also have significant impacts which are controlled for in the estimations.

The growth analyses of the second and third chapters can be discussed in a comparative manner by focusing on the growth determinants. The cross-sectional convergence analysis show that the provincial growth rate in GDP per capita is affected positively by human capital described the high school graduates, which appears as one of the main driving forces of provincial convergence over the 1991-2009 period. The panel data counterpart of this model indicates that the rates of high school graduates are not significant in determining the provincial growth before 2002. However, it contributed much to the provincial output growth in the 2002-2007 period and compensated the insignificance in the base period. The selected panel data specification for the regional growth convergence problem throughout the 1991-2009 period rely on the following variables: rate of university graduates, employment, public investments, deposits and population. The estimation outcomes suggest that the university graduates are not effective in promoting provincial growth in the post-2002 period. It appears that comparably less qualified labor seem to be more critical in creating output in Turkey. This result is crucial but not necessarily surprising given that the average years of schooling in Turkey is far below the averages in the developed countries.

In the cross-section analysis, the provincial growth rate in GDP per capita is affected positively by employment which appears as one of the main driving forces of provincial convergence over the 1991-2009 period. The panel data analysis, on the other hand, yields more detailed outcomes. In particular, during the 2002-2007 period the employment policies did not have a significant contribution as compared to the base period. Although this period is marked by high growth rates, employment creation mechanism was not functioning well enough. As the employment creation remains to be one of the weak spots of the economy, the so-called “jobless growth” has become part of the economy in the post-2002 period.

The impacts of public investment are not significant in the cross-section convergence analysis from 1991 to 2009. In the case of public investments, this may be caused by wrong policy instruments such that the distribution and operation mechanism may not be governed well enough in the overall period. If the yearly changes are taken into consideration in a panel data setting, it appears that public investments are insufficient to serve the purposes of provincial convergence during the base period. However, this pattern has been reversed in the post-2002 period as suggested by the significantly positive coefficients in the estimation and the increasing shares of public investments in the descriptive analysis.

The contributions of private investments to regional growth are measured either by loans or deposits in the growth analysis. For the cross-sectional convergence case, the impacts of loans are not significant possibly due to the insufficient incentives. In the underdeveloped PPDs, this may be caused by adverse effects of geographical locations, the instability caused by ethnic disputes and relatively low skilled labor. On the other hand, the panel data analysis indicates that the rates of deposits follow a similar path to the public investment. The insignificant coefficients in the base year have been recovered by the highly significant and positive coefficients in the post-2002 period.

The employment convergence problem of Turkey discussed in Chapter 4 is even more intricate as it exhibits sectoral, regional and time dimensions at the same time. Although the results can be evaluated at sector-specific level, the interactions across sectors remain essential. Throughout the 2004-2011 period, there is evidence of divergence in the growth of employment rates in the agriculture sector. The estimation results display negative spatial error parameters which imply the presence of regional competition for agricultural labor. This may be mainly caused by the fact that agricultural workers are scarcer than before as the employment shares of this sector have been diminishing.

For the industry sector, the static spatial panel SUR models indicate the presence of divergence. However, when the model is modified with dynamic initial employment rates, the divergent pattern is no more significant. The overall findings can be explained by the peculiar characteristics of the industry sector. As the sector necessitates substantial investments in both the infrastructure and the human capital, the entry and exit is relatively more difficult and the employment shares do not vary significantly. This is also reflected in the positive spatial error parameters found in the estimations such that any unexpected shock in a region would affect the industrial labor in the same direction. This result is reasonable especially for the industrial sector as the regions with similar substructure tend to be closer and create positive externalities via knowledge spillovers.

In the services sector, there is evidence of convergence throughout the 2004-2011 period as Turkish economy has considerably shifted towards the services sector. The estimation results validate the escape from agriculture to services. The unemployed labor caused by the shrink in the agricultural employment has mostly switched to new employment opportunities in the services sector. The positive spatial error parameters found in the model are indicative of the positive feedbacks across the regions.

There are at least four policy implications that can be driven from the overall analysis. First and foremost, regional development policies should be carried out by considering the spatial interactions among the provinces. Regional development agencies, in particular, can better function if they carry out policies at provincial level with special attention to spatial relations. Second, investment strategies should focus on the enhancement of qualified labor. Rate of high school graduates and the employment have shown substantial rises in Eastern Anatolia whereas they lagged behind in Southeastern provinces. The development policies targeting these provinces may better function if investments in human capital are increased. Third, public and private investments should focus on the improvement of infrastructure. The backwardness of the regions over the 1991-2009 period may also be due to insufficient incentives for private sector, lack of innovation, backward technology and physical infrastructure. Fourth, the labor market policies should be directed considering both regional and sectoral level. The monotype investment incentives would not be effective in generating employment, given the regional and sectoral differentiations. Instead, targeted investments like agricultural incentives in Black Sea and industrial infrastructure in Aegean regions may contribute more to the growth and the employment.

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APPENDICES

APPENDIX A

SUPPLEMENTARY INFORMATION FOR CHAPTER 2

A.1. Data Appendix

Table A.1. Provinces and NUTS-3 Level Codes (73 provinces as of 1991)

No	NUTS3_73	Province	No	NUTS3_73	Province	No	NUTS3_73	Province
1	TR621	Adana	26	TR412	Eskişehir	51	TR713	Niğde
2	TRC12	Adıyaman	27	TRC11	Gaziantep	52	TR902	Ordu
3	TR332	Afyon	28	TR903	Giresun	53	TR904	Rize
4	TRA21	Ağrı	29	TR906	Gümüşhane	54	TR422	Sakarya
5	TR834	Amasya	30	TRB24	Hakkari	55	TR831	Samsun
6	TR510	Ankara	31	TR631	Hatay	56	TRC34	Siirt
7	TR611	Antalya	32	TR612	Isparta	57	TR823	Sinop
8	TR905	Artvin	33	TR622	İçel	58	TR722	Sivas
9	TR321	Aydın	34	TR100	İstanbul	59	TR211	Tekirdağ
10	TR221	Balıkesir	35	TR310	İzmir	60	TR832	Tokat
11	TR413	Bilecik	36	TRA22	Kars	61	TR901	Trabzon
12	TRB13	Bingöl	37	TR821	Kastamonu	62	TRB14	Tunceli
13	TRB23	Bitlis	38	TR721	Kayseri	63	TRC21	Şanlıurfa
14	TR424	Bolu	39	TR213	Kırklareli	64	TR334	Uşak
15	TR613	Burdur	40	TR715	Kırşehir	65	TRB21	Van
16	TR411	Bursa	41	TR421	Kocaeli	66	TR723	Yozgat
17	TR222	Çanakkale	42	TR521	Konya	67	TR811	Zonguldak
18	TR822	Çankırı	43	TR333	Kütahya	68	TR712	Aksaray
19	TR833	Çorum	44	TRB11	Malatya	69	TRA13	Bayburt
20	TR322	Denizli	45	TR331	Manisa	70	TR522	Karaman
21	TRC22	Diyarbakır	46	TR632	K.Maraş	71	TR711	Kırıkkale
22	TR212	Edirne	47	TRC31	Mardin	72	TRC32	Batman
23	TRB12	Elazığ	48	TR323	Muğla	73	TRC33	Şırnak
24	TRA12	Erzincan	49	TRB22	Muş			
25	TRA11	Erzurum	50	TR714	Nevşehir			

Table A.2. Priority Provinces in Development (73 provinces as of 1991)

No	PPD	No	non-PPD
1	Adıyaman	1	Adana
2	Ağrı	2	Afyon
3	Aksaray	3	Ankara
4	Amasya	4	Antalya
5	Artvin	5	Aydın
6	Batman	6	Balıkesir
7	Bayburt	7	Bilecik
8	Bingöl	8	Bolu
9	Bitlis	9	Burdur
10	Çanakkale	10	Bursa
11	Çankırı	11	Denizli
12	Çorum	12	Edirne
13	Diyarbakır	13	Eskişehir
14	Elazığ	14	Gaziantep
15	Erzincan	15	Hatay
16	Erzurum	16	Isparta
17	Giresun	17	İçel
18	Gümüşhane	18	İstanbul
19	Hakkari	19	İzmir
20	K.Maraş	20	Kayseri
21	Karaman	21	Kırklareli
22	Kars	22	Kocaeli
23	Kastamonu	23	Konya
24	Kırıkkale	24	Kütahya
25	Kırşehir	25	Manisa
26	Malatya	26	Muğla
27	Mardin	27	Sakarya
28	Muş	28	Tekirdağ
29	Nevşehir	29	Uşak
30	Niğde		
31	Ordu		
32	Rize		
33	Samsun		
34	Siirt		
35	Sinop		
36	Sivas		
37	Şanlıurfa		
38	Şırnak		
39	Tokat		
40	Trabzon		
41	Tunceli		
42	Van		
43	Yozgat		
44	Zonguldak		

Note: From 1998 onwards there are 49 provinces and 2 districts (in Çanakkale province) designated as PPDs. Here, PPDs aggregated in line with the number of provinces in 1991. Accordingly, the table represents 44 PPD and 29 non-PPD provinces out of 73 in total.

Table A.3: Descriptive Statistics of the variables in Chapter 2

	min	*max*	*range*	*median*	*mean*	*std. dev*	*skewness*	*kurtosis*	*number of obs.*
growth	-0.0449	0.1070	0.1519	0.0328	0.0360	0.0238	0.2557	1.6123	73
gdppc91	0.1488	2.3749	2.2261	0.6682	0.7085	0.3809	1.2980	3.2762	73
gdppc09	0.6207	2.0174	1.3967	1.2025	1.2148	0.3264	0.4193	-0.2703	73
hc1pc91	0.0268	0.1336	0.1068	0.0579	0.0594	0.0210	0.7379	0.8463	73
hc1pc09	0.0547	0.2112	0.1564	0.1354	0.1329	0.0345	-0.1230	-0.2665	73
hc2pc91	0.0069	0.0677	0.0608	0.0189	0.0206	0.0100	1.9178	5.9218	73
hc2pc09	0.0160	0.1281	0.1121	0.0554	0.0525	0.0196	0.5887	1.7811	73
emppc91	0.0142	0.2227	0.2085	0.1289	0.1252	0.0523	-0.0809	-1.0199	73
emppc09	0.0639	0.2869	0.2229	0.1786	0.1743	0.0530	-0.2720	-0.5803	73
pinvpc91	0.0041	0.0915	0.0874	0.0123	0.0183	0.0172	2.2070	5.0105	73
pinvpc09	0.0055	0.2255	0.2200	0.0155	0.0200	0.0268	6.4639	45.4627	73
depospc91	0.0137	0.8198	0.8061	0.0627	0.0874	0.1076	4.8368	28.2165	73
depospc09	0.0299	0.9645	0.9346	0.1361	0.1788	0.1562	2.8955	10.7054	73
slenpc91	0.0004	0.6213	0.6209	0.0331	0.0486	0.0789	5.6219	36.0589	73
slenpc09	0.0039	0.0558	0.0519	0.0262	0.0257	0.0124	0.2458	-0.4572	73
loanpc91	0.0013	0.8168	0.8155	0.0514	0.0944	0.1462	3.6506	14.1032	73
loanpc09	0.0306	0.8356	0.8050	0.1809	0.1900	0.1277	2.5141	9.3623	73
pop91	106.2885	7543.3390	7437.0500	570.9584	784.6243	976.6320	4.8808	29.3420	73
pop09	74.7100	13117.6900	13042.9800	588.4750	993.9906	1648.1080	5.6702	37.6135	73

A.2. Testing for Spatiality

1) Global and Local Moran I

Moran I statistic, as introduced by Cliff and Ord (1972) based on the study of Moran (1950), is computed for the residuals of the OLS-estimated model and tested against the null hypothesis of no spatial autocorrelation. The statistic is defined as,

$$I = \frac{N}{S}\frac{\sum_i \sum_j w_{ij}\tilde{u}_i\tilde{u}_j}{\sum_i \tilde{u}_i^2} \qquad \text{and} \qquad S = \sum_i \sum_j w_{ij} \tag{A.1}$$

where N corresponds to the total number of spatial observations, $\tilde{u}_i = y_i - \hat{\gamma}' x_i$ and $\tilde{u}_j = y_j - \hat{\gamma}' x_j$ stand for the OLS regression residuals for any two spatial units i and j. For a row-standardized weights matrix $N = S$ and the statistic in matrix form becomes $I = \frac{\tilde{u}' W \tilde{u}}{\tilde{u}'\tilde{u}}$ which is analogous to the Durbin-Watson test for time-wise autocorrelation. Under the null hypothesis there is no spatial autocorrelation, Moran I equals to zero. By definition, the index values range between -1 and +1; negative and significant values imply negative spatial correlation whereas positive and significant values imply positive spatial correlation.

Global Moran I statistic can also be used for testing spatial autocorrelation in the variables. In this case the statistic becomes,

$$I = \frac{N}{S}\frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \qquad \text{and} \qquad S = \sum_i \sum_j w_{ij} \tag{A.2}$$

where N corresponds to the total number of spatial units and $(x_i - \bar{x})$ and $(x_j - \bar{x})$ stand for the variables expressed in mean-deviation form. For a row-standardized weights matrix, $n = S$. The expression is similar to a correlation coefficient between x_i and its spatial lagged counterpart. Under the null hypothesis, there is no spatial autocorrelation, hence Moran I equals to zero.

As one of the Local Indicators of Spatial Association (LISA), Local Moran I statistic à la Anselin (1995) is computed as,

$$I_i = (x_i - \bar{x}) \sum_j w_{ij} (x_j - \bar{x}) \tag{A.3}$$

where the terms correspond to the same arguments as in Moran I. The sum of local Moran I values gives the standard global Moran I.

2) Geary's C Test

The "contiguity ratio" C statistic is formulated "*to determine whether statistics given for each 'county' in a 'country' are distributed at random or whether they form a pattern*" (Geary, 1954). Using a spatial weights matrix, the test statistic can now be re-defined as,

$$C = \frac{(N-1)}{S} \frac{\sum_i \sum_j w_{ij} (x_i - x_j)^2}{2 \sum_i (x_i - \bar{x})^2} \quad \text{and} \quad S = \sum_i \sum_j w_{ij}$$

(A.4)

where N corresponds to the total number of spatial units and $(x_i - x_j)$ is the difference between the values of the variable x in locations i and j. The statistic is inversely related to Moran I and its values lie between 0 and 2 where 1 corresponds to the absence of spatial autocorrelation. Values between 0 and 1 imply positive spatial autocorrelation whereas the ones between 1 and 2 imply negative spatial autocorrelation.

3) Getis-Ord Global G and Local Gi statistics

Moran I and Geary's C statistics can detect the existence of clusters when they find positive spatial autocorrelation in the data. Yet, they are not able to define whether these are "hot spots" where high values cluster together or "cold spots" in which low values cluster together. Getis and Ord (1992) define the Global G statistic as follows:

$$G(d) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(d) x_i x_j}{\sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j} \tag{A.5}$$

where d is the distance band within which clustering occurs, $w_{ij}(d)$ is the weights matrix such that

$$w_{ij}(d) = \begin{cases} 1 & \text{if j is within d distance of i} \\ 0 & \text{if j is beyond d distance} \end{cases}$$

If the high values cluster together, the number in the numerator will be large and the G value is greater than the expected value, then these are *hot spots*. If, on the other hand, values in the nearby regions are both small, the numerator will be small and G value is less than the expected value, these regions are called *cold spots*.

The interpretation of this statistic is different from Moran I and Geary's C in the sense that as long as the null hypothesis is rejected, there is always positive spatial autocorrelation which reflects itself as clustering. The question is rather, what kind of cluster the data exhibit. Furthermore, the original test statistic is formulated essentially using a binary weights matrix. The distribution of the test statistic is normal whereas Moran I and Geary's C are mostly performed under randomization, without necessitating the assumption of normality.

General G statistic is helpful for identifying the type of clusters, though it does not provide much information without illustrating the values on a regional basis. To this end, Getis and Ord (1995) extend their study by defining local G_i statistics such that non-binary weights are allowed for. The statistic measures the concentration of a variable as follows:

$$G_i(d) = \frac{\sum_{j=1}^{N} w_{ij}(d) x_j}{\sum_{j=1}^{N} x_j} \tag{A.6}$$

where $x_j > 0$ and $w_{ij}(d)$ as defined above. Using this test statistic, it is possible to detect hot spots and cold spots at local/regional level. Significant positive (negative) values of the test imply concentration of high (low) values of the variable.

4) LM and RLM Tests for Spatial Lag and Spatial Error in OLS Residuals

In order to uncover not only the existence of spatial autocorrelation but also the form of spatial relation, Lagrange multiplier (LM) tests are proposed by Burridge (1980). Whether the spatial structure is in the form of spatial error or lag can be determined via LMerr and LMlag tests. In matrix form, LMerr which allows for testing spatial heterogeneity is described as:

$$LM_{err} = \frac{\left[\frac{\tilde{u}'W\tilde{u}}{\tilde{\sigma}^2}\right]^2}{T_1} \tag{A.7}$$

where $T_1 = tr\left[(W' + W)W\right]$ with weights matrix W, $\tilde{u} = y - \hat{\gamma}'x$ corresponds to the OLS residuals and $\tilde{\sigma}^2 = \frac{\tilde{u}'\tilde{u}}{N}$ is the variance estimate from the OLS model. One can observe that this statistic correspond to the square of Moran I calculated for the OLS residuals. LMlag statistic for testing the spatial dependence is:

$$LM_{lag} = \frac{\left[\frac{\tilde{u}'Wy}{\tilde{\sigma}^2}\right]^2}{\tilde{\sigma}^2\left[(WX\tilde{\gamma})'W(WX\tilde{\gamma}) + T_1\tilde{\sigma}^2\right]^{-1}} \quad \text{(A.8)}$$

where T_1, $\tilde{u}$ and $\tilde{\sigma}^2$ are as defined above.

Anselin et al.(1996) derived the robust counterparts of these statistics under local misspecification. They defined the robust LMerr statistic for detecting spatial error in the presence of possible spatial lag dependence as follows:

$$RLM_{err} = \frac{\left[\frac{\tilde{u}'W\tilde{u}}{\tilde{\sigma}^2} - T_1\tilde{\sigma}^2\left[(WX\tilde{\gamma})'W(WX\tilde{\gamma}) + T_1\tilde{\sigma}^2\right]^{-1}\frac{\tilde{u}'Wy}{\tilde{\sigma}^2}\right]^2}{T_1\left[1 - T_1\left[WX\tilde{\gamma})'W(WX\tilde{\gamma}) + T_1\tilde{\sigma}^2\right]^{-1}\right]} \quad \text{(A.9)}$$

Similarly for the spatial lag statistic, robust test statistic in the possible presence of spatial error term is derived as:

$$RLM_{lag} = \frac{\left[\frac{\tilde{u}'Wy}{\tilde{\sigma}^2} - \frac{\tilde{u}'W\tilde{u}}{\tilde{\sigma}^2}\right]^2}{\tilde{\sigma}^2\left[(WX\tilde{\gamma})'W(WX\tilde{\gamma}) + T_1\tilde{\sigma}^2\right]^{-1} - T_1}$$

(A.10)

Note that the correction factors in the spatial lag statistic are now coming from the error statistic and vice versa.

A.3. Comparing ML and GMM Estimates for the Selected Model

The likelihood function for ML as well as the argmin image for GMM can be traced using the contour plots. The following figures present the plot of the spatial error model for both the absolute and conditional convergence hypotheses. The horizontal axis shows the spatial error component (lambda) and the vertical axis correspond to the estimated variance. ML, GM and GM AW stand for the maximum likelihood, GMM approach based on Kelejian and Prucha (1999) method and the GMM approach based on Arnold and Wied (2010) respectively.

Although the three estimations give close and reliable results, the contour plots in Figure A.1. and Figure A.2. indicate that for the spatial error specification, ML gives higher likelihood and hence better outcomes as compared to the GMM alternatives.

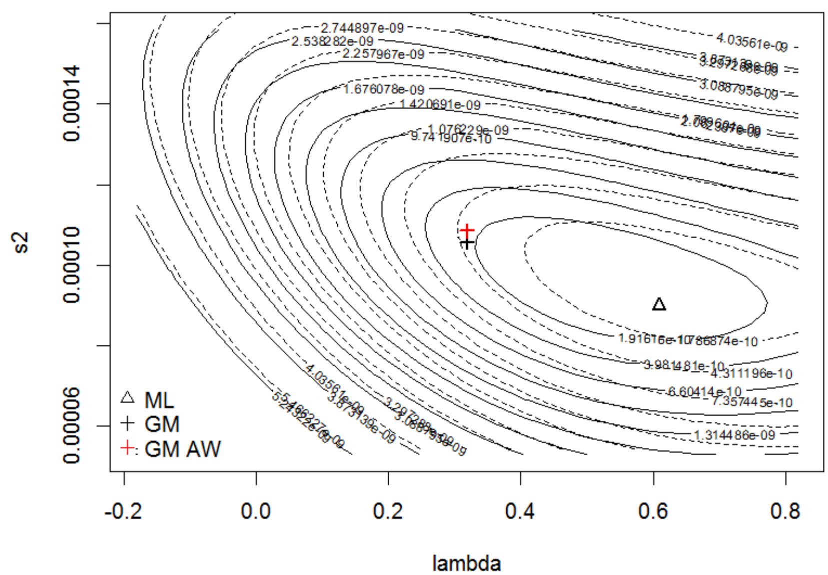

Figure A.1: Contour Plots of ML and GMM Estimated Spatial Error Model for Absolute Convergence Hypothesis

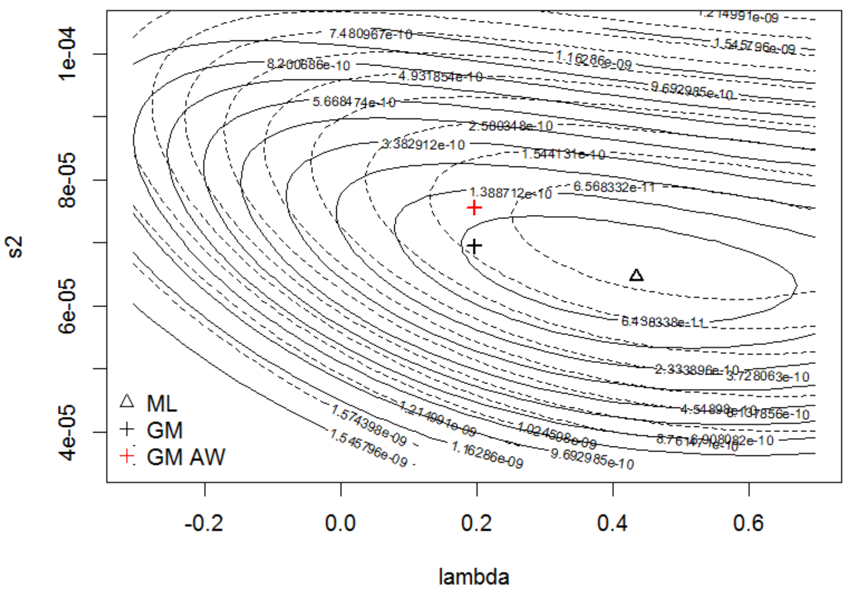

Figure A.2: Contour Plots of ML and GMM Estimated Spatial Error Model for Conditional Convergence Hypothesis

APPENDIX B

SUPPLEMENTARY INFORMATION FOR CHAPTER 3

B.1. Data Appendix

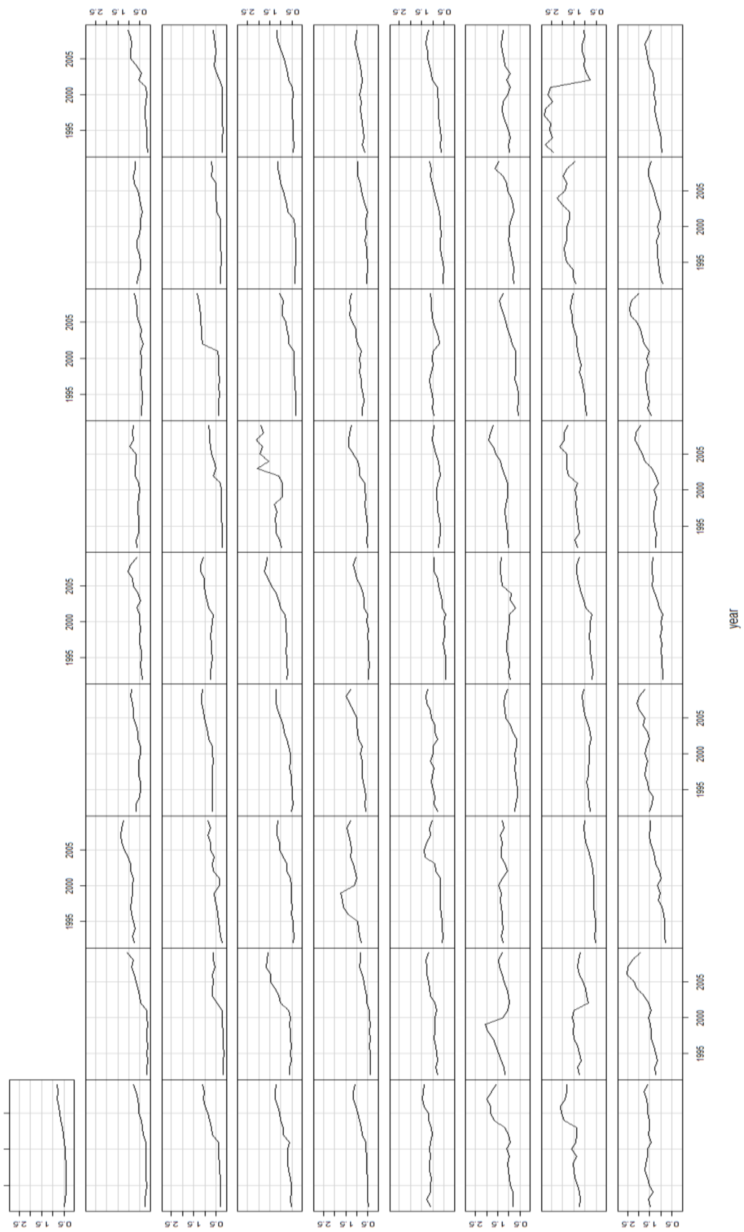

Figure B.1: GDPPC – Conditioning Plots for NUTS 73

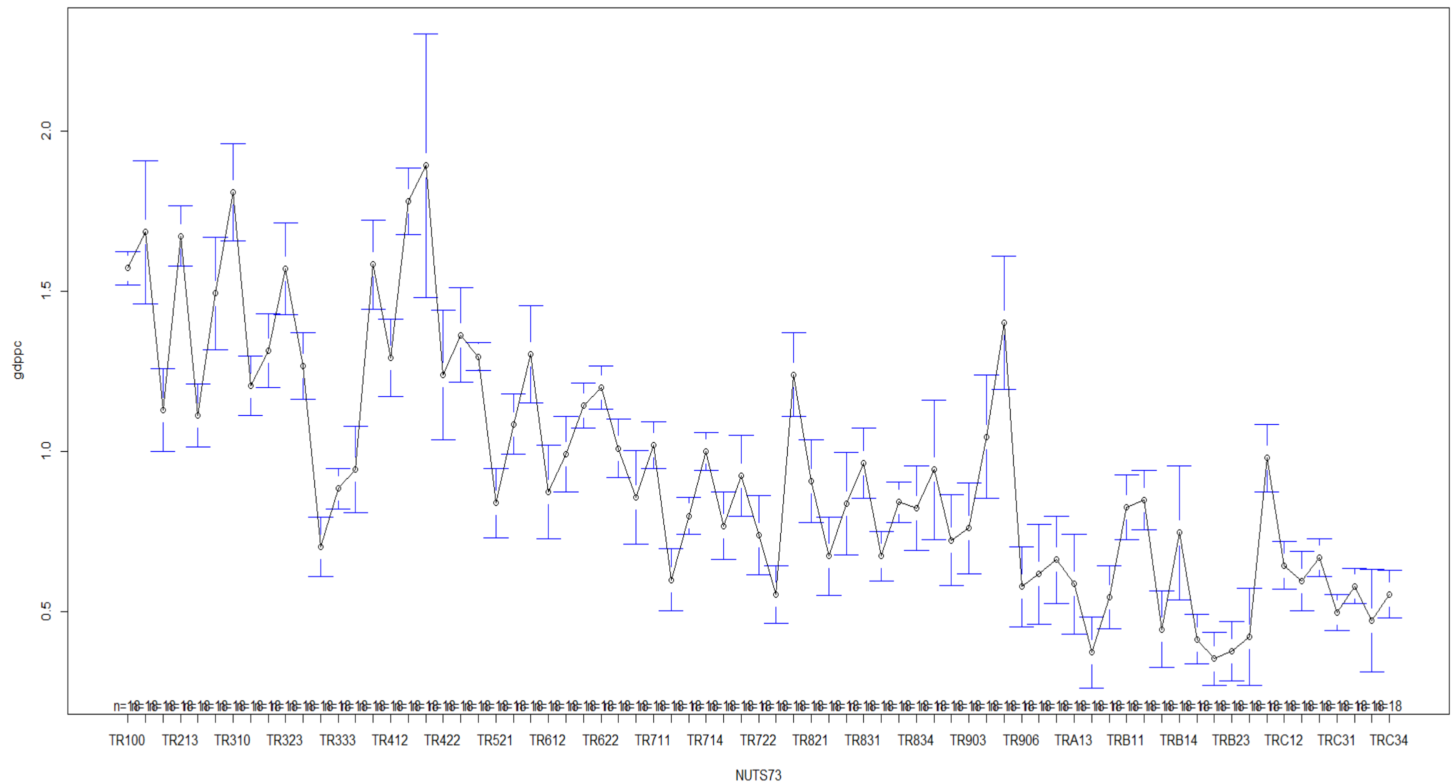

Figure B.2: GDPPC – Heterogeneity across provinces (95% confidence interval around the means)

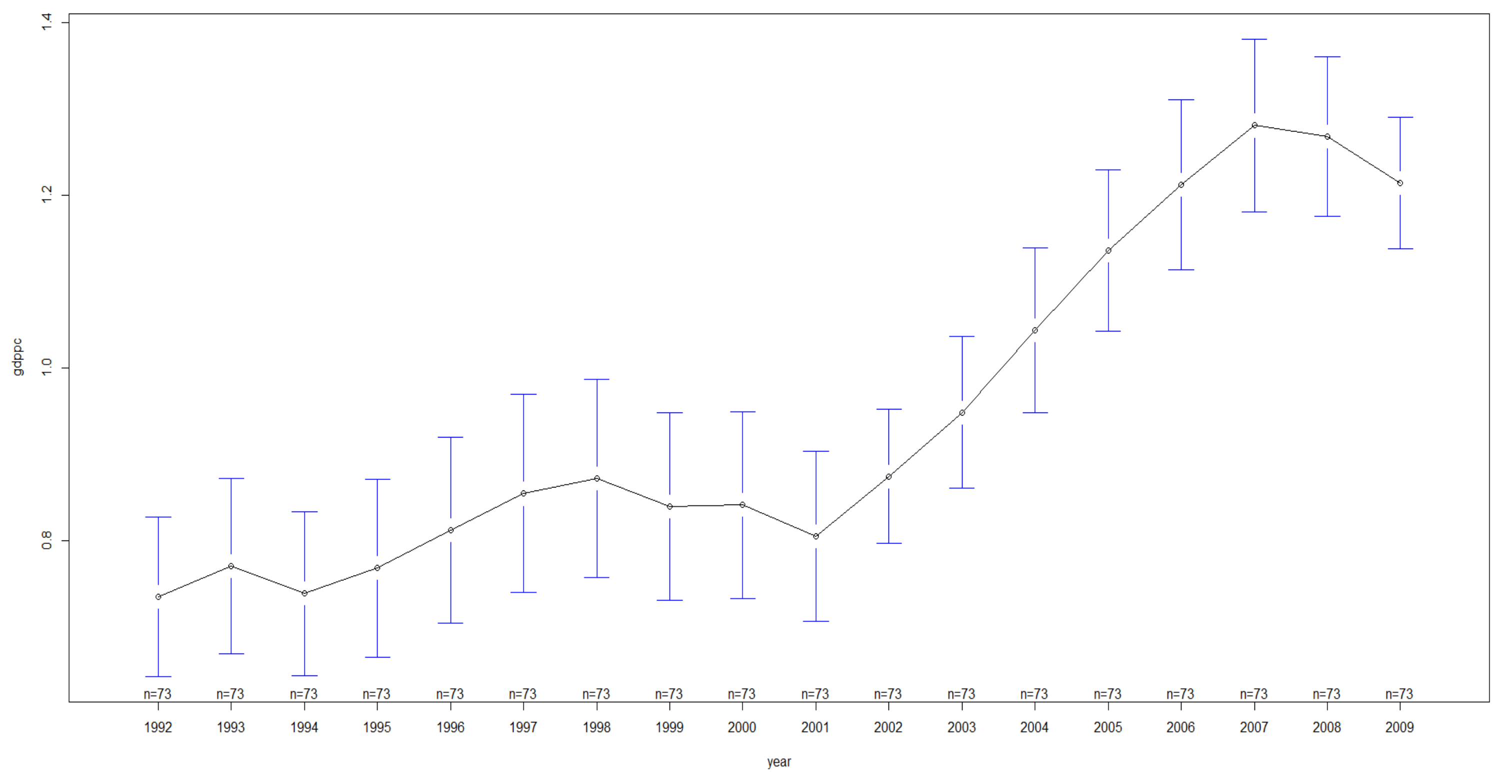

Figure B.3: GDPPC – Heterogeneity across years (95% confidence interval around the means)

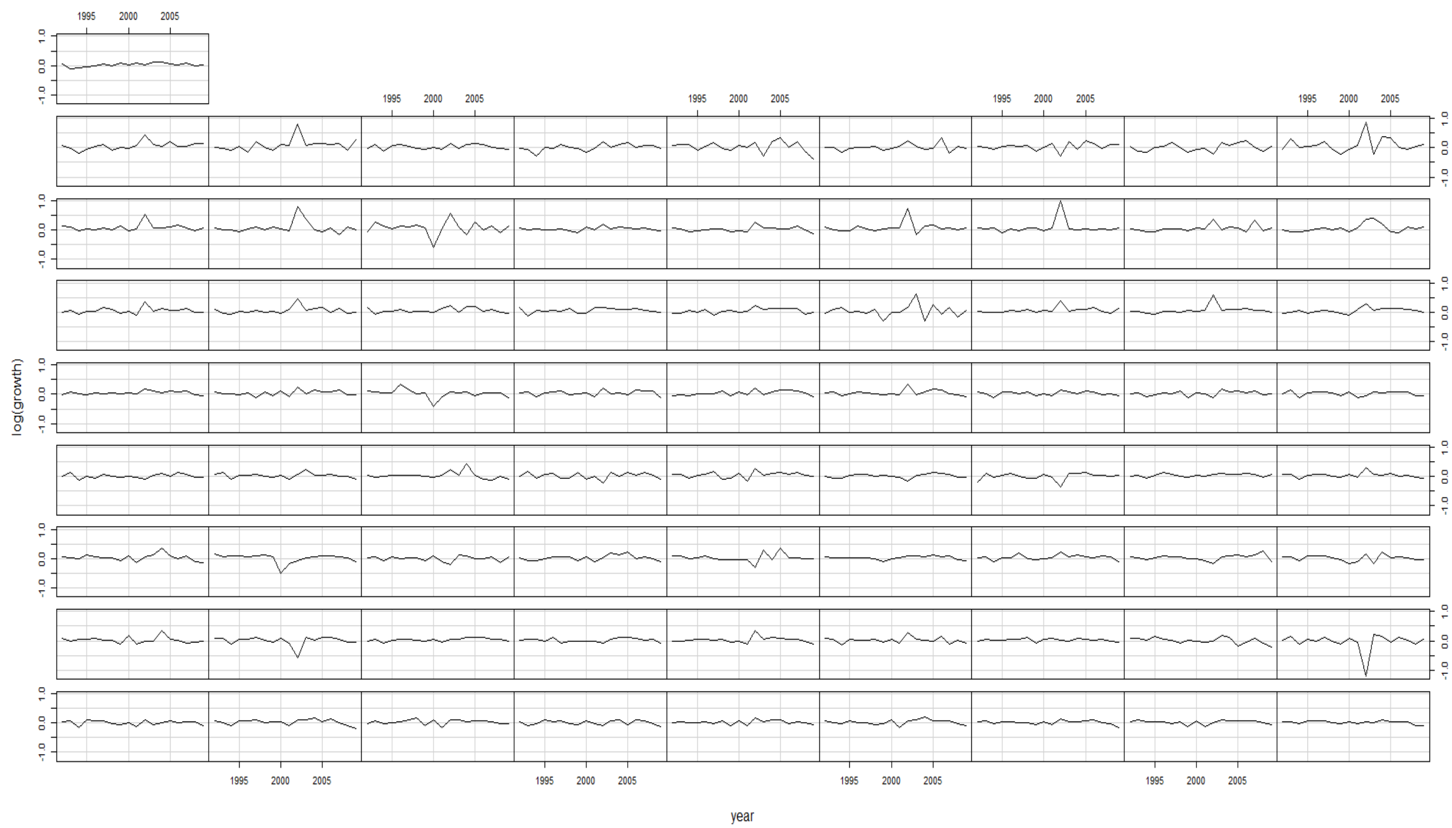

Figure B.4: Growth – Conditioning Plots for NUTS 73 provinces

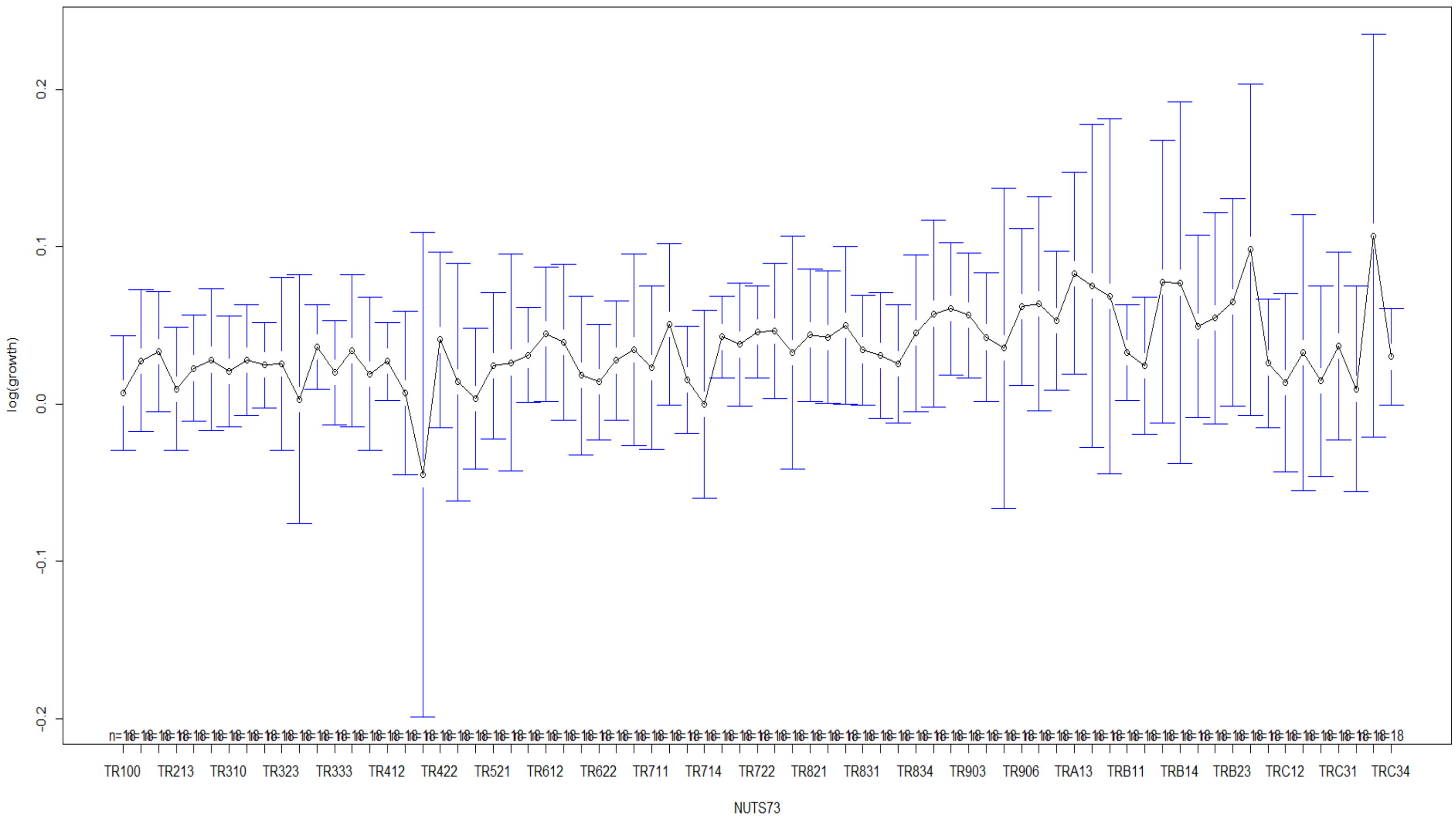

Figure B.5: Growth – Heterogeneity across provinces (95% confidence interval around the means)

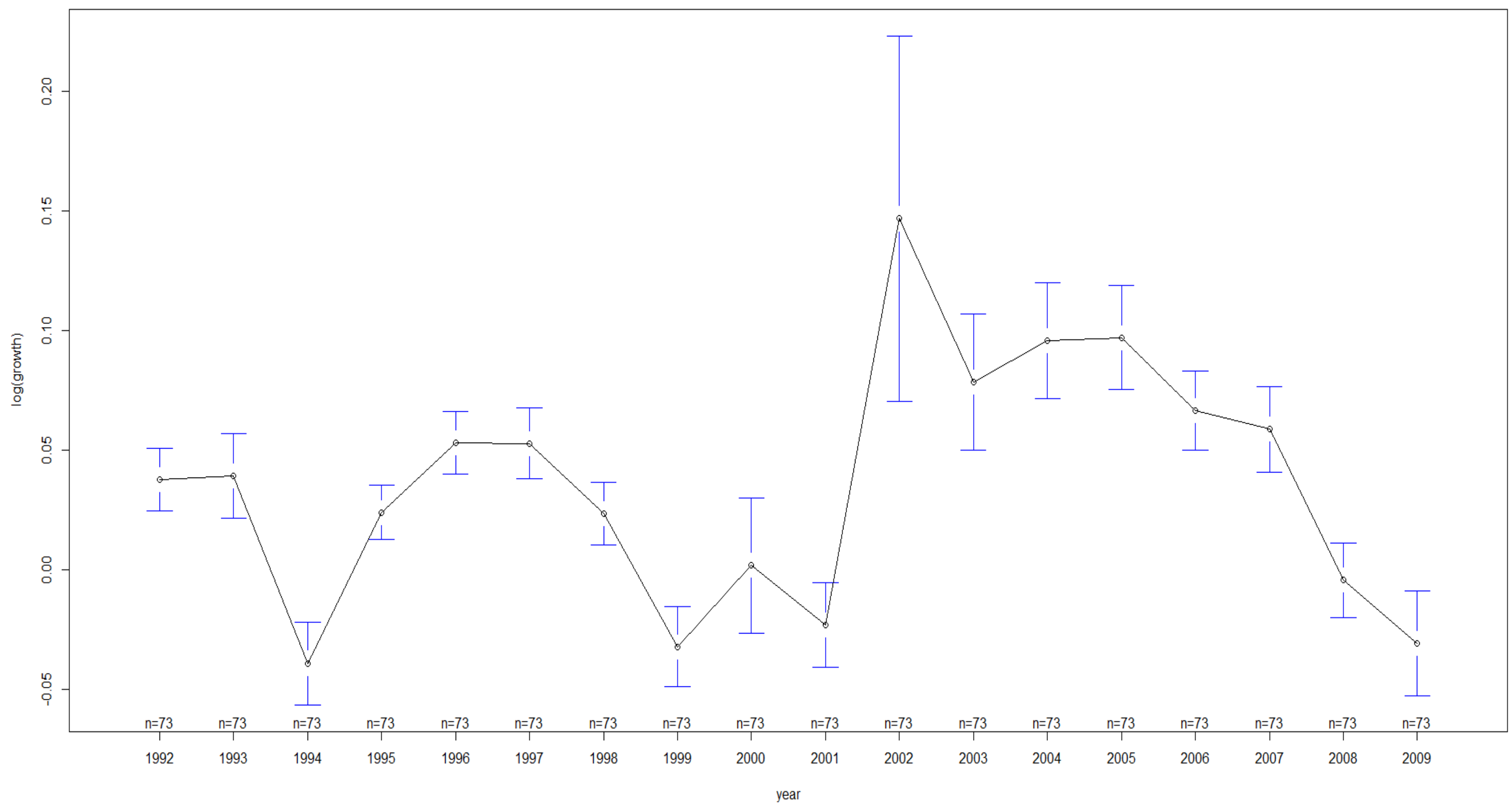

Figure B.6: Growth – Heterogeneity across years (95% confidence interval around the means)

Table B.1: Descriptive Statistics of the variables in Chapter 3

	min	*max*	*range*	*median*	*mean*	*std. dev*	*skewness*	*kurtosis*	*number of obs.*
growth	0.2945	2.6821	2.3876	1.0355	1.0444	0.1389	3.8141	34.9713	1314
gdppc	0.1433	2.8261	2.6828	0.8965	0.9456	0.4597	0.7699	0.7409	1314
hc1pc	0.0291	0.2197	0.1906	0.1003	0.1024	0.0362	0.3415	-0.2894	1314
hc2pc	0.0076	0.1281	0.1205	0.0324	0.0346	0.0165	1.2572	2.7928	1314
emppc	0.0156	0.3164	0.3009	0.1488	0.1466	0.0594	-0.0323	-0.7186	1314
pinvpc	0.0019	0.4375	0.4356	0.0121	0.0184	0.0267	7.6252	86.4149	1314
slenpc	0.0003	0.8574	0.8571	0.0180	0.0269	0.0525	8.2958	87.3062	1314
depospc	0.0074	1.0249	1.0175	0.0680	0.0998	0.1180	3.9946	21.0107	1314
loanpc	0.0007	1.0631	1.0624	0.0519	0.0957	0.1209	3.2072	13.9242	1314
pop	74.7100	13117.6890	13042.9790	593.7818	904.0914	1328.9751	5.7643	40.5900	1314

B.2. Testing for Spatiality in Panel Data Models

1) Pesaran (2004) Cross-Section Dependence Test

For a panel of short T and large N, Pesaran (2004) develops a cross-section dependence (CD) test based on the pairwise correlation coefficients of OLS residuals:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{B.1}$$

where $\hat{\rho}_{ij}$ is the estimate of the pairwise correlation of the residuals. The novelty of this test is that unlike the usual cross section dependence tests provided in the spatial statistics literature, this technique does not require any a priori form of spatial weight matrix.

2) Baltagi, Song and Koh (2003) LM tests

Baltagi et al. (2003) derive various Lagrange Multiplier tests for panel data with spatial error components. Apart from the joint test statistics for both random effects and spatial error correlation, the authors provide marginal tests and conditional LM tests for random effects (spatial error correlation) given the presence of spatial error correlation (random effects). They consider the following panel data model:

$$\begin{aligned} y_{ti} &= X'_{ti}\beta + u_{ti} \\ u_{ti} &= \mu_i + \varepsilon_{ti} \\ \varepsilon_{ti} &= \lambda W\varepsilon_{ti} + v_{ti} \qquad i = 1,\dots,N \qquad t = t,\dots,T \end{aligned} \tag{B.2}$$

with λ corresponding to the spatial error parameter and the random effects identified by μ_i. The overall experiment takes account of the following problems:

1. Joint LM test for $H_0^a : \lambda = \sigma_\mu^2 = 0$
2. Marginal LM test for $H_0^b : \sigma_\mu^2 = 0$ (assuming $\lambda = 0$)

3. Marginal LM test for $H_0^c: \lambda = 0$ (assuming $\sigma_\mu^2 = 0$)
4. One-sided joint LM test for $H_0^a: \lambda = \sigma_\mu^2 = 0$
5. LR test for $H_0^a: \lambda = \sigma_\mu^2 = 0$
6. Conditional LM test for $H_0^d: \lambda = 0$ (assuming $\sigma_\mu^2 \geq 0$)
7. Conditional LM test for $H_0^e: \sigma_\mu^2 = 0$ (assuming λ may or may not be =0)

where $\sigma_\mu^2 > 0$ implies the presence of random effects.

3) Baltagi, Song, Jung and Koh (2007) LM tests

Baltagi et al. (2007) extend Baltagi et al. (2003) framework by taking serial correlation into account. Hence the model becomes a more generalized form of panel data:

$$
\begin{aligned}
y_{ti} &= X_{ti}'\beta + u_{ti} \\
u_{ti} &= \mu_i + \varepsilon_{ti} \\
\varepsilon_{ti} &= \lambda W \varepsilon_{ti} + v_{ti} \\
v_{ti} &= \rho v_{t-1,i} + e_t \qquad i = 1, \ldots, N \qquad t = t, \ldots, T
\end{aligned}
\tag{B.3}
$$

where λ corresponds to the spatial error coefficient, ρ is the serial error correlation parameter and μ_i characterizes the random effects. The incorporation of these additional effects renders the possibility of deriving the following test statistics:

1. Joint test for $H_0^a: \lambda = \rho = \sigma_\mu^2 = 0$
2. Marginal test for $H_0^b: \lambda = 0$ (assuming $\rho = \sigma_\mu^2 = 0$)
3. Marginal test for $H_0^c: \rho = 0$ (assuming $\lambda = \sigma_\mu^2 = 0$)
4. Marginal test for $H_0^d: \sigma_\mu^2 = 0$ (assuming $\rho = \lambda = 0$)
5. Marginal test for $H_0^e: \lambda = \rho = 0$ (assuming $\sigma_\mu^2 = 0$)

6. Marginal test for $H_0^f: \lambda = \sigma_\mu^2 = 0$ (assuming $\rho = 0$)

7. Marginal test for $H_0^g: \sigma_\mu^2 = \rho = 0$ (assuming $\lambda = 0$)

8. Conditional test for $H_0^h: \lambda = 0$ (allowing $\rho \neq 0$ and $\sigma_\mu^2 > 0$)

9. Conditional test for $H_0^i: \rho = 0$ (allowing $\lambda \neq 0$ and $\sigma_\mu^2 > 0$)

10. Conditional test for $H_0^j: \sigma_\mu^2 = 0$ (allowing $\rho \neq 0$ and $\lambda \neq 0$)

11. Conditional test for $H_0^k: \lambda = \rho = 0$ (allowing $\sigma_\mu^2 > 0$)

12. Conditional test for $H_0^l: \lambda = \sigma_\mu^2 = 0$ (allowing $\rho \neq 0$)

13. Conditional test for $H_0^m: \sigma_\mu^2 = \rho = 0$ (allowing $\lambda \neq 0$)

Again, $\sigma_\mu^2 > 0$ implies the presence of random effects.

4) Further tests for spatiality in spatial panel data models

Additional tests for spatiality are also available in the literature but mostly constrained to some specific cases which are not pertinent to the context of this thesis. Baltagi and Liu (2008) derive joint and conditional LM tests for a random effects panel data model including the spatial lag dependence. Pesaran et al. (2008) derive a bias-adjusted LM test for cross-section dependence for the case of panel data models with strictly exogenous regressors and normally distributed error terms. Debarsy and Ertur (2010) suggest LM and LR test statistics to distinguish between the spatial lag and spatial error components in a fixed effects panel data framework. Montes-Rojas (2010) considers testing for serial correlation and random effects in static panel data models with spatial autoregressive process. Sen and Bera (2011) study robust testing methods for spatial lag, spatial error, random effects and serial correlation in panel data. For these purposes, the authors derive Rao Score (or Lagrange Multiplier) tests for each component under possible local misspecification and obtain test statistics which are robust to the presence of other effects. Baltagi and Yang (2013) propose methods for standardizing the tests for spatial error dependence by controlling for the finite sample behavior and by providing robust alternatives through mean and variance adjustment. Pfaffermayr (2013) proposes a test for unbalanced panel data with spatially correlated error terms by deriving a test statistic in pursuit of applying within transformation on the unbalanced data.

B.3. Diagnostics for Panel Data

Table B.2: Diagnostic Tests for Panel Data

	Test Statistic	Alternative Hypothesis	Abs. Conv. Model 0	Conditional Convergence Model 1	Model 2	Model 3	Model 4
Locally robust tests for random effects and autocorrelation	Test for autocorrelation in the presence of random effects (Bera et al., 2001)	AR(1) errors under random effects	2.2220	1.1724	0.6961	1.0938	0.7351
			(0.1361)	(0.2789)	(0.4041)	(0.2956)	(0.3912)
	Test for random effects in the presence of autocorrelation (Bera et al., 2001)	Random effects under AR(1) errors	-4.4384	1.8160	2.0477**	1.7921**	2.0188**
			(1.0000)	(0.0347)	(0.0203)	(0.0366)	(0.0218)
	Joint test for random effects or autocorrelation (Baltagi and Li, 1991, 1995)	AR(1) errors or random effects	19.6990***	6.5037**	6.7818***	6.2495**	6.7103***
			(0.0000)	(0.0108)	(0.0092)	(0.0124)	(0.0096)

APPENDIX C

SUPPLEMENTARY INFORMATION FOR CHAPTER 4

C.1. Data Appendix

Table C.1: Provinces and NUTS-2 Level Regions (81 provinces as of 2004)

NUTS-2 regions	Provinces
TR10	İstanbul
TR21	Tekirdağ, Edirne, Kırklareli
TR22	Balıkesir, Çanakkale
TR31	İzmir
TR32	Aydın, Denizli, Muğla
TR33	Manisa, Afyon, Kütahya, Uşak
TR41	Bursa, Eskişehir, Bilecik
TR42	Kocaeli, Sakarya, Düzce, Bolu, Yalova
TR51	Ankara
TR52	Konya, Karaman
TR61	Antalya, Isparta, Burdur
TR62	Adana, Mersin
TR63	Hatay, Kahramanmaraş, Osmaniye
TR71	Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir
TR72	Kayseri, Sivas, Yozgat
TR81	Zonguldak, Karabük, Bartın
TR82	Kastamonu, Çankırı, Sinop
TR83	Samsun, Tokat, Çorum, Amasya
TR90	Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane
TRA1	Erzurum, Erzincan, Bayburt
TRA2	Ağrı, Kars, Iğdır, Ardahan
TRB1	Malatya, Elazığ, Bingöl, Tunceli
TRB2	Van, Muş, Bitlis, Hakkari
TRC1	Gaziantep, Adıyaman, Kilis
TRC2	Şanlıurfa, Diyarbakır
TRC3	Mardin, Batman, Şırnak, Siirt
Total number: 26	***Total number: 81***

Table C.2: Descriptive Statistics of the variables in Chapter 4

	min	*max*	*range*	*median*	*mean*	*std. dev*	*skewness*	*kurtosis*	*number of obs.*
growth_eagr	0.5101	2.3117	1.8016	1.0217	1.0254	0.2245	1.5830	7.0450	182
growth_eind	0.8333	1.5856	0.7522	1.0278	1.0520	0.1270	1.5941	3.9211	182
growth_eser	0.7946	1.2275	0.4329	1.0168	1.0200	0.0690	0.1304	0.6278	182
eagr04	0.0018	0.3935	0.3917	0.1380	0.1578	0.0969	0.7257	0.2702	182
eagr	0.0011	0.3439	0.3427	0.1306	0.1411	0.0827	0.4038	-0.5126	182
eind04	0.0213	0.1926	0.1713	0.0761	0.0826	0.0430	0.7659	0.0067	182
eind	0.0238	0.2093	0.1855	0.0875	0.0937	0.0417	0.7071	0.0390	182
eser04	0.1373	0.2692	0.1319	0.1703	0.1757	0.0338	1.2190	1.0909	182
eser	0.1206	0.3106	0.1900	0.1827	0.1912	0.0385	0.9437	0.5016	182

C.2. Checking for Contemporaneous Correlation

Table C.3: The covariance matrix of the residuals in Pooled OLS models

			Static Models				
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	0.0426	-0.0010	-0.0035	Agr.	0.0431	-0.0010	-0.0035
Ind.	-0.0010	0.0114	0.0018	Ind.	-0.0010	0.0114	0.0018
Serv.	-0.0035	0.0018	0.0046	Serv.	-0.0035	0.0018	0.0047
			Dynamic Models				
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	0.0424	-0.0008	-0.0033	Agr.	0.0426	-0.0006	-0.0033
Ind.	-0.0008	0.0112	0.0015	Ind.	-0.0006	0.0112	0.0015
Serv.	-0.0033	0.0015	0.0045	Serv.	-0.0033	0.0015	0.0045

Table C.4: The correlations of the residuals in Pooled OLS models

			Static Models				
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	1.0000	-0.0434	-0.2498	Agr.	1.0000	-0.0441	-0.2498
Ind.	-0.0434	1.0000	0.2433	Ind.	-0.0441	1.0000	0.2426
Serv.	-0.2498	0.2433	1.0000	Serv.	-0.2498	0.2426	1.0000
			Dynamic Models				
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	1.0000	-0.0357	-0.2367	Agr	1.0000	-0.0295	-0.2358
Ind.	-0.0357	1.0000	0.2144	Ind.	-0.0295	1.0000	0.2133
Serv.	-0.2367	0.2144	1.0000	Serv.	-0.2358	0.2133	1.0000

Table C.5: The covariance matrix of the residuals in Pooled SUR models

Static Models							
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	0.0422	-0.0009	-0.0035	Agr.	0.0421	-0.0010	-0.0035
Ind.	-0.0009	0.0113	0.0018	Ind.	-0.0010	0.0112	0.0017
Serv.	-0.0035	0.0018	0.0046	Serv.	-0.0035	0.0017	0.0046
Dynamic Models							
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	0.0419	-0.0008	-0.0032	Agr.	0.0417	-0.0006	-0.0032
Ind.	-0.0008	0.0111	0.0015	Ind.	-0.0006	0.0110	0.0015
Serv.	-0.0032	0.0015	0.0044	Serv.	-0.0032	0.0015	0.0044

Table C.6: The correlations of the residuals in Pooled SUR models

Static Models							
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	1.0000	-0.0435	-0.2500	Agr.	1.0000	-0.0441	-0.2498
Ind.	-0.0435	1.0000	0.2447	Ind.	-0.0441	1.0000	0.2426
Serv.	-0.2500	0.2447	1.0000	Serv.	-0.2498	0.2426	1.0000
Dynamic Models							
	Base Model				**Interaction Model**		
	Agr.	Ind.	Serv.		Agr.	Ind.	Serv.
Agr.	1.0000	-0.0356	-0.2388	Agr.	1.0000	-0.0295	-0.2358
Ind.	-0.0356	1.0000	0.2174	Ind.	-0.0295	1.0000	0.2133
Serv.	-0.2388	0.2174	1.0000	Serv.	-0.2358	0.2133	1.0000

C.3. Kernel Density Estimations

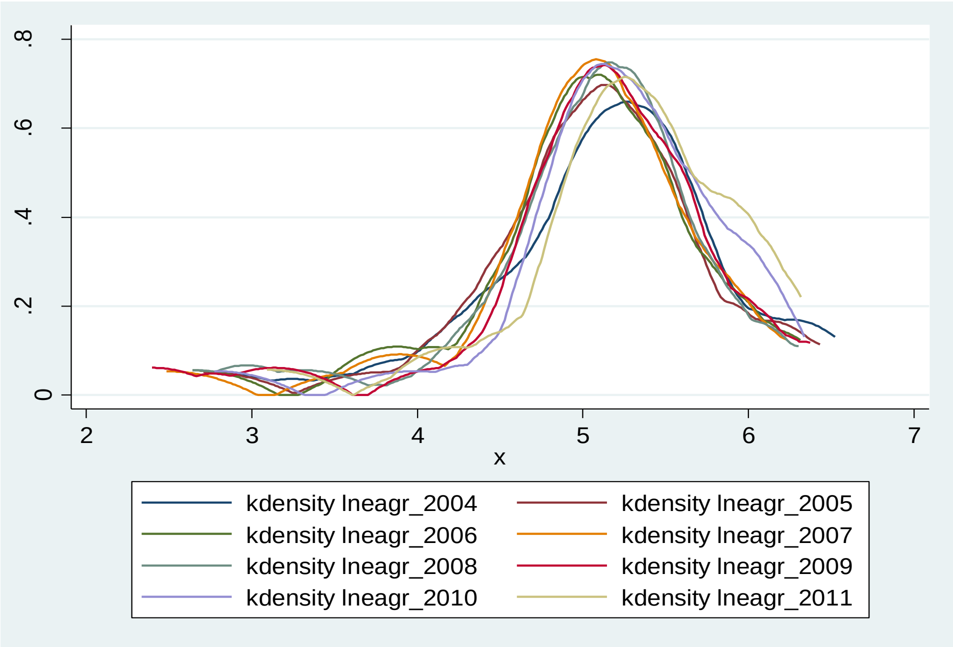

Figure C.1: Kernel Density Plots for Agriculture Sector Employment Rates

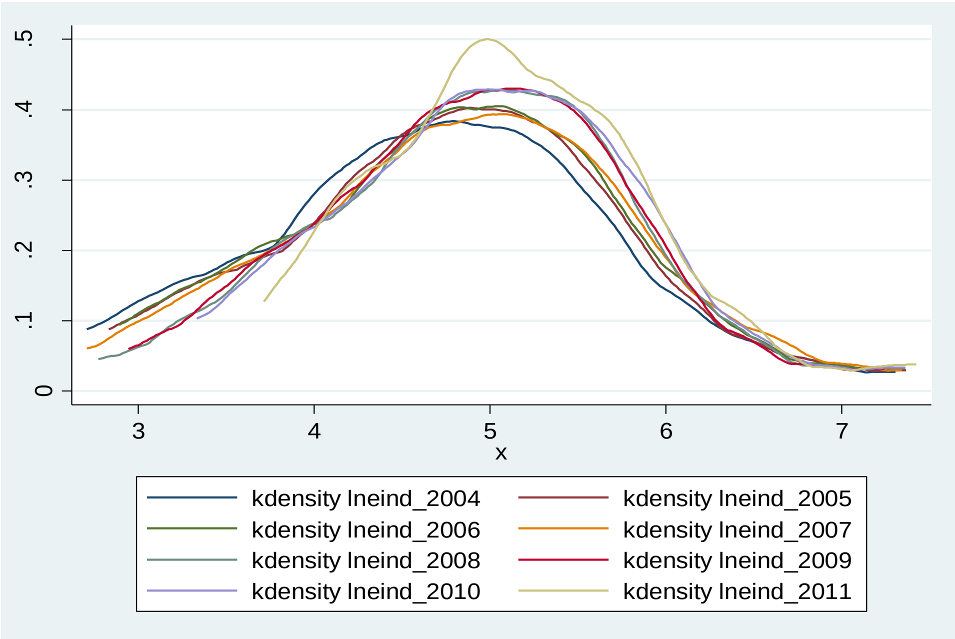

Figure C.2: Kernel Density Plots for Industry Sector Employment Rates

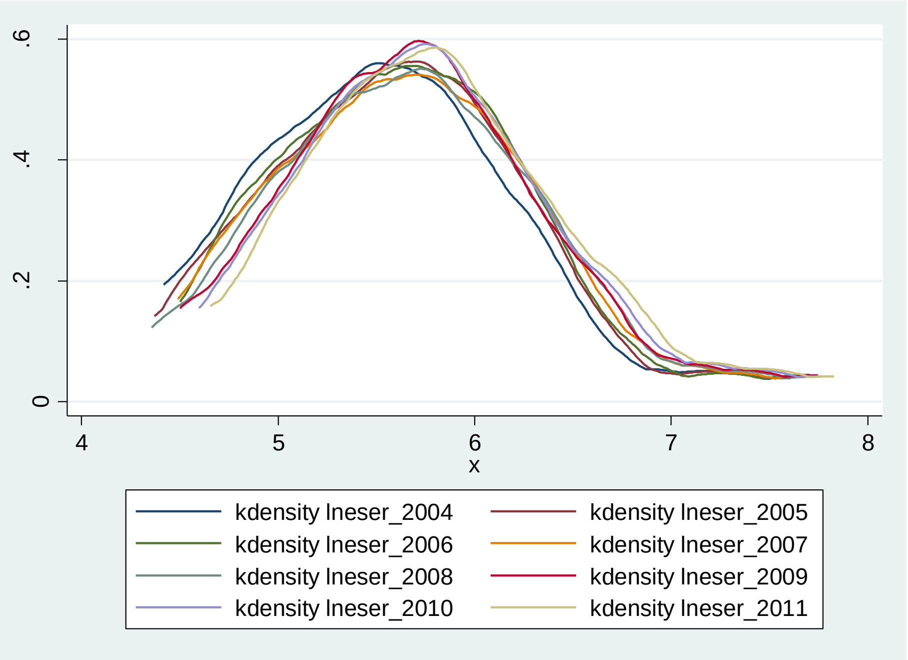

Figure C.3: Kernel Density Plots for Services Sector Employment Rates

APPENDIX D

TURKISH SUMMARY

Bölüm 1: Giriş

Bölgesel kalkınma politika yapıcıların en başlıca hedeflerinden ve en zorlu görevlerinden biri olagelmiş; temel amaç uygun iktisadi gereçler ile bölgesel eşitsizliklerin giderilmesi üzerine kurulmuştur. Bilim insanları bu eşitsizliklerin yalnızca büyüklüğü ve sebeplerini değil, aynı zamanda ülkeler arası ve ülke içindeki evrimini de araştırmışlardırlar. Bu durum, iktisadi büyüme teorisine yapılan en önemli katkılardan biri olan yakınsama modellerine olan ilgiyi her daim canlı kılmıştır. Aynı ülke sınırları içindeki bölgelerin ortak iktisadi ve sosyal zemine sahip olmaları nedeniyle yakınsamanın bölgesel düzeyde daha muhtemel olduğu tartışılmış; bölgesel etkileşimler üzerine artan vurgunun doğal bir sonucu olarak yakınsama modellerinin mekânsal ilişkiler göz önüne alınarak tekrar yorumlanması gerekmiştir.

Bu tezde Türkiye'de iller ve bölgeler arası mekânsal etkileşimlerin bölgesel büyüme ve istihdam yakınsaması dinamiklerini nasıl etkilediği araştırılmaktır. Coğrafyanın birinci yasası gereği "*Her şey birbiri ile ilişkilidir, fakat yakın şeyler uzak şeylere göre daha çok ilişkilidir*" (Tobler, 1970). Tezin ana amacı Solow-Swan yakınsama hipotezini bu yasa bağlamında tekrar değerlendirmektir. Yapılan analizlerde mekânsal ekonometri yazınındaki en güncel teorik katkılar ile mevcut en yeni veri seti ele alınmıştır. Tezde yer alan üç temel bölüm, veri seti ve kullanılan modeller açısından alanındaki ilk örnekler olma özelliğini taşımaktadır.

Bölgesel yakınsama modellerinde mekânsal etkilerin hesaba katılmasının iktisadi ve yöntemsel gerekçeleri vardır. İktisaden, beş temel hareket noktasından söz etmek mümkündür. İlk olarak, sosyal, ekonomik ve siyasi şartlar birbirine yakın olan bölgelerde uzak bölgelere nazaran daha benzerdir. Bu durum komşu iller arasındaki etkileşimi artırmakta ve bölgesel büyüme ve istihdamı doğrudan etkilemektedir. İkincisi, işgücü piyasalarını ve büyümeyi belirleyen beşeri sermaye, emek, özel yatırımlar ve nüfus gibi değişkenler bölgeler arasında kolayca yer değiştirmektedirler. Birbirine yakın iller arasında göreli düşük nakliye ve dağıtım maliyeti ile ulaşım kolaylığı sebebiyle emek ve sermaye daha devingendir. Üçüncü olarak, komşu bölgeler arasında girdi-çıktı bağlantıları görece daha yüksektir. Sektörel düzeyde de geçerli olduğu üzere, bir bölgede üretilen bir ürün diğer bir bölgede ara mal olarak kullanılabilmekte ve bu karşılıklı bağlılık mekânsal yakınlık arttıkça daha çok göze çarpmaktadır. Bu bağlamda, bir bölgede ortaya çıkan üretim sürecindeki verimsizlik komşu bölgelerdeki büyüme ve istihdam dinamiklerini etkileyecektir. Dördüncüsü, coğrafi yakınlık yayılma etkisini güçlendirmektedir. Ekonomik büyümeyi ilerleten bilginin yayılımı, yakın bölgeler arasında pozitif dışsallıkların daha etkili olması sebebiyle büyük ölçüde mekânsal bir olgudur. Beşincisi, belli bir yöreyi etkileyen iktisadi bir şokun komşu bölgeler üzerinde daha çabuk ve ciddi yansımaları olacaktır. Doğal afet, terör, iklim ve toprak yapısındaki ani değişimler gibi bölgesel ekonomileri etkileyen ani olaylar yakın bölgeleri daha çok etkileyecektir. Üretim ve istihdamı vuran böylesi koşullar hiç şüphesiz mekânsal etkileri açısından da değerlendirilmelidir.

Ekonometrik çalışmalarda mekânsal analiz aynı zamanda yöntemsel nedenlerden dolayı da gereklidir. İktisadi nedenlerin doğal bir sonucu olarak mekânsallık ekonometrik spesifikasyonlarda değişik formlarda kendini gösterebilmekte, bağımlı ve bağımsız değişkenlerde olabildiği gibi regresyonun hata terimlerinde de ortaya çıkabilmektedir. Bu etkilerin farklı kombinasyonları bir araya gelerek bir dizi mekânsal model oluşturabilmektedir. Özünde modelde bulunması gereken, fakat ihmal edilen mekânsal yapılar tahmin edilen parametrelerde ciddi problemlere yol açabilmektedir. Bağımlı değişkende göz ardı edilen mekânsallık yanlı ve tutarsız, hata terimlerinde dikkate alınmayan mekânsallık ise etkinsiz tahmin sonuçlarına neden olabilmektedir. Bu problemlerin üstesinden gelebilmek tüm olası mekânsal faktörleri göz önünde bulunduran kapsamlı bir analiz ile mümkündür.

Bir sonraki bölüm 1991-2009 yılları arasında Türkiye'de il bazında büyüme yakınsamasını ele almaktadır. Gerçek mekânsal yapının ortaya çıkarılabilmesi için tüm olası kombinasyonlar değerlendirilmekte ve kesit analizi için önerilen bütün mekânsal modellerden faydalanılmaktadır. Model seçimi sonucu ortaya çıkan mekânsal hata modeli bahsi geçen yıllar arası il bazında büyümede mekânsal heterojenliğin varlığını kanıtlamaktadır. Bulunan pozitif mekânsal içsel bağıntı bir ilin üretim yapısını etkileyen olası bir şokun komşu illeri de aynı yönlü olarak etkilediğini göstermektedir. Maksimum olabilirlik tahmin sonuçları mutlak ve koşullu yakınsamanın varlığını göstermekte, 1991 yılından 2009 yılına kadar gerçekleşen il bazında büyümede itici gücün beşeri sermaye ve istihdam olduğu ortaya konmaktadır. Diğer yandan, kamu yatırımları ve özel yatırımlar toplamda beklenen etkiyi yaratamamışlardır.

Üçüncü bölümde, il bazında yakınsama modeline zaman etkisi dahil edilerek analizin seviyesi genişletilmektedir. Bu çerçevede, mekânsal dinamik panel veri (SDPD) modelleri farklı formlarda uygulanmakta ve tahmin yöntemleri üzerine detaylı bir tartışma sunulmaktadır. Kurulan regresyonlarda 1994, 1999, 2001 ve 2009 yıllarındaki krizlerin yanı sıra 2002 yılındaki yapısal kırılma dikkate alınmakta; böylece farklı ekonomik ve politik koşullarda yakınsama dinamiklerinin nasıl değiştiği gözlenmektedir. Uygulanan detaylı yöntemsel analiz ve ilgili test istatistikleri ışığında, Türkiye'de iller arası yakınsama dinamiklerini en iyi temsil eden modelin mekânsal gecikmeli dinamik sabit etkiler modeli olduğu ortaya çıkmaktadır. Genelleştirilmiş momentler yöntemiyle tahmin edilen pozitif mekânsal gecikme parametreleri komşu iller arasında büyüme oranlarının birbiriyle doğrudan ve aynı yönlü ilişki taşıdığını göstermektedir.

Son bölümde Türkiye'de 2004-2011 yılları boyunca iktisadi bölge birimleri sınıflandırması İBBS-2 düzeyindeki bölgesel istihdam yakınsaması bölgesel, sektörel ve zaman boyutu ele alınarak incelenmektedir. İlk aşamada, tarım, sanayi ve hizmet sektörleri için ayrı ayrı mekânsal panel veri modelleri tahmin edilmekte; daha sonra sektörel istihdam regresyonları mekânsal panel görünürde ilişkisiz regresyon (SUR) sistemiyle birleştirilmektedir. Uygulanabilir genelleştirilmiş mekânsal üç aşamalı en küçük kareler (FGS3SLS) yöntemi ile tahmin edilen modeller sektörlere özgü sonuçlar ortaya koymaktadır. Tarımda ıraksama gözlenirken hizmet sektöründe yakınsama bulunmakta; bunun yanı sıra tarımdan hizmet sektörüne istihdam geçişleri olduğu kanıtlanmaktadır. Sanayi sektörü ise kendine özgü karakteri gereği statik modelde ıraksama gösterirken dinamik modelde bu bulgu ortadan kalkmaktadır. Mekânsal hata parametreleri de benzer şekilde sektörel farklılıklar göstermektedir. Tarım sektöründe negatif olan parametre komşular arası işgücü rekabetini düşündürürken sanayi ve hizmetlerdeki pozitif parametreler pozitif geri besleme etkilerine işaret etmekte, olası dışsal şokların tesirinin komşu bölgeler arasında aynı yönlü olduğunu ortaya koymaktadır.

Bir bütün olarak, elde edilen sonuçlar Türkiye'de bölgesel büyüme ve yakınsama probleminin modellenmesinde uyguladığımız mekânsal ekonometrik yöntemlerin yalnızca geçerliliğini değil, aynı zamanda üstünlüğünü de göstermektedir. İhmal edilmiş mekânsallık yalnızca bölgeler arasındaki ekonomik bağların ortaya çıkarılamamasına değil, fakat aynı zamanda yanlı, tutarsız ve etkinsiz parametre tahminlerine ve dolayısıyla yanlış çıkarımlara neden olabilmektedir. Dahası, temel birkaç formla sınırlı tutulan ve alternatif spesifikasyonları göz ardı eden bir yaklaşım bölgeler arasındaki gerçek mekânsal ilişkileri göstermede yetersiz kalabilecektir.

Bölüm 2: Türkiye'de Bölgesel Büyüme Yakınsamasının Mekânsal Kesit Analizi

Son 20 yıldır kesit düzeyinde ele alınan bölgesel büyüme modellerinde mekânsal teknikler sıklıkla kullanılmış olsa da bu çalışmalar daha ziyade gelişmiş ülke ekonomilerine yoğunlaşmış ve çoğunlukla temel birkaç mekânsal formun ötesine geçmemişlerdir. Tezin bu bölümü Türkiye için kesit analizinde daha önce dikkate alınmamış mekânsal ilişkileri sorgulamayı ve olası tüm mekânsal kombinasyonları değerlendirmeyi amaçlamaktadır. Bu bağlamda, 1991-2009 yılları arası iller düzeyinde mutlak ve koşullu yakınsama hipotezleri incelenmektedir.

Söz konusu dönemde Türkiye ekonomisinde ciddi dönüşümler meydana gelmiş, bölgesel kalkınma politikaları ve yakınsama dinamikleri de bu konjonktürden etkilenmiştir. 1980'lerin başından itibaren ihracata dayalı büyüme modeline geçilmesi ve ithalat rejiminin serbestleştirilmesini takiben 1989 yılında sermaye hareketlerinin de serbest bırakılmasıyla birlikte 1990'lı yıllara hayli dışa açık bir ekonomi olarak girilmiştir. Finansal serbestleştirmeyle birlikte ülke spekülatif sermaye hareketlerine karşı kırılgan hale gelmiş; Türk lirasının aşırı değerlenmesi, faiz oranlarının artması ve yurtiçi talebin yükselmesiyle birlikte 1994 krizi patlak vermiş ve devalüasyonla sonuçlanmıştır. 1996 yılına gelindiğinde Avrupa Birliği (AB) ile Gümrük Birliği anlaşması imzalanmıştır. Kısa bir toparlanma sürecinden hemen sonra 1997 Asya, 1998 Rusya krizleri ve 1999 depremi ile Türkiye ekonomisi yeniden sarsılmıştır. 2001 yılındaki büyük kriz ile birlikte reel gayri safi yurt içi hasıla (GSYİH) yüzde 7.4 oranında düşmüş, Türk lirası yabancı paralar karşısında yüzde 51 oranında değer kaybetmiş, işsizlik oranı yüzde 10'un üzerine çıkmış ve reel ücretler yüzde 20 düşmüştür (Yeldan, 2011). Bu büyük krizden sonra ekonomide bir çıkış dönemi yaşanmış, 2008-09 küresel krizine dek önemli düşüşler yaşanmadan devam etmiştir. 1990 sonrası dönemdeki bu çalkantıların bölgesel eşitsizlik üzerine de yansımaları olmuştur.

Türkiye'de bölgesel eşitsizliklerin giderilmesi amacıyla 1963 yılında yayımlanan Birinci Kalkınma Planı'ndan itibaren çeşitli adımlar atılmış, 1980 sonrası liberalleşme dönemiyle birlikte kalkınmada daha dışa açık bir bakış açısı benimsenmiştir. 1990 yılında ortaya konan Altıncı Kalkınma Planı bölgesel kalkınmada Avrupa Birliği politikalarıyla uyumu gündeme getirmiş, 1999 yılında yapılan Helsinki zirvesinde Türkiye'nin AB'ye adaylık statüsü kazanması ile birlikte bu vurgu daha da artmıştır. 2002 yılı itibariyle Türkiye'de İktisadi Bölge Birimleri Sınıflandırması (İBBS) kullanılmaya başlanmıştır.

Türkiye'de bölgesel eşitsizliklerin giderilmesi amacıyla üç temel politikanın ortaya konduğunu söylemek mümkündür. İlk önemli adım, 1968 yılında Kalkınmada Öncelikli Yöre (KÖY) tanımlamasına geçilmesi ile birlikte görece az gelişmiş olan bölgelere özel tedbirlerin alınmasıdır. Önceleri 22 Doğu ve Güneydoğu Anadolu ili için belirlenen bu tanım zaman içinde değişikliklere uğramış, son olarak 1998 yılı itibariyle 49 il ve 2 ilçe KÖY ilan edilmiştir. İkinci büyük adım 1970'lerin başından itibaren ortaya konan ve az gelişmiş bölgenin karakterine özgü önlemler almayı hedefleyen Bölgesel Kalkınma Projeleri'dir. Tarımda sulama için büyük yatırımlar öngören Güneydoğu Anadolu Projesi (GAP) örnek teşkil etmiş, daha sonra farklı hedeflerle Zonguldak-Bartın-Karabük (ZBK), Doğu Anadolu Projesi (DAP), Doğu Karadeniz Projesi (DOKAP), Yeşilırmak Havza Gelişim Projesi (YHGP) ve Konya Ovası Projesi (KOP) ortaya konmuştur. Üçüncü önemli adım ise 2006 yılında 26 İBBS-2 bölgesi için kurulan Bölgesel Kalkınma Ajansları'dır. 2014-2018 dönemi için yayımlanan Onuncu Kalkınma Planı'nda Başbakanlık'a bağlı olarak faaliyet yürüten bu ajansların yerli ve yabancı yatırımları bölgeye çekmek amacıyla tamamlayıcı bir rol üstelenecekleri ifade edilmiştir (SPO, 2014).

Tezin bu bölümünde 1991-2009 döneminde iller arası yakınsama dinamiklerini incelemek üzere kullanılan değişkenler, veri setinin el verdiği en güncel ve ayrıntılı düzeyde tutulmuştur. Ekonometrik analize konu edilen değişkenler reel GSYİH, beşeri sermaye, nüfus, istihdam, reel kamu yatırımları ve reel özel yatırımları kapsamaktadır. Beşeri sermaye göstergesi olarak lise ve üniversite mezun oranları kullanılmıştır. Reel özel yatırım göstergesi olarak toplam mevduat (ticari kuruluşlar, resmi kuruluşlar, bankalar, tasarruf ve diğer mevduatlar), ihtisas kredileri (tarım, gayrimenkul, mesleki, denizcilik, turizm, diğer) ve toplam krediler ele alınmıştır. Tüm reel göstergeler 1998 fiyatlarıyla ifade edilmektedir. Buna göre il bazında kişi başına GSYİH, büyüme, lise ve üniversite mezunlarının il nüfusundaki oranı, istihdam oranı, kişi başına kamu yatırımı, kişi başına mevduat/ihtisas kredileri/toplam krediler hesaplanmış ve Türkiye'nin dijital haritasına aktarılmıştır. Veriler başlangıç yılı olan 1991'deki 73 il düzeyinde toplulaştırılmıştır.

Betimsel analiz kişi başına gayrisafi yurt içi hasılanın hem 1991, hem de 2009 yıllarında ülkenin doğusu ile batısı arasında ciddi şekilde farklılaştığını göstermektedir. 2009 yılına gelindiğinde batıda özellikle kıyı kesimindeki illerin refah seviyelerinin arttığı gözlenmektedir. Lise ve üniversite mezunlarının nüfustaki oranına bakıldığında Güneydoğu Anadolu en geri kalan bölge görünümündedir. İstihdam oranlarında ise 1991 yılındaki yüksek bölgesel farklar 2009 yılına gelindiğinde Doğu Anadolu'daki belirli iller için kısmen telafi edilmiş olsa da, özellikle Güneydoğu Anadolu'da devam etmektedir. Diğer yandan, nüfusa oranla kamu yatırımlarının tüm bölgelerde belli bir aralıkta seyrettiğini söylemek mümkündür. Özel yatırım göstergelerinde genellikle ülkenin doğusundaki illerde zaman içinde çok fazla değişim yaşanmazken batıdaki illerde artış gözlenmekte, bölgesel gelişmişliğe paralel bir tablo ortaya çıkmaktadır. Genel olarak, ülkede 1990'ların başından itibaren temel ekonomik göstergelerde bölgesel farklılıkların azalması anlamında birtakım iyileşmeler olmakla birlikte, halen belli bölgelerdeki kümelenmeler varlığını korumaktadır. Bu durum, il bazında milli gelir serilerini ve büyüme verisini incelerken mekânsal etkilerin göz ardı edilmemesi gerektiğini düşündürmektedir.

Yakınsama ilişkisini gösteren Solow-Swan modeline göre ilk dönemde daha düşük bir GSYİH seviyesiyle başlayan iller zaman içinde daha yüksek bir büyüme oranı yakalayabilirlerse mutlak bir yakınsamadan bahsedilebilir. Koşullu yakınsama hipotezi ise ekonometrik modele eklenen kontrol değişkenleri yoluyla iller arasındaki yapısal farklılıkları da hesaba katmaktadır. Tahmin edilen modellerde beşeri sermaye göstergesi olarak lise mezun oranları, özel sermaye göstergesi olarak toplam krediler alınmaktadır. Kestirim sonucunda negatif ve anlamlı bulunan beta katsayısı başlangıç yılında düşük kişi başına milli gelir seviyesinde başlayan illerin daha hızlı büyüdüğü, yakınsama olduğu anlamına gelmektedir.

Mutlak ve koşullu yakınsama hipotezleri öncelikle En Küçük Kareler (EKK) yöntemi ile tahmin edilmiştir. EKK ile tahmin edilen bu modellerde yanlış belirleme sorununun olduğu görülmektedir. Tanılayıcı testler hata terimlerinin normal dağıldığını, öte yandan koşullu yakınsama hipotezinde değişen varyans probleminin olduğunu göstermektedir. Dahası, modelin artık terimlerinin dağılımında bir kümelenme göze çarpmaktadır. Hata terimleri arasında böyle bir bölgesel ilişkinin gözlenmesi, ihmal edilen mekânsal heterojenlik olduğunu akla getirmektedir.

Mekânsal korelasyonun varlığını test etmek üzere kullanılan istatistiklerde ve model tahminlerinde mekânsal ağırlık matrisi ikili komşuluk yaklaşımına göre oluşturulmuştur. Buna göre ortak bir sınır paylaşan iki il birbirine komşu sayılmış, matris üzerinde komşu iller 1 (bir), komşu olmayan iller 0 (sıfır) olarak gösterilmiştir. Bir il kendisine komşu sayılmayacağı için tanım gereği köşegendeki değerler sıfır olacaktır. Bu komşuluk ilişkilerini gösteren mekânsal ağırlık matrisi satır toplamları 1 olacak şekilde standardize edilmiştir.

EKK ile tahmin edilen modellerde Moran I ve lokal Moran I test sonuçları hem mutlak, hem de koşullu yakınsama tahminlerinde pozitif mekânsal içsel bağıntının var olduğunu göstermektedir. Bu etki mekânsal bağımlılık ilişkisinin öngördüğü gibi mekânsal gecikme terimlerinde veya mekânsal heterojenlik ilişkisinin öngördüğü biçimde hata terimlerinde olabilir, dolayısıyla mekânsal bağıntının formu test edilmelidir. Mekânsallığın formu LM (*lagrange multiplier*) ve RLM (*robust lagrange multiplier*) istatistikleri ile test edildiğinde hem mutlak yakınsama, hem de koşullu yakınsama denklemleri için uygun spesifikasyonunun mekânsal hata modeli olduğu görülmektedir. Ancak bu istatistik önsel bilgi vermekle birlikte bağımsız değişkendeki mekânsallığı ayırt etmek için yeterli olmamaktadır. Bu nedenle tüm alternatif kombinasyonlar göz önünde bulundurulmaktadır.

Benzer biçimde kişi başına GSYİH göstergelerinde mekânsal ilişkilerin varlığı global Moran I, Geary'nin C testi ve Getis-Ord'un global G testi ile sınanmıştır. Bulunan pozitif mekânsal içsel bağıntı kümelenmenin varlığını işaret etmektedir. Kümelenmenin karakterini anlamak amacıyla kümedeki gözlem değerlerinin düşük veya yüksek olduğu bölgeleri lokal Moran I ve lokal Gi testleri ile sınamak mümkündür. Buna göre, 1991 ve 2009 yıllarının gözlemlerine bakıldığında Marmara ve Ege bölgelerinde yüksek değerler kümelenirken Güneydoğu Anadolu'da düşük kişi başına GSYİH değerlerinin bir araya gelmesiyle kümelenme oluştuğu görülmektedir. Doğu Anadolu bölgesinde ise 1991 yılında gözlemlenen düşük GSYİH kümelenmesi 2009 yılına gelindiğinde büyük ölçüde ortadan kalkmıştır. Genel mekânsal veri analizi sonucunda bulunan bu bağıntılar yakınsama modellerinin mekânsal ekonometrik tekniklerle tahmin edilmesini gerekli kılmaktadır.

Elhorst (2010a), mekânsal ekonometrik yöntemler kullanılarak oluşturulabilecek yatay kesit modellerini özetlemiş, regresyonların genelden özele bir yöntemle tahmin edilerek uygun olan modele ulaşılması gerektiğini öne sürmüştür. Bu bölümde de benzer bir yöntem izlenmekte ve altı farklı mekansal model tahmin edilmektedir. Bunlar genelden özele SAC Durbin, SAC, mekânsal Durbin, mekânsal Durbin hata, mekânsal gecikme ve mekânsal hata modelleridir. En genel model olan SAC Durbin modeli bir ildeki büyümenin komşu ildeki büyümeden, başlangıç yılındaki kendi kişi başına milli gelirinden, başlangıç yılındaki komşu milli gelirinden ve modelde tahmin edilmeyen hata terimleri arasındaki mekânsal heterojenlikten etkilendiğini göstermektedir. Koşullu yakınsama modelleri benzer biçimde yorumlandığında bu kez yalnızca kişi başına milli gelir değil, diğer açıklayıcı değişkenler de tahmin sonuçlarının değerlendirilmesine dahil edilmektedir. Diğer beş mekânsal model ise SAC Durbin modeline adım adım kısıtlar konarak elde edilebilmekte; olabilirlik oranı (LR) testleri kullanılarak doğru mekânsal modele ulaşılabilmektedir.

Mekânsal gecikmesi alınmış terimin açıklayıcı değişken olarak eklenmesinin hata terimleri ile yarattığı korelasyon sonucunda modelde içsellik ortaya çıkmaktadır. Bu durumda parametreleri tutarlı olarak tahmin edebilmek için maksimum olabilirlik (ML) yöntemi veya genelleştirilmiş momentler yöntemi (GMM) kullanılabilmektedir. Bu bölümde hata terimlerinin normal dağıldığı gösterilmiş ve mekânsal ekonometrik modeller maksimum olabilirlik yöntemi ile tahmin edilerek daha etkin sonuçlar elde edilmiştir.

Tahmin edilen tüm mutlak yakınsama modellerinde başlangıç yılı milli gelirinin büyüme üzerine etkisini gösteren beta katsayısı negatif ve anlamlı bulunmuş, mutlak yakınsama hipotezi doğrulanmıştır. Koşullu yakınsama hipotezi sonuçları ek değişkenlerin modele konmasının yakınsama oranını artırdığını göstermektedir. Tahmin edilen tüm modellerde beşeri sermaye ve istihdam beklendiği üzere büyümeyi pozitif ve anlamlı düzeyde etkilemektedir. Başlangıç yılındaki kamu yatırımları ve kredilerin ise büyüme üzerinde %5 anlamlılık düzeyinde bir etkisi bulunamamıştır.

Mutlak ve koşullu yakınsama hipotezleri için tahmin edilen mekânsal modellerde katsayılar birbirine yakın olmakla birlikte yakınsama oranlarında farklılıklar görülmektedir. Dolayısıyla doğru oranların seçilebilmesi için model karşılaştırması yapılmakta, uygun spesifikasyonu seçmek amacıyla genelden özele tüm modeller değerlendirilmektedir. Mutlak ve koşullu yakınsama için SAC Durbin, SAC, mekânsal Durbin ve mekânsal Durbin hata modelleri olabilirlik oranı test sonuçlarına göre elenmektedir. Mekânsal gecikme modeli ise üç temel nedenle seçilmemiştir. Birincisi, LR test sonuçlarına göre mekânsal gecikme modelinde ihmal edilmiş değişkenler bulunmaktadır. İkincisi, bu modelin artık terimlerinde içsel bağıntı bulunmuştur. Üçüncüsü, daha önce yapılmış olan LM ve RLM testleri mekânsal hata modelinin mekânsal gecikme modeline kıyasla yakınsamayı daha iyi açıkladığını göstermiştir. Sonuç olarak, diğer spesifikasyonlar elenerek mutlak ve koşullu yakınsama hipotezlerini en iyi açıklayan model olarak mekânsal hata modeli seçilmiştir. Pozitif ve anlamlı bulunan mekânsal hata terimleri, bir ildeki büyüme oranlarını etkileyen olası bir şokun komşu illeri de aynı yönde ve anlamlı düzeyde etkilediğini göstermektedir.

Elde edilen sonuçlara göre, 1991-2009 dönemi için Türkiye'de iller arası mutlak yakınsama oranı yüzde 7.88 koşullu yakınsama oranı ise yüzde 13.79 olarak hesaplanmıştır. İl bazında kişi başına GSYİH'deki büyümenin beşeri sermaye ve istihdamdan pozitif yönde etkilendiği gösterilmiş, kamu yatırımlarının ve kredilerin ise anlamlı düzeyde bir etkisi bulunamamıştır. Kamu yatırımları açısından bakılacak olursa, dağıtım ve işletim mekanizmasının büyümeyi olumlu etkileyecek biçimde değerlendirilememiş olması mümkündür. Özel yatırımların büyümeye anlamlı bir katkı sunmamış olması ise olumsuz coğrafi konum, etnik ihtilaflar, görece daha az kalifiye işgücü koşulları altında teşvik mekanizmalarının kalkınmada öncelikli yörelere yatırım için yetersiz kalmasından kaynaklanmış olabilir. 1991'den 2009'a kadar 73 ilde gözlemlenen büyümenin temel tetikleyicisinin beşeri sermaye ve istihdam olduğu anlaşılmaktadır. Marmara ve Ege bölgelerinde yüksek refah düzeyindeki kümelenme buradaki görece kalifiye emek gücünden kaynaklanmış olabilir. Tersine, Güneydoğu Anadolu Bölgesinde istihdamda kayıt dışılık ve verimsizliğin daha düşük refah düzeyindeki kümelenmeye sebep olduğu düşünülebilir. Kamu ve özel yatırım stratejilerinin kalifiye işgücünü teşvik edecek ve işgücü piyasasında verimliliği artıracak şekilde düzenlenmesi ve altyapı olanaklarının geliştirilmesi bölgesel kalkınmada istenilen sonuçların elde edilmesine katkıda bulunacaktır.

Bölüm 3: Türkiye'de Bölgesel Büyüme Yakınsamasının Mekânsal Dinamik Panel Veri Analizi

Tezin bu bölümünde Türkiye'de 1991-2009 döneminde il bazında büyüme yakınsaması problemi hem mekânsal, hem de zaman boyutundaki değişimleri hesaba katabilmek adına mekânsal dinamik panel veri (SDPD) analizi kullanılarak incelenmektedir. Bu etkileri hesaba katmasının yanı sıra, mekânsal panel veri modelinin dinamik olarak formüle edilmesi sayesinde başlangıç yılı GSYİH değerlerinin zaman içindeki değişimi ve büyüme üzerine yaptığı dinamik etkilerin göz önüne alınması mümkündür. SDPD analizi ekonometri yazınında oldukça yeni bir yöntem olması sebebiyle bölgesel yakınsama uygulamaları sınırlıdır ve Türkiye için henüz böyle bir çalışma yapılmamıştır. Dolayısıyla, bu bölümün en önemli katkısı Türkiye için yapılan yakınsama modellerine yöntemsel bir açılım getirmek, daha kapsayıcı modelleme yöntemleri sayesinde daha iyi tahmin sonuçlarına ulaşmaktır.

Panel veri modellerinin kesit analizine kıyasla heterojenliği hesaba katabilmesi, daha detaylı veri bilgisi sağlaması, değişkenliği yansıtabilmesi, çoklu doğrusallığı azaltması, daha fazla serbestlik derecesi ve etkinlik sağlaması ve uyum dinamiklerini göstermesi gibi üstünlükleri bulunmaktadır (Baltagi, 2010: 6-7). Ampirik yazında genellikle sabit etkiler ve rassal etkiler modelleri kullanılmakta, bu modeller statik veya dinamik olarak formüle edilebilmektedirler.

Standart dinamik panel çerçevesinde ele alınan yakınsama modellerinde baskın olarak sabit etkiler modeli kullanılmakta, genelleştirilmiş momentler (GMM) veya araç değişkenler (IV) yöntemleri tercih edilmektedir. Bu tekniklerin kullanılması durumunda hata terimlerinde serisel korelasyon bulunmaması gerekmekte ve kullanılan araç değişkenlerin geçerliliği Sargan testleri ile sınanmaktadır. Genel olarak bu tahminler kesit analizine kıyasla daha yüksek yakınsama oranları ortaya koymaktadır. Ancak bu tip standart panel veri yöntemiyle tahmin edilen modellerde coğrafi olarak yakın bölgelerin ticaret ortağı olması ve ortak şoklara maruz kalması gibi durumların yatay kesit bağımlılığı yarattığı gözlemlenmiştir. Bundan hareketle yakınsama yazınında mekânsal panel veri modelleri dikkat çekmeye başlamıştır.

Bu bölümde 1991-2009 yılları boyunca iller arası yakınsama dinamiklerini incelemek amacıyla ikinci bölümde tanımlanan veri seti kullanılmış, farklı spesifikasyonlardaki ayrı değişken setleri ile alternatif formlar hesaba katılmıştır. Reel GSYİH değişkeni dinamik yapıda kullanılmıştır; buna göre t zamanındaki büyüme modelinde (t-1) zamanındaki kişi başına GSYİH değişkeninin katsayısı yakınsama dinamiklerini göstermektedir. Beşeri sermaye göstergesi olarak farklı spesifikasyonlarda lise ve üniversite mezun oranları kullanılmıştır. İstihdam oranları ve kişi başına kamu yatırımı değişkenlerinden bütün modellerde yararlanılmıştır. Özel yatırım göstergesi olarak alternatif spesifikasyonlarda kişi başına toplam mevduatlar ve kişi başına toplam krediler dikkate alınmıştır. Son olarak, nüfus değişkeni bu dönemdeki yüksek değişimi hesaba katabilmesi için açıklayıcı değişken olarak modele eklenmiştir. Tüm değişkenlerin logaritmik dönüşümü yapılmış ve reel değişkenler 1998 fiyatlarıyla ifade edilmiştir. 2002-2007 yılları arasındaki yüksek büyüme dönemi için yapısal kırılma, modellerde kukla değişken ile dikkate alınmıştır. Bunun yanında 1994, 1999, 2001 ve 2009 kriz yıllarındaki aykırı gözlemler ilgili kukla değişkenler ile kontrol edilmiştir.

Panel veri modellerinin sabit etkiler veya rassal etkiler ile tahmin edilmesi üzerine yapılan tartışmalar iki açıdan ele alınmaktadır. Birincisi, her bir modelin geçerliliği, varsayımları ve mantığı açısından değerlendirilebilir. Bu bağlamda, sözü edilen modellerin avantaj ve dezavantajları ortaya konmalıdır. Sabit etkiler modelleri için zaman boyutunun kısa olduğu panel veri setlerinde rastlantısal parametre problemi ortaya çıkabilmektedir. Bu durumda kesit boyutu olan N arttıkça bilinmeyen parametre sayısı da artmaktadır ve mekânsal sabit etkiler yalnızca zaman boyutu T yeterince büyükse tahmin edilebilmektedir. Ayrıca, sabit etkiler tahmininde LSDV yöntemi kullanılacak olursa zaman boyutunda değişmeyen gözlemler ortalamadan fark dönüştürmesi esnasında elenmekte ve ilgili parametreler tahmin edilememektedir. Aynı zamanda modele eklenen kukla değişkenler serbestlik derecesinde ciddi bir düşüşe sebep olmaktadırlar. Bu sebeplerle ampirik çalışmalarda sabit etkiler yerine rassal etkiler modeli tercih edilebilmektedir. Diğer yandan, rassal etkilerin bölgesel yakınsama modeli çerçevesinde daha önemli sorunları bulunmaktadır. Özünde bu model büyük bir kitleden N tane terimin rassal olarak seçilmesi ilkesine dayanmakta ve rassal etkiler ile açıklayıcı değişkenlerin arasında korelasyon bulunmamasını gerektirmektedir. Bölgesel yakınsama problemleri ise, doğası gereği, bir ülkedeki tüm bölge veya illeri ele almaktadır. Bu durumda örneklem, kitlenin rassal seçilmiş bir bölümünü yansıtmaktan ziyade kitlenin kendisi haline gelmekte ve rassal etkilerin temel varsayımına ters düşmektedir. Tartışmanın ikinci unsuru olarak, sabit ekiler ve rassal etkiler modellerinin geçerlilikleri ilgili test istatistikleri ile sorgulanabilir. Standart panel veri modellerine benzer biçimde mekânsal panel veri modellerinde de Hausman tipi test istatistikleri Mutl ve Pfaffermayr (2008, 2011), Sen ve ark. (2012) ile Baltagi ve Liu (2014) tarafında ortaya konmuştur.

Bu bölümde, sabit etkiler ve rassal etkiler modelleri mekânsal gecikme ve mekânsal hata terimleriyle birlikte tartışılmaktadır. Sabit etkiler modeli yakınsama probleminin analizi için daha uygun görünmekle birlikte model tercihi baştan empoze edilmemekte, tahmin sonrasında model seçimi yapılmaktadır. Buna göre, dört farklı model (dinamik sabit etkiler mekânsal hata, dinamik rassal etkiler mekânsal hata, dinamik sabit etkiler mekânsal gecikme, dinamik rassal etkiler mekânsal gecikme modelleri) incelenmektedir. Mekânsal ağırlık matrisi olarak ikinci bölümde ikili komşuluk tanımına göre oluşturulan matris kullanılmaktadır. Her bir model için beş farklı spesifikasyon hesaba katılmaktadır. Bunlardan biri mutlak yakınsama modelini temsil ederken diğer dört model beşeri sermaye için kullanılan iki, özel sermaye için kullanılan iki farklı gösterge değişkenin oluşturduğu dört değişken kombinasyonunu yansıtmaktadır. Diğer değişkenler ile yapısal dönüşüm ve kriz yıllarını temsil eden kukla değişkenler tüm modellerde aynı şekilde ele alınmaktadır. Kesit analizine benzer biçimde $GSYİH_{t-1}$ teriminin katsayısı olan beta parametresinin negatif ve anlamlı olduğu durumda yakınsamadan söz etmek mümkündür.

İlgili test istatistikleri veri setinin mekânsal panel ile modellenmesinin gerekli olduğuna işaret etmektedir. Breusch ve Pagan (1980) ile Honda (1985) testleri bireysel etkilerin anlamlı olduğunu, dolayısıyla panel veri tahminlerinin havuzlanmış EKK tahminine göre daha açıklayıcı olduğunu göstermektedir. Pesaran (2004) testi ise panel veride yatay kesit bağımlılığının varlığını ortaya koymuştur. İhmal edilen mekânsallığın bu etkiye sebep olabileceği göz önünde bulundurularak mekânsal dinamik panel veri tahminleri yapılmakta, mekânsallığın formuna ilişkin diğer testler ise model seçimi ile birlikte tahmin sonrasında tartışılmaktadır.

Mekânsal dinamik panel veri modellerinin tahmininde hata düzeltmesi yapılmış en küçük kareler kukla değişkeni (LSDV), maksimum olabilirlik (ML) ve genelleştirilmiş momentler (GMM) yöntemlerini kullanmak mümkündür. Bu bölümdeki modeller belli üstünlükleri ve avantajları sebebiyle GMM yöntemi ile tahmin edilmektedir. İlk olarak, GMM yöntemi ML tahmininde olduğu gibi önsel olarak belirlenmiş bir dağılım fonksiyonu gerektirmemektedir. İkincisi, ML yönteminde olduğu gibi panel veri modeli için Jacobi determinantı hesaplanması problemi söz konusu olmamaktadır. Üçüncüsü, ML tahmincisinin aksine GMM yöntemi zaman boyutu kısa olan mekânsal panel veri setleri için uygundur. Başka birtakım avantajları da bulunmakla beraber bu üç temel unsur yapılan tahminlerde GMM kullanılmasının hareket noktalarını oluşturmuştur.

GMM yöntemini kullanan standart panel veri modelleri temelde Arellano & Bond (1991) tarafından önerilen fark GMM ile Arellano & Bover (1995) ve Blundell & Bond (1998) tarafından geliştirilen sistem GMM tahminlerine dayanmaktadır. Sistem GMM kullandığı ek araç değişken seti ile katsayıların daha etkin tahmin edilmesini sağlamaktadır. Ancak bu yöntemlerin uygulanmasında dikkat edilmesi gereken noktalar bulunmaktadır. GMM tahmin sonuçlarının etkin olması için açıklayıcı değişkenlerde içsellik olması beklenmektedir; dinamik modellerde bu durum kendiliğinden ortaya çıkmaktadır. Kullanılan araç değişkenlerin geçerliliği sınanmalıdır ve zayıf araç değişken kullanımına karşı dikkatli olunmalıdır. İlgili kısıtlar Sargan (1958) ve Hansen (1982) testleri ile kontrol edilmelidir ve hata terimlerinde içsel bağıntı bulunmamalıdır. Mekânsal dinamik panel veri modellerinde de benzer biçimde fark GMM ve sistem GMM yöntemleri kullanılmakta, ancak bu kez yalnızca zaman boyutundaki değil aynı zamanda mekân boyutundaki gecikme terimleri de hesaba katılmalıdır.

Bu çerçevede, mekânsal hata ve mekânsal gecikme modellerini sabit ve rassal etkiler ile ele alan dört farklı mekânsal dinamik panel veri modeli tahmini yapılmıştır. Mekânsal hata modelleri için yapılan Hausman testine göre rassal etkiler modeli reddedilmiş, sabit etkiler modelinin daha uygun olduğu gözlenmiştir. Baltagi ve ark. (2003) ile Baltagi ve ark. (2007) tarafından önerilen LM test istatistikleri de benzer biçimde kontrol edilmiş, hata terimlerinde mekânsallık tespit edilememiştir. Bu durumda bulunan yatay kesit bağımlılığının hata terimlerinden ziyade gecikme terimlerindeki mekânsal ilişkiden kaynaklandığı söylenebilir. Mekânsal gecikme modeli olarak formüle edilmiş mekânsal dinamik panel veri modellerinde ise rassal ve sabit etkiler karşılaştırması iki açıdan ele alınmıştır. İlk olarak, bölgesel yakınsama modellerinde örneklem tüm kitleyi temsil ediyorsa sabit etkiler ile ifade edilmesi daha uygundur. İkincisi, tahmin edilen regresyonlarda sabit etkiler modelinin hata terimlerinin varyansı rassal etkilere göre çok daha düşüktür. Buna göre dinamik sabit etkiler mekânsal gecikme modeli veri setini temsil etmek için daha uygun bir model olarak ortaya çıkmıştır. Mekânsal gecikme terimleri genellikle pozitif ve anlamlı bulunmuştur.

Seçilen mekânsal gecikmeli dinamik sabit etkiler modeli bir ildeki büyümenin komşu ildeki büyümeyi doğrudan etkilediğini ve bu etkinin iller arasında aynı yönlü olduğunu göstermiştir. Zaman boyutunun da hesaba katılmasıyla kesit analizinden daha ayrıntılı ve kısmen daha farklı sonuçlara ulaşılmıştır. Sonuçlar 1991-2009 yılları arasında il bazında yakınsama olduğuna işaret etmektedir. İl bazında büyüme, beşeri sermaye, istihdam, reel kamu yatırımları, reel özel yatırımlar ve nüfus tarafından belirlenmektedir. 2002-2007 yılları arasındaki hızlı büyüme dönemi yapısal kırılmaya sebep olmuş; bunun yanında 1994, 1999, 2001 ve 2009 yıllarında yaşanan krizler ekonometrik analizde kontrol edilmiş ve istatistiksel olarak anlamlı uç değerler göstermiştir.

Elde edilen sonuçlar, ikinci bölümde kesit analizinde kullanılan modelin dinamik panele genişletilmesi durumunda değişkenlerin büyüme üzerinde farklı zaman dilimlerinde farklı etkiler yarattığını göstermektedir. Buna göre, lise mezunlarının büyüme üzerine pozitif ve anlamlı katkısı esas olarak 2002 sonrası dönemde gözlenmiştir. İstihdam oranları ise yapısal kırılmadan önce ve sonra, tüm dönem boyunca, büyümeyi olumlu yönde etkilemiştir. Öte yandan, krizler için kullanılan kukla değişkenlerin işaretleri göz önüne alındığında beşeri sermaye göstergesi olarak üniversite mezunlarının, özel yatırım göstergesi olarak mevduatların ele alındığı model daha anlamlı sonuçlar ortaya koymuştur. Bu modele göre, 2002 sonrası dönemde üniversite mezunları ve istihdam oranları il bazında büyüme üzerinde baz döneme kıyasla fark yaratamamış görünmektedir. Diğer yandan, 2002-2007 döneminde kamu yatırımları ve özel yatırımlar için ilk dönemin aksine istatistiksel olarak anlamlı katsayılar elde edilmiş, il bazında büyümeyi olumlu yönde etkiledikleri gözlenmiştir.

Toplamda, politika önermelerini de içeren dört temel gözlem yapmak mümkündür. Birincisi, üniversite mezunlarının lise mezunlarına kıyasla büyüme dinamiklerini belirlemede yetersiz kaldığı söylenebilir. Yetişmiş iş gücünden daha fazla yararlanılması için politika geliştirilmesi bu etkiyi kırabilecektir. İkincisi, 2002-2007 döneminde kaydedilen yüksek büyüme oranlarına rağmen istihdam-büyüme bağlantısı yeterince kurulamamıştır. Üçüncüsü, başlangıçta büyüme üzerinde etkisiz görünen kamu yatırımlarının 2002 sonrası dönemde olumlu katkıda bulunduğu ortaya çıkmıştır. Bu durum, söz konusu dönemde kamu yatırımlarının daha etkin bir şekilde yönetilmesinden kaynaklanmış olabilir. Dördüncüsü, mevduatlar ile ölçülen özel yatırımlar kamu yatırımlarına benzer biçimde 2002-2007 sonrası dönemde büyümeye olumlu katkılar yapmış görünmektedir.

Bölüm 4: Türkiye'de Sektörel Bölgesel İstihdam Yakınsamasının Mekânsal Panel Görünürde İlişkisiz Regresyon Analizi

Türkiye'de işgücü piyasaları istihdamda bölgesel eşitsizliklerden uzun süredir etkilenmiş ve bunun yanında sektörler arası istihdam geçişlerine tanıklık etmiştir. Tarıma dayalı bir ekonomiden giderek hizmet sektörüne kaymaların yaşanması işgücü piyasasında da dönüşümleri beraberinde getirmiştir. Dolayısıyla, Türkiye'de istihdamın yıllar içindeki evrimi yalnızca bölgesel değil, sektörel dinamikler de taşımıştır. İktisadi yazında ise bölgesel istihdam tartışmaları yapılmış olmakla birlikte sektörel bağlantılar genellikle ihmal edilmiş; bu gözlemden hareketle istihdam dinamiklerine yeni bir bakış getirilmesi tezin bu bölümünün temel hareket noktasını oluşturmuştur.

Bu bölümde Türkiye'de istihdam yakınsaması problemi 2004-2011 yılları arasında 26 İBBS-2 bölgesi düzeyinde incelenmektedir. Tarım, sanayi ve hizmet sektörleri için kurulan ayrı ayrı mekânsal panel veri denklemleri mekânsal hata terimleri içeren rassal etkiler modelleri olarak oluşturulmaktadır. Uygulanabilir genelleştirilmiş mekânsal üç aşamalı en küçük kareler yöntemi ile tahmin edilen bu modeller her bir sektördeki istihdam yakınsaması dinamiklerini göstermektedir. Bir sonraki aşamada, sektörler arasındaki istihdam geçişlerini ve bir bütün olarak istihdam yakınsamasını ele alabilmek adına, tahmin edilen mekânsal panel veri modellerinin hata terimleri arasında korelasyon gösteren görünürde ilişkisiz regresyon modeli oluşturulmaktadır. İktisadi yazında sektörel, bölgesel ve zaman boyutundaki değişimleri aynı anda ele alan yakınsama analizinin örneği yok denecek kadar azdır. Angulo ve ark. (2011) İspanya'nın 19 bölgesinde 1998-2009 dönemi boyunca 5 sektördeki ücret yakınsaması problemini incelemişlerdir. Yazarlar daha sonra AB-15 ekonomilerinde 1980-2010 döneminde bölgesel üretkenlikleri incelemek amacıyla altı sektörlü bir model kurgulamışlardır (Lopez ve ark., 2014). Bu çalışmalar dışında mekânsal panel SUR tipi yakınsama model örnekleri bulmak oldukça güçtür; Türkiye için bilinen böyle bir çalışma ise bulunmamaktadır. Bu bölümün en önemli katkısı Türkiye'de istihdam yakınsaması probleminin bu etkileri birlikte ele alabilen bir modelle incelenmesidir.

Türkiye'de 2000'li yılların başından itibaren hizmet sektörünün istihdamdaki payında kayda değer bir artış gözlenmiştir. Diğer yandan, özellikle 2004 sonrasında tarım sektörü önemini yitirmiş, istihdam payı yüzde 23-30 aralığında giderek düşen bir seyir izlemiştir. Söz konusu göstergeler istihdamda tarım sektöründen hizmet sektörüne kaymalar yaşandığını düşündürmektedir. Diğer yandan, sanayi sektörünün payında çok önemli iniş ve çıkışlar gözlenmemiştir. Kullanılan veri seti 2004-2011 dönemi için 26 bölge ve üç ana sektör (tarım, sanayi, hizmetler) düzeyinde toplanmıştır. Çalışılan dönem ve kullanılan değişkenler hem sektörel hem bölgesel düzeyde veri bulunmaması nedeniyle kısıtlanmıştır. Kurumsal olmayan çalışabilir nüfusa göre hesaplanan istihdam oranları Türkiye'nin dijital haritasına aktarıldığında 2004 ve 2011 yıllarındaki değerlerde iki nokta göze çarpmaktadır. Birincisi, her iki yılda da bölgesel farklılıklar aynı zamanda sektörel düzeyde de hissedilmektedir. Kuzeydoğu ve İç Anadolu illeri tarımda daha fazla istihdam oranlarına sahipken batıdaki bölgelerin sanayi ve hizmetlerde daha fazla uzmanlaştığı anlaşılmaktadır. İkinci olarak, hizmet sektöründeki istihdam daha ziyade tarımsal olmayan bölgelerde yoğunlaşmış görünmektedir. 2004-2011 yılları arası tarımdaki istihdam oranlarının büyüme rakamları 9 bölge için negatif çıkmaktadır.

Ekonometrik analizde tahmin edilen modelleri dört grupta toplamak mümkündür. İlk grupta ana sektörlerde istihdam oranlarındaki büyüme, söz konusu sektörün başlangıç yılı istihdam oranları ile açıklanmaktadır (statik-baz model). İkinci grupta bu modeller diğer sektörlerdeki başlangıç yılı istihdam oranlarına bağlı olarak da ele alınmaktadır (statik-etkileşim modeli). Böylece sektörler arası ilişkiler doğrudan kontrol edilebilmektedir. Üçüncü grupta sektörlerin başlangıç yılı istihdam oranları dinamik olarak ele alınmakta, t zamanındaki büyüme (t-1) zamanındaki istihdam oranları ile açıklanmaktadır (dinamik-baz model). Son grupta ise bu dinamik modele diğer sektörlerin başlangıç yılı istihdam oranları da eklenmekte ve sektörler arası doğrudan etkiler hesaba katılmaktadır (dinamik-etkileşim modeli).

Statik modeller için yapılan havuzlanmış EKK ve SUR tahminleri 2004-2011 döneminde tarım sektöründe istihdam oranlarının yakınsadığını göstermektedir. Ancak sektörel etkileşimlerin ele alındığı durumda anlamlı bir yakınsama ilişkisinden söz etmek mümkün görünmemektedir. Sanayi sektöründe ise hem baz hem etkileşim modelleri için yakınsama gözlenmektedir. Hizmet sektöründe istatistiksel olarak anlamlı bir yakınsama veya ıraksama bulunmamaktadır. Dinamik modeller için yapılan havuzlanmış EKK ve SUR tahminleri hizmet sektörü dışında statik duruma benzer özellikler göstermektedir. Hizmet sektöründe bu kez hem baz, hem de etkileşim modelleri için yakınsama olduğu görülmektedir. Ancak bu sonuçlar zaman boyutunu ve olası mekânsallığı ihmal ettiğinden yeterli olduklarını söylemek mümkün değildir.

Mekânsal etkileri modele katabilmek için ikinci bölümdekine benzer biçimde ikili komşuluk matrisi kullanılmıştır. Buna göre, 26 bölgeyi temsilen 26x26 boyutunda mekânsal ağırlık matrisi elde edilmiş ve satır toplamları 1 olacak şekilde standardize edilmiştir. Bölge (N), zaman (T) ve sektör (G) boyutlarını ele alan (NTxG) denklem sistemi önce her bir sektör kendi içinde mekânsal panel modelleri ile, daha sonra tüm sektörel denklemlerin birlikte ele alındığı mekânsal panel SUR modelleri ile tahmin edilmiştir. Mekânsal panel çerçevesinde kurulan model Wang & Kockelman (2007) ve Baltagi & Bresson (2011)'de olduğu gibi rassal etkiler varsayımına dayanmaktadır. Sektörel istihdam sorunsalında her bir denklem tüm istihdamı değil, fakat bölgesel istihdamın yalnızca o sektöre ait bölümünü ifade ettiğinden sabit etkiler kullanılmamasında bir sakınca görülmemektedir. Bu panel veri modelindeki söz konusu mekânsal ilişkinin mekânsal hata formunda olduğu varsayılmıştır. Bir bölgedeki üreticilerin ve tüketicilerin karşılaştığı şoklar, yakın bölgeleri de ara mal ilişkisi ve ortak pazar için ürün üretmeleri nedeniyle sarsmaktadır. Dolayısıyla bir bölgenin istihdamını etkileyen beklenmedik bir gelişme, komşu bölgelerin istihdam dinamiklerini de etkilemektedir. Sonuç olarak, tarım, sanayi ve hizmet için, sektörel istihdam probleminin doğasına uygun olarak, rassal etkiler mekânsal hata modelleri tanımlanmıştır.

FGS3SLS ile tahmin edilen sektörel mekânsal panel veri modellerinde statik ve dinamik regresyonlar için sonuçlar ayrı ayrı ortaya konmaktadır. Statik baz model yapısında tarım sektörü için yakınsama bulunmuştur. Diğer sektörlerle olan etkileşimler hesaba katıldığında ise yakınsama veya ıraksama bulgusuna rastlanmamıştır. Diğer sektörlerin tarım üzerine etkileri de istatistiksel olarak anlamlı bulunmamıştır. Sanayi sektöründe ise hem baz hem de etkileşim modelleri için yakınsama olduğu anlaşılmaktadır. Etkileşim modeli sonuçlarına göre sanayi sektöründeki istihdam oranlarının büyümesi ile tarım ve hizmet sektörlerinin başlangıç yılı istihdam oranları arasında negatif bir ilişki görülmektedir. Hizmet sektöründe belirgin bir yakınsama veya ıraksama bulgusuna rastlanmamıştır. Dinamik regresyonlar için statik modellere benzer sonuçlar elde edilmiştir. Tahmin edilen katsayıların büyüklükleri değişmekle beraber işaretleri ve istatistiksel olarak anlamlılık düzeyleri aynı kalmaktadır. Buna göre, sonuçlar tarım sektörünün baz modelinde ve sanayi sektörünün baz ve etkileşim modellerinde yakınsama olduğunu göstermektedir. Hizmet sektöründe ise istihdamda herhangi bir yakınsama veya ıraksamadan söz edilemememektedir.

Mekânsal hata parametreleri tarım sektörü modelleri için negatif bulunmuştur. Bu durum tarımda giderek azalan işgücü nedeniyle komşu illerin istihdam için rekabet halinde olduğunu düşündürmektedir. Diğer yandan, sanayi ve hizmet sektörleri için mekânsal hata katsayıları pozitif bulunmuştur. Özellikle sanayi sektöründe üretim belli altyapı imkânlarını ve yetişmiş işgücünü gerektirmektedir. Bu şartlar bölgesel gelişmişlik düzeyi ile doğrudan bağlantılı olup komşu iller arasında benzerlik göstermektedirler.

Mekânsal panel SUR tahminlerinde ise ayrı ayrı tahmin edilen mekânsal panel modellerine kıyasla oldukça farklı sonuçlar bulunmuştur. Statik modeller için baz regresyonlar sektörel istihdam oranlarında yakınsama veya ıraksama göstermemektedir. Diğer yandan, sektörel etkileşimler hesaba katıldığında istatistiksel olarak anlamlı katsayılar elde edilmiştir. Tarım sektöründe istihdam oranlarında ıraksama bulunmuştur. Sanayi ve hizmet sektörlerinin başlangıç istihdam oranları tarımdaki istihdam büyümesini pozitif etkilemektedir. Benzer biçimde sanayi sektörünün etkileşim modelinde de ıraksama bulunmuştur. Sonuçlar, tarım (hizmet) sektöründeki başlangıç istihdam oranlarının sanayideki istihdam büyümesi ile pozitif (negatif) ilişkili olduğunu göstermektedir. Hizmet sektöründe ise bölgeler arası istihdam yakınsaması bulunmuştur. Tarımdaki başlangıç yılı istihdam oranının hizmet sektöründeki istihdam büyümesine etkisi negatif bulunmuştur.

Dinamik modellerde ise statik duruma kıyasla sonuçlar farklılık arz etmektedir. Bu kez, tüm sektörler için baz modellerde istihdam yakınsaması görülmektedir. Ancak baz model yalnızca mutlak yakınsama dinamiklerini gösterebildiğinden ihmal edilmiş değişken problemi söz konusu olabilir. Etkileşim modelleri hem bunu belli ölçüde bertaraf etmesi, hem de işgücünde sektörler arası geçişleri hesaba katması bakımından daha doğru sonuçlar verebilecektir. Etkileşim modeli sonuçlarına göre tarım sektörü istihdam oranlarında ıraksama, hizmet sektörü istihdam oranlarında ise yakınsama bulunmuştur. Sanayi sektöründe ise istatistiksel olarak anlamlı bir ıraksama ilişkisi bulunmamıştır. Buna göre, statik durumda 2004 yılı başlangıç değerlerinden ıraksadığı gözlenmiş olan istihdam oranlarında yıllık değişimler göz önüne alındığı takdirde bariz bir ıraksama ilişkisi gözlenmemektedir. Hizmet sektöründeki gecikmesi alınmış istihdam oranlarının sanayideki istihdam büyümesine negatif etkisi olduğu gözlenmiş ve bu ilişkinin karşılıklı olduğu anlaşılmıştır. Mekânsal hata parametreleri ise ayrı ayrı sektörel modellerin tahminlerinde bulunduğu gibi tarım modelinde negatif, sanayi ve hizmetlerde ise pozitiftir.

Sonuç olarak, tarım sektöründe istihdam oranları 2004-2011 dönemi boyunca bölgeler arasında ıraksama göstermektedir. Bu durum tarımın istihdam payları dikkate alındığında özellikle anlamlıdır. Söz konusu dönem boyunca 9 bölge için tarımsal istihdamdaki büyüme negatiftir. Tarım sektörü giderek ağırlığını yitirmekte, üretim yapılan bölgeler daralmakta ve daha çok İç Anadolu ve Kuzey Doğu Anadolu’da yoğunlaşmaktadır. Bunun bir sonucu olarak, tarımsal emek için komşu bölgeler arası rekabetin arttığı bulunan negatif mekânsal hata parametrelerine bakılarak söylenebilir.

Sanayi sektöründe istihdam statik ve dinamik modellerde farklı dinamikler göstermiştir. Statik mekânsal panel SUR modeli ıraksamaya işret ederken başlangıç yılı istihdam oranları dinamik alındığında istatistiksel olarak anlamlı bir ıraksama ilişkisi bulunmamıştır. Betimsel analizde sanayinin istihdam oranlarında ülke bazında çok büyük dalgalanmalar olmadığı ve bölgesel farklılıklardaki örüntünün de zaman içinde çok fazla değişiklik arz etmediği gösterilmiştir. Bu durum sektörün doğasından kaynaklanmış olabilir. Zira altyapı imkânları ve yetişmiş sermaye için önemli yatırımlar gerektiren bu sektöre giriş ve çıkışın daha yavaş olduğu düşünülebilir. Tahmin edilen modellerde mekânsal hata parametreleri pozitif bulunmuştur. Benzer altyapıya sahip illerin birbirlerine yakın olması nedeniyle sanayi sektöründeki istihdamda pozitif dışsallıklar söz konusu olabilir. Bir bölgeye gelen şok komşu bölgeleri de aynı yönde etkilemektedir.

Hizmet sektörü için sonuçlar beklendiği gibi yakınsama olduğunu göstermektedir. Betimsel analiz ve ekonometrik tahminler Türkiye'de hizmet sektörüne doğru bir kayma olduğunu ve bunun tüm bölgelerdeki istihdam oranlarını etkilediğini göstermektedir. Tahmin edilen modellerde mekânsal hata parametreleri pozitif bulunmuş, gelen şoklara komşu bölgelerin benzer tepkiler verdiği ortaya çıkmıştır. Son olarak, etkileşim modelleri tarımdan hizmetlere geçiş olduğunu doğrulamaktadır. Tarımdan uzaklaşan istihdamın hizmet sektöründeki işlere yöneldiği söylenebilir.

Bölüm 5: Sonuç

Bölgesel yakınsama modelleri yaklaşık son elli yıldır tartışılmakla birlikte yakınsama dinamiklerinde mekânsallık yakın dönemde analizin bir parçası haline gelmiştir. Yapılan mekânsal ekonometrik çalışmalar önceleri iki temel mekânsal yapıyı dikkate almışlardır: mekânsal gecikme modellerindeki bağımlılık ve mekânsal hata terimleriyle ifade edilen heterojenlik. Mekânsal panel veri modelleri ise genellikle statik modellerle sınırlı tutulmuş, ampirik yazında SDPD modelleri oldukça az uygulanmıştır. Diğer yandan, bölgesel yakınsama bağlamında ele alınan mekânsal panel SUR modelleri ise yok denecek kadar azdır.

Bu tezin üç temel bölümünün de kendine özgü katkıları bulunmaktadır. Bölüm 2'de Türkiye'de 1991-2009 dönemindeki bölgesel büyüme yakınsaması için yazında kullanılan olası tüm mekânsal ekonometrik spesifikasyonlar incelenmekte ve en doğru modele ulaşmak amacıyla genelde özele model seçimi yapılmaktadır. Bu analiz özellikle iki açıdan önem taşımaktadır. Birincisi, Türkiye için yapılmış ampirik çalışmalar bölgesel yakınsamada genellikle mekânsal gecikme ve mekânsal hata modellerine yoğunlaşmış, alternatif kombinasyonlar ihmal edilmiştir. Ancak yalnızca birkaç temel mekânsal formun incelenmesi verideki gerçek mekânsal ilişkiyi ortaya koymakta yetersiz kalabileceğinden yanlış çıkarımlara neden olabilir. Tezin bu bölümü Türkiye'de kesit analizine dayalı bölgesel yakınsama problemi için olası mekânsal ilişkilerin tamamını kapsayan ilk çalışmadır. İkincisi, bu bölümde kullanılan veri seti Türkiye'de il bazında en yeni ve güncel veri olma özelliğini taşımaktadır. Daha önceki ampirik yazın genellikle 2001'e kadar olan dönemle sınırlı tutulmakta iken burada kullanılan verinin daha güncel olması son dönemdeki bilgileri de içermesi sayesinde çalışmaya zenginlik kazandırmaktadır.

Üçüncü bölümde, bir önceki bölümde ele alınan bölgesel büyüme yakınsaması analizi genelleştirilmiş momentler yöntemi ile tahmin edilen mekânsal dinamik panel veri modelleri ile genişletilmiştir. Bu bölümün en önemli katkısı Türkiye için yapılmış ampirik çalışmalardan metodolojik bir ayrışmadır. Türkiye'de yakınsama problemi için bilinen bir SDPD modeli incelemesi bulunmamaktadır. Burada elde edilen sonuçlar hem zaman, hem de mekân boyutundaki heterojenliği hesaba katması sebebiyle önem taşımaktadır.

Dördüncü bölümde Türkiye'de 2004-2011 dönemi boyunca İBBS-2 düzeyindeki 26 bölge için istihdam yakınsaması incelenmiştir. Bu bölümde kullanılan mekânsal panel SUR modelleri yazında oldukça yeni bir katkı olması sebebiyle yapılan ampirik çalışmalar çok sınırlıdır. Zaman ve mekân boyutunun yanı sıra sektörel dinamikleri de içine alan kapsayıcı bir modelleme yapısının tartışılması yalnızca Türkiye'deki bölgesel yakınsama problemi için değil, fakat benzer ülkeler için de önemli bir katkı olma özelliğini taşımaktadır.

Tüm analizin genel bir değerlendirmesi yapıldığında dört temel politika önerisi yapmak mümkün olmaktadır. Birincisi, bölgesel kalkınma politikaları iller arasındaki mekânsal etkileşimleri dikkate alarak gerçekleştirilmelidir. Özellikle bölgesel kalkınma ajansları il düzeyinde mekânsal ilişkileri de hesaba katan politikalar uygulamaları halinde daha etkin sonuçlar elde edebileceklerdir. İkincisi, yatırım stratejileri yetişmiş işgücünün güçlendirilmesine daha fazla önem vermelidir. Doğu Anadolu illerinde lise mezun oranı ve istihdamda önemli artışlar gözlenmekte iken bu göstergeler Güneydoğu Anadolu bölgesinde hala çok gerilerde kalmıştır. Beşeri sermaye yatırımlarının güçlendirilmesi bu illerde kalkınmayı hedefleyen politikaların işlerliğini artıracaktır. Üçüncüsü, kamu ve özel yatırımlar altyapı olanaklarının iyileştirilmesine önem vermelidir. 1991-2009 döneminde az gelişmiş bölgeler özel sektör için yeterli teşviklerin olmaması, inovasyon yokluğu, teknolojik yetersizlikler ve fiziksel altyapı imkânsızlıkları nedeniyle geri kalmış olabilirler. Dördüncüsü, istihdam politikaları hem bölgesel, hem de sektörel düzeyde yönetilmelidir. Sektörel ve bölgesel farklılıklar altında tek tip yatırım teşvikleri etkili olamamaktadır. Bunun yerine, Doğu Karadeniz bölgesinde tarım sektörü teşviği, Ege bölgesinde daha çok sanayi altyapısına kanalize olma gibi hedef odaklı yatırımlar, hem katma değere, hem de istihdama daha çok katkı sağlayabilir.

APPENDIX E

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Akçagün, Pelin

Nationality: Turkish (TC)

Date of Birth: November 19, 1983

Phone: +90 312 210 20 60

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EDUCATION

2008 February - 2015 September: Ph.D. in Department of Economics, Middle East Technical University, Ankara, Turkey.

2005 September - 2008 February: M.Sc. in Department of Economics, Middle East Technical University, Ankara, Turkey.

2001 August - 2005 June: B.Sc. in Department of Economics, Middle East Technical University, Ankara, Turkey.

ACADEMIC POSITIONS

Permanent Position

2005 September - Present: Teaching & Research Assistant, Department of Economics, Middle East Technical University, Ankara, Turkey.

Visiting Position

2013 August – 2014 May: Visiting Research Scholar, Department of Economics, University of Illinois at Urbana-Champaign, Urbana, Illinois, U.S.A.

FIELDS OF ACADEMIC INTEREST

Regional Development, Growth Economics, Spatial Econometrics, Applied Econometrics, Panel Data, Nonlinear Time Series.

PUBLICATIONS

2011 September: "Agricultural Master Plan for Samsun Province" *(with Assoc. Prof. Hakkı Ozan Eruygur, Dr. Ümit Özcan, Assist. Prof. Tolga Pusatlı, Res. Assist. Onur Kaya, Serkan Arabacı, Dilek Bilgin Mantı)*, *Republic of Turkey Samsun Provincial Special Administration*, Aydan Publishing (print date: March 2012), Ankara, Turkey.

DEGREES AND AWARDS

2011 November: Third Prize with paper "Türkiye'de Bölgesel Kalkınma ve Büyümenin Mekansal Ekonometrik Yöntemlerle Modellenmesi" [Modeling Regional Convergence and Growth in Turkey using Spatial Econometric Methods (in Turkish)], *Kalkınmada Bölgesel Dinamikler Sempozyumu: Küreselden Yerele Stratejiler ve Uygulamalar, TÜRKONFED*, Denizli, Turkey, 18 November 2011.

2015 September: Graduated with High-honor degree in Ph.D. in Department of Economics, Middle East Technical University, Ankara, Turkey.

2008 February: Graduated with Honor degree in M.Sc. in Department of Economics, Middle East Technical University, Ankara, Turkey.

2005 June: Graduated with Honor degree in B.Sc. in Department of Economics, Middle East Technical University, Ankara, Turkey.

CERTIFICATES

2012 July: *Economics Summer Seminars 2012*, "Spatial Panel Data" by Prof. Anil K. Bera, Pamukkale University, Denizli, 11th edition, 16-20 July 2012.

2011 May - June: *Spatial Econometrics Advanced Institute 2011*, Sapienza University of Rome, Italy, 4th Edition, 16 May- 10 June 2011.

GRANTS AND SCHOLARSHIPS

2013 August – 2014 May: International Research Fellowship, The Scientific and Technological Research Council of Turkey

CONFERENCE PRESENTATIONS

2014 October: “Regional Income Convergence in Turkey: A Dynamic Spatial Econometric Approach” *(with Prof. Nadir Öcal)*, *14th Eurasia Business and Economics Society*, Barcelona, Spain, 23-25 October 2014.

2014 April: “A Dynamic Spatial Panel Data Approach to Regional Growth Convergence in Turkey”, *7th Graduate Student Midwest Conference in Applied Economics, Regional and Urban Studies*, University of Illinois at Urbana-Champaign, U.S.A., 4-6 April 2014.

2013 July: “Reconsidering the Regional Employment Convergence Problem in Turkey: Spatial Panel Data Estimation in an SUR Framework” *(with Prof. Nadir Öcal and Prof. Jülide Yıldırım)*, *The VII World Conference of the Spatial Econometrics Association*, Washington DC, U.S.A., 10-12 July 2013.

2013 June: “Regional Analysis of Sectoral Employment Dynamics in Turkey” *(with Prof. Nadir Öcal and Prof. Jülide Yıldırım), Anadolu International Conference in Economics*, Eskişehir, Turkey, 19-21 June 2013.

2013 May: “Sectoral Analysis of Regional Employment Dynamics in Turkey: A Panel Seemingly Unrelated Regression Model with Spatial Error Components” *(with Prof. Nadir Öcal and Prof. Jülide Yıldırım), 39th Annual Eastern Economic Association Conference,* New York, U.S.A., 9-11 May 2013.

2013 April: “Bölgesel Kalkınmanın Mekansal Ekonometrik Yöntemlerle Analizi: Türkiye Üzerine Bir Uygulama” [The Analysis of Regional Development with Spatial Econometric Methods: An Application to Turkey (in Turkish)], *Workshop: Türkiye Ekonomisi'nin Dünü, Bugünü, Yarını - Yakup Kepenek'e ve Oktar Türel'e Armağan*, Middle East Technical University Northern Cyprus Campus, Turkey, 25-26 April 2013.

2012 January: “Türkiye’de Bölgesel Kalkınma ve Büyümenin Mekansal Ekonometrik Analizi” [Spatial Econometric Analysis of Regional Convergence and Growth in Turkey (in Turkish)], Stratejik Düşünce Enstitüsü-Ekonometrik Araştırmalar Derneği, Ankara, Turkey, 17 January 2012.

2011 December: “Thirlwall Yasasının Ampirik Analizi: Türkiye Örneği” [Empirical Analysis of Thirlwall Law: Turkey Case (in Turkish)] *(with Res. Assist. Aykut Mert Yakut), Ekonomik Yaklaşım Kongreler Dizisi VII: Türkiye Ekonomisinin Dinamikleri: Politika Arayışları*, Ankara, Turkey, 22-23 December.

2011 November: "Türkiye'de Bölgesel Kalkınma ve Büyümenin Mekansal Ekonometrik Yöntemlerle Modellenmesi", [Modeling Regional Convergence and Growth in Turkey using Spatial Econometric Methods (in Turkish)], *Kalkınmada Bölgesel Dinamikler Sempozyumu: Küreselden Yerele Stratejiler ve Uygulamalar, TÜRKONFED*, Denizli, Turkey, 18 November 2011.

2011 November: "Modeling Regional Growth and Convergence in Turkey: A Spatial Panel Data Analysis" *(with Prof. Nadir Öcal), 58th Annual North American Meetings of the Regional Science Association International and the Second Conference of the Regional Science Association of the Americas, North American Regional Science Council*, Miami, U.S.A., 9-12 November 2011.

2009 June: "Discussions on Trade Regime in Turkey: A CGE Analysis", *Anadolu International Conference in Economics*, Eskişehir, Turkey, 17-19 June 2009.

RESEARCH EXPERIENCE

2015 April – present: *Research Assistant*, in the project "A Comparative Analysis of National, Regional, Sectoral and Firm Size Trends and Levels in Regulatory Burden and Corruption: The Case of Turkey in 2008&2013", supervised by Prof. Nadir Öcal, financed by World Bank.

2014 January – present: *Research Assistant*, in the project "Avrupa Birliği'nde Sektörel İstihdamın Bölgesel Yakınsaması: Mekansal Veri Analizi", [Regional Convergence of Sectoral Employment in European Union: Spatial Data Analysis], supervised by Prof. Nadir Öcal, financed by Middle East Technical University, BAP-04-03-2014-001.

2013 January - present: *Research Assistant*, in the project "Türkiye'de Bölgeler Arası Sektörel İstihdam Farklarının Mekansal Analizi", [The Spatial Analysis of Inter-Regional Sectoral Employment Differences in Turkey], supervised by Prof. Nadir Öcal, financed by Middle East Technical University, BAP-04-03-2013-003.

2012 January – 2013 December: *Research Assistant*, in the project "Türkiye'de Bölgesel Kalkınma, Büyüme ve Yakınsama Dinamiklerinin Ekonometrik Yöntemlerle İncelenmesi", [The Analysis of Regional Development, Growth and Convergence Dynamics in Turkey using Econometric Methods], supervised by Prof. Nadir Öcal, financed by Middle East Technical University, BAP-04-03-2012-003.

2011 February – October: *Research Assistant*, in the project "The Support Project for Constructing the Provincial Agriculture and Rural Development Master Plans", supervised by Assoc. Prof. Hakkı Ozan Eruygur, financed by The Ministry of Agriculture and Rural Affairs, Samsun Provincial Directorate of Agriculture.

2009 December – 2011 February: *Research Assistant*, in the project "The Impact of Agricultural Enterprises on Productivity and Efficiency of Agricultural Production in Turkey and Chaotic Dynamic Analysis of Selected Products: Problems, Solutions and Policy Proposals", supervised by Assoc. Prof. Yılmaz Kılıçaslan, financed by The Scientific and Technological Research Council of Turkey, 1001-109K129.

COMPUTER SKILLS

R, STATA, ARCGIS, RATS, GAMS, SAS, E-Views, Microfit.

LINGUISTIC SKILLS

Turkish: Native

English: Advanced

APPENDIX F

TEZ FOTOKOPİSİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü	☐
Sosyal Bilimler Enstitüsü	☒
Uygulamalı Matematik Enstitüsü	☐
Enformatik Enstitüsü	☐
Deniz Bilimleri Enstitüsü	☐

YAZARIN

Soyadı : Akçagün
Adı : Pelin
Bölümü : İktisat

TEZİN ADI (İngilizce) : Spatial Econometric Analysis of Regional Growth and Employment Convergence in Turkey

TEZİN TÜRÜ : Yüksek Lisans ☐ Doktora ☒

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. ☐
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. ☐
3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. ☒

TEZİN KÜTÜPHANEYE TESLİM TARİHİ: