To My Dear Family …

REGIONAL INEQUALITIES AND ECONOMIC CONVERGENCE IN TURKEY

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I hereby certify that this thesis meets all the requirements of the Graduate School of Social Sciences for a Master's degree.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I have therefore fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

REGIONAL INEQUALITIES AND ECONOMIC CONVERGENCE IN TURKEY

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Large and persistent regional development disparities between eastern and western regions have always been the main concerns of policy makers and regional development policies of the government. Turkey has developed a set of regional development tools and mechanisms to reduce these disparities However, traditional top-down and state-oriented regional policies implemented until the 2000s could not meet the needs of the country. Thus, Turkey went through a transformation in its regional development paradigm after 2000 and started to internalize more bottom-up and participatory approach.

The purpose of this study is to analyze regional inequalities and investigate the evidence of economic convergence across NUTS 2 regions in the post-2000 period. Although there are earlier empirical studies on regional convergence, studies concentrating on the post-2000 period are very limited. Thus, this study aims to provide new insights into the nature of the convergence debate in Turkey. We employed both sigma and beta convergence analyses. Findings of sigma convergence are in line with the literature that inequality between regions decreases in the recession periods and increases in the economic expansion periods. Beta convergence results obtained from cross-sectional and panel estimations indicate the existence of absolute convergence. Moreover, exploratory spatial data analysis and beta convergence analysis illustrate the strong evidence of spatial autocorrelation in distribution of regional income and suggest taking spatiality into account in convergence analysis.

Keywords: Regional Disparities, Regional Inequality, Convergence, Sigma, Beta, Spatial Autocorrelation, Spatial Econometrics

ÖZET

TÜRKİYE’DE BÖLGESEL EŞİTSİZLİKLER VE EKONOMİK YAKINSAMA

Kındap, Ahmet
Yüksek Lisans, İktisat Bölümü
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Doğu ve batı bölgeleri arasındaki ciddi düzeydeki bölgesel gelişmişlik farkları politikacıların ve devletin bölgesel gelişme politikalarının temel ilgi alanı ola gelmiştir. Türkiye bu gelişmişlik farklarını azaltmak için bir takım bölgesel gelişme araçları ve mekanizmaları geliştirmiştir. Ancak, 2000’li yıllara kadar uygulanan geleneksel yukarıdan aşağıya ve devlet merkezli bölgesel politikalar, ülkenin ihtiyaçlarını karşılamada yetersiz kalmıştır. Bu nedenle, Türkiye, 2000 yılından sonra bölgesel kalkınma paradigmasında bir dönüşüme gitmiş ve aşağıdan yukarıya ve katılımcı bir yaklaşımı içselleştirmeye başlamıştır.

Bu çalışmanın amacı, 2000 sonrası dönemde NUTS 2 bölgeleri seviyesinde bölgesel eşitsizlikleri analiz etmek ve ekonomik yakınsamanın bulgularını araştırmaktır. Bölgesel yakınsamaya ilişkin daha önce yapılmış ampirik çalışmalar bulunmakla birlikte 2000 sonrası döneme odaklanan çalışmalar oldukça sınırlıdır. Bu nedenle, bu çalışmada ülkemizdeki yakınsama tartışmalarına yeni bir bakış açısı sunmayı amaçlamaktadır. Çalışmada hem sigma hem de beta yakınsaması kullanılmıştır. Sigma yakınsama bulguları literatür ile uyumlu olarak bölgeler arası eşitsizliklerin ekonmik resesyon dönemlerinde arrtığı, ekonomik genişleme dönemlerinde ise azaldığını göstermektedir. Kesit ve panel tahminleri ile elde edilen beta yakınsama sonuçları mutlak yakınsamanın varlığına işaret etmektedir. Ayrıca, açıklayıcı mekansal veri analizi ve beta yakınsama analizi, bölgesel gelir dağılımında mekansal otokorelasyonun varlığına yönelik güçlü kanıtlar sunmakta ve yakınsama analizlerinde meksansal boyutun dikkate alınmasını gerektiğini belirtmektedir.

Anahtar Kelimeler: Bölgesel Farklar, Bölgesel Eşitsizlikler, Yakınsama, Sigma, Beta, Mekansal Otokorelasyon, Mekansal Ekonometri

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LIST OF ABBREVIATIONS

CV	:	Coefficient of Variation
DA	:	Development Agency
ESDA	:	Exploratory Spatial Data Analysis
EU	:	European Union
FE	:	Fixed Effects
GDP	:	Gross Regional Domestic Product
GE	:	Generalized Entropy
GVA	:	Gross Value Added
LISA	:	Local Indicators of Spatial Association
LM	:	Lagrange Multiplier
LR	:	Likelihood Ratio
MMR	:	Maximum to Minimum Ratio
NEG	:	New Economic Geography
NUTS	:	Nomenclature of Territorial Units for Statistics
OLS	:	Ordinary Least Squares
RE	:	Random Effects
RMD	:	Relative Mean Deviation
SAR	:	Spatial Autoregressive Model

SDEM	:	Spatial Durbin Error Model
SEM	:	Spatial Error Model
SLM	:	Spatial Lag Model
SLX	:	Spatial Lag of X
TURKSTAT	:	Turkish Statistical Institute
UK	:	United Kingdom
WDR	:	World Development Report

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CHAPTER ONE

INTRODUCTION

Turkey suffers from large and persistent development disparities between western and eastern regions for a long period of time. While western regions attract most of the economic activities and investment, eastern regions struggle with severe economic and social problems such as inadequate investment and services, unemployment and poverty. This economic divide in geography triggers migration from east to west and results in extra problems in eastern and western part of the county. Thus, reducing these development disparities and ensuring coherent development across country have been the main concerns of the policy makers in Turkey, and regional development is always listed among high priority polices in the national development plans. Turkey has developed a set of regional development tools and mechanisms including priority regions for development, comprehensive regional development projects and plans, state aids/investment incentives and large public investment projects. However, these traditional top-down and state-oriented regional policies mainly targeted lagging behind regions and regions with special challenges and were far from meeting the needs of the country. Turkey could not ensure a stable trend in reducing disparities. Most empirical studies analyzing regional economic convergence in the pre-2001 period also indicate the non-existence of significant convergence.

Thus, with the process of harmonization to European Union, Turkey went through a transformation in its regional development policy approach after 2000 and started to internalize more bottom-up and participatory approach in line with the contemporary approach in the field of regional development. Main pillars of this transformation and new policy agenda are: (i) adaptation of a new regional classification and statistical system and (ii) the establishment of Development Agencies (DAs), which brings about the institutionalization of regional level governance and creation of regional development fund/budget for the first time in Turkish history. The new regional policy approach targets all regions of Turkey with the newly established 26 DAs. Thus, the DAs became the main actors of regional and local development in the country. They supported 5,845 projects with the budget of approximately TRY 800 Million in the period of 2008-2011 (Ministry of Development, 2011).

In addition, Turkey redesigned its investment incentive system in 2008 and 2012, with the active involvement of local actors through the DAs. Regional perspective was incorporated into the new system in order to reduce regional inequalities. Number of investment certificates and amount of fixed investments have highly increased since 2008. Turkey also enacted new regulations to empower the local authorities. For example, the amount of financial resources transferred from central budget has increased from 1.55% to 2.35% (Law No: 5779 and 6360). Consequently, the period after 2000 deserves special attention for convergence studies.

The latest regional statistics show that regional development disparities between eastern and western regions still exist in Turkey (Figure 1) but they also indicate some preliminary signals for the progress achieved so far. For example, while GVA per capita level of the most developed region is nearly 4.29 times that of the least developed region in 2004, the ratio decreased to 3.94 in 2011. As seen in the Figure 2, lagging behind regions showed better growth performance during 2004-2011 period and, as a result, improved their relative positon in Turkey.

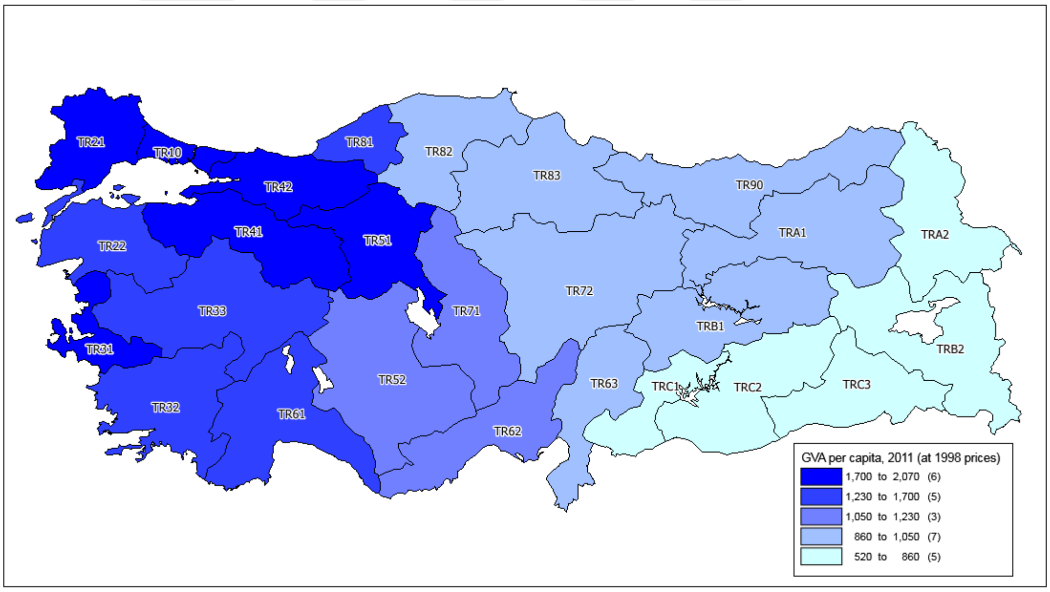


Figure 1 GVA per capita by NUTS 2 Regions (2011)

Notes: The map shows how GVA per capita varies across NUTS 2 regions in 2011. GVA per capita values are presented at constant 1998 prices. Natural break method in ArcGIS is used to classify regions.

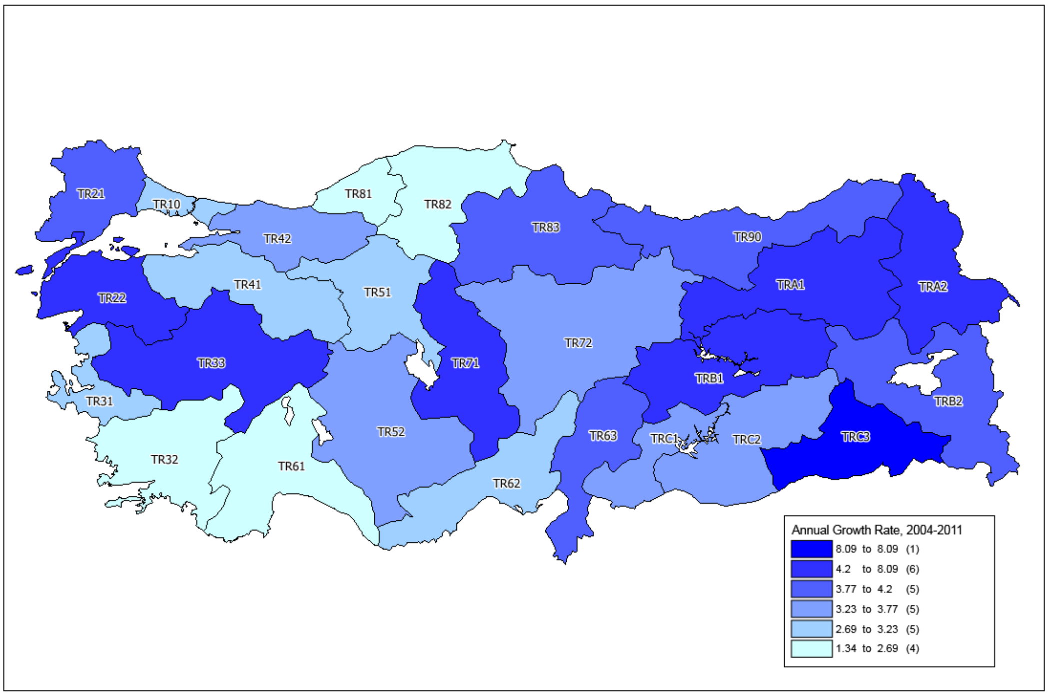


Figure 2 Annual Growth Rate of GVA per capita by NUTS 2 Regions (2004-2011)

Notes: The map shows how annual growth rate of GVA per capita varies across NUTS 2 regions in the period of 2004-2011. Growth rates are presented in percentages. Natural break method in ArcGIS is used to classify regions.

On the other hand, Figure 3 displays relative positions of NUTS II regions with reference to the country average in the initial and terminal years, and clearly points out that both developed and lagging behind regions converge towards the country average. When we look at the absolute values, we see that in the 2004-2011 period, income per capita values of all regions and Turkey have increased by their own positive growth rates (Figure 2). Thus, we argue that relative convergence in Figure 3 happened because regions with the lowest GVA per capita located in the eastern part of the country showed better development performance and made relatively more contribution to national growth than they did in the past.

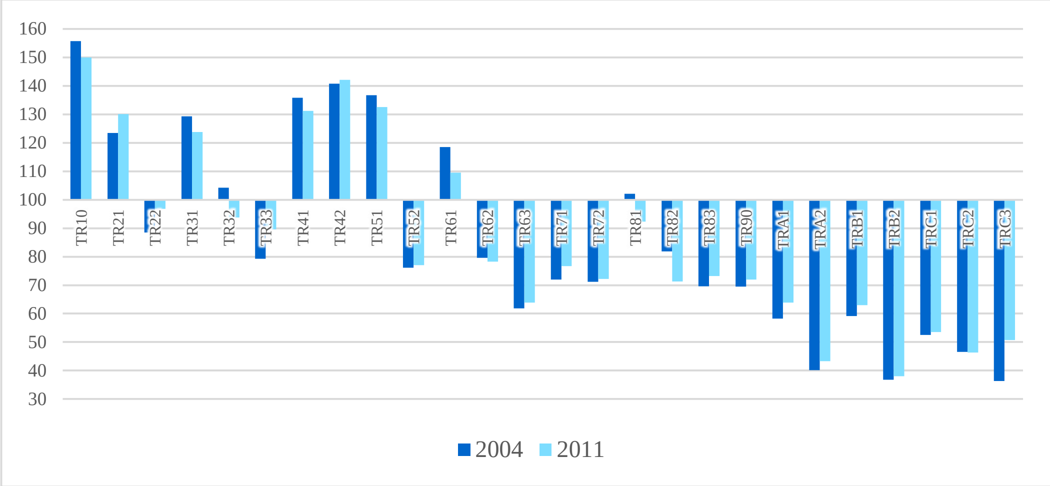


Figure 3 GVA per capita by NUTS II Regions (Turkey =100)
Notes: The figure shows how the relative position of NUTS 2 regions changes, in terms of GVA per capita, in relation to the country average set to equal to 100. GVA per capita values of regions are expressed as a percentage of the country average. In order to better express our findings, the origin of the figure is set to 100.

Although general overview of the latest statistics provides some evidence of convergence across regions, reaching an accurate conclusion for the existence of convergence necessitates further analysis. Thus, the purpose of this study is to analyze regional disparities in Turkey and investigate the evidence of economic convergence across NUTS 2 regions. This study mainly aims at testing the hypothesis of whether the regions of Turkey convergence or divergence by using contemporary methods in the literature and endeavors to answer the questions of (i) whether regional development disparities decreased between 2004 and 2011, and (ii) whether new regional development polices made a verifiable contribution to the achievement of this goal.

The thesis is divided into five chapters. Apart from this introduction, the second chapter is devoted to the regional convergence literature. The perspectives of different growth theories on convergence concept is discussed. Second chapter also covers a literature of influential empirical studies in the literature with a special focus on the literature in Turkey. Third chapter attempts to present methods of convergence analysis, namely sigma and beta convergence. Fourth chapter focuses on the empirical findings of the study and presents the results of sigma and beta convergence analysis of Turkish regions. The final chapter synthesizes discussions of all chapters and provides answers to the research questions.

CHAPTER TWO

LITERATURE REVIEW

The question of whether poor economies and rich economies converge or diverge has attracted extensive attention in the growth literature. Neoclassical theory, endogenous growth theory and new economic geography provide different views and explanations for this debate. In addition, researchers try to extract more explanations and results thorough empirical studies in order to test and support these theoretical discussions.

2.1 Economic Theories and Concept of Convergence

The mainstream neoclassical theory relies on the literature of national economic growth determined mainly by the accumulation of physical and human capital. This theory is also referred as exogenous growth theory because parameters like saving rate, population growth rate and technological progress are determined outside the model. Neoclassical growth models developed by Solow (1956) and Swan (1956) have heavily influenced the growth literature. In the Solow-Swan growth model, set out within the framework of neoclassical economics, it is assumed that all economies have the same production function with the only difference in factors of production and they converge to a steady-state equilibrium. At the equilibrium, the level of income per capita grows at an exogenous rate of technological change, while capital and output per unit of effective labor are constant. In this model, as there are diminishing returns to capital, economies with lower capital per unit of effective labor have higher rates of return and thus higher output growth rates. Given the diminishing return in the high-income economies, growth is viewed as a process of resource reallocation i.e., mobility of capital and labor implies the equalization of the value of the marginal products and leads to overall decline of the dispersion of per capita income or outputs. Therefore, for any given economy, it is expected that the lower the initial level of GDP per capita, the higher the growth rate. In sum, neoclassical growth model asserts that relatively poor economies grow faster than the rich ones and they would catch up with their rich counterparts over time.

On the other hand, endogenous growth theory pioneered by Romer (1986) and Lucas (1988) questioned the assumptions of diminishing returns to capital and decreasing returns to factors of production. This new theory made technological change and innovation endogenous to the growth models and also regarded human capital accumulation, knowledge externalities and knowledge spillovers as the main factors/drivers of economic growth. These endogenous drivers prevent the marginal product of physical capital from diminishing and asserts increasing returns to scale. This new approach to economic growth argues that economies would not converge to the same steady state but rather to their own steady states conditioning on their basic initial conditions (conditional convergence). Moreover, as opposed to absolute convergence prediction of neoclassical growth theory, endogenous growth theory implies divergence, and predicts the agglomeration of factors of production in certain places due to positive returns to scale. In endogenous growth theory, government policy and intervention are considered as necessary to reduce disparities across economies (Yıldırım et al., 2009).

New economic geography (NEG) introduced by Krugman (1991) provides a new perspective to convergence debate by supporting clearly neither convergence nor divergence assumptions. In the NEG, increasing return to scale, monopolistic competition, transport costs and externalities associated with agglomeration are key factors in explaining economic phenomena and fundamental to a proper understanding of disparities in economic geography. According to Krugman's core-periphery model, regional clusters and inequalities emerge due to a combination of "centrifugal forces" pulling economic activities together and "centripetal forces" pushing it apart. Depending on which force is stronger, models of new economic geography could generate regional divergence or convergence (Dawkins, 2003). Krugman (1991) also argues that location and agglomeration play an important role in the economic activity of a region and the economic situation of a region cannot be considered independent of interrelations with its neighbors. Regions with rich neighbors have higher opportunities to develop than the ones surrounded by poor neighbors. NEG models predict the spread of economic activities across space in the further level of economic integration associated with low transportation costs (Paas and Schlitte, 2006). Findings of WDR 2009-Resahping Economic Geography prepared by the World Bank (2009) also support the proposition of first divergence, then convergence between leading and lagging areas.

2.2 Empirical Studies on Convergence

The increasing interest on convergence debate in economic growth theory has attracted great attention and led to the appearance of numerous empirical studies. First, the idea of beta (β) convergence was introduced by Barro and Sala-i-Martin (1990) based on the theoretical framework developed by neoclassical growth theory. β-convergence refers to the question of whether economies with low per capita income grow faster than the economies with relatively higher income per capita. This is to say that if convergence occurs, ceteris paribus, poor economies tend to catch up with wealthy ones. Even though the concept is developed by Barro and Sala-i-Martin (1990), Baumol (1986) and Abramovitz (1986) pioneered the application before its conceptualization. In his seminal work, Baumol (1986) did a simple regression analysis over a cross-sectional sample to test income convergence. He found that the higher a country's initial productivity level (i.e in 1870), the more slowly that level grew (in the 1870-1979 period). On the other hand, Abramovitz (1986) proposed the catch-up hypothesis claiming that being backward in productivity level caries a potential for rapid advancement and implies a long-run tendency towards the equalization of income or productivity levels. In his paper, he employed three measures: (i) averages of the productivity levels of the various countries relative to that of the United States (ii) measures of relative variance around the mean levels of relative productivity (iii) rank correlations between initial levels of productivity and subsequent growth rates.

The beta convergence concept is further enhanced by Barro (1991) and Barro and Sala-i-Martin (1992) by bringing the idea that the poor and wealthy economies may not converge to the same steady-state. They categorize the convergence towards the same steady-state as absolute (or unconditional) and convergence towards the different steady-states as conditional convergence. In conditional convergence, they argue, the expected negative relationship between initial per capita income (or product per worker) level and growth rate holds only when the structural differences between poor and wealthy economies are held constant.

Some other researchers also suggested to test whether convergence occurs within the groups of similar economies, a phenomenon widely referred to as the club convergence hypothesis proposed firstly by Chatterji (1992) and further developed by Galor (1996). Like conditional convergence, club convergence analyses have almost always find convergence.

Another convergence concept, developed by Baumol (1986) and later named as sigma (σ) convergence by Barro and Sala-i-Martin (1990) is related to the cross-sectional distribution of per capita income across economies. Within this concept, if convergence occurs, ceteris paribus, the dispersion of per capita income across economies tends to decline and economies would be expected to converge to a common rate or level.

Following these influential papers, cross-country income convergence studies have been extensively increased in the literature of economics. Similar discussions have taken place for state, regional, and provincial levels. Studies on income convergence across subnational units are pioneered by Barro and Sala-i-Martin (1992) which found empirical evidence for convergence within the US states and European regions. Subsequently, Coulombe and Lee (1995) found absolute β convergence for Canadian provinces, Cashin (1995) for Australian states, Sala-i Martin (1996) for Japanese prefectures and regions of Germany, France, UK, Italy and Spain, Hofer and Wörgötter (1997) for Austrian regions, Persson (1997) for Swedish counties, and Kangasharju (1998) for Finnish subregions, De La Fuente (2002) for Spanish regions, Michelis et al. (2004) for Greek regions, Serra et al. (2006) for Argentina, Brazil, Chile, Colombia, Mexico and Peru, and Eckey et al. (2007) for German regions. Conversely, other studies such as Mauro and Podrecca (1994) for Italian regions, Siriopoulos and Asteriou (1998) for Greek regions, and Gripaios et al. (2000) for UK counties did not find absolute β convergence.

As a reflection of these groundbreaking development in literature, empirical studies on regional disparities and convergence has also gained momentum in Turkey where there are large development disparities between western and eastern regions. Socio-economic development index of State Planning Organization, published first in 1969, can be named as the primary study of regional disparities ranking regions, provinces and districts on the basis of their relative development levels. Even though these studies are useful for monitoring the relative development levels of regions, they are not applicable for making inference about the existence of convergence. However, starting from the 1990s, researchers began to integrate contemporary methods of sigma and beta convergence approaches into Turkish experience. As summarized in Table 1 below, we can say that findings of the literature on absolute convergence is inconclusive while conditional convergence hypothesis holds almost for all of the studies. We also see that presence of high level of spatial autocorrelation between regions/provinces in Turkey made spatial analysis and spatial econometrics methods an inevitable part of convergence analysis. On the other hand, we also see that most of these studies covers the period before 2001 in which traditional regional development policies were active. Empirical studies analyzing the trends of economic convergence after the implementation of the new regional development policies are very limited. We think that this study will provide valuable contributions to the current literature on regional convergence.

Table 1 Empirical Studies of Regional Convergence in Turkey

Study	Period	Data	Unit	Analysis/Method	Findings
Atalik (1990)	1975-1985	GDP per capita	Programming Regions (8) Functional Regions (16)	Sigma Convergence	Divergence (σ)
Filiztekin (1998)	1975-1995	GDP per capita	NUTS 3-Provinces (81)	Sigma Convergence Beta Convergence	Divergence (σ) No Absolute Convergence (β) Conditional Convergence (β)
Tansel and Gungor (1998)	1975-1995	Labor productivity	NUTS 3-Provinces (81)	Beta Convergence	Absolute Convergence (β)
Berber et al. (2000)	1975-1997	GDP per capita	NUTS 3-Provinces (81)	Sigma Convergence Beta Convergence	Divergence (σ) No Absolute Convergence/Divergence (β)
Dogruel and Dogruel (2003)	1987-1999	GDP per capita	NUTS 3-Provinces (81)	Sigma Convergence Beta Convergence	Convergence only for Rich Regions (σ) Absolute Convergence (β) Conditional Convergence (β)
Karaca (2004)	1975-2000	GDP per capita	NUTS 3-Provinces (81)	Sigma Convergence Beta Convergence	Divergence (σ) Divergence (β)
Gezici and Hewings (2002)	1980-1997	GDP per capita	NUTS 3-Provinces (81) Geographical Regions (7) Functional Regions (16) Costal-Interior Provinces	Sigma Convergence (Theil Index) Spatial Analysis	Divergence between regions (σ) Convergence within regions (σ)
Gezici and Hewings (2004)	1980-1997	GDP per capita	NUTS 3-Provinces (81) Functional Regions (16)	Sigma Convergence Beta Convergence Spatial Analysis	Divergence (σ) No Absolute Convergence (β) No Conditional Convergence (β)
Erlat (2005)	1975-2001	GDP per capita	NUTS 3-Provinces (81) Geographical Regions (7)	Beta Convergence (Time Series Approach-Panel Unit Root Test)	Convergence for some regions and provinces

Table 1 Empirical Studies of Regional Convergence in Turkey (Continued)

Study	Period	Data	Unit	Analysis/Method	Findings
Yıldırım and Ocal (2006)	1979-2001	GDP per capita	NUTS 3-Provinces (81) NUTS 2 (26)	Sigma Convergence (Theil Index) Beta Convergence Spatial Analysis	Convergence (σ) Absolute Convergence (β)
Aldan and Gaygisiz (2006)	1987-2001	GDP per capita	NUTS 3-Provinces (81)	Beta Convergence Markov Chain Spatial Analysis	No Absolute Convergence (β)
Kırdar and Saracoğlu (2008)	1975-1990	GDP per capita	NUTS 3-Provinces (81)	Beta Convergence	No Absolute Convergence (β) Conditional Convergence (β)
Yıldırım et al. (2009)	1987-2001	GDP per capita	NUTS 3-Provinces (81) NUTS 2 (26)	Sigma Convergence (Theil Index) Beta Convergence Spatial Analysis	Convergence (σ) Absolute Convergence (β) Conditional Convergence (β)
Ozturk (2012)	1987-2001	GDP per capita by sectors	NUTS 3-Provinces (81)	Sigma Convergence	Convergence (σ)
Karahasan (2014)	1975-2001	GDP per capita	NUTS 3-Provinces (81)	Sigma Convergence Beta Convergence Spatial Analysis	Divergence (σ) for 1975-2001 Weak Evidence of Absolute Convergence (β) for 1975-2001
Celbis and de Crombrugghe (2014)	1999-2011	GVA per capita	NUTS 2 (26)	Sigma Convergence Beta Convergence Spatial Analysis	Convergence (σ) Absolute Convergence (β) Conditional Convergence (β)
Karahasan (2015)	2003-2008	Wage Income	NUTS 2 (26)	Sigma Convergence Beta Convergence Spatial Analysis	Convergence (σ) Absolute Convergence (β) Conditional Convergence (β) No Convergence in dynamic panel setting

CHAPTER THREE

METHODOLOGY

Measuring regional convergence and inequalities present some complexities. Main reason for this complexity is related to the definition of convergence. Although, in general terms, convergence can be defined as the decline in per capita income differences among economies or regions over time, there are several competing definitions of convergence corresponding to the different methods of testing. In addition, none of these measures/methods are capable of capturing all relevant aspects of a convergence process. This study will focus on the following two most common definitions/measures used in the literature: “sigma-convergence” and “beta-convergence”.

Sigma-convergence refers to the cross sectional dispersion of per capita income across economies. Existence of sigma convergence indicates that the dispersion of per capita income of economies tends to fall over time. On the other hand, beta-convergence tests the neoclassical growth model prediction that regions with low income level grow faster than rich regions and implies the existence of a longer-term catch-up mechanism. Beta-convergence is necessary but not sufficient condition for sigma-convergence.

On the other hand, in the literature, regional convergence analysis is generally performed with GDP data. Thus, explanations and formulas in this section are expressed by using GDP, even though we use GVA data in estimations in the next chapter.

3.1 Sigma Convergence and Static Measures of Regional Disparities

There are several measures that can be used for measuring the sigma-convergence and changes in regional disparities. We will use the following measures and methods: (i) Maximum to Minimum Ratio, (ii) Gini Index, (iii) Coefficient of Variation, (iv) Relative Mean Deviation, (v) Atkinson Index, (vi) Generalized Entropy Measures.

It is also important to note that some of these measures can be decomposed into within-region and between-region components. However, this study is not able to cover the analysis of within-region and between-region inequalities because TURKSTAT does not provide any GDP or GVA data at NUTS III level (provincial level) after 2001.

3.1.1 Maximum to Minimum Ratio (MMR)

Maximum to Minimum Ratio (MMR) basically compares the GDP per capita of the region with the highest income level to that of the region with the lowest income level and measures the range of disparity between them.

$$MMR=\frac{\text{GDP Per Capita}_{\max}}{\text{GDP Per Capita}_{\min}} \tag{3.1}$$

As can be seen from the equation 3.1, the MMR is a very simple and direct measure used for analyzing inequalities. However, it is highly sensitive to the presence of outliers. If this ratio is small (close to 1), then it is easy to interpret that the regions have a relatively equal level of income but if it is large, then the interpretation becomes more problematic. It has limitations for capturing the real variation in the distribution so the presence of high ratio can be attributable to substantial variation in the distribution of GDP per capita (high regional disparities) or existence of outliers in the distribution (Shankar and Shah, 2008). In other words, this measure does not allow us to include GDP per capita values falling between maximum and minimum into analysis.

3.1.2 Gini Index

The Gini index (coefficient) is the most widely used inequality index. It is based on the Lorenz curve, a cumulative frequency curve that compares the distribution of a specific variable with the uniform distribution that represents equality (Haughton and Khandker, 2009). It varies between 0 and 1. The value of 0 represents "perfect equality" where each individual has an equal share. On the other hand, the value of 1 represents "complete inequality" where income is concentrated in the hands of one individual (Monfort, 2008).

The Gini index is originally developed to measure the income inequality among different income groups but later it is adapted to measure regional income equalities. Now there are several formulas of the Gini index which are developed to measure regional disparities. Following Kakwani (1980, 1988), Shankar and Shah (2003) computed the unweighted and weighted Gini Indexes adapted for regional inequalities.

The unweighted Gini Index is calculated as follows:

$$G_u=\left(\frac{1}{2\bar{y}_u}\right)\frac{1}{n(n-1)}\sum_{i}^{n}\sum_{j}^{n}\left|y_i-y_j\right| \tag{3.2}$$

where y_i and y_j are the GDP per capita of region i and j respectively, n is the number of regions, and $\bar{y}_u$ is the unweighted (arithmetic) mean of the per capita GDP of regions. $\bar{y}_u$ is computed as the mean of the GDP per capita values of regions without weighting them by population (Shankar and Shah, 2003):

$$\bar{y}_u=\frac{1}{n}\sum_{i=1}^{N}y_i \tag{3.3}$$

Moreover, OECD (2013) uses the following equation to calculate the unweighted Gini index to measure regional disparities:

$$G_u = \frac{2}{N-1} \sum_{i=1}^{N-1} \left| F_i - Q_i \right| \tag{3.4}$$

where N is the number of regions, $F_i = \frac{i}{N}$, $Q_i = \frac{\sum_{j=1}^{i} y_j}{\sum_{i=1}^{N} y_i}$ and y_i is the value of variable y (e.g. GDP per capita) in region j when ranked from low (y_i) to high (y_N) among all regions within a country.

The weighted Gini Index is calculated as follows:

$$G_w = \left(\frac{1}{2\bar{y}}\right) \sum_{i}^{n} \sum_{j}^{n} \left| y_i - y_j \right| \frac{p_i p_j}{p^2} \tag{3.5}$$

where y_i and y_j are the GDP per capita of region i and j, n is the number of regions, p_i and p_j are the populations of region i and j respectively, p is the national population, and $\bar{y}$ is the national GDP per capita.

As seen in the above equations, the unweighted Gini index assigns equal weight to each region regardless of its size, whereas the weighted Gini index weights the difference between per capita GDP values of regions by the product of population proportions of region i and j. Furthermore, the unweighted Gini index varies between 0 and 1 but the weighted Gini index varies between 0 and 1-(p_i/p). If p_i is small compared to p, i.e., if the region with a small proportion of the population produced all the GDP then the value for perfect inequality would approach 1 (Shankar and Shah, 2003).

3.1.3 Coefficient of Variation (CV)

The coefficient of variation (CV) is the most widely used measure of sigma convergence in the literature. The CV is a normalized measure of dispersion of a probability distribution and basically defined as the ratio of the standard deviation to the non-zero mean. The CV is often presented as the given ratio multiplied by 100 and known as the relative standard deviation (Neagu, 2013; Monfort, 2008).

The coefficient of variation is calculated in two different ways: (i) simple/unweighted coefficient of variation and (ii) weighted coefficient of variation. The unweighted coefficient of variation is calculated with the following formula (Shankar and Shah, 2003):

$$CV_u = \frac{\sqrt{\sum_{i=1}^{N} \frac{\left[y_i - \bar{y}_u\right]^2}{N}}}{\bar{y}_u} \tag{3.6}$$

where y_i is the GDP per capita of region i, N is the number of regions and $\bar{y}_u$ is the unweighted (arithmetic) mean GDP per capita.

With reference to Williamson (1965), some authors have used national GDP per capita in the denominator of the above equation. Following the convention of Shankar and Shah (2003), an unweighted simple average of GDP capita values of regions is generally considered as appropriate. The value of unweighted coefficient of variation varies from 0 for perfect equality to $\sqrt{N-1}$ for perfect inequality. This measure can be problematic for comparisons either across time or countries due to its sensitivity to the number and varying population size of regions, and outliers (Wijerathna et al, 2014).

The problem is somewhat overcome by using the weighted coefficient of variation. Contrary to the unweighted coefficient of variation, the weighted coefficient of variation takes the impact of population share of each region into account and weighs each regional deviation by its share in the national population. It also does not depend on the number of regions. The weighted coefficient of variation is calculated as given below (Shankar and Shah, 2003):

$$CV_w = \frac{\sqrt{\sum_{i=1}^{N}\left[y_i - \bar{y}\right]^2 \frac{p_i}{p}}}{\bar{y}} \qquad (3.7)$$

where y_i is the per capita GDP of region i, $\bar{y}$ is the per capita GDP of the nation, p_i is the population of region i, and p is the population of the nation. The value of the weighted coefficient of variation varies from 0 for perfect equality to $\sqrt{(p - p_i)p_i}$ for perfect inequality where a single region generates the entire national GDP.

3.1.4 Relative Mean Deviation (RMD)

The relative mean deviation (RMD) is one of the simplest inequality measures but also compensates for some disadvantages of other measures. It includes the overall distribution in the measurement of inequality instead of only taking into account the extreme values of the distribution. It avoids the unnecessary sensitivity to outliers because it is not computed by squaring the differences (Charles-Coll, 2011; Shankar and Shah, 2003). The relative mean deviation is basically calculated as given below (Kakwani, 1980, 1990; Williamson, 1965; Wahiba, 2014) but some researchers, including Cowell (1988), Bellù and Liberati (2006), and Hakizimana and Geyer (2014) do not divide the RMD by 2 and excludes $\left[\frac{1}{2}\right]$ from the formula:

$$RMD = \frac{1}{2\bar{y}_u}\left[\frac{1}{N}\sum_{i=1}^{N}|y_i - \bar{y}_u|\right] \tag{3.8}$$

where y_i is the GDP per capita of region i, N is the number of regions, and $\bar{y}_u$ is the unweighted (arithmetic) mean GDP per capita. The RMD varies from 0 to (N-1)/N. If the RMD equals to 0, every unit/region receives the same income (perfect equality). When one unit/region receives all the income (perfect inequality), the RMD becomes (N-1)/N.

Moreover, Shankar and Shah (2003), and Wijerathna et al (2014) computes the population weighted version of the relative mean deviation by using the formula below:

$$\mathrm{RMD_w} = \frac{\sum_{i=1}^{N}\left|y_i - \bar{y}\right|\frac{p_i}{p}}{\bar{y}} \tag{3.9}$$

where y_i is the GDP per capita of region i, N is the number of regions, $\bar{y}$ is the national GDP per capita, p_i is the population of region i, and p is the national population. The weighted RMD varies from from 0 for perfect equality to 2 for perfect inequality.

3.1.5 Atkinson Index

Atkinson (1970) proposes another method for measuring disparities. Main and distinguishing feature of the Atkinson Index is its ability to highlight movements in particular segments of the distribution (Neagu, 2013). The index uses a parameter (adjustment factor) which allows for giving more or less weight to changes in a given portion of the income distribution. This parameter defines the level of “inequality version” and generally denoted by Ɛ. In other words, the parameter Ɛ reflects the strength of society's preference for equality. It can take values from zero to infinity. If Ɛ >0, there is a social preference for equality. If the value of Ɛ increases, the society becomes more concerned with the issue of inequality and attaches more weight to income transfers at the lower end of the distribution and less weight to transfers at the top (Shahateet, 2006; Litchfield, 1999). As Ɛ approaches 1, the index becomes more sensitive to changes at the lower end of the income distribution. Conversely, as Ɛ approaches 0, this index becomes more sensitive to changes in the upper end of the income distribution (Monfort, 2008).

The Atkinson Index is basically calculated as given below (Atkinson, 1970, 1975, 1983; Schlör et al., 2011):

$$A_w = 1 - \left[\sum_{i=1}^{N} \left[\frac{y_i}{\bar{y}}\right]^{1-\varepsilon} \left[\frac{p_i}{p}\right]\right]^{\frac{1}{1-\varepsilon}} \qquad \text{If } \varepsilon \neq 1$$

$$A_w = 1 - \exp\left[\sum_{i=1}^{N} \left[\frac{p_i}{p}\right] log_e \left[\frac{y_i}{\bar{y}}\right]\right] \qquad \text{If } \varepsilon = 1 \qquad (3.10)$$

where y_i is the GDP per capita of region i, N is the number of regions, $\bar{y}$ is the national GDP per capita, p_i is the population of region i, and p is the national population.

If we assume the equal weight for each region or calculate the index for individuals instead of regions, the population share $\left[\frac{p_i}{p}\right]$ becomes $\left[\frac{1}{N}\right]$. In this case, the (arithmetic) mean GDP per capita $\left[\bar{y}_u = \frac{1}{N}\sum_{i=1}^{N} y_i\right]$ is used instead of the national GDP per capita-$[\bar{y}]$. The unweighted Atkinson Index is calculated as follows:

$$A_u = 1 - \left[\frac{1}{N}\sum_{i=1}^{N} \left[\frac{y_i}{\bar{y}_u}\right]^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \qquad \text{If } \varepsilon \neq 1$$

$$A_u = 1 - \frac{\prod_{i=1}^{N} \left[[y_i]^{\frac{1}{N}}\right]}{\bar{y}_u} \qquad \text{If } \varepsilon = 1 \qquad (3.11)$$

3.1.6 Generalized Entropy Measures

Family of the Generalized Entropy inequality measures has the general formula as follows:

$$GE_{(u)}(\alpha) = \frac{1}{\alpha[\alpha - 1]}\left[\frac{1}{N}\sum_{i=1}^{N}\left[\frac{y_i}{\bar{y}_u}\right]^{\alpha} - 1\right] \tag{3.12}$$

where N is the number of individuals (regions) in the sample, y_i is the income of individual i (the GDP per capita of region i) , and $\left[\bar{y}_u = \frac{1}{N}\sum_{i=1}^{N} y_i\right]$, the unweighted (arithmetic) mean income (GDP per capita). The value of GE ranges from zero to infinity, with zero representing an equal distribution and higher values representing higher levels of inequality. The parameter α in the GE class indicates the weight given to distances between incomes at different parts of the income distribution, and can take any real value. For lower values of α, GE is more sensitive to changes in the lower tail of the distribution, and for higher values, GE is more sensitive to changes that affect the upper tail (Haughton and Khandker, 2009; Litchfield, 1999). The commonly used values of α are 0, 1 and 2. The GE measures with parameters 0 and 1 become, with l'Hopital's rule, two of Theil's measures of inequality (Theil, 1967): (i) GE (α=0): Mean Log Deviation (known as Theil's L) and (ii) GE (α=1): Theil Index (known as Theil's T).

$$GE_{(u)}(\alpha)=\frac{1}{N}\sum_{i=1}^{N}\log\left[\frac{\bar{y}_u}{y_i}\right] \qquad \alpha=0 \tag{3.13}$$

$$GE_{(u)}(\alpha)=\frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}_u}\log\left[\frac{y_i}{\bar{y}_u}\right] \qquad \alpha=1 \tag{3.14}$$

where y_i is the GDP per capita of region i, N is the number of regions, $\bar{y}_u$ is the unweighted (arithmetic) mean GDP per capita.

Since this notion is not convenient for territorial analysis, the population-weighted generalized entropy index GE $_{(w)}$ can be expressed as follows (Theil, 1967; Wang et al, 2012; Banerjee and Kuri, 2015):

$$GE_{(w)}(\alpha)=\sum_{i=1}^{N}\left[\frac{p_i}{p}\right]\left[\left[\frac{y_i}{\bar{y}}\right]^{\alpha}-1\right] \qquad \alpha\neq 0,1 \qquad (3.15)$$

$$GE_{(w)}(\alpha)=\sum_{i=1}^{N}\left[\frac{p_i}{p}\right]\log\left[\frac{\bar{y}}{y_i}\right] \qquad \alpha=0 \qquad (3.16)$$

$$GE_{(w)}(\alpha)=\sum_{i=1}^{N}\left[\frac{p_i}{p}\right]\left[\frac{y_i}{\bar{y}}\right]\log\left[\frac{y_i}{\bar{y}}\right] \qquad \alpha=1 \qquad (3.17)$$

where y_i is the GDP per capita of region i, N is the number of regions, $\bar{y}$ is the national GDP per capita, p_i is the population of region i, and p is the national population.

3.2 Beta Convergence

Static measures and sigma convergence present a snapshot view of regional disparities and dispersion of regional income. This is very helpful but not sufficient for understanding the convergence phenomenon. Thus, beta convergence analysis can be employed to capture growth dynamics between poor and rich regions within a longer-term perspective. As mentioned in the second chapter, there are two specifications of beta convergence: absolute (unconditional) convergence and conditional convergence.

This study seeks an answer to the question of whether there is an absolute regional convergence in Turkey because reducing the regional development disparities in “absolute terms” has been a major policy issue in Turkey since 1960s. Moreover, structural differences across regions are expected to be much smaller than they are across countries given the fact that regions are under the same macroeconomic policy environment. The inquiry of absolute convergence itself is important regardless of the structure of the convergence, i.e convergence within a certain club or to different steady-states. Therefore, absolute convergence is more relevant than other methods in analysis of regional disparities and convergence in Turkey.

A real methodology for measuring beta convergence across countries and states is first introduced by Barro and Sala-i Martin (1990, 1991, 1992) via using cross-sectional GDP per capital data. Their model is as follows:

$$\frac{1}{T} log\left[\frac{y_{i,t+T}}{y_{it}}\right] = \alpha - \left[\frac{1-e^{-\beta T}}{T}\right] log[y_{it}] + u_{it} \qquad (3.18)$$

where i denotes the economy, t indexes time, y_{it} is per capita income, T is the length of the observation interval, the coefficient β is the rate of convergence, and u_{it} is an error term. For our purposes, the equation (3.18) can be rearranged and simply estimated by the following equation:

$$log\left[\frac{y_{i,t+T}}{y_{it}}\right] = \alpha + \beta\ log[y_{it}] + u_{it} \qquad (3.19)$$

where β is the coefficient to be estimated for detecting the convergence. A negative value of β indicates convergence. On the other hand, convergence rate/speed in the equation (3.18) can be calculated by using the following equality between beta values of equation (3.18) and (3.19):

$$\beta_{(3.19)} = -\left[1 - e^{-T\beta_{(3.18)}}\right]$$

$$\text{Convergence Speed - } \beta_{(3.18)} = -\frac{ln\left[1 + \beta_{(3.19)}\right]}{T} \tag{3.20}$$

In addition, another common indicator to characterize the speed of convergence is the so-called half-life (τ), defined as the necessary period for half of the initial income inequalities to disappear. The half-life period can be calculated from the following formula:

$$\tau = \frac{ln[2]}{\beta_{(3.18)}} \tag{3.21}$$

On the other hand, in the literature, beta convergence analysis is performed generally without taking spatial dimension and effects into account. According to the general approach, regions are considered as independent entities in space so spatial interdependencies and interactions between regions are ignored. However, empirical studies reconsidering regional convergence from a spatial econometric perspective have showed that spatial externalities and spillovers are highly important in the analysis of growth patterns and provided richer insights to regional economic growth and convergence process (Rey and Montouri, 1999).

3.2.1 Spatial Dependence in Analysis of Regional Disparities

Spatial dependence basically occurs when certain values for some phenomenon measured at one location are associated/correlated with the same values measured at other locations (Anselin, 1988). The well-known and most common spatial statistic used for testing spatial dependence is "Moran's I" statistic, which is a measure of spatial autocorrelation. Spatial autocorrelation is defined as the correlation among values of a single variable strictly attributable to the proximity of those values in geographic space, introducing a deviation from the independent observations assumption of classical statistics (Griffith, 2003). Spatial autocorrelation indicates the degree of dependency among observations in geographic space, and it is very helpful for identifying spatial clusters in space.

Moran's I Statistics and Spatial Autocorrelation

Moran's I statistics provide tests and visualization of both *global spatial autocorrelation* (test for spatial pattern and clustering) and *local spatial autocorrelation* (test for spatial clusters) (Celebioglu and Dall'erba, 2010).

Global spatial autocorrelation is measured by using Moran's I, defined as (Anselin, 1988, 1995):

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}[y_i - \bar{y}][y_j - \bar{y}]}{\sum_{i=1}^{N}[y_i - \bar{y}]^2} \qquad (3.22)$$

where N is the number of regions, y_i is the GDP per capita of region i, y_j is the GDP per capita of region j, $\bar{y}$ is the average (mean) GDP per capita for all regions, and w_{ij} is an element of binary spatial weights matrix (W).

Spatial weights (w_{ij}) are key components in any spatial data analysis, and crucially depend on the definition of a neighborhood set for each observation. In other words, the weights indicate the neighbor structure between the observations as binary relationship in a N × N spatial weights matrix (W). The spatial weights are non-zero when region i and j are neighbors, and zero otherwise. By convention, the self-neighbor relation w_{ii} is excluded, so that the diagonal elements of the spatial weights matrix (W) are zero, w_{ii}=0. Although there are many criteria to construct the spatial weights, the two most common approaches used for defining a neighborhood relation are distance and contiguity. Distance based definition of neighbors is suitable for point data structure whereas contiguity refers to cases where two spatial units share a common border of non-zero length and it is very appropriate for geographic data expressed as polygons (Anselin and Rey, 2014). As shown in the figure bellows, there are basically three types of neighborhood structure of binary contiguity weights (Anselin, 1988; LeSage, 1999). This study uses queen contiguity neighborhood structure, as it is the union of rook and bishop and thus is the most comprehensive structure.

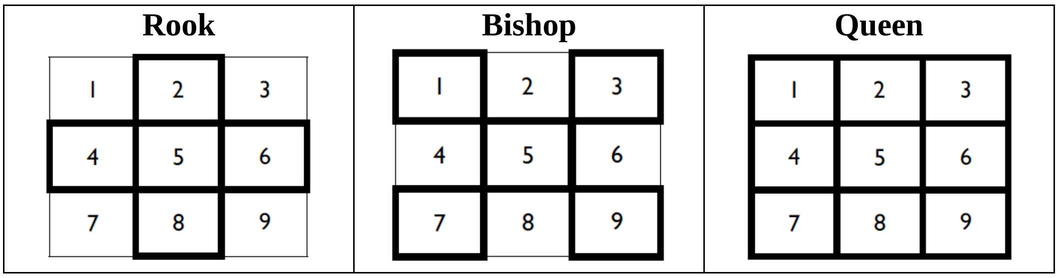


Figure 4 Neighborhood Structure of Binary Contiguity Weights
Source: Anselin, 2014

Global spatial autocorrelation as a measure of overall clustering is used to test the null hypothesis of "no spatial association" or "spatial randomness" which assumes the absence of any spatial pattern. Rejection of the null hypothesis implies that there is an evidence of spatial structure and clustering so this would simply mean that location matters. However, high values of spatial autocorrelation do not indicate any significance. Significance of spatial autocorrelation is tested by using permutation approach to yield empirical so-called pseudo significance levels. In the permutation approach, observed values are randomly reshuffling over space and reallocated to locations and then Moran's I statistic is recomputed for each such random pattern. The resulting empirical distribution function provides the basis or reference for a statement about the extremeness of the observed statistic, relative to (and conditional on) the values computed under the null hypothesis of spatial randomness (Anselin, 1992, 1995).

Spatial autocorrelation can take both negative and positive values. Positive and significant spatial autocorrelation indicates that similar values are likely to concentrate in space, that is, regions with high (low) GDP per capita tends to be located nearby other region with high (low) GDP per capita more often than would be expected to occur due to random chance (Rey and Montouri, 1999). Negative and significant spatial autocorrelation indicates that dissimilar values in neighboring regions (spatial outliers) tends to be located together more frequently than would be expected to occur due to spatial randomness like high-low or low-high.

On the other hand, *local spatial autocorrelation* is a local spatial statistic assessing the significance for each location and allows for the decomposition of global indicators. It indicates to what extent each location is surrounded by neighbors having similar or dissimilar values, so it is used to identify spatial clusters and spatial outliers:

- Positive and significant local spatial autocorrelation: spatial clusters
  - High-High
  - Low-Low
- Negative and significant local spatial autocorrelation: spatial outliers
  - High-Low
  - Low-High

Local spatial autocorrelation is calculated by using local Moran's I statistic as follows (Anselin, 1995):

$$I_i = \frac{[y_i - \bar{y}]}{\frac{1}{N}\sum_{i=1}^{N}[y_i - \bar{y}]^2} \sum_{j=1}^{N} w_{ij}[y_j - \bar{y}] \tag{3.23}$$

where N is the number of regions, y_i is the GDP per capita of region i, y_j is the GDP per capita of region j, $\bar{y}$ is the average (mean) GDP per capita for all regions, and w_{ij} is the an element of binary spatial weights matrix (W).

In sum, Moran's I statistics as a measure of spatial autocorrelation basically provides descriptive statistics to determine the existence of spatial dependence. In the existence of significant spatial autocorrelation, it is needed to include spatial parameters and interaction into econometric analysis designed for testing beta convergence hypothesis.

3.2.2 Spatial Econometric Models

In spatial econometrics literature, spatial dependence is basically handled through "three different types of interaction effects" which may explain why an observation associated with a specific location may be dependent on observations at other locations: (i) endogenous interaction effects among the dependent variable (Y), (ii) exogenous interaction effects among the independent variables (X), (iii) interaction effects among the error terms (e) (Elhorst, 2014). These interactions provide a very useful framework for defining different forms and econometric models of spatial dependence in space.

Elhorst (2014) develops a general nesting spatial model containing all types of interaction effects as follows:

$$\begin{aligned} Y &= \alpha + \delta WY + X\beta + WX\theta + \mu \\ \mu &= \lambda W\mu + \varepsilon \end{aligned} \tag{3.24}$$

where WY denotes the endogenous interaction effects among the dependent variable, WX denotes the exogenous interaction effects among the independent variables, Wu denotes the interaction effects among the disturbance term of the different units, Ɛ is the independent and identically distributed error term, and W is the spatial weights matrix.

A family of linear spatial econometric models can be derived by imposing restrictions on one or more of parameters (δ, θ, λ) of the general nesting spatial model. As can be seen from Figure 3.1, seven econometric models can be obtained from this general model. Some of these spatial econometric models like SDEM, SLX are hardly considered or used in econometric-theoretic and empirical research, so these models are not generally a part of the toolbox of researchers for the econometric theory of spatial models. Theoreticians are mainly interested in the Spatial Lag Model/Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM), as well as the SAC model that combines endogenous interaction effects and interaction effects among the error terms (Elhorst, 2014).

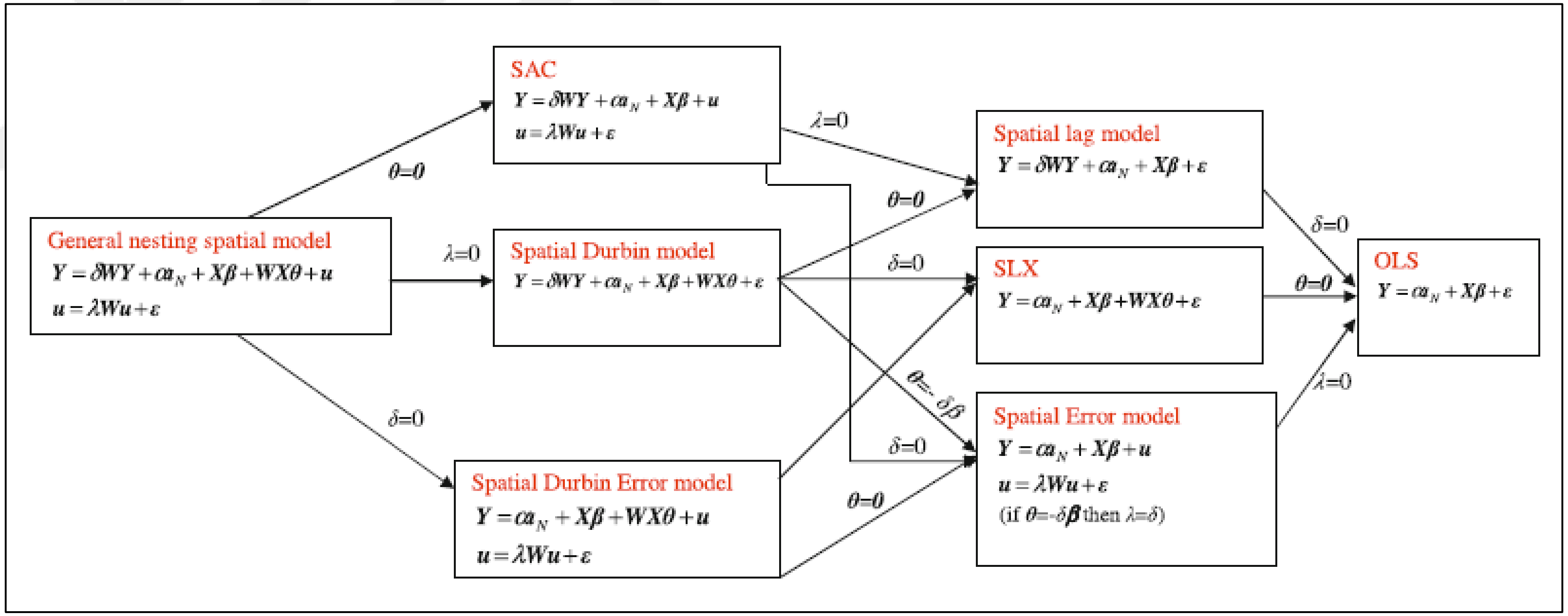


Figure 5 A Taxonomy of Linear Spatial Dependence Models
Source: Elhorst, 2014

We can customize the above general model for our analysis on beta convergence as follows:

$$log\left[\frac{y_{i,t+T}}{y_{it}}\right] = \alpha + \delta W log\left[\frac{y_{i,t+T}}{y_{it}}\right] + \beta\ log[y_{it}] + \theta W log[y_{it}] + u_{it} \quad (3.25)$$

$$u_{it} = \lambda W u_{it} + \varepsilon_{it}$$

Spatial Error Model (SEM) can be customized as in equation (3.26). The SEM Model assumes that the spatial dependence works through the error process due to the omitted random factors (nuisance spatial dependence) such that the errors from different regions may have spatial covariance (Rey and Montouri, 1999).

$$log\left[\frac{y_{i,t+T}}{y_{it}}\right] = \alpha + \beta\ log[y_{it}] + u_{it} \quad (3.26)$$

$$u_{it} = \lambda W u_{it} + \varepsilon_{it}$$

Spatial Lag Model (SLM) belongs to the class of the Spatial Autoregressive Models (SAR) so it is also known as the spatial autoregressive (SAR) model. The SAR Model examines how GDP per capita growth rates of regions are related not only to their own initial level of income but also to the growth rates of neighboring regions. The SAR/SLM can be expressed by the following equation:

$$log\left[\frac{y_{i,t+T}}{y_{it}}\right] = \alpha + \beta\ log[y_{it}] + \delta W log\left[\frac{y_{i,t+T}}{y_{it}}\right] + u_{it} \quad (3.27)$$

The growing interest in spatial econometrics brought about the exploration of new models containing more than just one spatial interaction effect. The SAC Model[1] as one of the well-known models of this kind includes both a spatially lagged dependent variable and a spatially autocorrelated error term. In other words, this model is a combination of the above SAR and SEM specifications.

$$log\left[\frac{y_{i,t+T}}{y_{it}}\right] = \alpha + \delta W log\left[\frac{y_{i,t+T}}{y_{it}}\right] + \beta\ log[y_{it}] + u_{it} \tag{3.28}$$
$$u_{it} = \lambda W u_{it} + \varepsilon_{it}$$

[1] This model is denoted by the term SAC in LeSage and Pace (2009), though without pointing out what this acronym is standing for (Elhorts, 2014).

CHAPTER FOUR

EMPIRICAL FINDINGS

This section of the study aims to analyze regional economic convergence in Turkey for the period of 2004-2011 with a special focus on spatial dependence and spatial econometrics.

4.1 Unit of Analysis and Data

With the effect of harmonization to European Union, Turkey transformed its approach to regional development after 2000. Transformation agenda was not limited to the adaptation of a new regional development policy; it brought about the adaptation of a new regional classification and statistical system. Turkey adapted the EU Regional Statistics System in 2002, and the Decision of the Council of Ministers No.2002/4720 on the definition of Nomenclature of Territorial Units for Statistics (NUTS) was published in the Official Gazette on 22 September 2002.

According to this Decree, 12 NUTS I, 26 NUTS II and 81 NUTS III regions were defined. The Turkish Statistical Institute (TURKSTAT) started to publish regional statistics according to the new regional classification.

The new definition of regions aims to collect and develop regional statistics, to make socio-economic analysis of the regions, to determine the framework of regional policies and to establish a statistical data base in line with the EU Regional Statistics System. Accordingly, NUTS II regions became the main territorial level for the implementation and analysis of regional development policies. This study takes NUTS II regions as the main units of analysis.

The data set used in the study was obtained from the TURKSTAT. However, it should be noted that the TURKSTAT has not published any GDP data at regional level since 2001 and started to produce GVA data at NUTS I and II levels only after 2004. The time series of regional GDP data is no longer available. Currently, the only regional level income data we have is GVA per capita of NUTS I and II regions for the period of 2004-2011. Moreover, we do not have any regional level income data between 2001 and 2004.

In sum, such constraints and limitations on the data (including a change in statistical classification of regions, a shift from GDP data to GVA data, a break in time series of regional income data and lack of GVA data at provincial level) make it impossible to monitor the long term trends in convergence and compare the results of convergence analysis obtained before 2001 and those obtained after 2001. As a result, this study concentrates on the period of 2004-2011 and uses GVA per capita values for NUTS II regions at 1998 prices.

4.2 Empirical Results of Regional Disparities in Turkey

We performed sigma and beta convergence analyses to provide empirical evidence for the presence or absence of regional convergence in Turkey for the period 2004-2011. We believe that findings of the study provide new insights into the debate on regional convergence in Turkey. Adaptation of a new regional development approach after 2000 necessitates paying special attention to the progress achieved in the period 2004-2011. In the meantime, we need to consider the effects of 2008 financial crisis as it coincides with the period of the study.

4.2.1 Sigma Convergence

Sigma convergence is used to test whether the dispersion of per capita income of economies (or regions) tends to fall over time. The box plot presented in Figure 6 shows the distribution of GVA per capita of NUTS regions into quartiles, highlighting the mean and median. As seen in the figure, all regions increased their income per capita and showed positive growth from 2004 to 2011, and at the same time, the income gap between regions or variation in regional income per capita decreased over time.

Actually, we see that variation in regional income per capita increased between 2004 and 2007. This is the period when Turkey experienced real economic expansion. Then, we see a reduction in the dispersion of regional income per capita in 2008 and 2009. These are the years when Turkey felt the impact of the 2008 financial crisis, and also experienced regional sigma convergence. When we check the income per capita growth rates of regions in these years, we notice that while developed regions located in the western part of the country were experiencing a negative income per capita growth rate, relatively poorer regions located in the eastern part were either only slightly affected by the crisis or achieved positive growth. This is the main reason behind the sigma converge achieved in 2008 and 2009. Moreover, we see that dispersion in regional income per capita began to rise again after 2010 in parallel to the increasing growth performance of the country. Thus, our findings on sigma convergence are in line with the literature which reports that inter-regional inequality decreases in the recession periods and increases in the economic expansion periods.

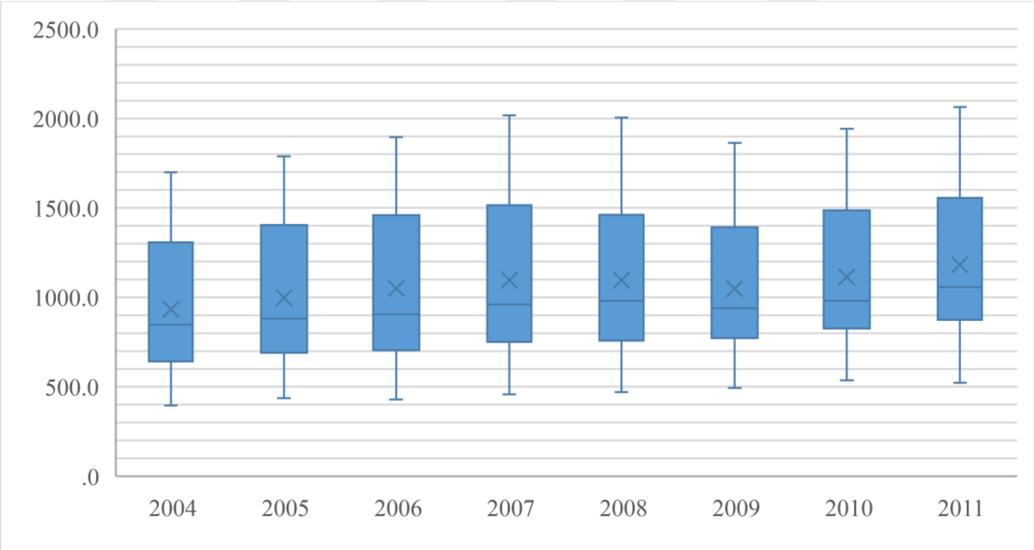


Figure 6 Dispersion of GVA per capita of NUTS II Regions

Notes: The figure presents the box plot of per capita income (GVA per capita) of NUTS 2 regions from 2004 to 2011 to examine how the spread of the distribution of regional GVA per capita changes over time. The figure basically shows the full range of variation in data through the reference numbers: the minimum, first quartile, median, mean, third quartile, and maximum. GVA per capita values are expressed at constant 1998 prices.

Figure 7 shows that all inequity indexes follow more or less the same trend in the box plot and support our findings regarding sigma convergence. Inequality decreased in 2005 and increased in 2006 for all indexes. We start to see a reduction in equality again between 2006 and 2010 for the MMR, Gini Index, CV and RMD and between 2008 and 2010 for the Atkinson Index and Theil Index. On the other hand, it should be noted that for most of the measures, the weighted values are larger than the unweighted values. This indicates that the regions with extreme/high per capita GVAs are generally those with larger populations.

As a result, we can conclude that descriptive evidence based static measures of regional inequalities support the hypothesis of sigma convergence between 2004-2011.

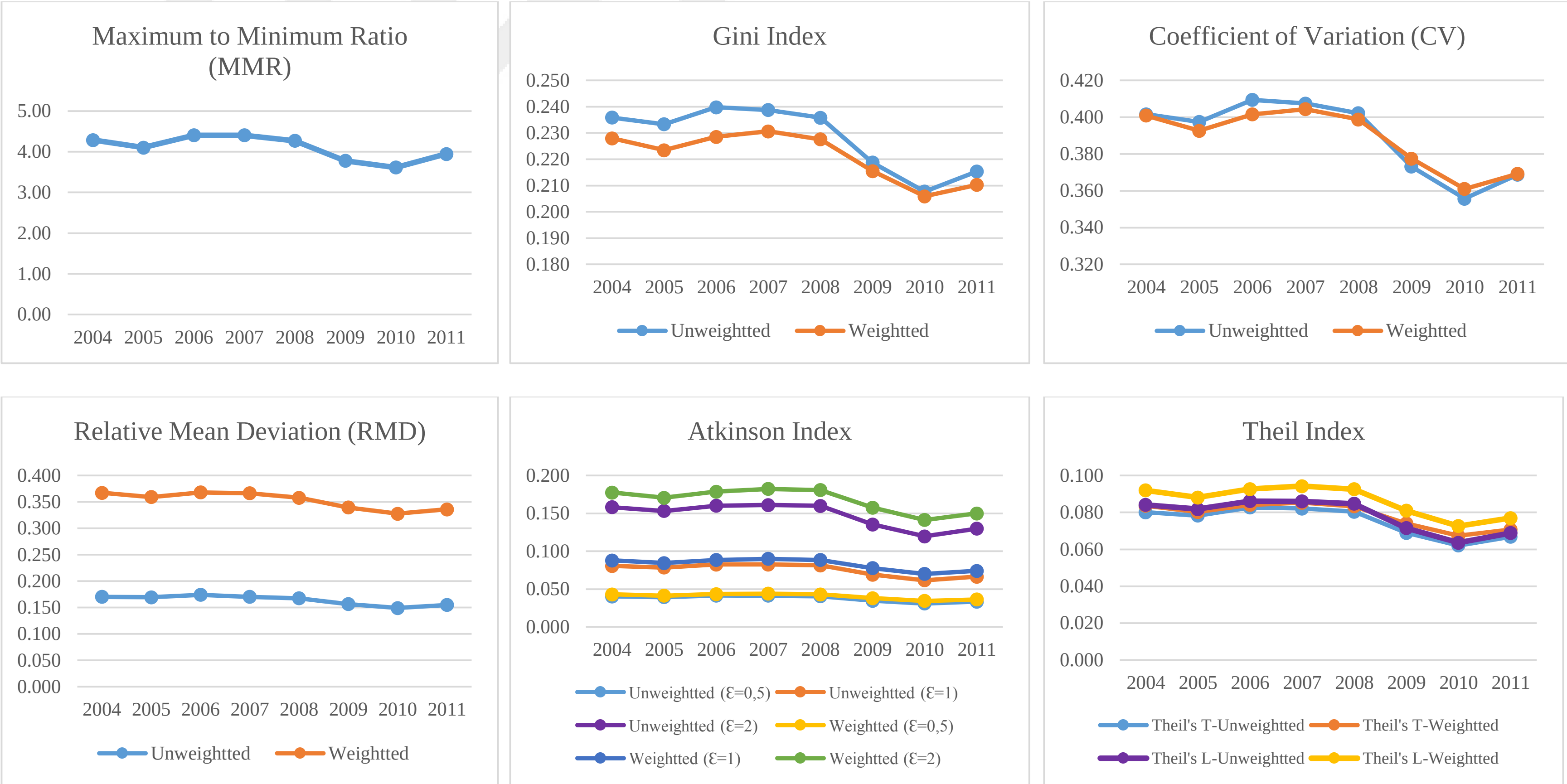


Figure 7 Inequality Indexes: Static Measures of Regional Disparities

4.2.2 Beta Convergence

After examining the trends and change in the dispersion of regional income per capita, it is important to check the existence of long-term catch-up mechanism, which would imply that relatively poorer regions tend to grow faster than richer ones. In other words, we would expect to see a negative correlation between per capita income growth rate and initial per capita income levels of regions. Figure 8, which presents the relationship between growth rate and initial level of per capita income (GVA per capita), supports our expectation of beta convergence and displays the negative slope of the fitted regression line.

Before performing more formal econometric and statistical modelling of beta convergence, we think that it is wise to investigate the existence of spatial dependence among NUTS II regions and decide whether we should take spatial autocorrelation/dependence into account in our econometric models.

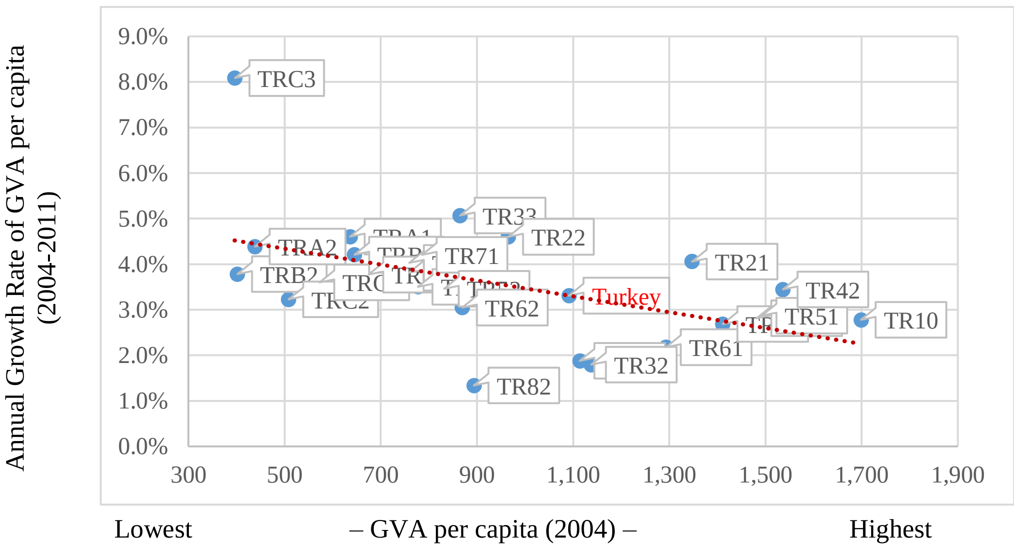


Figure 8 Scatterplot of Income Growth Rate by Initial Income

Notes: The figure displays the relationship between annual growth rate of regional income (GVA per capita) and initial income level. Growth rates are presented in percentages. GVA per capita values on the x-axis are expressed at constant 1998 prices.

Spatial Dependence

Moran scatterplot is a useful and most commonly used visualization tool to analyze spatial dependence, more specifically spatial autocorrelation and spatial clusters. The Moran scatter plot visualizes a spatial autocorrelation statistic as the slope of the regression line in a scatterplot with the spatial lag (Wz-a weighted average of the same variable in the neighboring regions) on the vertical axis and the original variable (z) on the horizontal axis (using the variables in standardized form compared to the mean). This follows from the structure of Moran's I statistic, which has a cross product between z and Wz in the numerator, and the sum of squares of z in the denominator. For standardized variates, Moran's I statistic corresponds to the slope of a regression line of Wz on z. The significance of the spatial correlation is mainly assessed by means of a randomization (or permutation) approach. The observed values for one of the variables are randomly reallocated to locations and the statistic is recomputed for each such random pattern so randomization is used to generate a spatially random reference distribution to assess statistical significance. The resulting empirical reference distribution provides a way to quantify how "extreme" the observed statistic is relative to what its distribution would be under spatial randomness (Anselin et al., 2002).

In addition, as seen in Figure 9, the four quadrants of the scatterplot correspond to four different types of local spatial association between a region and its neighbors: Quadrant 1 - a high income region with high income neighbors (High-High); Quadrant 2 - a low income region with high income neighbors (Low-High); Quadrant 3 - a high income region with low income neighbors (High-Low);

Quadrant 4 - a low income region with low income neighbors (Low-Low). Thus, the scatter plot presents two classes of positive spatial correlation, or spatial clusters (HH and LL), and two classes of negative spatial correlation, or spatial outliers (HL and LH) (Rey and Montouri, 1999).

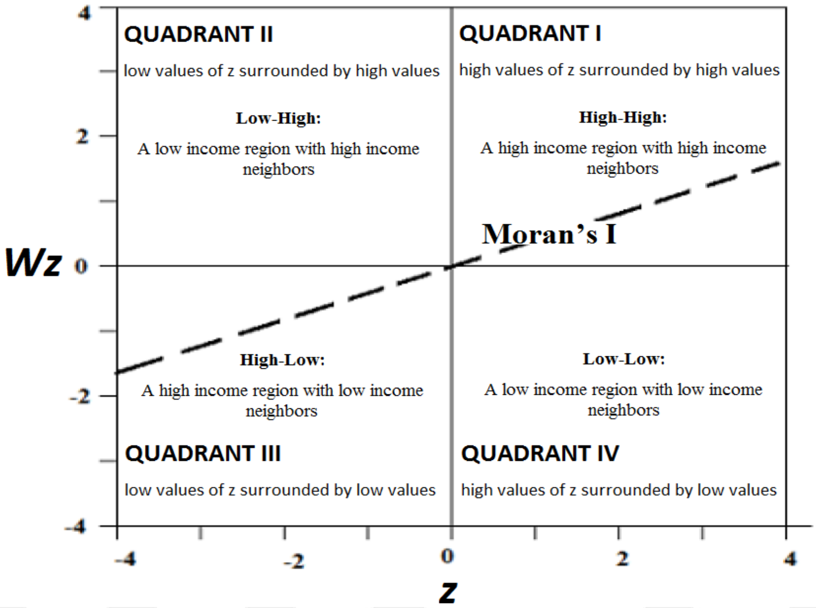


Figure 9 Anselin's Moran Scatter Plot Interpretation Guide
Source: Guţoiu, 2015

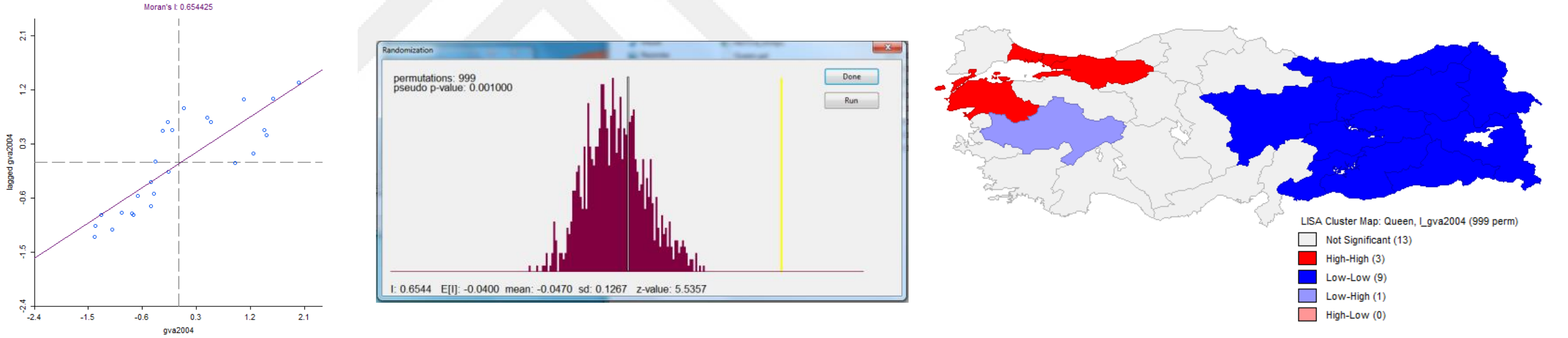
Figure 10 provides a disaggregated view of the nature of the spatial autocorrelation diagnostics for GVA per capita for the initial and terminal years. It shows that there is a highly significant positive spatial autocorrelation i.e. the value of GVA per capita in a region depends positively on the values in the neighboring regions. The figure also reveals that most of the regions are located in the quadrants I (HH) and III (LL): western regions with high income values are mainly located in the quadrant 1 (HH) while eastern region with low income values are mainly located in the quadrant 3 (LL). Table 2, which displays the Moran's I statistic calculated for each year, supports our finding of statistically significant positive spatial autocorrelation for GVA per capita across NUTS II regions because our Moran's I values are very different from the expect values and our p-values are less than 0.05.

Table 2 Global Moran's I for GVA per capita

GVA per capita/ Years	Moran's I	E(I)	sd(I)	z	p-value
2004	0.654	-0.040	0.131	5.313	0.000
2005	0.656	-0.040	0.131	5.315	0.000
2006	0.651	-0.040	0.131	5.282	0.000
2007	0.656	-0.040	0.130	5.331	0.000
2008	0.684	-0.040	0.130	5.549	0.000
2009	0.676	-0.040	0.130	5.492	0.000
2010	0.669	-0.040	0.130	5.435	0.000
2011	0.682	-0.040	0.130	5.534	0.000

Notes: Moran's I: Moran statistic for GVA per capita. E[I]: expected value of Moran's I statistic= -1/(n-1). sd(I): standard error of Moran's I computed from its simulated distribution. z: z score calculated for the randomization null hypotheses test. p-value: pseudo p-value obtained from one-tailed test.

GVA per capita, 2004



GVA per capita, 2011

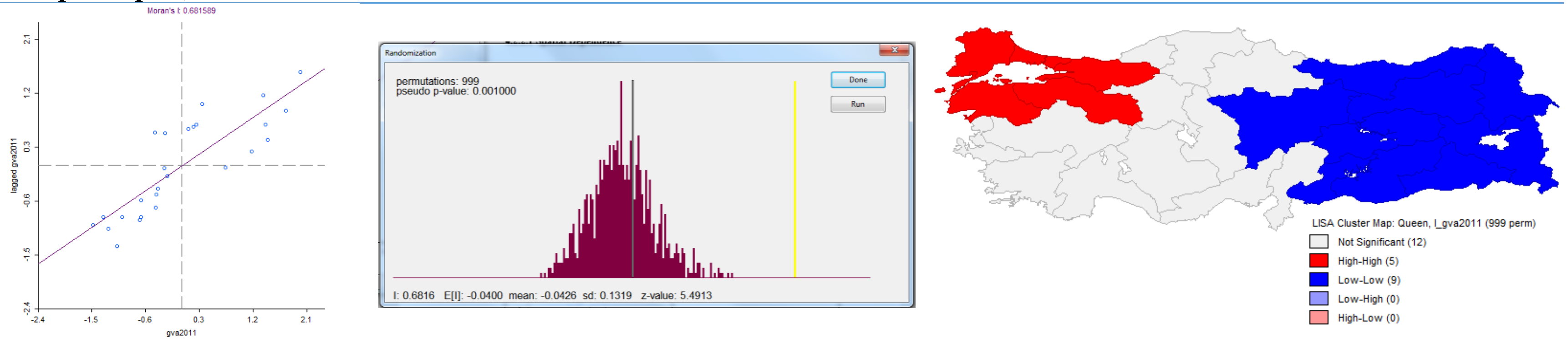


Figure 10 Moran's I Statistics for GVA per capita of NUTS II Regions

Notes: The Moran scatter plots on the left visualize the relationship between the standardized GVA per capita of a region and its spatial lag (GVA per capita of the neighboring regions). The slope of the regression line corresponds to the Moran's I statistic. The distributions in the middle display a random reference distribution and statistics of Moran's I obtained through permutation approach (999 permutations). LISA maps on the right display spatial clusters ant outliers obtained after the pseudo significance test generated under permutation approach.

When we analyze the Moran's I statistics for the growth rate of GVA per capita presented in Table 3 and Figure 11, we do not see very obvious results of spatial autocorrelation and spatial dependence. However, they still provide some preliminary signals or weak evidence for detecting spatial autocorrelation. Moran's I value of growth rate for 2004-2001 period is not significant (p-value >0.05) but positive, and LISA (Local Indicators of Spatial Association) map shows that HH clusters (a region with high growth rate surrounded by regions with high growth rate) are mainly located in eastern part of the country (lagging behind area) while LL clusters (a region with low growth rate surrounded by regions with low growth rate) are mainly located in the western part (developed area).

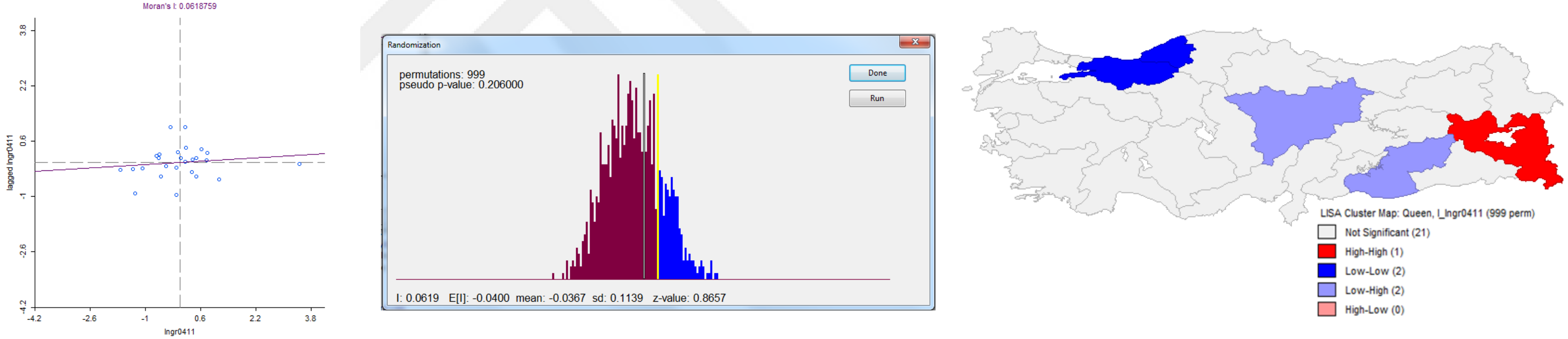
On the other hand, when we look at the yearly based Moran's I statistic in Table 3, we see that 4 of 7 test statistics indicate positive spatial autocorrelation and 2 of them (2008-2009 and 2009-2010) are statistically highly significant (p-value<0.05). 4 of the 8 test statistics in the table produce statistically significant results at the 10% significance level (p-value<0.10). In addition, LISA maps for the 2008-2009 and 2009-2010 periods presented in Figure 11 more clearly points out that HH clusters with high growth rate of GVA per capita are located in the eastern part of the country whereas LL clusters with low growth rate values are located in the western part.

Table 3 Global Moran's I for Growth Rate of GVA per capita

Growth Rate/ Periods	Moran's I	E(I)	sd(I)	z	p-value*
2004-2011	0.062	-0.040	0.116	0.876	0.190
2004-2005	-0.227	-0.040	0.124	-1.506	0.066
2005-2006	-0.140	-0.040	0.128	-0.782	0.217
2006-2007	0.109	-0.040	0.128	1.157	0.124
2007-2008	-0.021	-0.040	0.129	0.145	0.442
2008-2009	0.594	-0.040	0.130	4.894	0.000
2009-2010	0.370	-0.040	0.126	3.245	0.001
2010-2011	0.156	-0.040	0.126	1.556	0.060

Notes: Moran's I: Moran statistic for GVA per capita. E[I]: expected value of Moran's I statistic= -1/(n-1). sd(I): standard error of Moran's I computed from its simulated distribution. z: z-test statistic. p-value: pseudo p-value obtained from one-tailed test.

Growth Rate of GVA per capita, 2004-2011



Growth Rate of GVA per capita, 2004-2005

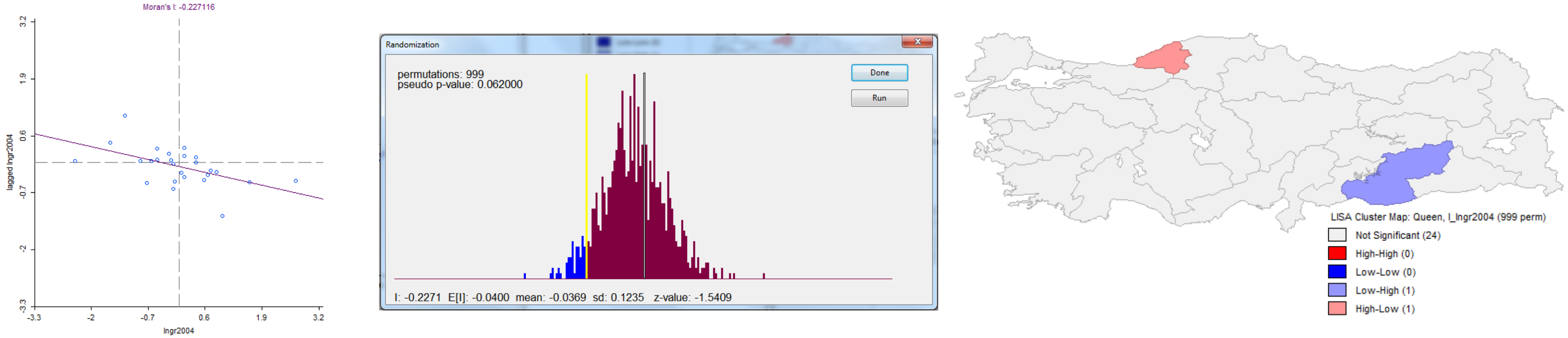
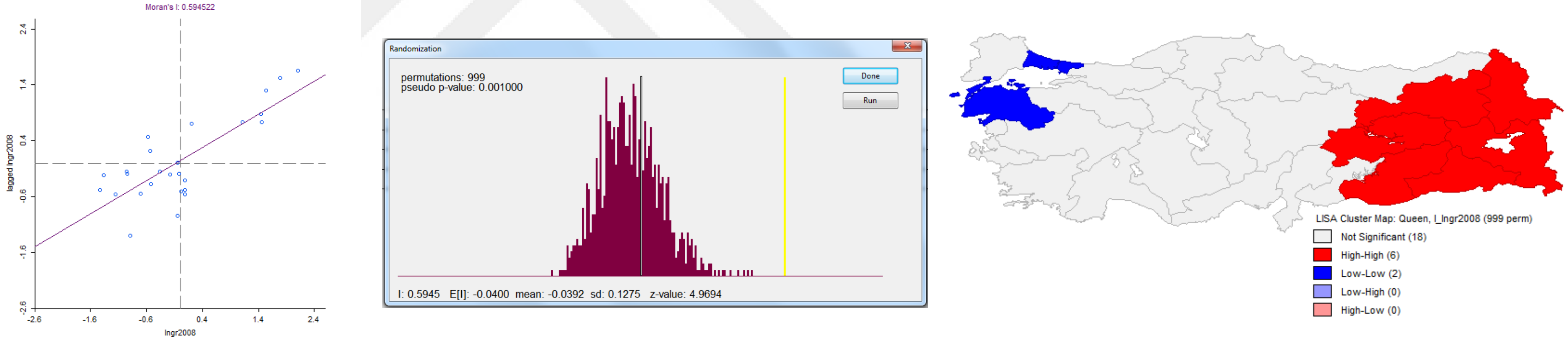


Figure 11 Moran's I Statistics for Growth Rate of GVA per capita

Notes: The Moran scatter plots on the left visualize the relationship between the standardized growth rate of GVA per capita of a region and its spatial lag (growth rate of GVA per capita of the neighboring regions). The slope of the regression line corresponds to the Moran's I statistic. The distributions in the middle display a random reference distribution and statistics of Moran's I obtained through permutation approach (999 permutations). LISA maps on the right display spatial clusters ant outliers obtained after the pseudo significance test generated under permutation approach.

Growth Rate of GVA per capita, 2008-2009



Growth Rate of GVA per capita, 2009-2010

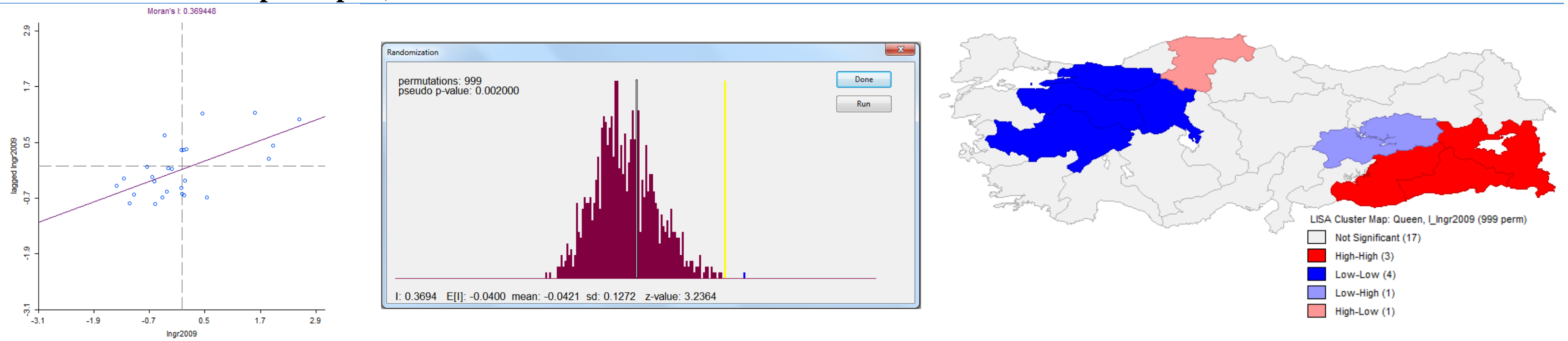


Figure 11 Moran's I Statistics for Growth Rate of GVA per capita (Continued)

Notes: The Moran scatter plots on the left visualize the relationship between the standardized growth rate of GVA per capita of a region and its spatial lag (growth rate of GVA per capita of the neighboring regions). The slope of the regression line corresponds to the Moran's I statistic. The distributions in the middle display a random reference distribution and statistics of Moran's I obtained through permutation approach (999 permutations). LISA maps on the right display spatial clusters ant outliers obtained after the pseudo significance test generated under permutation approach.

Estimation Results of Regression Models

In order to test the beta convergence hypothesis, we estimated regression models for equations (3.19), (3.26), (3.27) and (3.28) in both cross-sectional and panel data settings. Table 4 presents the estimation results for cross-sectional settings. The dependent variable for all models is the growth rate of GVA per capita of NUTS II regions for the period of 2004-2011. The main explanatory variable in all models is GVA per capita of NUTS II regions in 2004. We also included two other explanatory variables to control for spatial dependence. We first estimated the OLS model to replicate the most basic approach in the literature. Then, we extended the traditional OLS model by integrating endogenous interaction effects in three ways: first, by adding interaction effects among of the growth rates of GVA per capita of regions (SAR model) and later by adding interaction effects among the error terms (SEM model). Thirdly, we estimate the SAC model, which includes both of the two endogenous effects.

All models presented in Table 4 show that GVA per capita growth rate is negatively and statistically significantly associated with the initial GVA per capita, indicating evidence for regional convergence. The estimated speed of convergence ranges from 1.7% to 2%, which imply a half-life of 34 to 40 years. Our findings are in line with Barro and Sala-i-Martin’s 2% convergence rate, which is accepted as the iron law in the convergence literature (Barro and Sala-i-Martin, 1991,1992). In other words, the interval we estimated for the speed of convergence contains the iron law rate of 2% per year, which means a half-life of about 35 years. Furthermore, we see that when we incorporate spatial variables or parameters into the cross-sectional model, our estimations for convergence speed get closer to the iron law rate.

Table 4 Cross-sectional Estimations of Beta Convergence

	OLS	SAR	SEM	SAC
	GVA pc growth rate	GVA pc growth rate	GVA pc growth rate	GVA pc growth rate
ln (initial GVA pc)	-0.121** (0.0464)	-0.132*** (0.0466)	-0.113*** (0.0306)	-0.125** (0.0568)
Constant	1.899*** (0.640)	2.110*** (0.678)	1.795*** (0.418)	1.991** (0.898)
W*GVA pc growth rate		-0.225 (0.306)		-0.142 (0.578)
W*Error term			-0.230 (0.304)	-0.0994 (0.601)
Convergence Speed	0.018	0.020	0.017	0.019
Half-life Period	38 Years	34 Years	40 Years	36 Years
Observations	26	26	26	26
R-sq	0.316	0.243	0.315	0.3150
Adj. R-sq	0.287	0.243	0.315	0.3150
Root MSE	0.0772	0.0757	0.0757	0.0757
Log-likelihood	30.745	31.043	31.028	31.057
AIC	-57.489	-54.086	-54.056	-52.115
BIC	-54.973	-49.054	-49.023	-45.824

Notes: Standard errors are shown in parentheses. Significance at the 1% (***), 5% (**), and 10% (*) levels are indicated. Robust standard errors (except SEM and SAC) are used. W corresponds to the binary queen continuity matrix.

We also see that spatial models that take spatial dependence into account have better explanatory power than the basic OLS model and they achieve a better fit in terms of the summary statistics (R-sq, Log-likelihood, AIC, BIC) presented in the bottom portion of Table 4. However, none of the spatial dependence coefficients (spatial lag and error) are significant. Moreover, given the p-values, model selection tests presented in Tables 5 and 6 do not indicate statistically significant results for any type of spatial dependence. In other words, cross sectional estimates reject the existence of spatial dependence among Turkish regions and indicate the OLS as the correct specification. However, one limitation that could have flawed the estimators for the existence of spatial dependence is the number of observations. As the number of observations in the cross-section regressions is only 26, the models do not have much cross sectional variation to statistically show that the spatial dependence effect is different from zero. We should be cautious about interpreting our results obtained from cross-sectional estimations, which rely only on 26 observations. As a result, these limitations direct us to use panel data analysis in order to take advantage of time series variation in data in addition to the cross sectional variation. One claimed advantage of panel data over traditional cross-sectional approach is that it is not necessary to keep constant the steady-state because it can be implicitly estimated using fixed effects (Barro and Sala-i-Martin, 1995).

Table 5 Model Selection Tests of Cross-sectional Estimations: LR and Wald

Tests	SAC vs OLS	SAC vs SAR	SAC vs SEM
Likelihood Ratio (LR) test			
-Value	0.625	0.029	0.059
-P-value	0.732	0.866	0.808
Wald Test			
-Value	0.63	0.03	0.06
-P-value	0.728	0.869	0.806

Notes: The LR test is calculated based on minus two times the difference between the value of the log-likelihood function in the restricted model and the value of the log-likelihood function of the unrestricted model. The LR test statistic follows a chi-squared distribution with degrees of freedom equal to the number of restrictions imposed (Elhorst, 2014).

Table 6 Model Selection Tests of Cross-sectional Estimations: LM

Tests	MI/DF	Value	P-Value
Lagrange Multiplier (LM) Test			
LM (Lag/SAR)	1	0.464	0.4955
Robust LM (Lag/SAR)	1	0.020	0.8884
LM (Error)	1	0.454	0.5003
Robust LM (Error)	1	0.009	0.9225
LM (SARMA)	2	0.474	0.7890

Notes: LM tests are calculated based on Anselin (1988, 2001) and Anselin et al. (1996). The LM tests were estimated by using GeoDa and GeoDaSpace.

Table 7 reports the results of panel data estimations of the fixed effects and spatial maximum likelihood estimations. We basically replicated the estimations of the same econometric models used in the cross-sectional estimations in panel data settings. We prefer the fixed effects model to the random effects model because the results of Hausman's specification test presented in Table 8 rejects the null hypothesis where the preferred model is random effects. Moreover, we run a joint test to see whether the dummies for all years are equal to 0, and rejected the null hypothesis (F-statistics=95.56, p-value=0000). As a result, we included both entity (region) and time fixed effects into our fixed effects estimations.

Table 7 Panel Estimations of Beta Convergence

	Pooled OLS	Fixed Effects (FE)	SAR	SEM	SAC
	GVA pc growth rate	GVA pc growth rate	GVA pc growth rate	GVA pc growth rate	GVA pc growth rate
ln (Initial GVA pc)	-0.0316** (0.0155)	-0.395*** (0.0674)	-0.389*** (0.0634)	-0.424*** (0.0734)	-0.418*** (0.0696)
Constant	0.253** (0.107)	2.735*** (0.454)			
W* GVA pc growth rate			0.154** (0.0684)		-0.565*** (0.146)
W*Error term				0.243*** (0.0640)	0.645*** (0.085)
Region Effects	No	Yes	Yes	Yes	Yes
Time Effects	No	Yes	Yes	Yes	Yes
Convergence Speed	0.032	0.503	0.493	0.552	0.541
Half-life Period	22 Years	1.4 Years	1.4 Years	1.3 Years	1.3 Years
Observations	182	182	182	182	182
R-sq	0.027	0.832	0.245	0.239	0.194
Adj. R-sq	0.022	0.826			
Root MSE	0.0786	0.328			
Log-likelihood	205.558	368.015	369.428	371.134	374.748
AIC	-407.116	-722.030	-732.856	-736.268	-741.496
BIC	-400.708	-699.602	-723.244	-726.656	-728.680

Notes: Standard errors are shown in parentheses. Significance at the 1% (***), 5% (**), and 10% (*) levels are indicated. Robust standard errors, clustered by region (except column 1), are used. W corresponds to the binary queen continuity matrix

Table 8 Model Selection Tests of Panel Estimations: Hausman

Tests	Value	P-Value
Panel (FE vs RE)	33.09	0.0000

As in the case of the cross sectional estimates, panel data estimations also yield highly significant and negative coefficients for the initial income levels, confirming the consensus result of absolute beta convergence for Turkish regions. Based on this strong result, we can say that our evidence for regional convergence is really robust. On the other hand, we observe a sharp difference in the convergence rate estimated by the two models: Our pooled OLS estimation yield a convergence speed of 3.2% per year, implying a half-life of 22 years. However, panel data estimations yield very high rates of convergence speed varying from 49.3% to 54.1. In the literature, it is known that estimates of the speed of convergence from panel data with fixed effects tend to be much higher than the 2% per-year estimated from cross-sections or panels without fixed effects. Speeds of convergence ranging from 12 to 20 percent per year are not very uncommon in this literature. One potential problem with the fixed-effects approach is that estimations are generally carried out by shortening the time periods within which the growth rate is computed (like yearly growth rate or the growth rate over two to five years) so the growth rates computed for such short time spans tend to capture short-term adjustments around the trend rather than long-term convergence (Barro and Sala-i-Martin, 1995). Shioji (1997) suggest a method to overcome this problem but this method improves estimations results with a long time series. We only have data for 8 years (for years 2004-2011). Thus, the only thing we can do at this moment is to be cautious when interpreting our estimates for convergence speed and half-life period.

Our panel data estimates, unlike our cross-sectional estimates, yield highly significant results for both spatial coefficients. Summary statistics in the bottom section of Table 7 show that inclusion of spatial parameters increases the explanatory power of our models and produces a better fit for our estimations. Model specification tests presented in Table 9 also indicate that both spatial lag and error dependences should be included into model estimations so the SAC model is suggested as the correct specification. In sum, our results underline the necessity of taking spatial dependence into account in convergence analysis and also point out that Turkish regions are affected by the developments in the neighboring regions.

Table 9 Model Selection Tests of Panel Estimations: LR and Wald

Tests	SAC vs FE	SAC vs SAR	SAC vs SEM
Likelihood Ratio (LR) Test			
-Value	13.466	10.640	7.227
-P-value	0.001	0.001	0.007
Wald Test			
-Value	95.39	57.68	15.07
-P-value	0.000	0.000	0.000

Notes: The LR test is calculated based on minus two times the difference between the value of the log-likelihood function in the restricted model and the value of the log-likelihood function of the unrestricted model. The LR test statistic follows a chi-squared distribution with degrees of freedom equal to the number of restrictions imposed (Elhorst, 2014).

In addition, the presence of significant and positive spatial error dependence obtained through the SEM and SAC models indicates that any random shock originating in a specific region can easily spillover into adjacent regions and propagate throughout the country by resulting in higher growth rates for all regions. The presence of significant spatial lag dependence in the SAR and SAC models implies that there is an endogenous interaction between growth rate of a region and growth rates of its neighboring regions. However, the sign of this interaction (spatial lag coefficient) changes with the inclusion of spatial error dependence in the model (SAC model) and spatial dependence in the spatially lagged dependent variable starts to produce a negative spillover effects. As a result, the presence of significant and negative spatial lag dependence in the selected SAC model asserts that growth rate of income in a region is negatively impacted by the growth rates of its neighboring regions.

In sum, we conclude that there is statistically significant absolute beta convergence in Turkey between 2004 and 2011. In other words, regions that lag behind in income exhibit a relatively better growth performance than rich regions. Moreover, the OLS model is selected as the correct specification for cross-sectional estimations while the SAC model is selected for panel estimations.

CHAPTER FIVE

CONCLUSION

Due to the existence of considerable development disparities across regions of Turkey, regional economic convergence has always been the center of academic studies and policy agenda. With respect to current empirical studies and the literature on convergence, this study aims at providing new insights into the nature of the convergence debate by investigating regional economic convergence over the period of 2004-2011. In fact, the period of the study deserves a special interest in the current academic literature because Turkey has experienced a significant transformation in the regional development agenda after 2000. This transformation has provided a new framework to regional economic convergence, so regional development policies put into practice under the new agenda became a part of regional economic convergence debate. This study, by its nature, incorporates a new dimension into the analysis of nature and trends of convergence patterns in Turkey. On the other hand, while making inferences about the findings of our study, one should be aware of the fact that the existence of regional economic convergence does not associate a direct causal relationship with the success of the new regional development policies, and the period of the study coincides with the 2008 financial crisis.

In addition to the above contributions, we believe our study provides some extra explanations for the existence or absence of regional economic convergence in Turkey. The study was developed by using sigma and beta convergence methods. We also benefitted from recent developments in exploratory spatial data analysis (ESDA) and spatial econometrics. Our findings generally support previous researches in this field, and provide new insights for spatial dependence and geographical dimension of convergence phenomenon.

Results of exploratory spatial data analysis confirm the dualistic structure (east-west division) of economic geography in Turkey and indicate a strong evidence of positive spatial autocorrelation for income levels (GVA per capita) of regions. Significance test produced through randomization approach shows that GVA per capita is not randomly distributed in space. LISA analysis also verifies that high income regions with high income neighbors (HH) are clustered in the western part of the country, and low income regions with low income neighbors (LL) are clustered in the eastern part of the country. We do not see any significant structure of spatial autocorrelation for the regions located in Central Anatolia and Mediterranean Region. In the meantime, spatial autocorrelation diagnostics prepared for the growth rate of GVA per capita highlight weak evidence for spatial dependence. However, LISA statistics and maps point out that HH clusters having high growth rate are located in the lagging behind part (eastern) of the country whereas LL clusters having low growth rate values are located in the developed part (western). These results reveals that regions of Turkey are not independent of each other and rather present similar pattern of movements to their neighbors in terms of both income level and growth rate. Inverse relation and clustering of income level and growth rate in space (high growth rate in lagging regions and low growth rate in rich regions) signalizes a preliminary evidence for the presence of convergence.

Results of sigma and beta convergence analysis support this preliminary evidence and confirms the presence of regional economic convergence in Turkey for the period of 2004-2011. Static measures of regional inequalities employed for sigma convergence imply that dispersion in income level of regions declines from 2004 to 2011. Relative reduction in the dispersion exhibits a very sharp trend in the years 2008 and 2009 when Turkey felt the impact of the 2008 financial crisis. Moreover, inequality increases in the pre-2006 period and in the post-2010 period when Turkey experienced real economic expansion. Thus, our findings are in line with the literature that inequality between regions decreases in the recession periods and increases in the economic expansion periods.

We employed both cross-sectional and panel estimations to test the existence of absolute beta convergence. All of the models imply that GVA per capita growth rate is negatively and statistically significantly associated with initial GVA per capita indicating the evidence for regional convergence. Thus, our empirical findings support the beta convergence hypothesis such that relatively poor regions grow faster than the rich ones. Moreover, we incorporated spatial dependence into our model specifications. While model selection tests of cross-sectional specifications do not support the evidence of spatiality, panel models exhibit statistically significant results for the existence of spatial dependence and indicate SAC model as the correct specification. Our findings point out the role of spatial effects in regional income convergence.

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