FUNCTIONAL REGIONS AND DEVELOPMENT DISPARITIES IN TURKEY

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İZMİR

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ABSTRACT

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In the current thesis, we would like to address two of them. First, in many existing studies, administrative regions are used in terms of spatial units. They might differ from functional regions as economic boundaries do not always coincide with geographical or administrative boundaries (Magrini 2007). In this study, we would like to focus on functional regions and compare the results provided by NUTS-2 regions. Second, in the calculation of HDI, the majority of studies have used traditional income, education, and health indicators. However, we think that employment and the labor market is a very crucial aspect that employment/unemployment directly points to a welfare loss. Hence, we would like to incorporate the employment rate in the calculation of HDI analysis.

We focused on 26 NUTS-2 Turkish regions and functional 26 regions detected by Burak Beyhan's (2019) study. The period of the analysis is between 2009-2018. In terms of methodology, the explorative maps, Local and Global Moran’s I, Kernel Density estimations, and spatial panel regressions are employed. Our analyses revealed 4 main results. First, there are sizable differences in human development across regions in Turkey. Second, the level of disparities was observed as worse when functional regions are used instead of NUTS-2 regions. Third, convergence across regions in development is more evident and pronounced under functional regions whereas no/weak such pattern is observed for NUTS-2 regions. Four, the development disparities are observed in a spatially correlated manner.

Keywords: *Regional Development, Functional regions, HDI, Employment rate, Panel Regression analysis*

ÖZET

TÜRKİYE'DE FONKSİYONEL BÖLGELER VE GELİŞMİŞLİK FARKLILIKLARI

Bu tezin amacı bölgeler arası gelişmişlik farklılıkları üzerine olan literatürün yöntemsel iki sorununu araştırmaktır. Birincisi, ilgili yazın analizlerinde çokça idari bölgeleri kullanmış, işlevsel bölgeler genellikle göz ardı edilmiştir. İşlevsel bölgeler ile idari sınırlar her zaman örtüşmemektedir (Magrini 2007). Bu çalışmada resmi Düzey-2 bölgeler ile Burak Beyhan'ın (2019) çalışmasında bulunan işlevsel bölgeler, gelişmişlik farklılıkları bakımından analiz edilmiş ve karşılaştırılmıştır. İkinci yöntemsel sorun olarak, ilgili yazın gelişmişliği ağırlıklı olarak İGE (İnsani Gelişmişlik Endeksi) kullanarak araştırılmıştır. Ancak bu ölçüt, gelir, eğitim ve sağlık göstergelerini içerirken, çok önemli bir sosyal değeri olan iş piyasası göstergelerini (istihdam ve işsizlik gibi) dışlamıştır. Bu çalışmada İGE, istihdam oranlarını da içerecek şekilde hesaplanmıştır.

Araştırma Türkiye'nin 26 bölgesi üzerine olup, 2009-2018 dönemini kapsamaktadır. Kullanılan yöntemler, haritalar, Global ve Yerel Moran I, mekansal regresyonlar ve Kernel yoğunluk tahminlerinden oluşmaktadır. Analizler 4 temel sonucu doğurmuştur: Birincisi, ülkemizde bölgeler arası gelişmişlik farklılıkları önemli bir boyuttadır. İkincisi, Düzey-2 bölgeleri yerine işlevsel bölgeler kullanıldığında gelişmişlik farklılıkları daha da yüksek bulunmaktadır. Üçüncüsü, işlevsel bölgeler arasında gelişmişlik yakınsaması gözlenirken aynı eğilim Düzey-2 bölgeler arasında gözlenmemektedir. Sonuç olarak, gelişmişlik, mekansal kümeler şeklinde gözlenmektedir.

Anahtar kelimeler: *Bölgesel gelişme, İşlevsel Bölgeler, İGE, İstihdam oranı, Panel regresyon analizi*

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LIST OF ABBREVIATIONS

UNDP: United Nations Development Programme

HDI: Human Development Index

TURKSTAT: Turkish Statistical Institute

OECD: Organisation for Economic Co-operation and Development

SPO: State Planning Organization

EU: European Union

SEGE: Ranking Of Socioeconomic Development

CHAPTER 1

INTRODUCTION

1.1. Motivation

In the literature on regional development, several theoretical and empirical studies have tried to investigate the level of development disparities, their underlying causes, consequences, and the evolution of these disparities over time (Marchante et al, 2006; Hardeman et al, 2014; Silva et al, 2013).

Human Development is referred to as a critically important issue for human well-being and policies. Awareness of the level of such disparities and recent tendencies shed light on possible policies to be applied. For instance, if the underdeveloped (or recently less developing) places are well known, it will be possible for policymakers to direct sources to these places. In such cases, the subsidies and promotions will be directed to these regions. Possibly, employment and income creating sectors such as industry, and manufacturing will be supported. Education and health infrastructures will be more improved in these places. Therefore, it is very crucial to know which regions are less developed and what are the recent tendencies in development disparities. Indeed, in many developing countries, there is a wide gap between regional levels of development (i.e. 4-5 times).

In theory, streams are approaching optimistic and pessimistic to the development disparities on the one hand, Neo-Classical convergence hypothesis claims declining disparities in income as the less developed places will experience higher growth in the long run due to diminishing returns on capital accumulation (Solow, 1956; Barro and Sala-I Martin, 1992). On the other hand, alternative approaches such as Cumulative Causation/Growth Pole theory streams adopt a pessimistic view and claim that disparities can hardly decrease as the economic growth evolves cumulatively, favoring the already developed places (Myrdal, 1957; 1958; Perroux, 1970).

Empirically, development literature has invented measures of human development. The most well-known one is the HDI (Human Development Index) calculated for countries by UNDP.[1] It combines income level, education, and health indicators of countries. In Turkey, Unal (2008), Yildirim, et al (2007), and Gezici et al (2007), have studies related to the regional income/development disparities by referring to these conventional measures. However, the issue is far less studied for regions and several shortcomings may be addressed.

1.2. Problem and Contribution

Methodologically, this literature has some drawbacks and gaps. We would like to address them and extend the empirical literature in two main directions.

1. In many existing studies, administrative regions are used in terms of spatial units. However, many authors emphasize the importance of functional regions since they avoid the nuisance effect and indicate compact economic zones (Karlsson et al, 2006; Beyhan, 2019). Most of the time, the administrative regions or NUTS level regions are adopted by official statistical institutes. However, they might differ from functional regions as economic boundaries do not always coincide with geographical or administrative boundaries (Magrini 2007). It is discussable whether TURKSTAT's NUTS-2 regions represent well the functional regions. In this study, we would like to focus on functional regions and compare the results provided by NUTS-2 regions

2. In the calculation of HDI, the majority of studies have used traditional income, education, and health indicators. However, we think that employment and the labor market is a very crucial aspect that unemployment directly points to a welfare loss. Hence, we would like to incorporate the employment rate to the calculation of HDI (as also suggested by Mıhçı et al, 2012).

1.3. Aim of Study and Research Questions

The purpose of this thesis is to investigate the level and evolution of development disparities across Turkish regions by applying the methodological innovations explained above.

Our research questions are as follows:

i. Are there sizable development disparities across regions?

[1] http://hdr.undp.org/sites/default/files/hdr2019.pdf

ii. Do these disparities decline over time?

iii. Do results change when functional regions are used instead of official NUTS-2 ones?

iv. Do results change when employment rate is incorporated into development measure (HDI)?

v. Do regional development patterns exhibit spatial dependence?

We focused on 26 NUTS-2 Turkish regions and functional 26 regions detected by Burak Beyhan (2019)'s study. The period of analyses is between 2009-2018 years.

In terms of methodology, explorative maps, Local and Global Moran's I, Kernel density estimations and spatial panel regressions are employed.

1.4. Organization of the Study

The study consists of five chapters. After the introduction, there is a literature review section. Literature on regional typology is described in this section, which includes different theoretical and empirical studies. Regional delimitation studies are summarized. In the last part of the literature review, theories of regional development disparities are explained.

Data and methods are described in Chapter 3. Per capita GDP, bachelor rate, and life expectation in functional and TURKSTAT NUTS2 regions were organized. Moran's I, Kernel Density, and Panel regression methods were used.

Chapter 4 presents the results of the study. In Chapter 5, we provide concluding remarks and policy discussions.

CHAPTER 2

THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1. Regional Typology and Functional Regions

In the literature on regional typology, several region types are depending on the definition of boundaries (Özçağlar, 2003). Over the last few decades, the impact of globalization has changed the scale of economic investments, and regional development has been adopted as part of national development. Hence, approaches to regional development and the definition of regions have also been evolving in these years.

This section is devoted to accounting for the regional typology and definitions of different region types along with their basic features. Particular attention is paid to the functional regions.

The first important research on the stratification of settlement centers in an area covering the whole country, with a method that can be considered valid for Turkey, was made in 1969 by the Regional Planning Department of the General Directorate of Planning and Zoning of the Ministry of Housing and Settlement (SPO, 1982).

The purpose of the State Planning Organization's research on the Grading of Settlement Centers in Turkey, which forms the basis for functional zoning in Turkey, is determined as addressing the spatial dimension of development planning in order to use economic and social development resources effectively and efficiently. Villages are considered as the basic settlement unit, 67 province centers, 572 district centers and 35,997 sub-districts and villages identified in the 1970 census are included in the present research. Indicators such as population size, immigration status, transport links are used. As a result, after examining the stratification pattern of the settlement centers and the pattern of their influence areas, it is revealed that the developments and changes in the socio-economic structure are effective on the structure and stratification of the space, even if they are not always and everywhere at the same intensity (SPO, 1982).

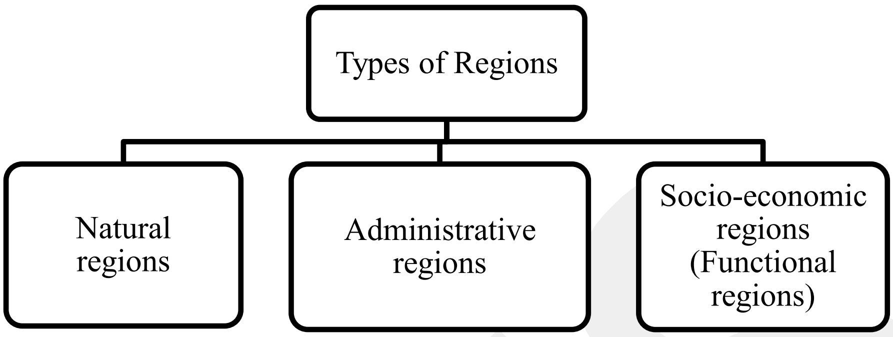

Figure 2.1. Types of Regions (Source: Author's own work)

The types of regions were separated into three main headings such as natural, socioeconomic, and geographical regions. Natural regions are similar regions of landforms, climatic characteristics, hydrographical features, fauna, or soil features. Geographical regions have a resemblance to natural and socioeconomic characteristics (Özcağlar, 2003). Socio-economic regions (Functional regions) are classified as residential, population, culture, raw materials, industry, and service regions (Özcağlar, 2003).

The secondary activity of natural events shapes natural regions. Types of natural regions include Geomorphogenetic regions, Climatic regions, Hydrographic regions, Floristic regions, Fauna regions, Pedogenetic regions, and Natural Disaster regions (Özçağlar, 2003).

The similarity of landforms determines geomorphogenetic regions. For instance, the North Anatolian Mountains, Konya Plain, Mississippi Delta are geomorphogenetic regions. Climatic regions are based on climate types. Hydrographic regions are shaped by oceans, rivers, lakes, and streams, as well as their feeding grounds. Natural vegetation, which develops under the control of climate, elevation, slope exposure, and ground cover, forms Floristic regions. Animal communities having similar characteristics form fauna regions. Pedogenetic regions take shape depending on the nature of the ground cover. Natural disaster regions are created to determine the negative effects of earthquakes, landslides, avalanches, etc (Özçağlar, 2003).

Özçağlar (2003) states that administrative regions are service regions, like the socio-economic regions. Contrary to this expression, some researchers claim that administrative regions do not have economic homogeneity (Prodromidis, 2006; Cörvers, 2009). Karlsson et al. (2006) report that functional regions include some administrative regions between 1986 and 1996 years. Therefore, some local governments are charged with planning a functional region. Eventually, this planning problem causes the identification of functional regions for the labor market and infrastructure planning.

Humanity depending on its knowledge, experience, and behavior establishes the socio-economic structure. It has enabled the formation of Socio-economic regions. Socio-economic regions are classified based on settlement status, population, raw material production, industry, and service production. They are called functional regions (Özçağlar, 2003).

According to the traditional approach, the boundaries of the region are determined depending on geographical proximity. This perspective has been replaced by an identifying functional region which includes the network of economic relations and regional functions being the main indicators.

The functional region has the highest frequency of economic movement within the regions. The most fundamental characteristics are an integrated labor market, intense intra-regional commuting, job creation, and job search (Konjar, 2010).

According to Farmer (2011), the functional region overlaps the borders of the local labor market, where employers seek jobs, and inexperienced job seekers go to find employment. Karlsson et al. (2006) explain that the purpose of identifying functional regions is to aggregate areas with high economic interaction, and intense commuting patterns (daily labor flow) are observed within the functional regions.

There are two common views on region identification: the first one is that regions consist of homogeneous space and entities, and the second one is based on "interaction" between region analyses. Depending on the latter view, the functional region definition can be made as follows: the functional region is where the interaction within the group is greater than the interaction with other groups (Brown, 1971).

The advantage of identifying functional regions is that it makes for a more comprehensive diagnosis of countries. Economic functional regions are defined to classify economically disadvantaged areas so that issues can be solved more quickly and effectively. They also make it easier to compare regions within and between countries (Cattan, 2002).

Klapka (2014) states that the functional region which is the smallest spatial unit created to allow spatial analyses is used in large areas. Functional regions defined by accurate analysis can be useful not only in geography or spatial planning but also in the regional economy and management decisions.

OECD defines functional regions in order to understand urban areas and to evaluate national policies in OECD countries. Urban areas determined in cooperation with OECD and EU are defined in harmony with functional economic units. Thus, the restrictive effect of administrative regions is overcome. The definition of urban areas in OECD countries uses population density to identify urban cores and travel flows to determine hinterlands that are highly integrated with labor market cores. Indicators are defined as population, GDP, surface, urbanised area, sprawl index, air population, employment-unemployment rate.[2]

Administrative boundaries are used to plan regions in Turkey. The number and size of connections among basic spatial units in a country are variable. In Turkey, these boundaries are depending on NUTS-2 regions. Functional regions are identified by Beyhan (2019) as districts consisting of basic spatial units and commuting flows being basic variables.

Crone (2005), a well-known economist, claims that short-term business cycles in functional economic regions can be similar to each other. Furthermore, he notes that ideal functional economic regions can be defined by analyzing asynchronicity among business cycles and treating geographic proximity as the restrictive factor.

In particular, the concepts of geographical proximity and homogeneity play an important role in the understanding of traditional zoning. These keys are starting to take on a restrictive function rather than a definitive function.

2.2. Empirical Studies on Functional Region Delimitation

To investigate the studies on the functional region delimitation, results of numerous empirical studies carried out at different countries are summarized in Table 2.1.

[2]https://www.oecd-ilibrary.org/deliver/d58cb34d-en.pdf?itemId=%2Fcontent%2Fpaper%2Fd58cb34d-en&mimeType=pdf

Table 2.1. Empirical Studies on Functional Region Delimitation (Source: Author's own work)

Author(s)	Year	Country	Period	Main Method and variable	Region type
BROWN et al.	1971	UK	1951	Hierarchical Clustering (Functional distance analysis, Markov chain analysis) / Journey to work	Functional regions, Nodal regions
PRODROMIDIS P.	2006	Greece	2001	Clustering / Income per capita, labor activity	Functional economic regions
KARLSSON	2006	Sweden	1986, 1996	Aggregation / Commuting data, Labor market data	Functional
MITCHELL W.	2010	Australia	2001	Aggregation (The Intramax Method) / Unemployment rate, labor force participant, employment, JTW	Functional
KONJAR M.	2010	Slovenia	2002	Aggregation / Commuting to work, daily interaction in the labour market	Functional
FARMER J.	2011	Republic of Ireland	2006	Aggregation / Commuter population	Functional
KLAPKA et al.	2014	Czech Republic	2001	Clustering (CURDS, Smart's measure) / Commuting data	Functional
BEYHAN B.	2019	Turkey	2010	Clustering (FRGIS) / Commuting flow, Graph Theoretical Geodesic Distance	Functional

Three methods used to define the functional region are as follows: 1-Hierarchical Clustering, 2-Multistage Aggregation, and 3-Central Place Aggregation (Farmer, 2011).

For the first time, a research on UK functional regions is conducted by Brown and Holmes (1971) who used the journey to work as variables and Hierarchical Clustering as a method in order to define functional regions. Prodromidis (2006), Klapka and Halas (2014), and Beyhan (2019) applied Clustering Method in their studies. Besides, Mitchell (2010), Konjar (2010), and Farmer (2011) put into account the Aggregation Method to determine the functional region.

The concept of a journey to work (JTW) is not sufficient alone to determine a functional region. In functional zoning, the movements of people depending on their economic choices should also be taken into consideration (Mitchell, 2010).

Functional regions, which show social and economic relations in the country, are usually determined using labour mobility (travel to work, commuting flows). The functional region is expected to be a self-sufficient region where supply-demand balance is achieved. The general framework for definitions of functional regions should show socio-economic analyses, labour market-related structural analyses, and development disparities (Cattan, 2002).

Overall, while different clustering and aggregation methods are applied in the literature, majority of the studies have employed labor mobility/commuting in terms of variable.

2.3 Regional Development Disparities

2.3.1 Theories behind regional inequalities

Among a large number of theories in this field, we can classify them into two as **optimistic** and **pessimistic** ones about the future of regional inequalities.

Optimistic Theories:

New-Classical growth theory and its proponents are quite hopeful for the elimination of income inequalities (Solow, 1956; Barro and Sala-i Martin, 1992). It mostly relies on the New Classical production theory:

The production function is often Cobb-Douglas type. It is represented by the following equation $Y = AK^{\alpha}L^{1-\alpha}$ or in per capita terms $y = Ak^{\alpha}$ where K: Capital, L: Labor, A: Technology (Solow, 1956; Barro and Sala-i Martin, 1992).

Countries/regions with lower k, can fastly increase production whereas countries/regions, which have a high level of k, can hardly grow.

It relies on the diminishing marginal returns assumption that suggests declining productivity of capital and labor over time. In other words, economic growth is higher at the initial stages of the capital accumulation process than in the later stages. It, thus, suggests a convergence hypothesis that claims "poorer countries/regions growing faster than the richer ones" catching up with them in the long run and converging to the same steady state. Hence, in the long run, incomes are equalized.

The modifications of this theory are continued with Endogenous Growth Theories. It is suggested that convergence to steady-state is conditional upon technology development, R&D, innovation (Romer, 1990) development of human capital (Lucas, 1988), and governmental (public) spendings (Barro,1992). In other words, endogenous growth models predict a possible balanced growth rate at the steady-state depending on the level of conditions above.

Pessimistic Theories:

Cumulative Causation Theory and, related, Growth Pole theories, as well as, New Economic Geography adopt a pessimistic view on regional inequalities.

Cumulative Causation Theory is written by Myrdal (1957; 1958). The main message of the theory is that once a region grows by increasing its exports, it will grow cumulatively more and widen the income gap with surrounding regions. One time increase in exports brings more production that leads to expertise/productivity in that sector and an increase in competitiveness against other regions. Hence, this region can offer lower export prices which brings another economic growth. This circular mechanism creates widening gaps between this region and surrounding ones. A similar model is offered by Dixon and Thrilwall (1975) which states that the same circular mechanism occurs with R&D and technology development of one region that grows cumulatively more and more.

The results of this stream of theories are consistent with Perroux's Growth Pole theory that predicts economic development taking place in particular growth poles/nuclei (Perroux, 1970).

As another pessimistic theory, New Economic Geography is written by Krugman (1990; 1991). He relates the economic growth to the agglomeration patterns. Economic agglomeration occurs in regions if centripetal forces (such as closeness to markets, the existence of ports, better infrastructure, transportation, knowledge, qualified labor force, etc.) outperforms the centrifugal forces (such as high land and labor cost).

Once agglomeration occurs in a region, it helps increase productivity and economic growth. It also attracts labor and investments as there is potential for growth and job incentives. Hence, it is expected that these regions' grow more and wider regional inequalities are consequently observed.

Hence, it is obvious that theoretical discussions are far from a consensus. The related debate is also ongoing for empirical studies.

2.3.2. Empirical studies on regional development disparities

In this section, findings obtained from many observational studies related to regional disparities performed at various countries focusing on present subject are summarized in Table 2.2.

The results vary considerably depending on the period analyzed as well as the study place (country) and the type of spatial units.

Table 2.2. Empirical studies on regional development disparities (Source: Author's own work) (Cont. to Page 12-13)

Author(s)	Year	Country	Period	Main Method and variable	Main Results
DHOLAKIA	2003	India	1977-1980, 1997-2000	Regression / Human Development Index (HDI)	Decreasing regional disparities

KARACA	2004	Turkey	1975, 2000	Regression / Income per capita	Increasing income disparities, Divergence
MARCHANTE A. & ORTEGA B.	2006	Spanish	1980-2001	Descriptive Analysis, Regression / Augmented Human Development Index (AHDI), per capita Gross Value Added	Convergence in AHDI is higher than PCVA
GEZİCİ F. & HEWINGS	2007	Turkey	1980-1997	Theil Index, Global and Local Moran I's tests / per capita Gross Domestic Product	Increasing interregional inequalities, Decreasing intraregional inequalities
YILDIRIM & ÖCAL	2007	Turkey	1987-2001	Theil Index, Geographically weighted regression (GWR) / GDP per capita	Increasing interregional inequalities
JAMAL HAROON.	2007	Pakistan	1998-2005	Min.-Max. Method/ Human Development Index (HDI)	Evaluating HDI in districts of Pakistan
ÜNAL Ç.	2008	Turkey	2003	Min.-Max. Method / Human Development Index	Evaluating regional HDI, important differences.
YANG	2008	China	1982, 1995, 1999, 2003	Cluster Analysis / Human Development Index (HDI)	Evaluating HDI in provinces of China
ERSUNGUR M. & POLAT, Ö.	2010	Turkey	1987-2000	Regression / per capita Gross Domestic Product	Low Convergence in NUTS I Regions of Turkey

SILVA	2013	Portugal	2004-2009	Min.-Max. Method / Portuguese Regional Development Index (PRDI)	Decreasing in the dispersion in all dimensions, except education, in NUTS III Regions of Portugal
HANDEMAN S.	2014	The EU member states	2012	Min.-Max. Method / Europan Unions Regional Human Developmen Index (EU-RHDI)	There are regional differences in human development success across countries.
ÖZPINAR et al.	2016	Turkey	2013	Min.-Max. Method/ Human Development Index (HDI), Local Human Development Index (LHDI)	Depending on LHDI, the west of Turkey has a high level of development, while the east has a middle level.
GÜLEL et al.	2017	Turkey	2013	Min.-Max. Method/ Human Development Index (HDI)	In Turkish cities, there is no comprehensive prosperity.

The majority of studies carried out in different countries find decreasing disparities in Human Development. Some studies conducted by Dholakia (2003), Marhcant and Ortega (2006) and Silvia (2013) on India, Spain and Portugal are given as example for these studies.

In Turkey, however, there are two streams of research. The first one focuses on regional income disparities whereas the second one analyzes the inequalities in the Human Development Index.

Regarding the former stream, some researchers examine disparities based on income level (Karaca, 2004; Marchante et al, 2006; Gezici et al, 2007; Yıldırım et al, 2007; Ersungur et al, 2010). Besides, the Human Development Index, or indexes created by the authors themselves, is also used to measure disparities. The study periods related to regional disparities are mainly between the 1970 and 2000 years. In general, the authors use regression methods. Althouıgh the results depend on the period analşyzed, it is found in general increasing income disparities during a period between 1975-2000. The post-2000 period is far less analyzed but the findings may favor the income convergence.

Regarding the second stream, it is generally found important differences across regions/provinces but the evolution of these disparities are not obvious.

Some examples of these studies are worth mentioning. Human Development Index was calculated by Gülel et al (2017) in 2013. Education, health, and income indexes are the main indexes used in this research, and especially Min-max Method was applied for calculating these indexes. Gülel et al (2017) found that the west of Turkey had a middle human development level. Özpınar et al (2016) discovered the Local Human Development Index using minimum and maximum values among the cities in Turkey. In contrast to previous research, depending on the Local Human Development Index, the west of Turkey had a high human development level. Unal (2003) conducted a study and found remarkable development differences across provinces.

In the 2003 SEGE (Ranking of Socio-economic Development) Research Report, the primary aim of the State Planning Organization (DPT is currently under the Strategy and Budget Presidency) is to determine and sort the socioeconomic development levels of the provinces. The second goal of the State Planning Organization is to obtain developmental rankings of similar provincial groups and geographic regions. The final aim is to make sectoral (industry, education, health) development ranking according to geographical and statistical regional units.[3]

The study emerges as one of the tools for monitoring and evaluating regional development policies in the 2017 SEGE Research Report. Different variables use to refer to the policy-making process of many institutions. GDP is the only variable in the 2017 SEGE report that differs from the 2011 SEGE report.

The first and last SEGE city-based research was conducted in 1969 and 2017, respectively. As state in the 2003 SEGE Research Report, due to differences in data sets and methods, there was no possibility to compare studies as of period series. Instead of research that allows dynamic analysis, studies are static studies that involve a cross-sectional period. One of the main motivations of this thesis is to observe the dynamic

[3] https://www.sanayi.gov.tr/merkez-birimi/b94224510b7b/sege/il-sege-raporlari

evolution of the development disparities, which is not provided by SEGE reports and requires a continous dataset.

As understood from this part, the evolution of development disparities is far from clear cut and there is a need for updated research. Also, it is necessary to develop methodological innovations which are pursued in the next section.

CHAPTER 3

DATA AND METHODS

3.1. Data

In this section, data types and data resources were explained. In this study, Human Development Indexes were calculated in functional and TURKSTAT NUTS2 regions of Turkey for periods of 2009 to 2018 (Figure 3.1, Figure 3.2). The United Nations Development Programme (UNDP) publishes a report on Human Development Indicators every year to give broad measurements of well-being around the world. In this report, Life expectancy, education, and purchasing power parity are the three data dimensions used.

In our study, we have chosen Per capita GDP, Bachelor Rate, and Life Expectancy as the main variables. Besides, the employment rate is the additional variable of this study, as it directly affects the social well-being, regional inequalities, and development level.

In terms of spatial units, we employ TURKSTAT's NUTS-2 regions and the functional regions detected by Burak Beyhan's (2019) study (referring to Beyhan (2019), page 23, Figure 3). Burak Beyhan's study is selected because it is the empirical study that gives the most up-to-date results in Turkey. His study creates functional regions at the district level and convert them into functional regions. We use these regions. In our usage, basic spatial units are provinces whereas Beyhan (2019) uses districts. That's why there may be small differences between Beyhan(2019)'s original study and the classification we use. In our study, NUTS-2 region conversion was decided based on their area. If most of the area of the province is in the functional region, the province is considered to be within that region. We provide TURKSTAT's NUTS-2 regions in Figure 3.1 and functional regions can bee seen in Burak Beyhan's (2019) study (page 23, Figure 3). They visually seem quite different from each other. However, we will provide a mathematical measure of these differences in the results part (chapter 3.2 Methods).

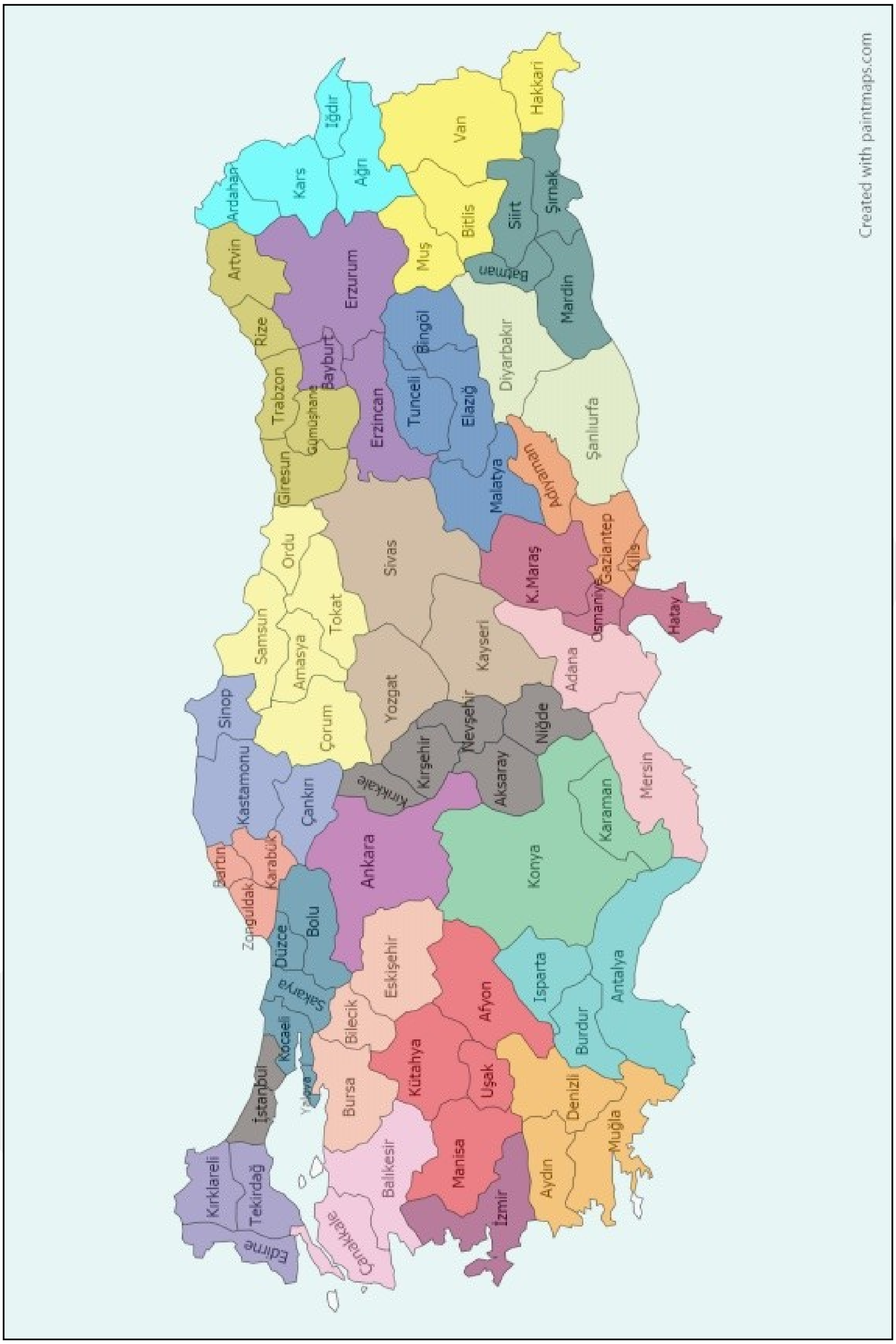

Figure 3.1. TURKSTAT NUTS-2 Regions
(Data Source: TURKSTAT and Author's own work)

Per capita GDP, Number of Bachelor's, and Population were obtained from TURKSTAT. The employment rate is a ratio of the number of active employees to the population. The number of active employees obtained from Social Security Institution (SSI) was calculated by June of each year. Also, Life Expectancy was attained from TURKSTAT only for 2013 and 2016. The arithmetic average was determined and approximate values were defined for other years.

In addition, all data were obtained based on provinces and averaged/aggregated to regions.

3.2. Methods

In terms of methods, firstly, relative development indexes for regions are constructured. To do so, average values concerning bachelor rate, life expectation, employment rate, per capita GDP values (based on provinces) were used for each functional and TURKSTAT's NUTS2 regions. For every 4 values, Relative indexes were calculated using the following formula:

Relative Index: x- min (x1,…,x26)/ (max(x,…,x26)-min(x1,…,x26)) where x is a variable of interest

In our study, HDI is constructued as a composite relative index by the averaging bachelor rate, life expectancy, and per capita GDP relative indexes. HDI - E was calculated by including the employment rate relative index in this average. HDI values for 2009 and 2018 were determined for both region types.

The computed development scores are illustrated by maps. To observe the distributional properties, Kernel Density Estimation was used to calculate the distribution of HDI, and HDI-E values for 2009 and 2018 years.

Local and Global Moran's I techniques were applied for spatial analyses. In statistics, Moran I is a measure of spatial autocorrelation developed by Patrick Alfred Pierce Moran. He states that spatial autocorrelation is more complex than one-dimensional autocorrelation. Spatial correlation is multidimensional and multifaceted. The general approach is base on the relationship between the two regions (Moran, 1950; Anselin, 1995).

Datawrapper was utilized for visualization. Eviews was used to discover Kernel Density Estimation. Lastly, Moran's I was determined via GeoData.

In order to analyze the development convergence, the following panel regression model is used:

$$\ln(Dev_{i,t}) - \ln(Dev_{i,t-1}) = \partial + \beta Dev_{i,t-1} + \exists_{i,t}$$

Dev represents a development indicator whereas i symbolizes regions 1,….26. t denotes between 2009,….,2018 years.

The dependent variable is the growth rate (ln first difference) of development. The independent variable is the initial year's development level of provinces. $\exists$ represents independently, identically and normally distributed error terms.

The four types of development indicators were considered as a variable. The first one is the type calculated by using TURKSTAT's NUTS-2 regions and standard composite HDI including income, health, and education indicators (abbreviated as TURKSTAT-HDI). The second one is the index computed again using TURKSTAT's regions but the development index incorporates the employment rates in addition to existing income, health, and education variables (named as TURKSTAT-HDI-E). The third one is the standard HDI detected by using Burak Beyhan's (2019) functional region definitions (named as BB-HDI). The fourth one is the HDI modified by the inclusion of an employment rate called BB-HDI-E.

As to this model a series of LM tests are applied to understand the severity of spatial dependence and to identify the correct model (Anselin, 1988; Anselin, et al., 1996; Anselin and Arribas-Bel, 2013; Paul Elhorst, 2014).

Additionally, it is important to select the correct panel model. On the other hand, Fixed effects models may be useful that eliminates the region-specific unobserved heterogeneity and handle the endogeneity issue in this way. Otherwise, random effect models may be beneficial when unobserved heterogeneity is observed randomly.

To be able distinguish between the two models, A Hausman test (1978), (Mutl and Pfaffermayr (2011) is applied to examine null and alternative hypotheses:

Ho: Two models are consistent (Random Effect model is more appropriate)

Ha: One model is inconsistent (Fixed Effect model is more appropriate)

As an outcome of the selection process, SEM (Spatial Error Model) appears more significant (Anselin, 1988; Elhorst, 2014). Therefore, it is preferred to be estimated by using the R SPLM package. Both pooling, fixed effect (within), and random effect models were estimated to provide robustness. The final version of the estimated model is as follows:

$$\ln(Dev_{i,t}) - \ln(Dev_{i,t-1}) = \partial + \beta Dev_{i,t-1} + \exists_{i,t} \qquad \exists_{i,t} = \lambda W \exists_{j,t}$$

Where λ represents the spatial spillovers in the error terms of the two regions. W symbolizes the spatial weight matrix in the form of raw standardized inverse distance. Half life of convergence rate (ln(2)/beta) is calculated as well by referring to the Dogan and Kındap (2019)'s study.

Finally, all results are presented by using tables, graphs and illustrative figures in the next chapter.

CHAPTER 4

RESULTS

In this chapter, the results of the empirical analysis are given. Initially, we start by presenting the maps that show the geographical distribution of development scores computed under different assumptions. In terms of notation, HDI-TURKSTAT represents the Human Development Index determined by employing TURKSTAT's NUTS-2 region classification and traditional HDI. Instead, HDI-E-TURKSTAT denotes the Human Development Index calculated by using TURKSTAT's NUTS-2 regions but the employment rate is added to the HDI calculation. Then, HDI-BB and HDI-E-BB represent respectively the traditional Human Development Index and employment rate added one under Burak Beyhan's (2019) functional region definitions, respectively. All maps are shown for the years 2009 and 2018 that stand for the start and end year of the analysis.

In all maps (Figure 4), developed regions are accumulated in the Western part whereas less developed parts are concentrated in the East and Southern parts.

In the first map (Figure 4.1), it is presented HDI-TURKSTAT for 2009. The most developed regions are TR51 (0.8647), TR10 (0.7345), and TR31 (0.6742) whereas the least developed regions are TRA2 (0.0679), TRC2 (0.0564), and TRB2 (0.0000). As seen, quite sizable disparities exist as the most developed place is about 15-20 times more developed than the least developed regions.

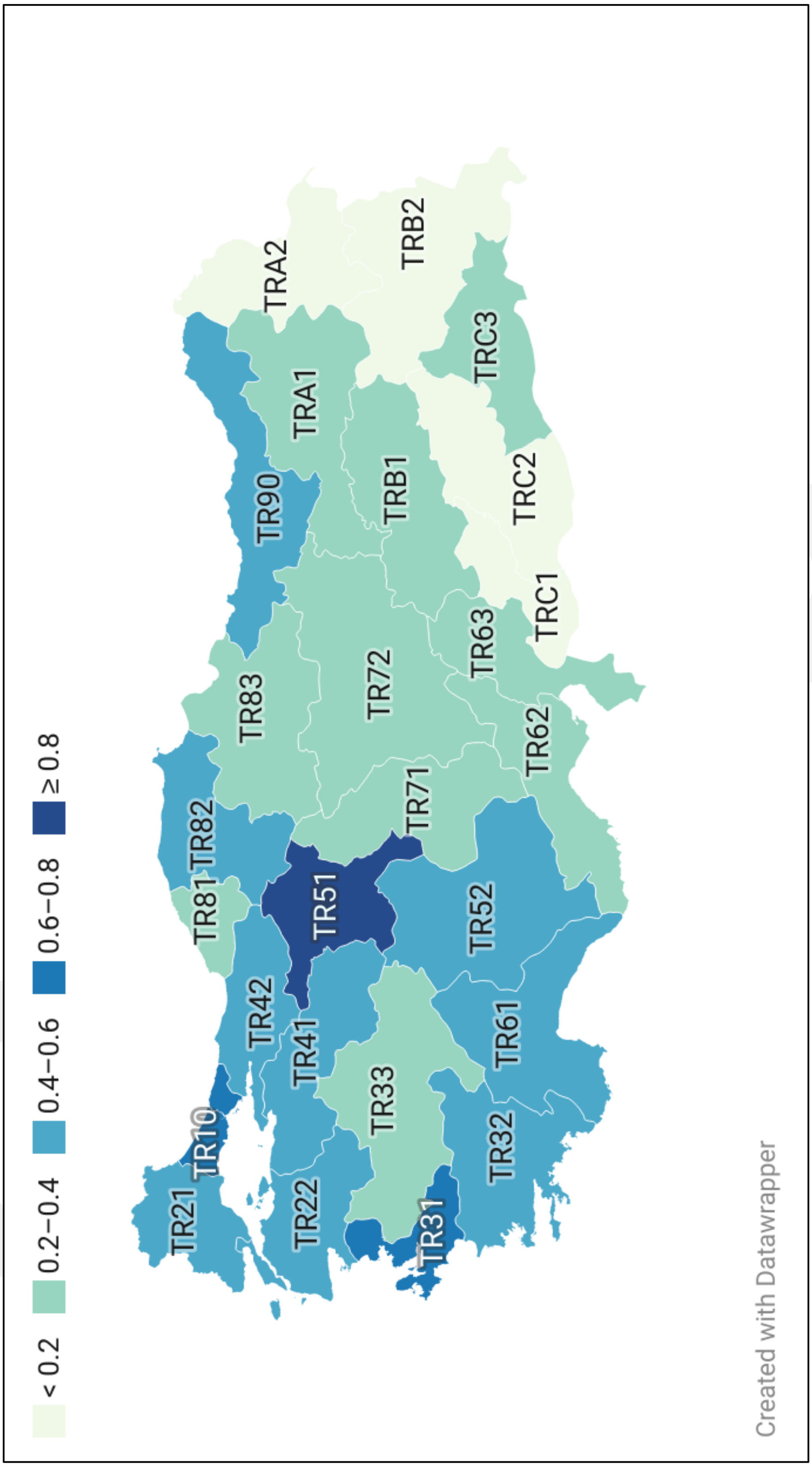

Figure 4.1. 2009 TURKSTAT HDI

(Data Source: TURKSTAT and Author's own work)

In the second map (Figure 4.2), it is presented as HDI-E-TURKSTAT for 2009. The most developed regions are TR51 (0.8985), TR10 (0.7688), and TR31 (0.6900) however the least developed regions are TRA2 (0.0760), TRC2 (0.0423), and TRB2 (0.0038). Similarly, sizable disparities are confirmed.

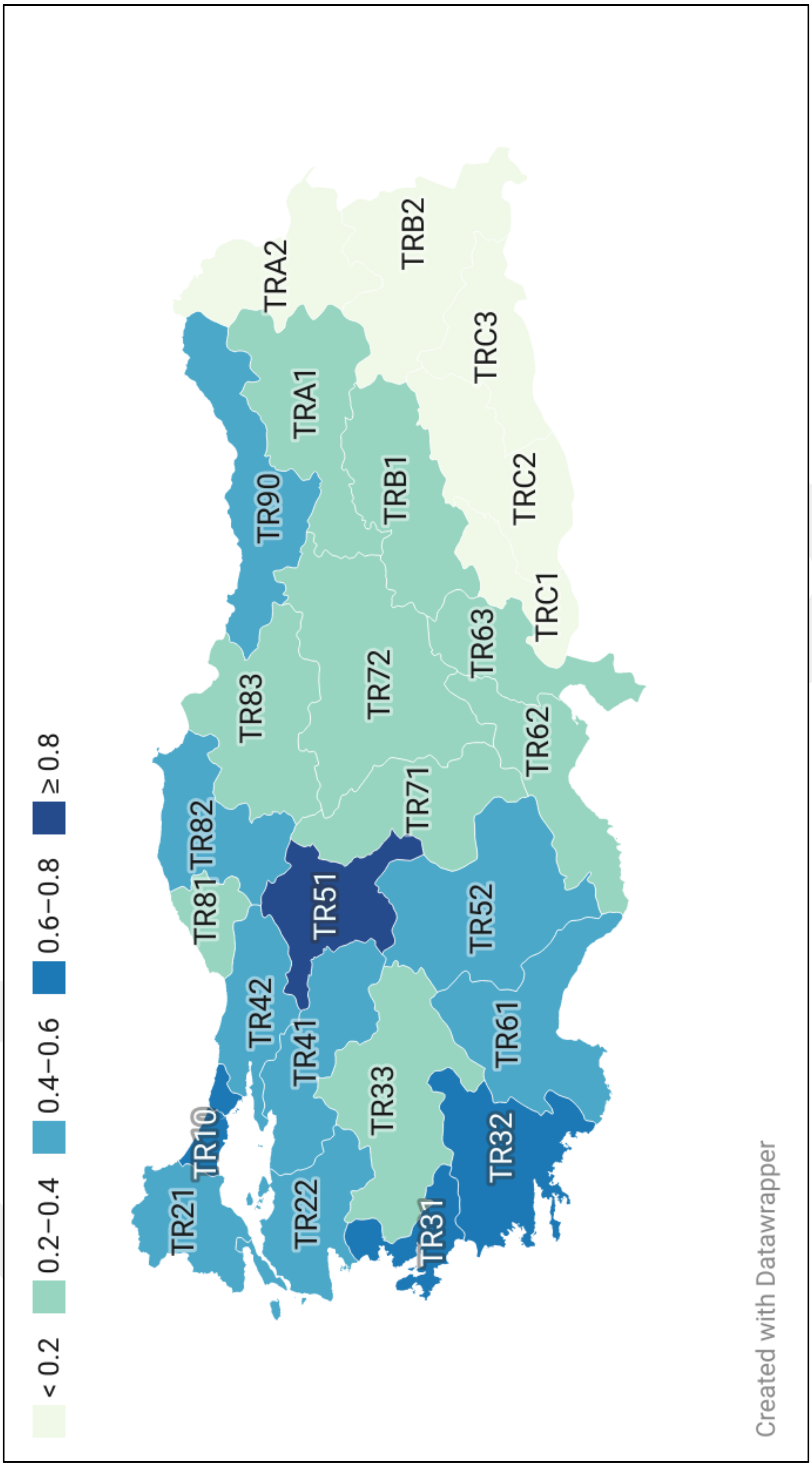

Figure 4.2. 2009 TURKSTAT HDI-E

(Data Source: TURKSTAT and Author's own work)

In the third map (Figure 4.3), it is symbolized HDI-TURKSTAT for 2018. The most developed regions are TR51 (0.8790), TR10 (0.7682), and TR31 (0.6379) while the least developed regions are TR33 (0.2044), TRA2 (0.1334), and TRB2 (0.1326).

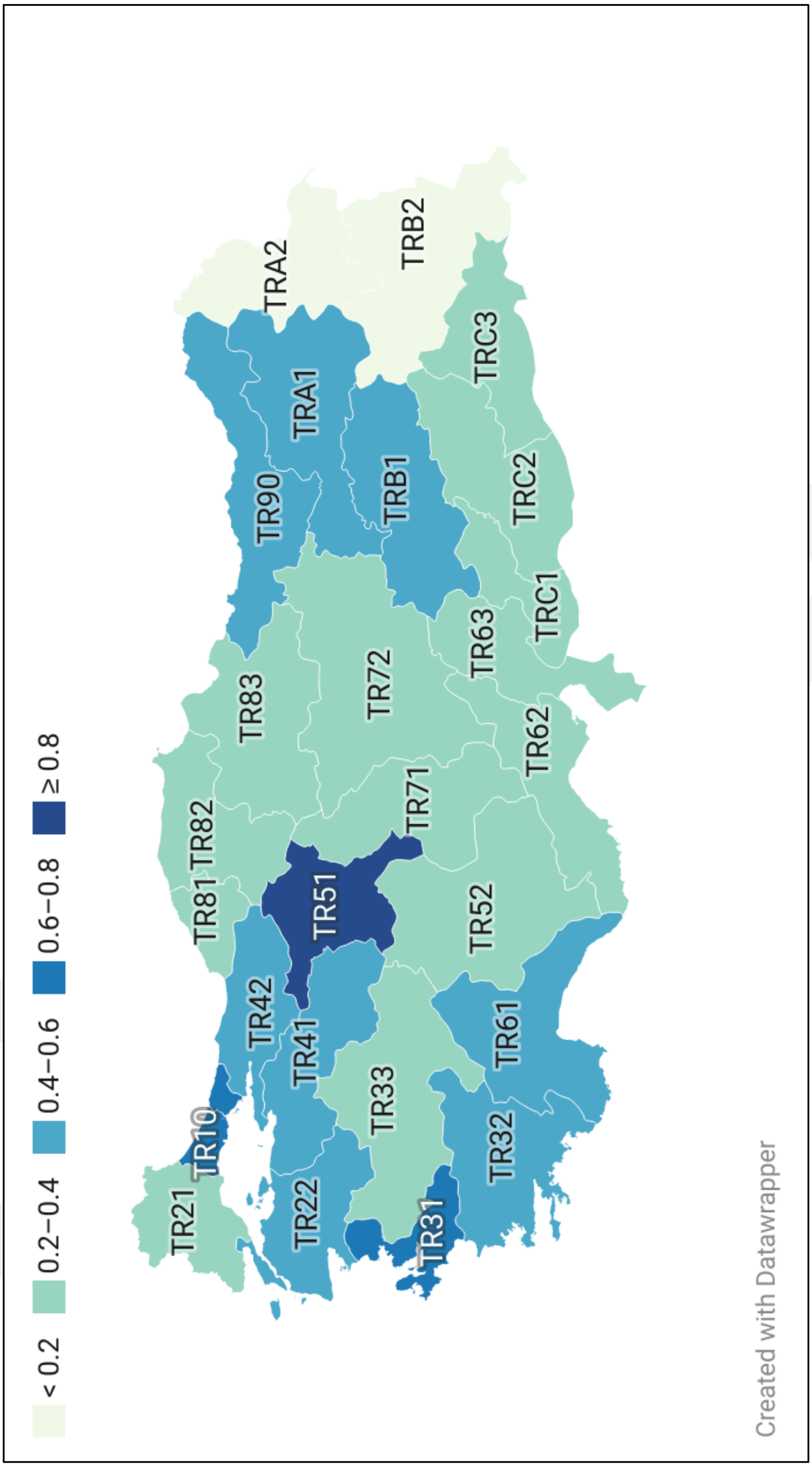

Figure 4.3. 2018 TURKSTAT HDI

(Data Source: TURKSTAT and Author's own work)

In the fourth map (Figure 4.4), it is presented HDI-E-TURKSTAT for 2018. The most developed regions are TR51 (0.9092), TR10 (0.8248), and TR31 (0.6787) whereas the least developed regions are TRC2 (0.1681), TRA2 (0.1528), and TRB2 (0.1260).

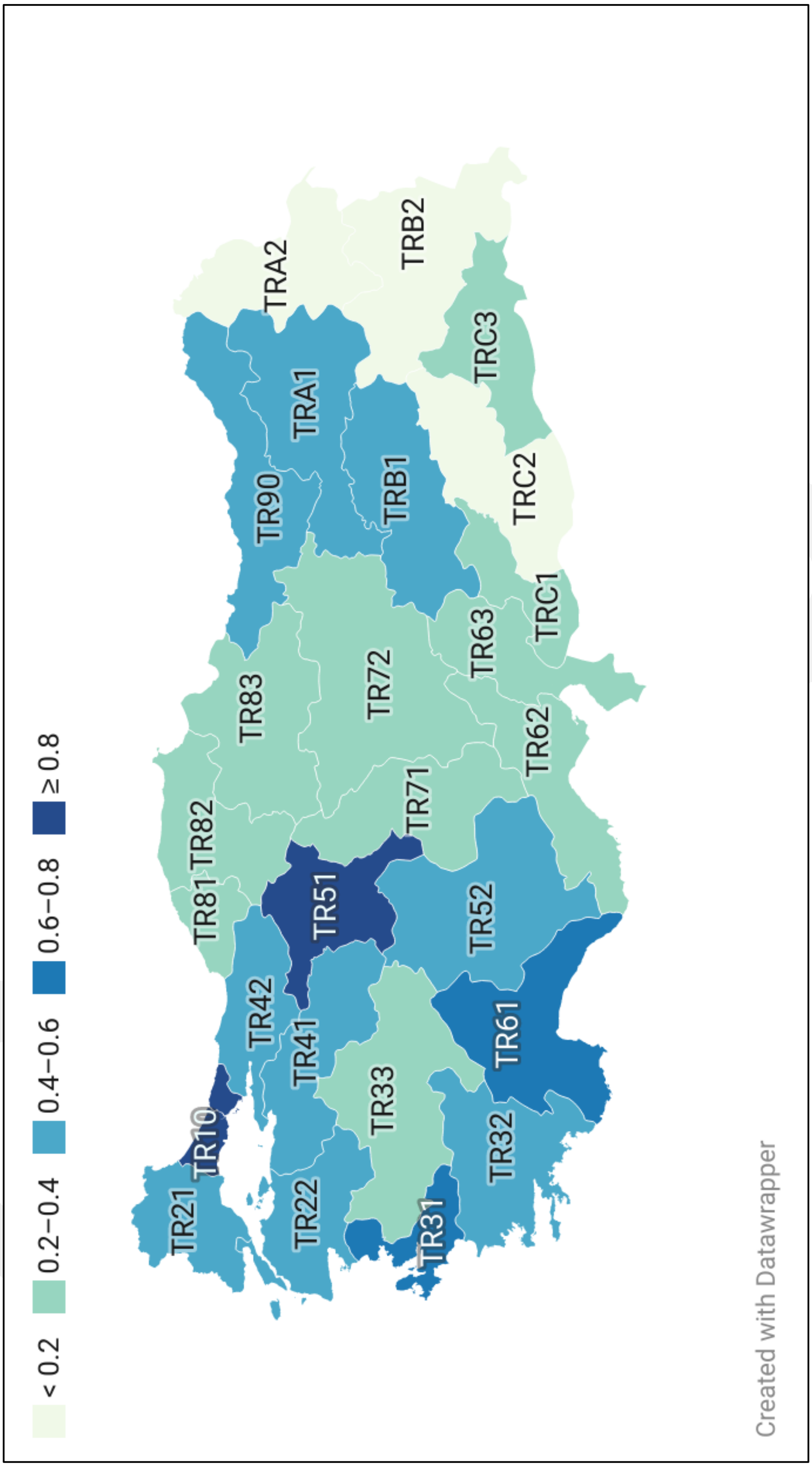

Figure 4.4. 2018 TURKSTAT HDI-E

(Data Source: TURKSTAT and Author's own work)

In the fifth map (Figure 4.5), it is presented HDI-BB for 2009. Metropolitan regions in the Aegean, and Marmara are developed regions. Coastal regions are developed whereas the Eastern Anatolia, and interior regions are the least developed regions. The most developed region is Muğla (0.9344) while the least developed region is Van, and surrounding provinces (0.0268).

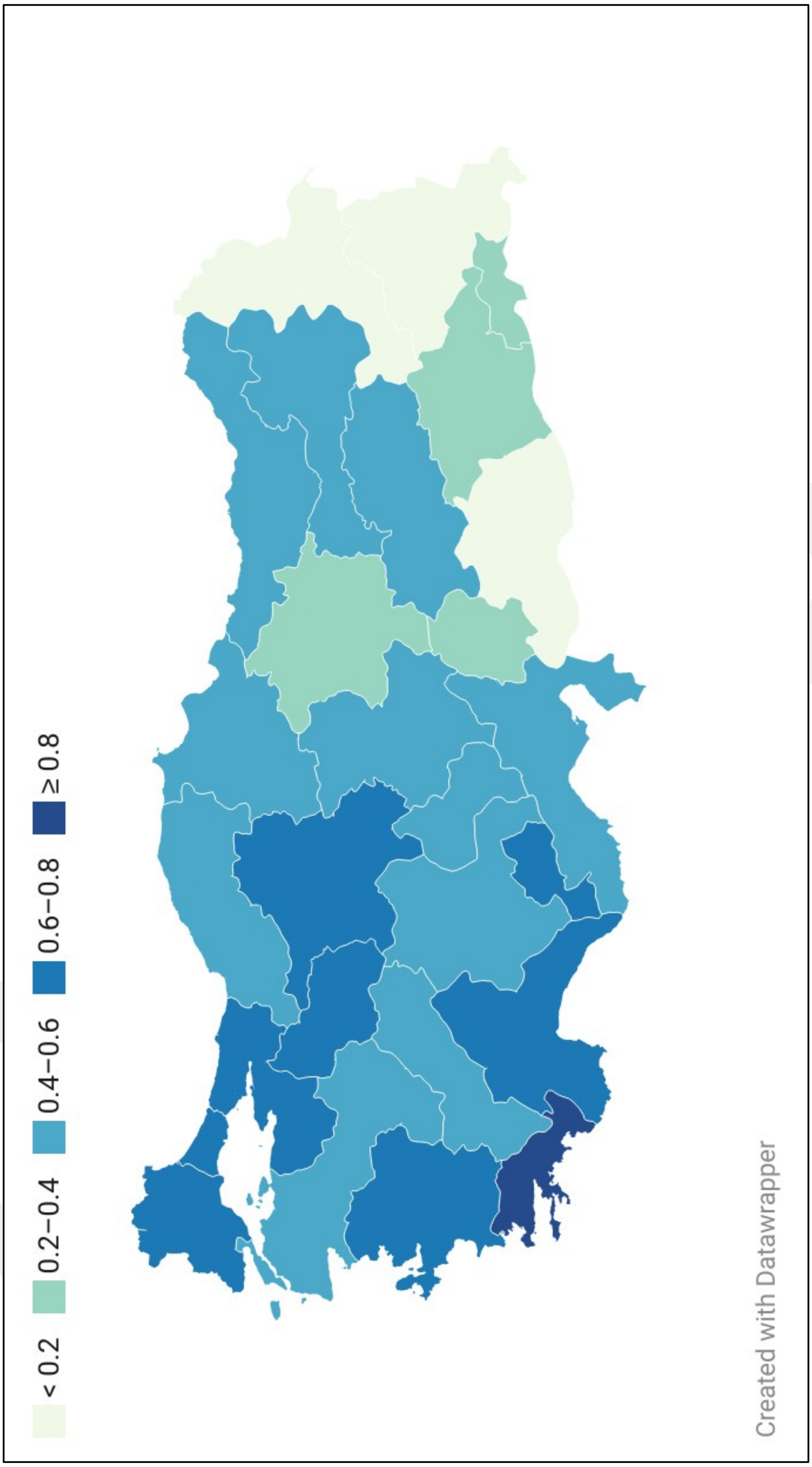

Figure 4.5. 2009 BB HDI (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

In the sixth map (Figure 4.6), it is presented HDI-E-BB for 2009. The most developed region is also Muğla (0.9508) however the least developed region is also Van, and surrounding provinces (0.0289).

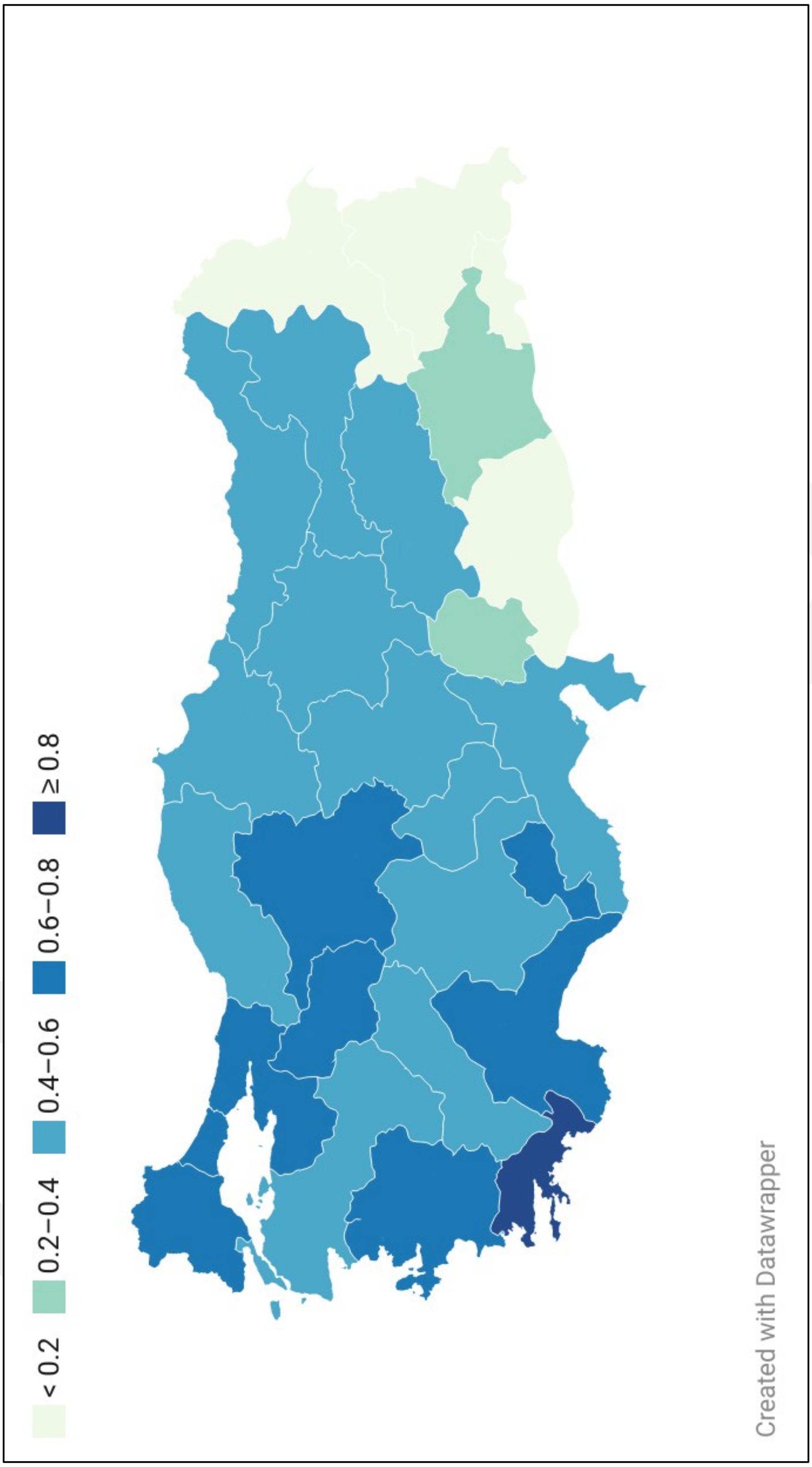

Figure 4.6. 2009 BB HDI-E (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

In the seventh map (Figure 4.7), it is presented HDI-BB for 2018. The most developed regions are Muğla (0.8716), Istanbul and surrounding provinces (0.6824) while the least developed region is Şırnak (0.0300). Metropolitan regions are developed such as Istanbul, Muğla, and Antalya whereas the East, and South of Turkey are the least developed regions.

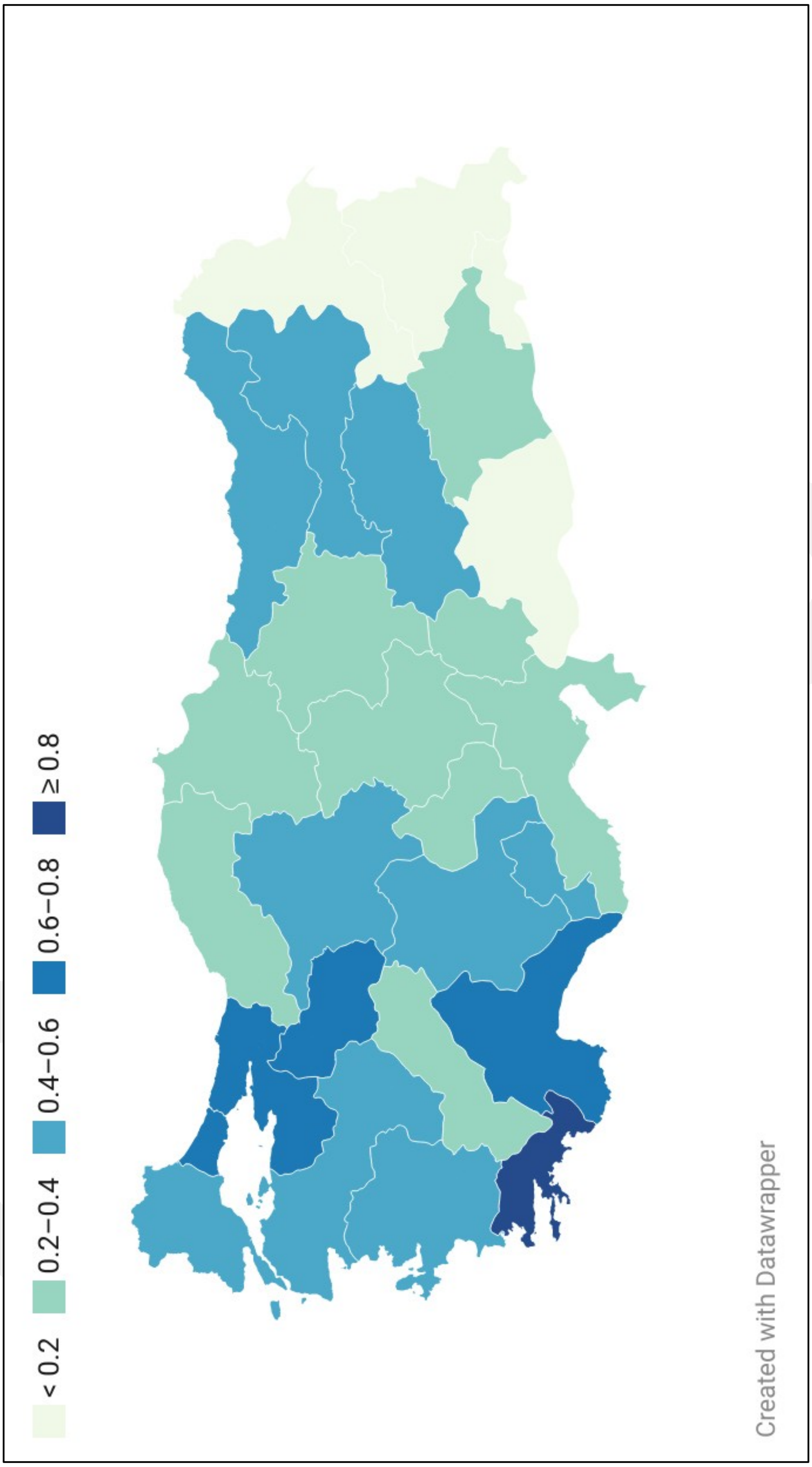

Figure 4.7. 2018 BB HDI (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

On the last map (Figure 4.8), it is presented HDI-E-BB for 2018. The most developed region is also Muğla (0.9037) whereas the least developed region is also Şırnak (0.0293).

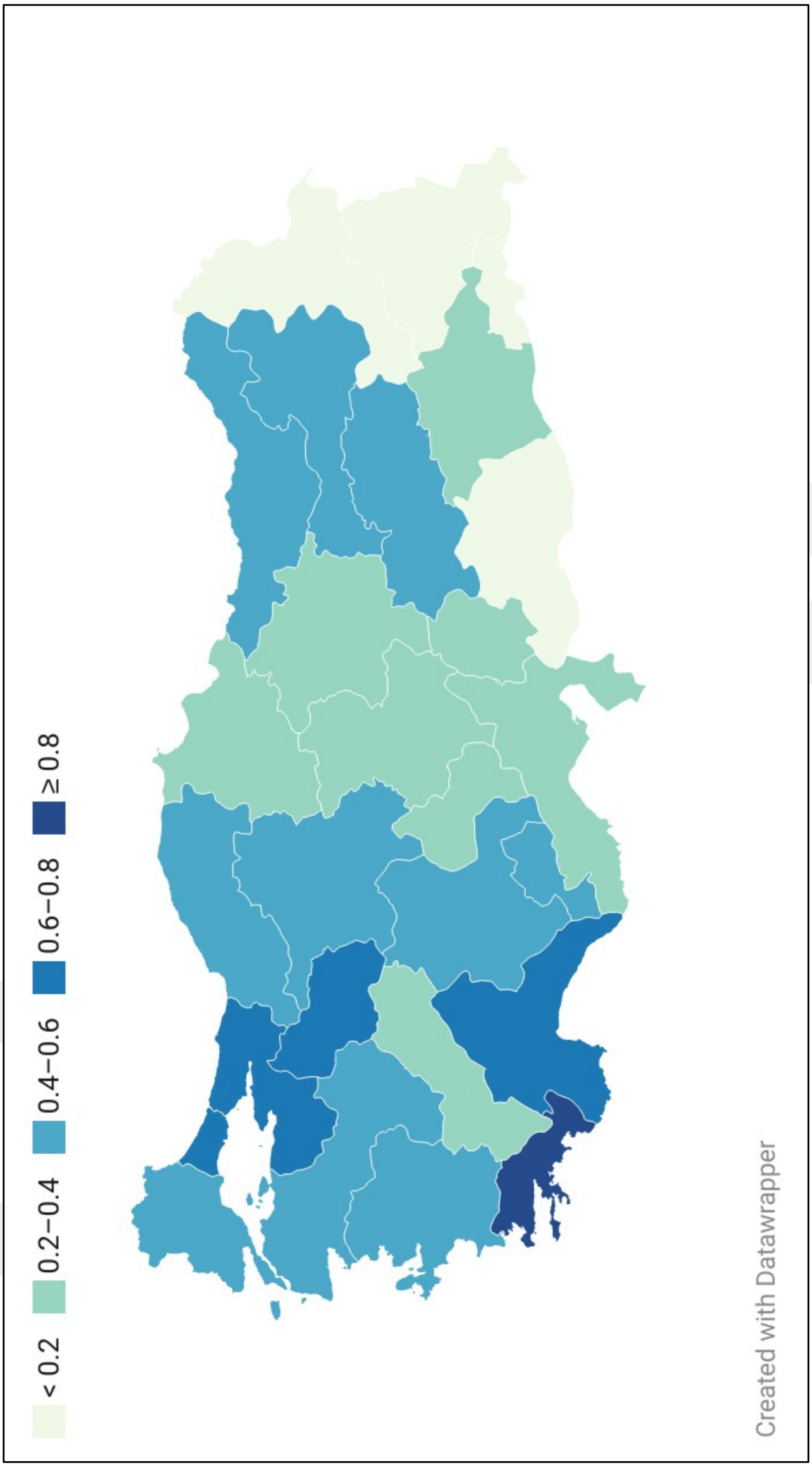

Figure 4.8. 2018 BB HDI-E (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

In 2009, TR32 and TRC3 regions are located in a different layer of development (Figure 4.1.- Figure 4.2). In Figure 4.2, clustering is more strongly. In both maps, the development index of big cities such as Istanbul, Ankara, and Izmir is similar. In addition, HDI values are gradually decreasing from West to East.

In maps of functional regions in 2009 (Figure 4.5 - Figure 4.6), changes are observed for HDI. Far Eastern regions are different from big cities. With the addition of employment rates to the HDI, Southeastern Anatolia (Figure 4.2 - Figure 4.6) experiences a decrease development in both functional regions and TURKSTAT regions. Ankara is the most developed of the TURKSTAT regions, while Muğla is the most developed of the functional regions.

In 2018, TR21, TR61, TR52 and TRC2 regions are located in a different layer of development (Figure 4.3 - Figure 4.4). The employment rate, compared to 2009, is a more decisive indicator of HDI.

On maps of functional regions in 2018 (Figure 4.7 - Figure 4.8), change of HDI is seen in the Western Black Sea. As been in 2009, Ankara is the most developed region in TURKSTAT regions, while Muğla is the most developed of the functional regions.

So, in almost all maps, it is observed quite substantial changes in development patterns under different assumptions as well significant differences between HDI and HDI-E distribution or between TURKSTAT's or functional regions.

In terms of spatial explorative analysis, we first presented the Moran I analysis, along with Moran's scatter plot (Figures 4.9 - 4.12). In all cases, we observed positive and significant moran I's statistics. It indicated that development is observed in a spatially correlated fashion. Highly developed places are surrounded by developed regions again whereas underdeveloped areas are encircled with less developed regions.

In both 2009 and 2018 years, Burak Beyhan's functional regions show a more significant spatial cluster than TURKSTAT, as to Moran's I statistics. In addition, compared to HDI and HDI-E, spatial clustering was observed higher when the employment rate joined to the Human Development Index.

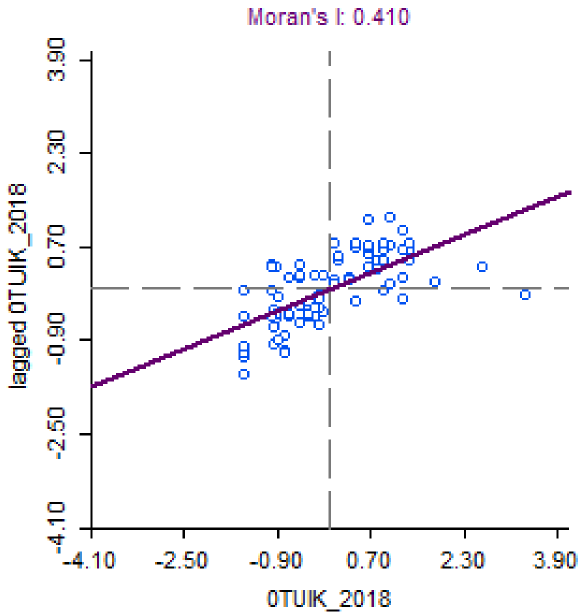

Figure 4.9. TURKSTAT-HDI Moran’s I Analysis (Data Source: TURKSTAT and Author's own work)

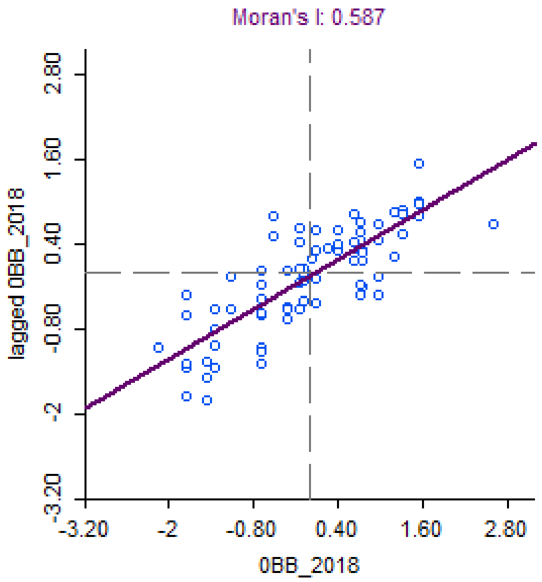

Figure 4.10. BB-HDI Moran’s I Analysis (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

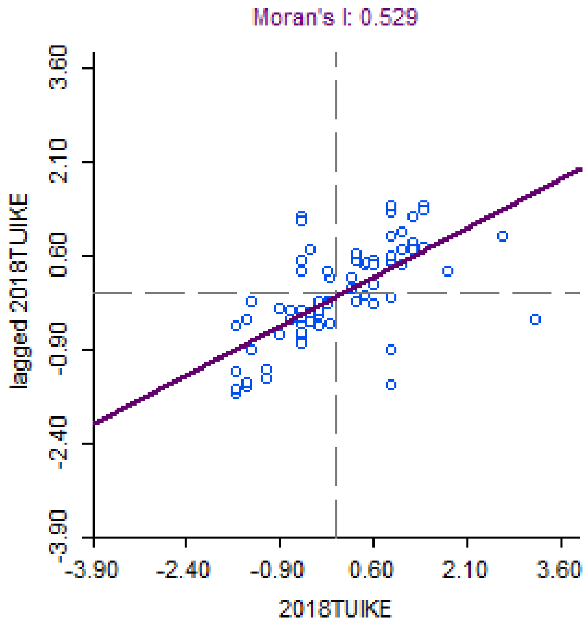

Figure 4.11. TURKSTAT-HDI-E Moran's I Analysis (Data Source: TURKSTAT and Author's own work)

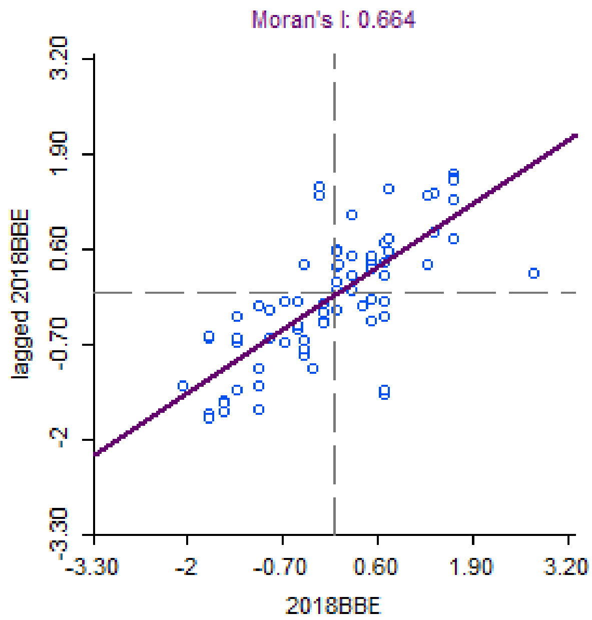

Figure 4.12. BB-HDI-E Moran's I Analysis (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

Second, we give the results of LISA analysis that shows local clusters of developed and less developed groups. The red color symbolizes the highly developed group whereas the blue color refers to the less developed clusters.

So, in Figure 4.13, we observe TR52, and TR61 are forming a high development cluster whereas TRA2, TRB2, TRC3, TRC2, and TRC1 create a less developed group. In Figure 4.15, the most developed regions are part of Marmara, and Southwestern Anatolia while the least developed regions are also the East of Turkey. In Figure 4.17, TRA2, TRB2, and TRC3 are low-low cluster regions however TR61, and TR10 are high-high cluster regions. In Figure 4.19, İstanbul, and surrounding provinces are high development cluster regions whereas East of Turkey is the least developed cluster region.

All of the maps show a cluster of low-development regions are Eastern and Southeastern Anatolia while a cluster of high-development regions are part of Marmara and Southwestern Anatolia.

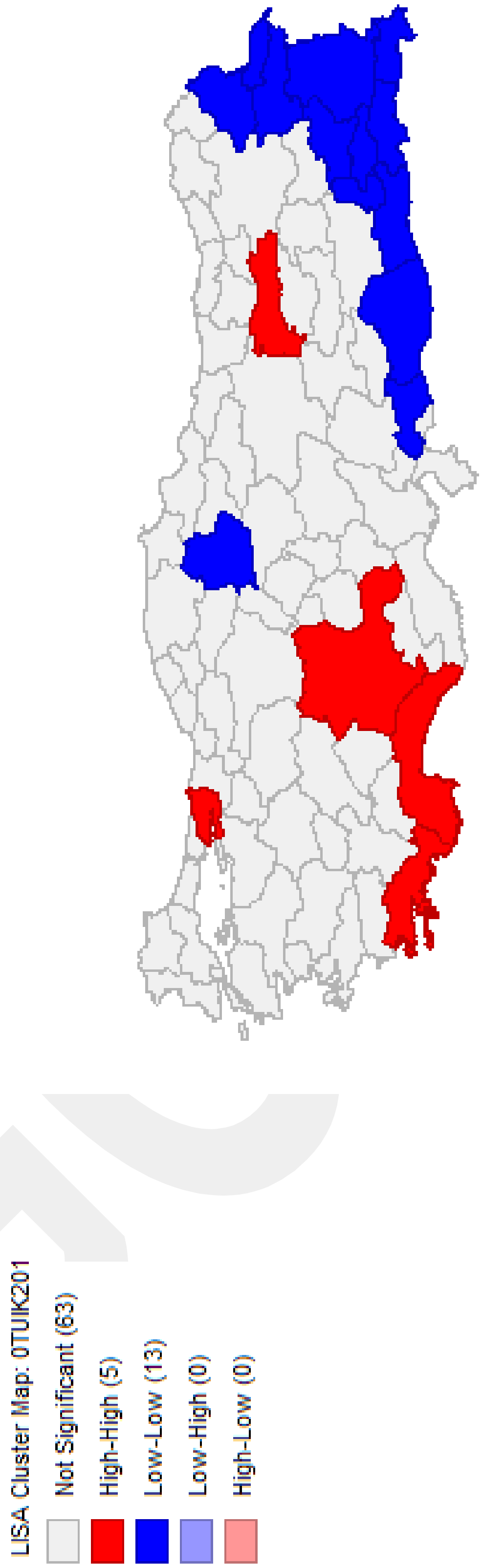

Figure 4.13. TURKSTAT- HDI LISA Cluster Map (Data Source: TURKSTAT and Author's own work)

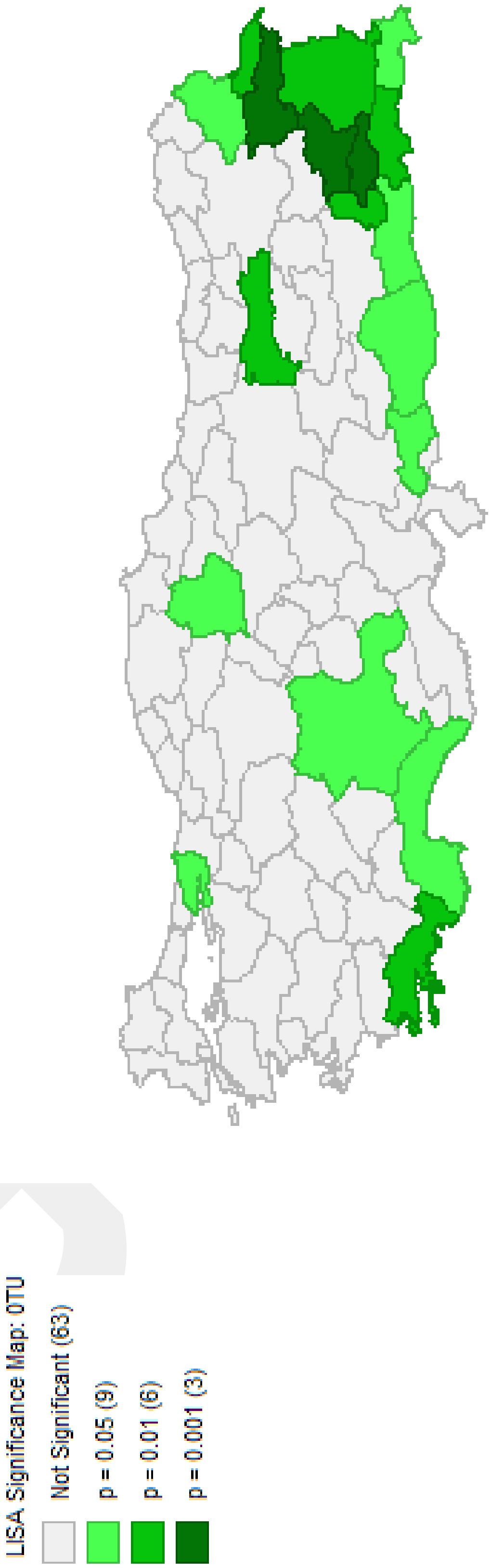

Figure 4.14. TURKSTAT-HDI LISA Significance Map(Data Source: TURKSTAT and Author's own work)

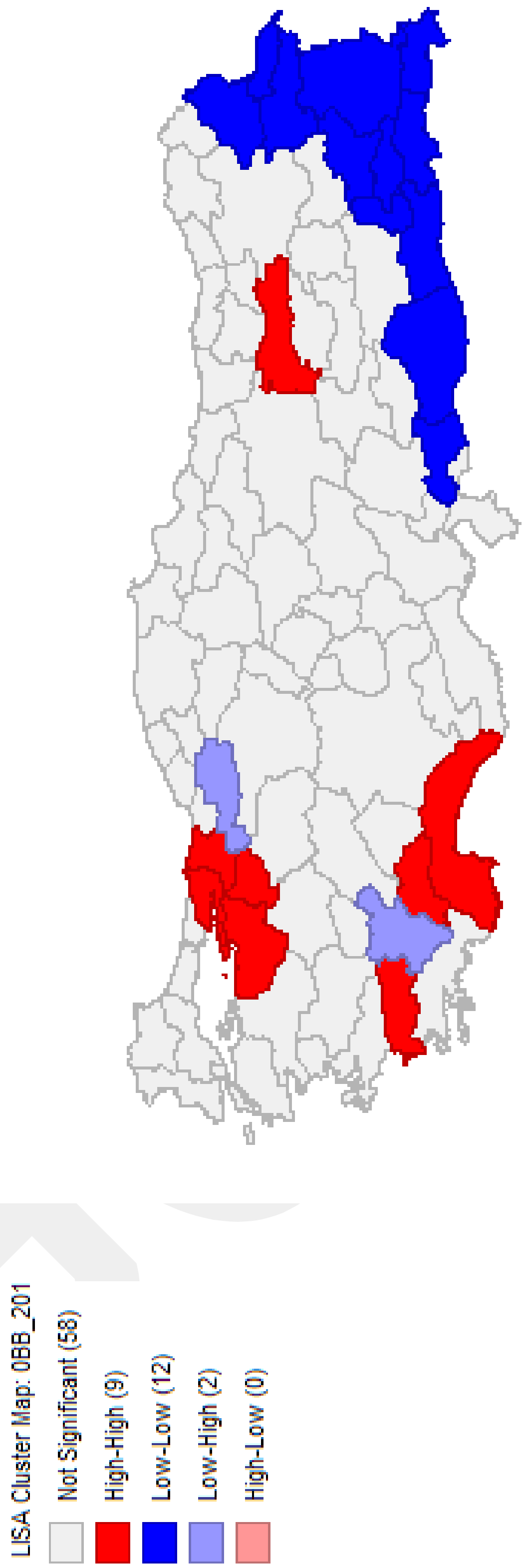

Figure 4.15. BB-HDI LISA Cluster Map (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

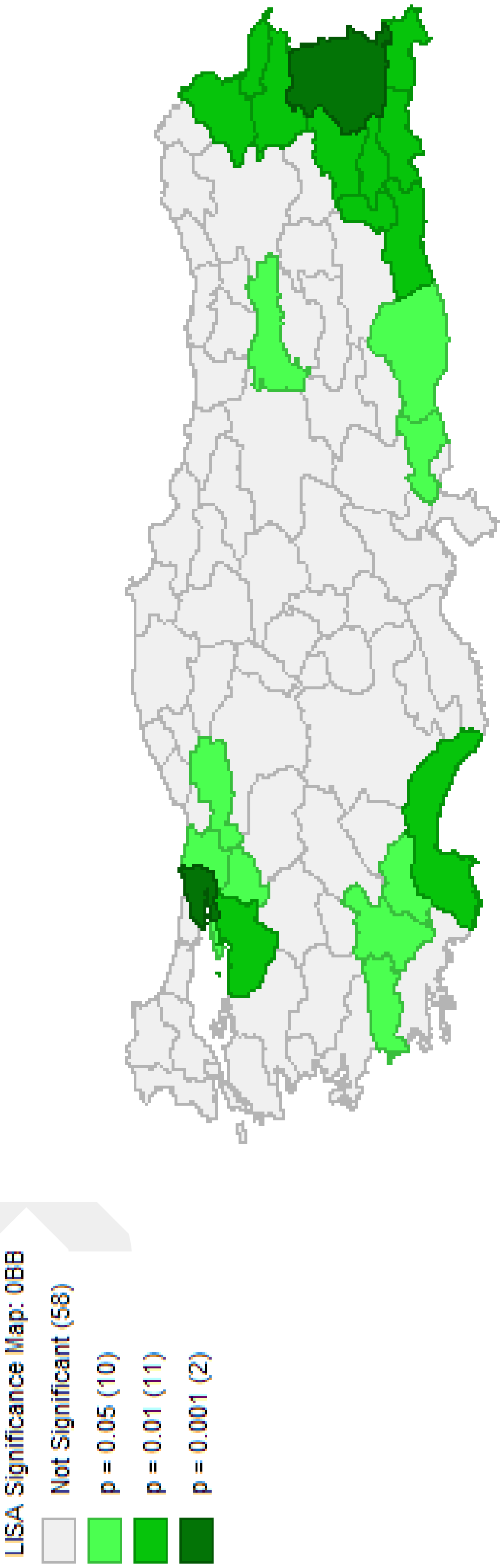

Figure 4.16. BB-HDI LISA Significance Map (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

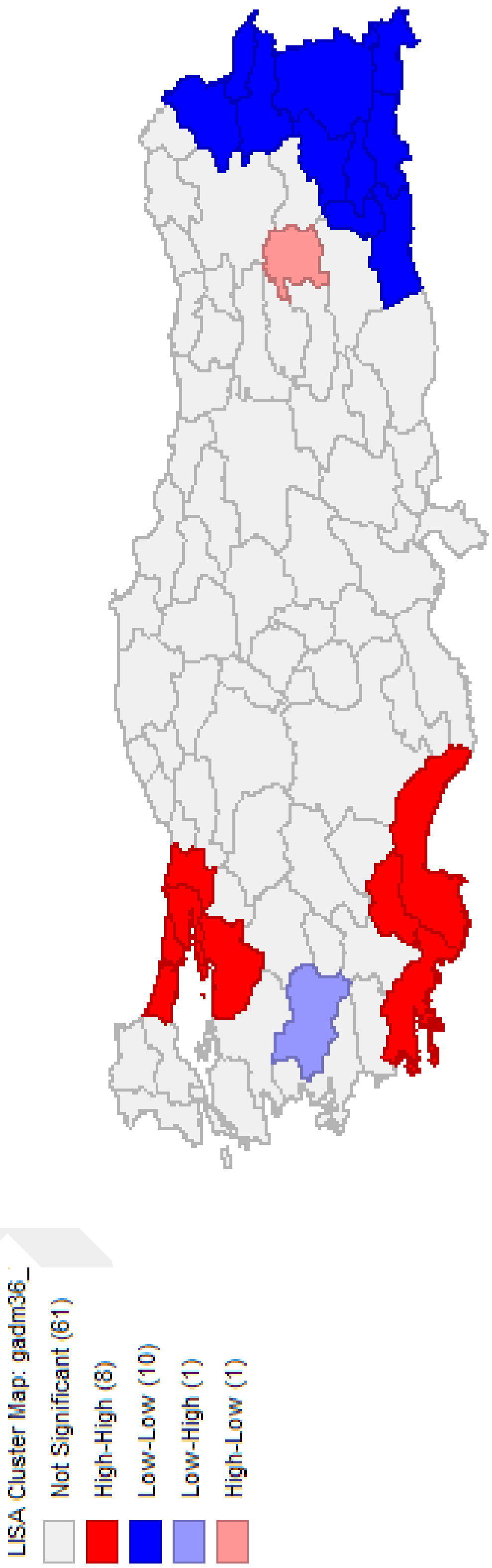

Figure 4.17. TURKSTAT-HDI-E LISA Cluster Map (Data Source: TURKSTAT and Author's own work)

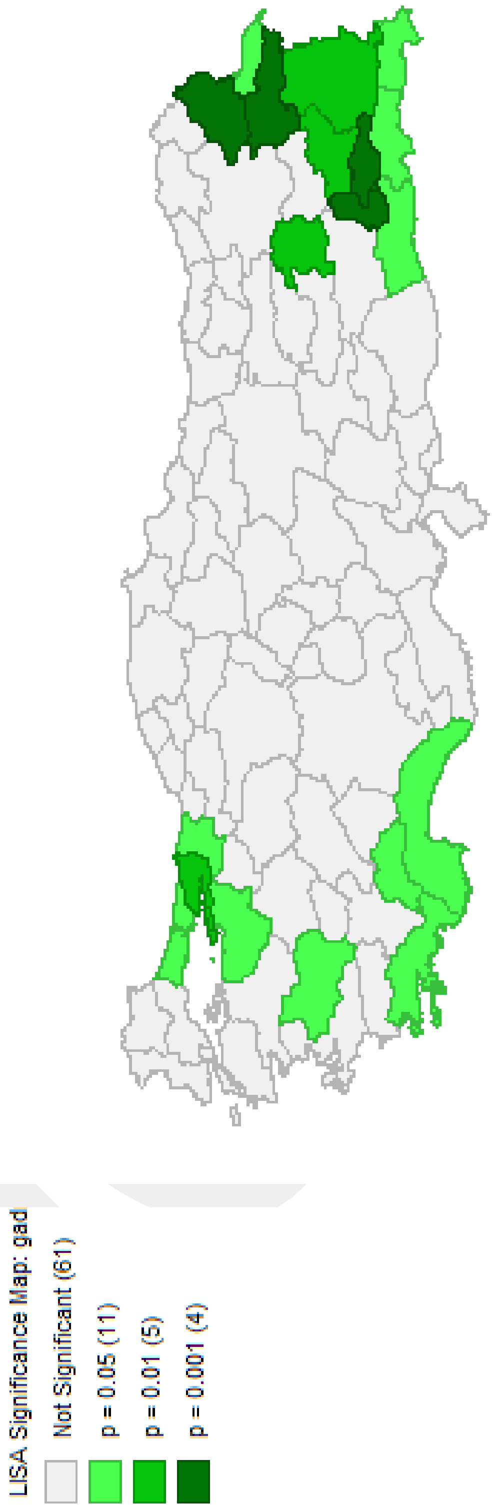

Figure 4.18. TURKSTAT-HDI-E LISA Significance Map (Data Source: TURKSTAT and Author's own work)

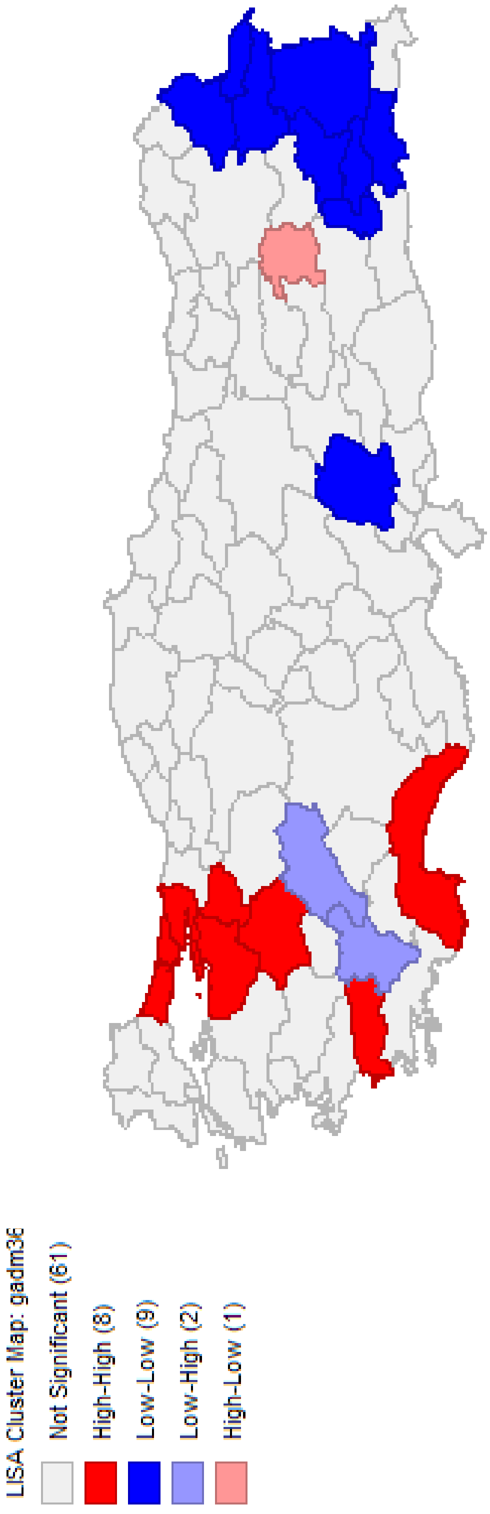

Figure 4.19. BB-HDI-E LISA Cluster Map (Data Source: Author(s) own work and borders of regions were adapted from Beyhan (2019) (page 23, Figure 3))

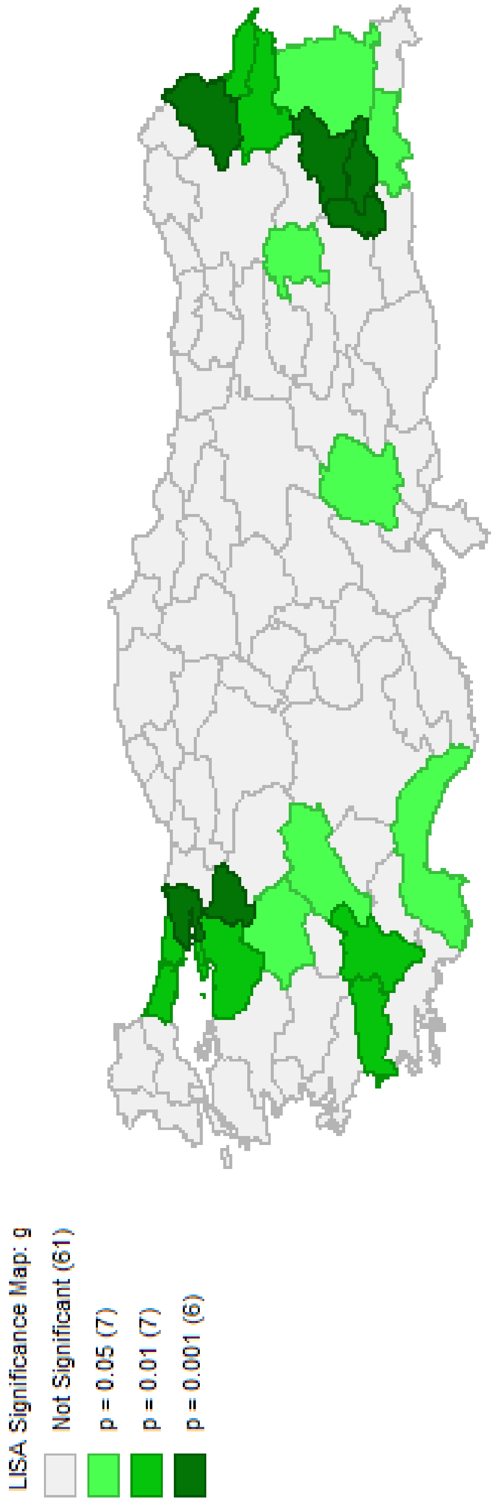

Figure 4.20. BB-HDI-E LISA Significance Map (Data Source: Author(s) own work and borders of regions were adapted from Beyhan (2019) (page 23, Figure 3))

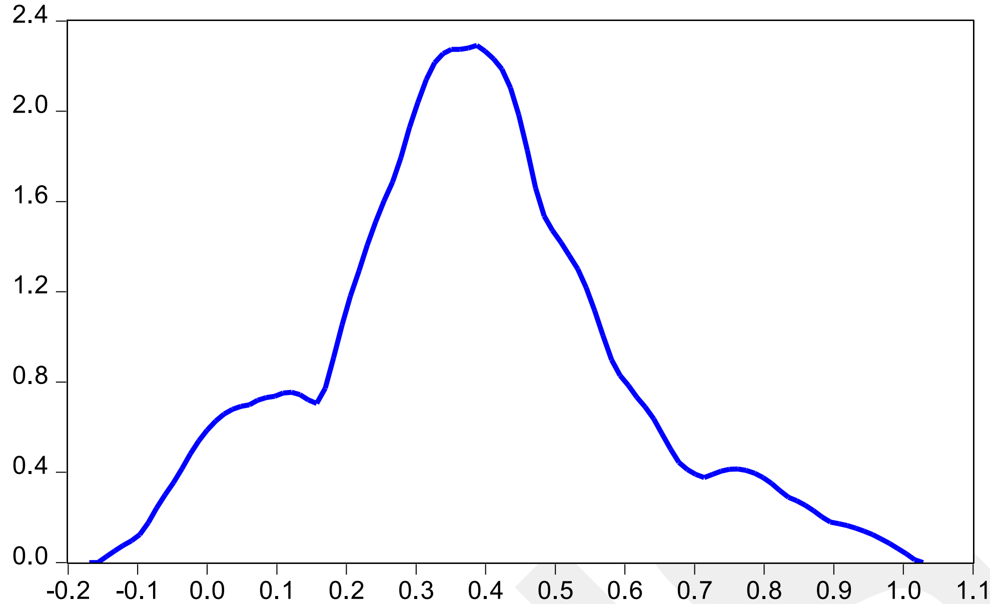

Figure 4.21. 2009 TURKSTAT-HDI Kernel Density (Data Source: TURKSTAT and Author's own work)

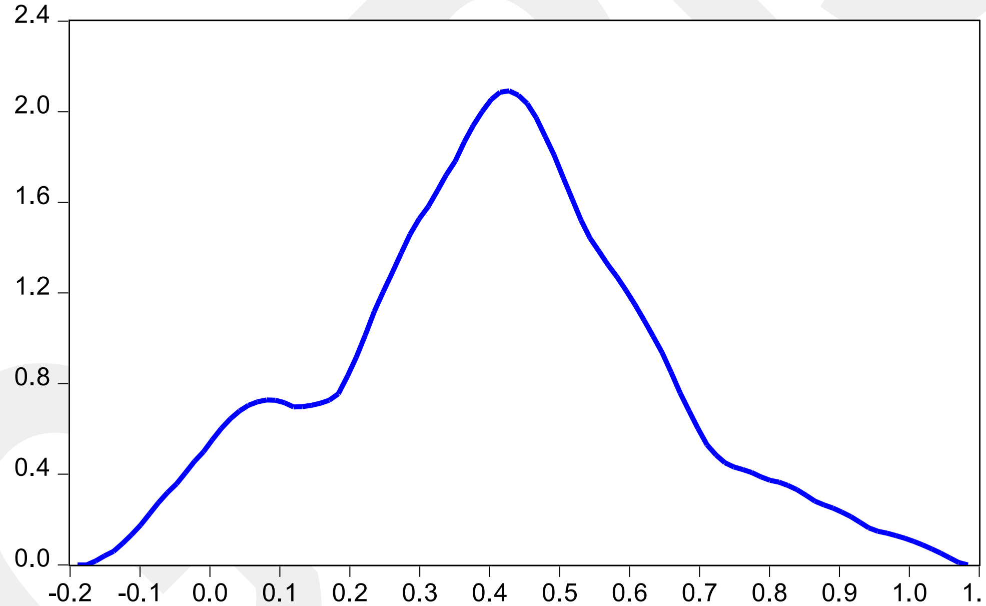

Figure 4.22. 2009 TURKSTAT-HDI- E Kernel Density (Data Source: TURKSTAT and Author's own work)

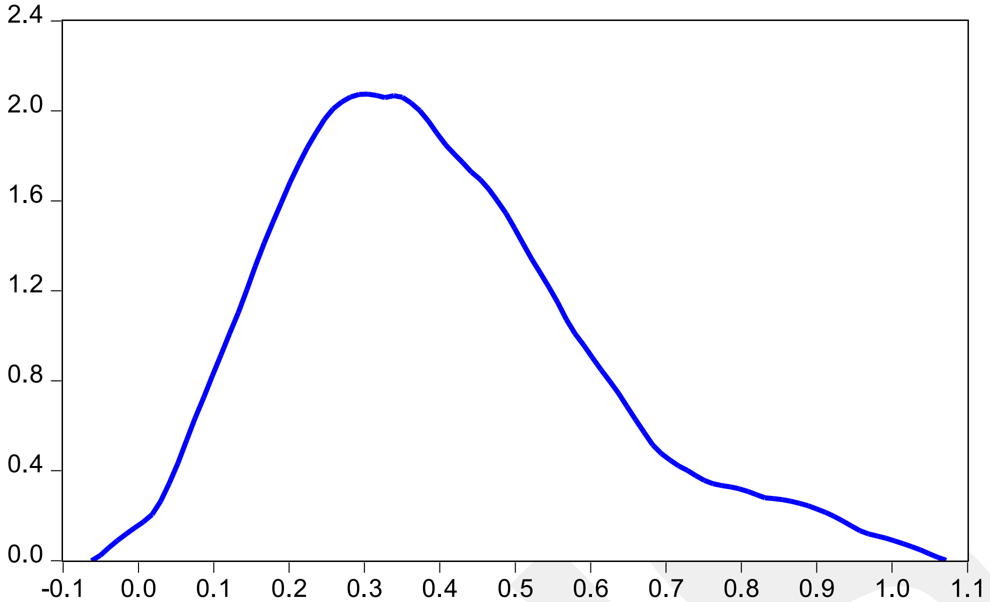

Figure 4.23. 2018 TURKSTAT-HDI Kernel Density (Data Source: TURKSTAT and Author's own work)

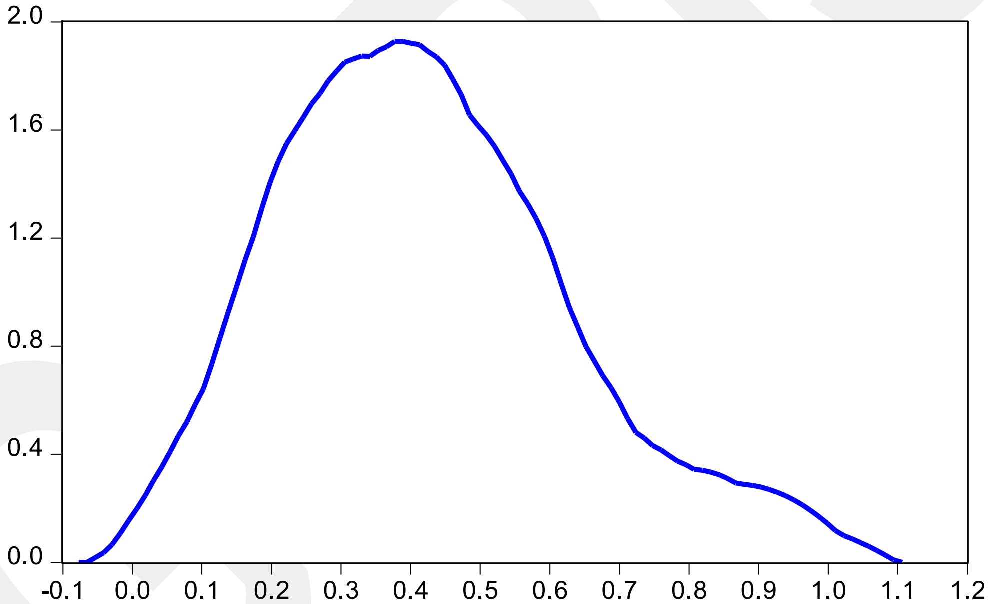

Figure 4.24. 2018 TURKSTAT-HDI-E Kernel Density (Data Source: TURKSTAT and Author's own work)

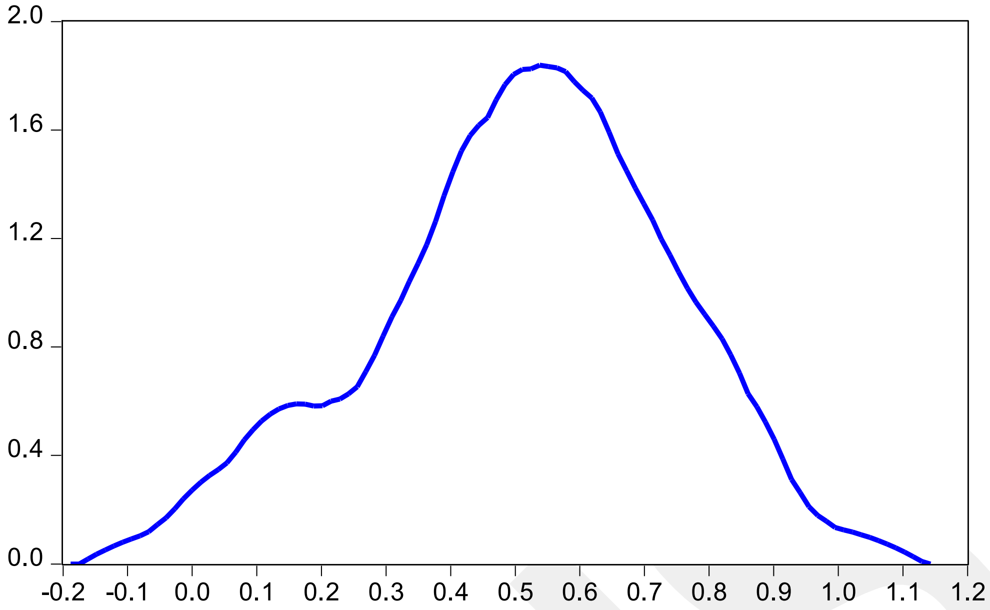

Figure 4.25. 2009 BB-HDI Kernel Density (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

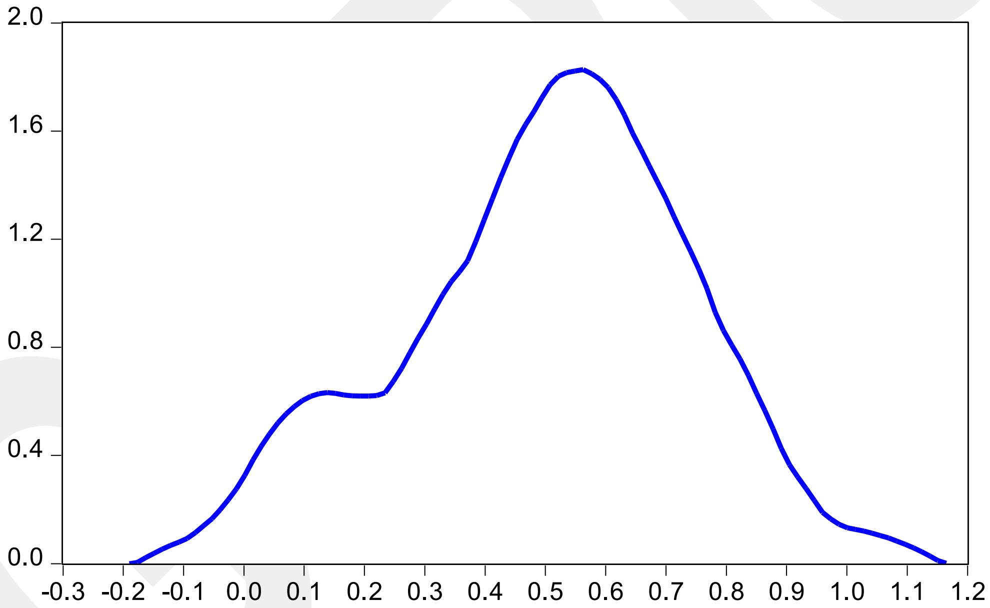

Figure 4.26. 2009 BB-HDI-E Kernel Density (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

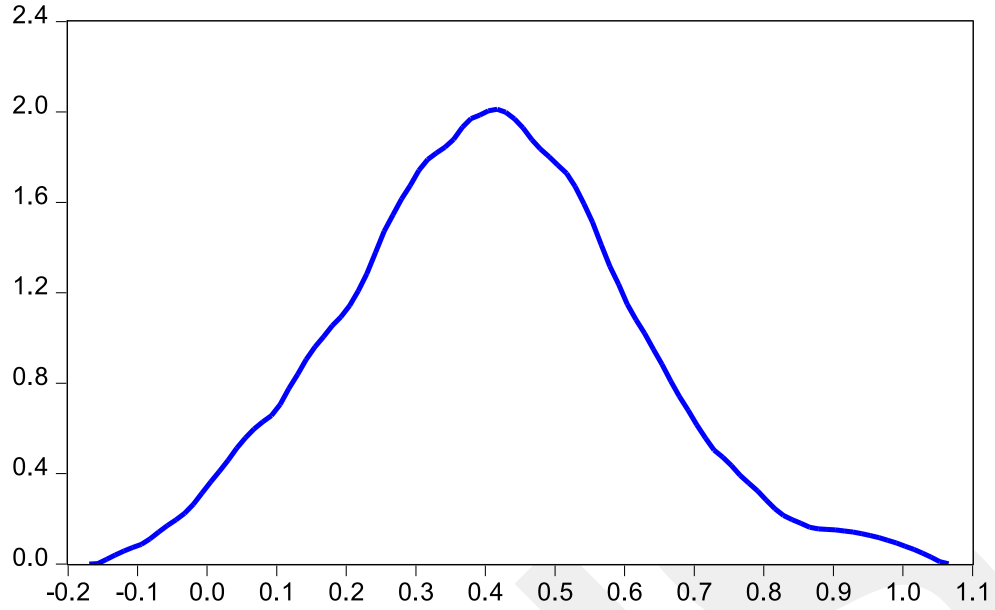

Figure 4.27. 2018 BB-HDI Kernel Density (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

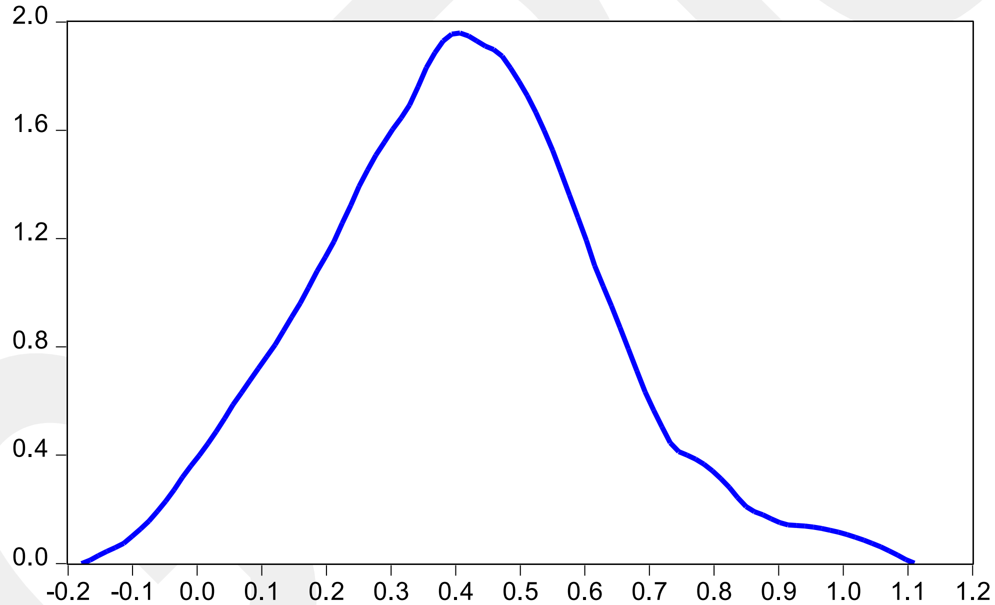

Figure 4.28. 2018 BB-HDI-E Kernel Density (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

Kernel densities from Figure 4.21 to Figure 4.28 show the probability density distributions of development indicators across regions. The figures are shown for the 2009 and 2018 years. Four different settings such as HDI-TURKSTAT, HDI-E-TURKSTAT, HDI-BB, and HDI-E-BB are employed in the present study.

Remarkable differences are observed in development disparities when Burak Beyhan's (2019) functional regions are used instead of TURKSTAT's NUTS-2 regions. In the functional region setting, for the year 2009, both HDI and HDI-E indicators exhibit a worse (unequal) distribution of development compared to TURKSTAT's NUTS-2 region setting. On the other hand, for the 2018 year, the distributions do not change much.

It is also observed that there are some moderate differences in distributions when the employment rate is added to HDI calculation. Such that in Figure 4.22 the Kernel density estimation of TURKSTAT's HDI for 2009 becomes worse (unequal distribution) when the employment rate is added. But in the remaining three cases (Burak Beyhan's classification and year 2018), the shape of the distributions does not change much.

When we analyze the evolution of development disparities, the development indicators show quite different results. Particularly, the results concerning TURKSTAT's regions and BB's functional regions vary significantly. As to TURKSTAT's classification, we find a slight tendency to worsening the development disparities. It is correct for both HDI and HDI-E measures. However, under functional regions, we observe a homogenization of development disparities. In other words, a convergence trend of development levels is determined for functional regions however an unclear/light divergence trend is observed for NUTS-2 regions.

We apply regression analysis to analyze the tendency of development disparities over the last decade. However, before that, two important specification tests are necessary.

First, the LM tests are presented in Table 4.1. It is evident the spatial autocorrelation especially in error terms since related p-values are quite low for all settings. Therefore, it is appropriate to estimate an SEM model.

Table 4.1. LM tests (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

Region Type	Development Indicator type	RLM Lag Test Stat	P-Value	RLM Error Test Stat	P-Value
TURKSTAT	HDI	27***	0.0000001 59	17,534***	0.000028 2
TURKSTAT	HDI_E	17***	0.0000379	6**	0.0144
BB	HDI	1.227	0.268	3.2329*	0.07217
BB	HDI_E	2.6213	0.1054	3.5599*	0.05919

*when p-value <0.1, ** when p-value <0.05, *** when p-value <0.01

Second, Hausman test findings are reported in Table 4.2. It shows a significant test result for Burak Beyhan's functional regions whereas there are insignificant test statistics for NUTS-2 regions. Therefore, it is appropriate to apply pooling, within, and random models for the sake of robustness.

Table 4.2. Hausman test (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3))

Development Indicator Type	Region Type	Test Stat	P-Value
HDI	TURKSTAT	0.61	0.43
HDI-E	TURKSTAT	0.18	0.67
HDI	BB	5.57**	0.02
HDI-E	BB	8.54***	0.003

Finally, spatial panel regression estimates are given in Table 4.3. The significance and rate of convergence (or divergence) are quite different under different assumptions.

To start with HDI-TURKSTAT, the beta is not significant, indicating an ambiguous evolution of development disparities. However, when the employment rate is added to the indicator, HDI-E-TURKSTAT, beta is negative and significant at 5 %. Then, in the case of BB-HDI, beta is weakly significant and negative. Finally, in the HDI-E-BB case, beta is negative and strongly significant. The spatial component lambda is positive and significant.

Table 4.3. Panel Regression (Data Source: Author(s) own work and borders of regions were obtained from Beyhan (2019) (page 23, Figure 3)) (Cont. to Page 55)

Development Indicator type	HDI	HDI	HDI	HDI	HDI	HDI
Region Type	TURKSTAT	TURKSTAT	TURKSTAT	BB	BB	BB
Panel Model Type	Pooling	Within	Random	Pooling	Within	Random
Constant	0.003854		0.0054798	-0.00043		0.0000754
y_1	-0.00667	0.009821	-0.0129798	-0.0209***	-0.103474***	-0.022**
Lambda	0.600436****	0.610112***	0.60758***	0.45863***	0.50198***	0.50045***
Half life convergence (ln(2)/beta)	-103.915	70.58022	-53.40199237	-33.0843	-6.698756988	

Development Indicator type	HDI-E	HDI-E	HDI-E	HDI-E	HDI-E	HDI-E
Region Type	TURKSTAT	TURKSTAT	TURKSTAT	BB	BB	BB
Panel Model Type	Pooling	Within	Random	Pooling	Within	Random
Constant	0.005092*		0.0069124**	-0.0006		-0.00034
y_1	-0.00914*	-0.03003	-0.0153585*	-0.01782***	-0.139195***	-0.01844**
Lambda	0.666154***	0.695099***	0.682406***	0.30844**	0.40722***	0.331**
Half life convergence (ln(2)/beta)	-75.8732	-23.0811	-45.13117691	-38.8957	-4.979684475	-37.5979

So, we understand that functional regions exhibit a convergence trend in development whereas NUTS-2 regions do not. Indeed, we determined the speed of convergence. The fastest convergence rate is obtained for functional regions. Such that in the HDI-E-BB case, the half-life is between 5-39 years, and in the HDI-BB case half-life is between 7-33 years. Instead, a quite slow convergence rate is found for TURKSTAT's NUTS-2 regions that range between 23-104 years.

CHAPTER 5

CONCLUSIONS

In this study, our analyses on development disparities indicated four main results. First, there are sizable differences in human development across regions in Turkey. Second, we observed important differences in results when functional regions are used instead of TURKSTAT's NUTS-2 regions and the employment rate is incorporated into HDI calculation. Such that the level of disparities was observed as worse when functional regions are used instead of TURKSTAT's NUTS-2 regions. Third, the convergence across regions in development disparities is more evident and pronounced under functional regions whereas no/weak such pattern is observed for NUTS-2 regions. Four, the development disparities evolved in a spatially correlated manner.

All these results provided important implications for regional development policies. Firstly, since employment is an important fact, job-creating sectors should be stimulated such as manufacturing in less developed regions, and Jobless growth should not be focused on. Job creation should be supported by incentives, tax exemptions, subsidies, and the improvement of education facilities in less developed regions. Functional regions should also be referred to in regional analysis next to TURKSTAT's NUTS-2 regions. In regional analyses and policies, functional relationships should be considered. The local actors and development programs may be formulated on this basis.

According to results obtained from present study, job creating sectors should be promoted. Underdeveloped places should be encouraged to industrialize since it is the most job creating sector, particularly manufacturing. Development agencies should be supported to finance such projects. Each region should be evaluted with respect to its function and priority should be given to the sectors in which the regions have a competitive advantage.

Nonetheless, also tradtional indicators of development should be supported for backward regions such as promotion of health services, income generating projects, foundation of universities, institutes and new education programs.

Overall, it has been understood the critical importance of employment and functional regions in the human development of regions. Hence, following all the related (above-mentioned) policies, prosperity and development can be homogenized.

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URL-5. http://www.sgk.gov.tr/index.html

APPENDIX 1. R Code for Spatial Regressions

```
************splm code***************
 library("MASS")
 library("coda")
 library("nlme")
 library("Matrix")
 library("boot")
 library("sp")
 library("splines")
 library("LearnBayes")
 library("spData")
 library("Formula")
 library("sandwich")
 library("spdep")
 library("bdsmatrix")
 library("ibdreg")
 library("lmtest")
 library("car")
 library("Ec-dat")
 library("maxlik")
 library("methods")
 library("grid")
library("miscTools")
 library("plm")
 library("splm")


dTURKSTAT<- read.table("E:/invdist_TURKSTAT.txt")
wTURKSTAT<- as.matrix(dTURKSTAT)
wTURKSTAT1 <- mat2listw(wTURKSTAT, row.names = NULL, style="W")
```

```
dbb<- read.table("E:/invdist_bb.txt")
wbb<- as.matrix(dbb)
wbb1 <- mat2listw(wbb, row.names = NULL, style="W")



data <- read.table("E:/aybikedata.txt")
d <- data.frame(data)
pd <- pdata.frame(d, index=NULL)

Regions     <-    pd$V1
years  <-    pd$V2
TURKSTAT_norm    <-    pd$V3
TURKSTAT_new     <-    pd$V4
bb_norm     <-    pd$V5
bb_new      <-    pd$V6
gr_TURKSTAT_norm      <-    pd$V7
gr_TURKSTAT_new<-    pd$V8
gr_bb_norm  <-    pd$V9
gr_bb_new   <-    pd$V10
ind_TURKSTAT_norm     <-    pd$V11
ind_TURKSTAT_new      <-    pd$V12
ind_bb_norm <-    pd$V13
ind_bb_new  <-    pd$V14
slag_ind_TURKSTAT_norm<- slag(ind_TURKSTAT_norm, listw=wTURKSTAT1)
slag_ind_TURKSTAT_new<- slag(ind_TURKSTAT_new, listw=wTURKSTAT1)
slag_ind_bb_norm<- slag(ind_bb_norm, listw=wbb1)
slag_ind_bb_new<- slag(ind_bb_new, listw=wbb1)
****************************************************

***********************************************************
LM Tests
```

```
slmtest( gr_TURKSTAT_norm ~ ind_TURKSTAT_norm, data=pd,
listw=wTURKSTAT1, test=c("rlml"))
slmtest( gr_TURKSTAT_norm ~ ind_TURKSTAT_norm,
data=pd,listw=wTURKSTAT1, test=c("rlme"))
slmtest( gr_TURKSTAT_new~ ind_TURKSTAT_new,data=pd, listw=wTURKSTAT1,
test=c("rlml"))
slmtest( gr_TURKSTAT_new ~ ind_TURKSTAT_new,
data=pd,listw=wTURKSTAT1, test=c("rlme"))
slmtest( gr_bb_norm ~ ind_bb_norm, data=pd,listw=wbb1, test=c("rlml"))
slmtest( gr_bb_norm ~ ind_bb_norm,data=pd, listw=wbb1, test=c("rlme"))
slmtest( gr_bb_new~ ind_bb_new, data=pd,listw=wbb1, test=c("rlml"))
slmtest( gr_bb_new ~ ind_bb_new,data=pd, listw=wbb1, test=c("rlme"))

***** panel models*****************
fmTURKSTATnorm <- gr_TURKSTAT_norm ~ ind_TURKSTAT_norm
fmTURKSTATnew <- gr_TURKSTAT_new ~ ind_TURKSTAT_new
fmbbnorm <- gr_bb_norm ~ ind_bb_norm
fmbbnew <- gr_bb_new ~ ind_bb_new


 summary(spml(fmTURKSTATnorm, data=pd, listw=wTURKSTAT1, effect =
c("individual"),model = c("pooling"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmTURKSTATnorm, data=pd, listw=wTURKSTAT1, effect =
c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmTURKSTATnorm, data=pd, listw=wTURKSTAT1, effect =
c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmTURKSTATnew, data=pd, listw=wTURKSTAT1, effect =
c("individual"),model = c("pooling"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmTURKSTATnew, data=pd, listw=wTURKSTAT1, effect =
c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmTURKSTATnew, data=pd, listw=wTURKSTAT1, effect =
c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b")))
```

```
summary(spml(fmbbnorm, data=pd, listw=wbb1, effect = c("individual"),model = c("pooling"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmbbnorm, data=pd, listw=wbb1, effect = c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmbbnorm, data=pd, listw=wbb1, effect = c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmbbnew, data=pd, listw=wbb1, effect = c("individual"),model = c("pooling"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmbbnew, data=pd, listw=wbb1, effect = c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b")))
 summary(spml(fmbbnew, data=pd, listw=wbb1, effect = c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b")))
```

Hausman Test

```
TURKSTATnorm_w <- spml(fmTURKSTATnorm, data=pd, listw=wTURKSTAT1, effect = c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b"))
TURKSTATnorm_r <- spml(fmTURKSTATnorm, data=pd, listw=wTURKSTAT1, effect = c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b"))

sphtest(TURKSTATnorm_w, TURKSTATnorm_r)

bbnorm_w <- spml(fmbbnorm, data=pd, listw=wbb1, effect = c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b"))
bbnorm_r <- spml(fmbbnorm, data=pd, listw=wbb1, effect = c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b"))

sphtest(bbnorm_w, bbnorm_r)

TURKSTATnew_w <- spml(fmTURKSTATnew, data=pd, listw=wTURKSTAT1, effect = c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b"))
TURKSTATnew_r <- spml(fmTURKSTATnew, data=pd, listw=wTURKSTAT1, effect = c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b"))
```

```
sphtest(TURKSTATnew_w, TURKSTATnew_r)

bbnew_w <- spml(fmbbnew, data=pd, listw=wbb1, effect = c("individual"),model = c("within"), lag=FALSE, spatial.error=c("b"))
bbnew_r <- spml(fmbbnew, data=pd, listw=wbb1, effect = c("individual"),model = c("random"), lag=FALSE, spatial.error=c("b"))

sphtest(bbnew_w, bbnew_r)
```