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**SPATIAL ANALYSIS OF INCOME INEQUALITY IN
TÜRKİYE**

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ABSTRACT

SPATIAL ANALYSIS OF INCOME INEQUALITY IN TÜRKİYE

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Income inequality is a major concern for a country. In recent years, income inequality has increased in most countries and also became a major concern in Türkiye. Regional disparities will be important in examining income inequality. In this context, the study conducted is necessary to examine and understand how these differences and factors affecting income inequality also create a pattern in the regions. In this thesis, Türkiye's Gini coefficient was examined for measuring income inequality by GEODA, which is a tool for analysing spatial measurement.

The spatial analysis takes into account regional clusters and observed the Gini coefficient at the NUTS 2 level, which consists of 26 regions in Türkiye. The factors that affect income inequality in Türkiye were examined from 2014 to 2023 by the method of bivariate analysis.

Spatial Autoregressive Model is the best fit for obtaining spatial associations for regional income inequality. Research and development expenditure shares in GDP is the most affective factor that decrease regional income inequality.

Key Words: Geoda, regional income inequality, Nuts 2 Level, spatial analysis, regional Gini index

ÖZ

TÜRKİYE’DE BÖLGESEL GELİR EŞİTSİZLİĞİ MEKÂNSAL ANALİZİ

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Gelir eşitsizliği bir ülke için büyük bir endişe kaynağıdır. Son yıllarda gelir eşitsizliği çoğu ülkede artmış ve Türkiye’de de büyük bir endişe kaynağı haline gelmiştir. Bölgesel farklılıklar gelir eşitsizliğinin incelenmesinde önemli olacaktır. Bu bağlamda, yapılan çalışmanın bu farklılıkların ve gelir eşitsizliğini etkileyen faktörlerin bölgelerde nasıl bir örüntü oluşturduğunu incelemek ve anlamak için gerekli olduğu düşünülmektedir. Bu tezde, mekansal ölçümü analiz eden bir araç olan GEODA ile gelir eşitsizliğini ölçmek için Türkiye'nin Gini katsayısı incelenmiştir.

Mekansal analiz bölgesel kümelenmeleri hesaba katmaktadır; Türkiye'nin 26 bölgesinin Gini katsayısını NUTS- 2 düzeyinde incelenmiştir. 2014 yılından 2023 yılına kadar, bölgesel gelir eşitsizliğini etkileyebilecek faktörler, iki değişkenli verilerin analizi yöntemiyle incelenmiştir.

Mekansal otoregresif model, bölgesel gelir eşitsizliği için uzamsal ilişkileri yakalamada en iyi sonucu vermiştir. Araştırma ve geliştirme giderlerinin gayri safhi yurtiçi hasıla içindeki payı, bölgesel gelir eşitsizliğini en çok azaltan faktör olmuştur.

Anahtar Kelimeler: Geoda, gelir eşitsizliği, Nuts 2 düzeyi, mekansal analiz, Gini katsayısı

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Fulya Ecem Tuzcuoğlu

İzmir, 2025



TEXT OF OATH

I declare and honestly confirm that my study, titled “Spatial analysis of regional income inequality in Türkiye” and presented as a Master’s Thesis, has been written without applying any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Fulya Ecem Tuzcuoğlu

June 25,2025



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SYMBOLS AND ABBREVIATIONS

ABBREVIATIONS

OECD	The Organization for Economic Cooperation and Development
GEODA	Geographic Data Analysis
TUSIAD	Turkish Industry and Business Association
TURKSTAT	Turkish Statistical Institute
ESA 10	The European System of National and Regional Accounts 2010
EUROSTAT	European Statistics
ESDA	Exploratory Spatial Data Analysis
LISA	Local Indicators of Spatial Association
EDA	Exploratory Data Analysis

1. CHAPTER: INTRODUCTION

A country must analyse the reasons behind regional income inequality, as it is one of the main factors preventing stable economic dynamics and an important reason for the lack of adequate capital for development. Social welfare is possible when income inequality is addressed; therefore, governments are responsible for ensuring this through taxes and interventions by economic regulations (Hayrulloğlu, Tuzun, 2020). Recently, there has been an increase in awareness regarding the corruptive effects of income on social associations (Kawachi, Subramanian, 2014). According to the Organization for Economic Cooperation and Development, societies with high income inequality may suffer from elevated poverty and crime rates, poor public health, and inadequate education levels (Birdsong, 2015). A decrease in income inequality will contribute to national economic growth (Jing et al., 2019). In the United States, during the period between the end of the Second World War and 1973, when the Oil Shock began to escalate, income did not change significantly. In 2013, thanks to economist Emmanuel Saez's insights on tax payment distributions, it can be interpreted that income inequality started to rise (Kawachi, Subramanian, 2014). The increasing level of income inequality worldwide is an important phenomenon that prompts researchers to examine distributional implications, regimes, and policies (Chen et al., 2022). Regional income inequality disrupts stable growth and hinders welfare enhancements; thus, the negative consequences of regional income inequality for states necessitate policies aimed at reducing inequality (Yaman, 2023). The main purpose of this study is to analyse regional inequalities through spatial analysis and identify the factors affecting them. Some studies indicate a significant relationship between geographic factors and economic performance, highlighting the need to examine income convergence using spatial econometric models (e.g., Lin, G., et al., 2005; Liu, S. and Zhang, J., 2009; Su, L. and Wang, Y., 2007; Wu, Y., 2006; Zhang, X. and Feng, Z., 2008; Zhu, G., et al., 2014) and also (Tian et al., 2016). Regional income inequality stems from personal income inequality (Rey, 2004). The historical background of income inequality is rooted in structural causes such as technological changes and globalisation; however, today it appears to be driven by privatisation and other neoliberal reforms (Polacko, 2021). According to Polacko, income inequality results in challenging negative outcomes, such as a lack of resources related to low incomes, which is not the only detrimental effect of

income inequality. In recent years, countries have begun to focus on regional inequality (Marchand et al., 2020). Over the past 20 years, researchers have examined the relationship between regional inequality and economic growth (Suparman, Muzakir, 2023). Türkiye experiences regional diversities and inequalities, and several scientific studies (Yılmaz, 2001; Karaca, 2004; Filiztekin & Çelik, 2010; Candaş & Yılmaz, 2012; Öztürk, 2003; Öztürk, 2012; Bul, 2016; Çapar & Yayla, 2019; Kayıkçı, 2019; Şık & Öztürk, 2019; Göksu & Kılıç, 2020; Göcen, 2021; Yoloğlu, 2021) exist to support this case (Yaman, 2023). Marchand and colleagues studied a dataset from Canada consisting of 284 regions over 5-year intervals from 1981 to 2011. Their findings suggest that, aside from unstable market conditions and various socioeconomic and developmental factors, the distribution of manufacturing activities plays a crucial role in income inequality. As the concentration of manufacturing increases, the level of inequality starts to decrease, whereas a rise in tertiary services, arts, and entertainment contributes to an increase in income inequality due to knowledge concentration and heightened business activities (Marchand et al., 2020).

2. CHAPTER: MEASUREMENT OF INCOME INEQUALITY

There are different ways to measure income inequality such as the Gini coefficient, Pareto, graphic representations, and other semi-logarithmic representations. (Robert, Schutz,1951). The Gini coefficient is a common measure to analyse, especially income equality between some of the groups. (Dorfman,1979). Because the Gini coefficient has a statistical approach, it helps us understand income distribution and how it changes over time. (Farris,2010). The Lorenz Curve shows the cumulative percentages of total income that has taken against the cumulative number of the individual who has this income and it starts at the lowest income level (Hayrulloğlu, Tuzun,2020). The Figure 2.1. below shows the Lorenz Curve and Perfect Distribution Line. The Gini coefficient is equal to the division between the area of A which is the area between the Perfect distribution line and the Lorenz Curve and the surplus of A and the area of 90 degrees to the Lorenz Curve. If the income distribution is perfectly equal, that means it has a 45-degree line, and that line represents a Perfect Distribution Line, which at that time reflects the Gini coefficient value of 0. Generally, its value is between 0 and 1, and if it approaches 1, it represents a high value of income inequality. However, it has a basic measurement, and it has been debated by some economists to use only analytical methods for income inequality (Farris,2010).

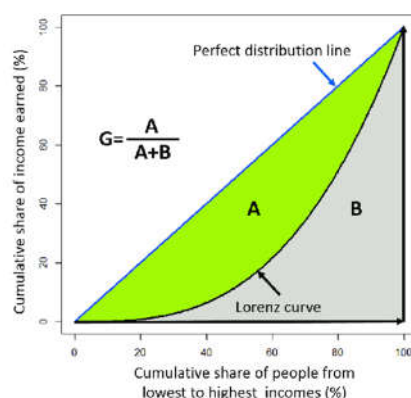


Figure 2.1. Lorenz curve and Gini coefficient (G)

Source: Kim et al. (2017) Inequality Status of Household Medical Expenditure Distribution by Household Income Quartile and Associated Factors with Household Catastrophic Medical Expenditure in Korea

The Gini coefficient is calculated by the equation:

$$1 - 2 \int_0^1 L(x) dx \quad (2.1)$$

Here, if $L(x)=x$, that means it is a uniform distribution, and at that time Gini coefficient equals 0, and there is a perfect equality, which means zero inequality (Catalano et al.,2009).

Also, there are other possibilities for inequality for example:

$L(x)=x^2$ in that case if we are assuming that is a continuous function the Gini coefficient would be (Catalano et al.,2009):

$$1 - 2 \int_0^1 x^2 dx = \frac{1}{3} \quad (2.2)$$

Another possibility if there is a greater inequality, then we can have the example of (Catalano et al.,2009):

$$1 - 2 \int_0^1 \frac{2^{10x}-1}{1023} dx = 1 - 2 \left(\frac{2^{10}-1}{10230 \ln 2} - \frac{1}{1023} \right) \approx 0.7134 \quad (2.3)$$

The Gini coefficient is calculated in some cases from any nation's population (Catalano et al.,2009). In 1906, the economist Vilfredo Pareto used this technique first and it is based on the fact that the 80s of Italy's 80s corresponded to only % of the 20s public of Italy (Rosing et al.,2015).

The main ideology of this principle is that 80% of problems can be solved by 20% of causes. (Rosing et al.,2015). Furthermore, according to the UNDP report, the top richest people in the World, which is approximately 20% of the population, control 87,2 % of the income. (Abyad,2021). This rule could apply to various fields because it is based on unequal distribution. (Abyad,2021). In the economic condition, the Pareto rule usage in the measurement of income and wealth can demonstrate the 80/20 rule (Abyad,2021).

Simply, if we are assuming N represents the number of people whose income is greater than any given limitation of x , then there is an equation of (Pridiksha, Archana,2023):

$$\log(N) = \log(A) - \alpha \log(x) \quad (2.4)$$

"A is constant,

α is constant,

$N=A/x$, which represents the power of α ."

The slope is α , which is known as the 'Pareto Index', and this statement's general definition is Pareto Distribution (Pridiksha, Archana,2023).

The Cumulative distribution function is to be shown as:

$$F_P(x) = \begin{cases} 1 - \left(\frac{x_m}{x}\right)^a, & \text{for } x \geq x_m \\ 0, & \text{for } x < x_m \end{cases} \quad (2.5)$$

$$f_P(x) = \begin{cases} \propto \frac{x_m^\alpha}{x^{\alpha+1}}, & \text{for } x \geq x_m \\ 0, & \text{for } x < x_m \end{cases} \quad (2.6)$$

The x_m is the minimum value of x .

If the 80/20 rule perfectly expresses the situation, the value of a would be 1.16. The value is coming from the cumulative distribution function:

$$F(X_{0.8})=0.8 \quad (2.7)$$

$$F(x)=1 - \left(\frac{x_m}{x}\right)^a \quad (2.8)$$

$$0.8=1 - \left(\frac{x_m}{x_{0.8}}\right)^a \quad (2.9)$$

$$\left(\frac{x_m}{x_{0.8}}\right)^a=0.2 \quad (2.10)$$

Taking the logarithm on both sides:

$$\alpha \cdot \log \left(\frac{x_m}{x_{0.8}}\right)=\log(0.2) \quad (2.11)$$

$$\left(\frac{x_{0.8}}{x_m}\right)=5.067 \quad (2.12)$$

were calculated. (Holmes, Moriarty,1999).

$$\alpha \cdot \log (5)=\log\left(\frac{1}{5}\right) \quad (2.13)$$

$$\alpha=\frac{\log 5}{\log 4} \quad (2.14)$$

$$\alpha=1.16$$

When the Pareto index equals 1.16, the field examining's effect is coming from 20% of causes (Pridiksha, Archana,2023).

A certain distribution function is $F(x)$, and the theoretical Lorenz Curve refers to (Dundorf et al.,2014):

$$L(p) = \mu^{-1} \int_0^p F^{-1}(t)dt \quad (2.15)$$

$$LP(p) = 1 - (1 - p)^{1-\frac{1}{\alpha}}, 0 < p < 1, \alpha > 1 \quad (2.16)$$

As in the mentioned Catalano's equations:

$$G = \frac{A}{A+B} \quad (2.17)$$

G is the Gini coefficient, and $A+B=0.5$ (half of the square's area) (Dundorf et al.,2014).

$$G = 1 - 2B \quad (2.18)$$

$$G = 1 - 2 \int_0^1 [1 - (1 - p)^{1-\frac{1}{\alpha}}] dp \approx 0.76 \quad (2.19)$$

This shows a high degree of income inequality in the years around 2014 World Gini coefficient was between 0.6 to 0.7 (Dundorf et al.,2014).

3. CHAPTER THE FACTORS THAT AFFECT REGIONAL INCOME INEQUALITY

Şaşmaz (2024) examined regional income inequality and trade openness in Türkiye. He used NUTS 2 Level and the data set was from 2014 to 2022, and examined trade openness, labour force participation, population density, and average years of schooling per capita. According to his results, trade openness had a significantly negative impact on income inequality, but surprisingly, average years of education did not significantly influence income inequality. There are additional factors that affect income inequality, which are based on the literature.

3.1. Social Transfers and Taxes

Transfer expenditures are essential and effective tools for the redistribution of income by the government to ensure justice in income inequality (Karaş,2024). Even transfer expenditures that do not correspond to a specific good or service are made to observe an improvement in income distribution if made under certain conditions (Dayar, Akıncı,2020). Taxation is one of the most important and direct tools to control income inequality in the short term (Hayrulloğlu, Tuzun,2020).

Hermansen and Causa examined OECD (Organisation for Economic Co-operation and Development) countries' income redistribution via taxes and transfers in 2018. The Gini index is a tool to measure income distribution; Türkiye, Mexico, and Hungary can be solely measured after taxes and before transfers (Hermansen, Causa,2018).

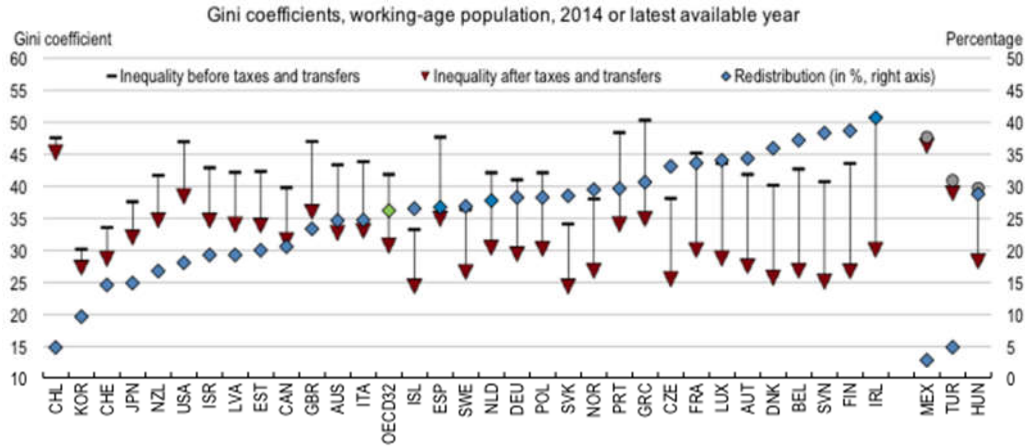


Figure 3.1. Effects of taxes and transfers

Source: Centre for Economic and Policy Research. (2001) Centre for Economic and Policy Research CEPR. United States (Hermansen, Causa,2018).

This may be due to the limited micro dataset available for Türkiye during the study period conducted by Hermansen. However, in 2025, the data is available, and in the table below, it can be seen the years between 2014 and 2023 (survey years: from 2015 to 2024) of the Gini coefficient of Türkiye after social transfers and pensions. The Gini coefficient was higher before social transfers and pensions, but it decreased in all years after transfers and payments in Türkiye.

In Figure 3.1 it can be observed that after taxes and transfers, the Gini coefficient decreases, indicating that income inequality decreases in the given countries. Bargain examined the effects of taxes on income distribution; he found income support and family tax credits are the most essential equal income distribution policies (Hayrulloğlu, Tuzun,2020). According to Demirgil's search, in 2018, an increase of 1% in the indirect tax rate increased the Gini index by 0.10%, while a direct tax increase of 1% decreased the Gini index by 0.05%. which includes the period between 1980-2014 in the Autoregressive Distributed Lag Bound Test (ARDL) test results (Hayrulloğlu, Tuzun,2020).

Table 3.1. The Gini Coefficient of Türkiye

Survey Year	Income Reference Year	P80/P20 Ratio	P90/P10 Ratio	Gini coefficient	Gini coefficient (Excluding Social Transfers)	Gini coefficient (Excluding Pension and All Social Transfers)
2015	2014	7.6	13.3	0.397	0.454	0.406
2016	2015	7.7	13.6	0.404	0.465	0.412
2017	2016	7.5	13.4	0.405	0.468	0.414
2018	2017	7.8	13.7	0.408	0.473	0.417
2019	2018	7.4	13	0.395	0.463	0.405
2020	2019	8	14.6	0.401	0.47	0.42
2021	2020	7.6	13.7	0.415	0.482	0.419
2022	2021	7.9	14.2	0.42	0.487	0.423
2023	2022	7.9	14.8	0.42	0.488	0.423
2024	2023	7.7	13.3	0.413	0.476	0.423

Source: <https://data.tuik.gov.tr/>

3.2. Gender Parity

Gender equality is one of the most important factors for the development of any country. In The Organization for Economic Cooperation and Development (OECD) countries, important findings show approximately half of the economic growth is because improved female educational attainment which causes enhanced female labour force participation, and also reports estimated that a full convergence in those participation rates by 2030, would cause to average GDP to increase of 12% in 20 years and the largest increase would be in Italy with more than %1; and it is exactly for these reasons it has central importance to examine changes in women employment that affect income distribution (Segato, 2021). Countries cannot be wealthy if they do not have high gender equality in education (Ward et al., 2010). Full participation of women is required to reduce income inequality and achieve financial stability (Gonzales et al., 2015; Kochhar et al., 2017; IMF, 2018; IMF, 2020), (Bertay et al., 2020). Women's participation in the workforce is important for

sustainable economic growth (Bertay et al.,2020). In Africa, women play an important role especially in agriculture according to Akpa et al., 's (2024), and their findings show that women's engagement in agriculture's effects are heterogeneous in African regions; especially women's engagement in agriculture decreases income inequality in Southern and Western Africa while increases in income inequality in Central and Eastern Africa. According to Akpa et al., increasing women's access to land and enhancing their educational quality will lead to a decreased income gap between men and women. According to the Solow-Swan Growth Model, effective labour, physical capital, and total factor productivity are the key players, and gender inequality plays an important role in effective labour and total labour productivity. (Devadas, Kim,2021). It is important to consider female participation in sectors as mentioned in the literature on income equality. Ray and Debnath (2020) studied the determinants of regional inequality in female work participation in the Lower Gangetic Plain Region of India. Their study was based on Geographic Information System (GIS) techniques for spatial pattern, and they also used different statistical measures to evaluate the degree of inequality among different social strata's work participation. According to their findings, there was great stress in regional differences in female work participation, and it depended on agro-ecological conditions in a physiographic region (Physiography especially studies the physical patterns and Earth's processes, such as geomorphology, hydrology, soil, rocks, biogeography and also the impact of tectonic forces on landscapes (NG, 2021)). S.P. Chatterjee divided India based on structure, physiography and geology, and not until 1971, when it was included in the National Volume of Census Atlas, which consists of three tiers of regional boundaries: Macro, Meso and Micro (Roy and Verma, 1988). Ray and Debnath's findings show that female participation was mostly lower than male, 16.69% and 41.63%, respectively.

3.3. Schooling Years

According to economic theory, if there is an increase in income inequality under the *ceteris paribus*, it causes an increase in inequality of schooling attendance, and also if the inequality of schooling attendance increases under the *ceteris paribus*, it causes sizeable inequality of income (Mayer, 2010). Muller highlighted Kaplan et al.'s study results to correlate income inequality to measures of human capital, which

consists of educational attainment in 2001. According to actual data, the data that consists of both attainment and its concentration, and average years of education negatively had impact income inequality (Checchi, 2001). Also, some studies argue there is a U-shaped relationship between education and income inequality, which suggests that it starts with a negative correlation and after some point, turns a positive one. In Checchi's study, after considering the negative relation, income inequality and average years of schooling have a U-shaped relation with the 6.5 years' lower turning point. Marin and Psacharopoulos studied income distribution and schooling in 1976. In their study, n is a group of people, Y_i is the initial income, r_i is the rate of return to i^{th} year of schooling, and S is the total years of schooling. There are two possible cases:

The first case is the situation where r and S are independent random variables:

$$var(logY_s) = \bar{r}^2 var(S) + \bar{S}^2 var(r) + var(S)var(r) \quad (3.1)$$

The second case is that r and S are dependent:

$$var(logY_s) = \bar{r}^2 var(S) + \bar{S}^2 var(r) + 2\bar{r}\bar{S} cov(r, S) \quad (3.2)$$

D_i the point of increase in income brought about by an increase in education, which results from extra schooling, for example:

$$D_i = \log(1 + r_{i+1}) \quad (3.3)$$

Equation (3.3) is required for one year of extra schooling.

$$D_i = \log(1 + r_{i+1}) + \log(1 + r_{i+2}) \quad (3.4)$$

Equation (3.4) is required for two years of extra schooling.

N is the size of the total labour force, $\overline{\log Y}$ is the arithmetic mean of the logarithm of income and Δ represents the change in variance.

So they have arrived at the equation (3.5) below:

$$\Delta var(logY) = \left(\frac{nD_i}{N}\right) [2(logY_i - \overline{\log Y}) + D_i(N - n)/N] \quad (3.5)$$

Marin and Psacharopoulos's study is also important for understanding multiple relationships and how these relationships affect income inequality. They worked on the Becker, Mincer and Chiswick model, which is called the “B-M-C Model”, and this model is widely used to estimate the returns depending on schooling quality, which is essential for developing countries (Heckman et al., 2006). They expect that this model's increase in schooling years will lead to an increase in income inequality; however, testing Hanoch rates these relationships turn in the opposite direction. The Hanoch ratio is an important model for understanding the income inequality and schooling relationship and includes the principle that if the number of schooling years increases, the income increase ratio decreases. As those with more schooling and lower ratios increase in income, thus income inequality decreases. The Hanoch ratio consists of negative covariance related to diminishing marginal rates, as greater schooling years correspond with income increases. Since their work was consistent with the Hanoch rate and they found a negative correlation between S and r, they concluded that their study's increase in average years of schooling can be beneficial for society and also for income distribution. Further research results show that schooling years are also related to mortality, and more schooling contributes to extending lifespans (Muller, 2001). He emphasized that schooling has a greater negative impact on age-adjusted mortality, even more than income per capita, when other variables are controlled, and the lack of high school education could play an important role in the lifetime effects of socioeconomic deprivation.

In this work, Türkiye's female school years and male school years are examined in bivariate analysis under the name of gender parity. The gender parity index is calculated by female education mean years schooling to male education mean years schooling and converted by calculating Turkstat's NUTS 3 level to NUTS 2 level.

3.4. Technological Changes

3.4.1. Skill Biased Technological Change (SBTC)

Understanding the relationship between income inequality, human capital, and research and development is important for a country's economic well-being (Skare et al., 2024). When the terms technology and income distribution are examined in the

literature, there can be seen that the main classical economist Adam Smith noted that the basis of development is the division of labour and specialisation, which leads to technical advances; this results in an increase in the quality of the workforce and raises labour prices, as articulated in his book, *The Wealth of Nations*, in 1776. Additionally, David Ricardo, a proponent of classical economics, assessed the process of mechanisation as a form of technology; he argued that during production, labour demand decreases, while in the mass production process, the demand for labour increases once again (Karabıyık, Akıncı, 2024). Technological progress and globalisation are crucial for driving economic growth (Jaumotte et al., 2013). Amani and Ahmadzadeh (2022) studied the impact of technological innovation and globalisation on income inequality, dividing countries into low-income (19 countries), middle-income (63 countries), and high-income (41 countries) categories from 2008 to 2019, using the Gini Index to measure income inequality. Their findings revealed that technology and innovation negatively impact income inequality (decrease inequality) across all three income groups—low, middle, and high—while globalisation has a positive effect on income inequality in low-income countries but a negative impact in middle and high-income countries. Since the 1970s, technological advancements have increased the demand for skilled workers, thereby raising the wages of these workers (Acemoglu, 2002). However, although numerous studies indicate a positive relationship between technology and income distribution, there are also findings suggesting a negative correlation due to shifts in the labour force. Artificial intelligence and automation contribute to the decline of low and medium-skill jobs, leading to increased unemployment (Goyal, Aneja, 2020). Permana et al. studied 28 European Union countries from 2003 to 2014, and their findings indicated that the income distribution gap has widened due to Skill-Biased Technical Change. Kuznets' work in 1956 can be linked to income inequality and technological progress (Hall, 2009).

According to early researchers, Kuznets separated income inequality and economic growth's relationship as the early economic growth step, in which the country has a positive relation and in the maturity step has a negative relation potentially caused by shifting labour in other sectors. (Mdingi, Ho, 2021). That can be explained if there is a shifting of labour from the agricultural to the developed sector, the shifted labour's individuals' income increases while the agricultural worker's income remains at a

low level and that is why income inequality exists but when the labour supply decreases by the time the income level of agricultural worker's start to increase (Mdingi, Ho,2021).

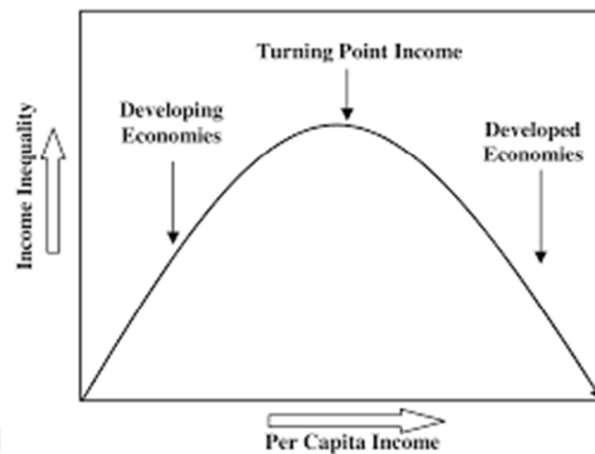


Figure 3.2. Kuznets Inverted U Curve Hypothesis

Source: Income Inequality, Ideology and Indifference of our Times - Scientific Figure on ResearchGate. Available from:(accessed 23 Jan 2025)

https://www.researchgate.net/figure/Kuznets-Inverted-U-Curve-Hypothesis_fig1_293012964

Kuznets explains in the U-Curved Shape Hypothesis that inequality tends to increase when the early economic development stage, and reverse in the later stage (Mdingi, Ho,2021), which is after the turning point of income.

Skill-biased technological Change could have a multi-dimensional effect on income inequality. While it increases skilled workers' payment since the demand for skilled workers increases depending on technology, it can cause unskilled workers to lose their jobs and harm to income distribution. Lehman found that skill-biased technology increases income inequality while investigating technology per capita with economic growth, examining the indirect impact of changes in falling income rates on income inequality using a two-stage Ordinary Least Squares (OLS) multiple regression technique (Karabıyık, Akıncı, 2024).

One of the reasons for an increase in income inequality can be greatly attributed to Skill-Biased Technological Change (SBTC) because the workers' need to learn additional knowledge to adapt to technological change increases the skill premium

(Hall,2009). In Hall's study quantitative method was shown as an equation for reducing the impact of SBTCs on income inequality by increasing education in the field of Skill Biased Technological Change.

$$\frac{\beta T(1+x) - \bar{a}}{(\beta T - \bar{a})(1+x)}^p \quad (3.6)$$

Equation 3.6 shows a relation between the arrival rate of new technologies and educational factors, and how they play a significant role in the effective efficiency of both high and low-skill workers.

$$\frac{\partial[(\frac{\beta T(1+x) - \bar{a}}{(\beta T - \bar{a})(1+x)})^p]^2}{\partial \beta \partial T} > 0 \quad (3.7)$$

Equation 3.7 is the derivation of β and T .

$\bar{a}$ is an increase in the arrival rate of new technologies (*ceteris paribus*), β is a higher quality of education, and T is a higher quantity of education. As a result, an increase in the arrival rate of new technology leads to a rise in income inequality however, depending on β and T , the effect could be less (Hall, 2009).

3.4.2. Research and Development (R&D)

Research and Development subsidies are often used as policy instruments to provide technological improvement and economic growth, which increases the innovation rate (Chan et al., 2022). Different from the literature and the theories, Chan et al. consider worker heterogeneity in terms of skill endowments, and according to their findings, not only do R&D subsidies affect income inequality, but also it depends on the correlation between asset and skill heterogeneity.

Harrod-Domar Growth Model is based on the Keynesian Economics Theory with the fundamental principle of the model being that net investments' double effect is the deterrent of economic growth and that can be explained as; the first effect is investment causes production to increase and the second one is it provides to accumulation of capital and demand to production thus increase in production if leads to increase in total demand in next term, investments will increase in next period and economic growth occurs (Çağan, Aydoğuş, 2021).

Whereas in Harrod-Domar, another name known as Knife-Edge Growth Model, technological advances and research and development activities are expressed as exogenous for economic growth, Joseph Schumpeter's approach expressed economic growths' two fundamental sources are initiatives and their creations as production process and products which caused by their innovation activities result (Çağan, Aydoğuş, 2021). According to Aydoğan and Yıldırım's study (2025), productivity and research and development (R&D) positively affect economic growth, while an increase in income inequality harms economic growth and has a negative relation based on their analysis of 29 countries over the period from 1998 to 2018. Tuncer and Algoni (2021) examined education and research and development expenditures on the regional economic growth of Türkiye. For this purpose, they used the panel fixed effects method for the period 2010-2019. According to their findings, education and R&D expenditures positively affect regional GDP per capita in Türkiye's level one (TR1) regions. Thus, increasing expenditures on education and R&D in the policy implementation increases the regional growth rate for Türkiye's 12 regions in level 1, and plays an important role in achieving national goals.

3.5. Unemployment Rate

Muller highlighted that Kaplan et al's other result was that income inequality has a strong correlation with the unemployment ratio and the homicide rate.

According to economic theory, as inflation rises, the unemployment rate decreases. That situation is represented by the Phillips Curve, which William Phillips developed; however, the stagflation that occurred in the 1970s, when high unemployment and high inflation occurred, is still a debated topic for economists to examine whether there is a relationship between unemployment and inflation. One of the last articles about the Phillips Curve corresponds to Selim Yıldırım and Sacit Sarı (2021). They examined the 2005 to 2020 monthly data of Türkiye, and they examined whether the hypothesis is significant for Türkiye or not. They used ADF (Augmented Dickey-Fuller) and Phillips-Perron. In their findings, the Dynamic Least Squares Method(DOLS) was used to test long-term coefficients.

According to their findings, they could not find a relation between the inflation rate and the unemployment rate, at least in the long run in Türkiye.

3.6. Consumer Price Index (CPI)

According to Laidler and Parkin (1975) and Fischer and Modigliani (1978), inflation damages the poor more compared to the rich (Yue,2011). It is vital for policy decisions and monitoring to extent income inequality and poverty vary within countries across regions (Piacentini, 2014). Namini and Hudson (2019) examined linear and non-linear effects of inflation on income inequality by the Vector Error Correction Model (VECM) and using 24 developed countries, 66 developing countries throughout 1990-2014. According to their findings, there wasn't any bidirectional Granger causality between inflation and income inequality in the short run, but in the long run, there was bidirectional causality.

3.7. Poverty

Poverty is one of the major concerns for economic development, and solving the problems of poverty by appropriate policies. There are regional variations in poverty rate and income inequalities, such as Sub-Saharan African countries have the highest level of poverty and also high income inequality (Ogbeide et al., 2015). Poverty eradication is one of the main objectives for the United Nations' (UN) Sustainable Development Goals (Lechheb et al., 2019). It is very important to observe to what extent does it changes in income inequality and poverty to determine the political decisions (OECD, 2014). The European Union (EU) headline indicator of poverty and income inequality is defined as the proportion of the population living 'at-risk-of-poverty' who live in households with total equalised income below 60 per cent of the median of equalised household income (Atkinson et al., 2010).

Apergis et al. (2011) have found that there is a bidirectional relationship between poverty and income inequality in both the long run and short run, and income inequality and the unemployment rate have a positive impact on poverty.

Since the finding of the poverty rate's bidirectional relationship, it is examined on both sides in bivariate analysis.

3.8. Trade Openness

According to most empirical studies, there is a complicated conditional relationship between globalisation on equality and poverty, and in general, financial globalisation

increases inequality; however, trade openness, inequality, and poverty have a conditional relationship (Lee, 2014). According to Lee and many scholars, it became an important issue because globalisation affected income inequality and many developed countries. One of the examples is the USA, and it exhibited a high Gini coefficient after the 1980s, and this situation was consistent with the Heckscher-Ohlin theorem, which says international trade would lower the share of workers in developed countries (Lee, 2014). Also, Lee mentions several other theoretical explanations that say rising income inequality in developing countries is linked to globalisation.

3.9. GDP Share

3.9.1. Agriculture

Agriculture's role is essential for a country's economic development and the contribution can be seen in advanced countries, especially in less developed countries the role of agriculture gains more importance; in rich countries the population's 5% work in agriculture whereas in poor countries more than 66% work in agriculture (Kiss, 2020).

The agricultural sector is leading to help facilitate growth in industrial and structural economic transformation by playing a multidimensional role in the development process, such as creating employment opportunities, reducing poverty and lowering disparities in income (Odusola, 2017). However, Ceddia (2019) discovered that the region he studied represents one of the most active agricultural areas while also experiencing the highest rate of inequality.

The role of agriculture changes in countries such as developing countries it is more important and less important in developed countries (Van Arendonk, 2015). For example, it is an important sector in Pakistan's economy because it is the fact of Pakistan that increased agricultural output and productivity tend to contribute substantially to its overall economic development (Anwer et al., 2015). Türkiye has a very suitable location because of its geographic location and its climate conditions, but rapid urbanisation and immigration from rural areas to cities have caused to decrease in the level of agricultural production activities (Sulak, 2018).

3.9.2. Construction

Whether it's public or private facilities, they play a critical and observable role in the process of development (Kheni et al., 2008), and both in developed and developing countries, it might be seen as a sector of economics (Isa et al., 2013). The construction sector for both Türkiye's economy and other countries' economies; it provides to economic growth by feeding the sub-sectors, and it helps contribute to the balance of macro, so it can be referred to as one of the lifelines of economics (Çetin, Doğaner, 2017).

3.9.3. Industry and Manufacturing

Libanio and Moro (2016) examined Kaldor's perspective in economics, which includes Kaldor's first and second laws about the manufacturing process and its relation to economics. Kaldor's first law states that there is a close relation between the growth of manufacturing output and the growth of GDP, while in the second law, also known as Verdoorn's law, there is a statistical relation between the growth of labour productivity in manufacturing (Libanio and Moro, 2016). They explained the relation between industrial growth and GDP by the transfer of labour from low productivity sectors to the industrial sector. Although they found confirmation in several studies, they underline that the manufacturing sector responded by promoting cost reduction strategies to maintain competitiveness so which can cause unemployment. Marchand et al. (2020) have found industrial mix of regions play an essential role in the distribution of income and regions with high manufacturing activities tend to lower income inequality on the other hand the regions with the high level of services, arts and entertainment and knowledge intensive business services tend to have higher income inequality level.

3.9.4. Financial Inclusion

Park and Mercado (2018) examined financial inclusion, poverty and income inequality. They constructed 176 economies, and 37 of them were developing Asia countries. According to their research results, per capita income, rule of law, and demographic characteristics significantly affect financial inclusion, moreover, financial inclusion is also significantly related to lower poverty and income

inequality levels, However, they underlined that there is no link between financial inclusion and income inequality for developing Asia.

3.9.5. Real Estate Activities

The rental income explains an increasing share of income inequality, and the primary residence contribution to wealth inequality has increased, while the other real estate contribution has decreased (Bartels, Schröder, 2020).

3.9.6. Information and Communication

Information and Communication Technology is significant for growth and development for a nation (Jing et al., 2019). Untari et al (2019) analysed to impact of Information and Communication Technology (ICT) on economic growth and according to their findings which based on panel data from 2011 to 2016 and the model of Two Stages Least Square (TSLS) and their infrastructure indicators cellular telephone internship, internet accessibility and the number of Base Transceiver Station (BTS) significantly has a positive effect on economic growth and indirectly effect on income inequality because of economic growth.

3.10. Migration

Low-skilled immigration to the US played a significant role in decreasing global inequality by moving millions of low-income Mexican families from poverty to the global middle class (Orrenius, Zavodny, 2018). Based on a conceptual analysis, expectations are consistent with in-migration into the formal sector, which regions receiving will mostly decrease inequality, whereas the regions' in-migration into the informal or unemployed sector increases the income inequality (Kollamparambil, 2017).

3.11. Population Size and Health

Recent analysis shows there is a contradictory relationship between income inequality and population size, using the Standard Metropolitan Statistical Area (SMSA) data, Farbman and Long, as well as Rasnussen, and Haworth, argue that income inequality increases with city size, however according to Danziger city size has no significant effect on income inequality (Nord, 1980). Most of the research is

about health, income inequality and population size. Franzini et al.'s (2001) article, which has the headline ‘ *The Effects of Income Inequality and Income Level on Mortality Vary by Population Size in Texas Counties*’ they tests predictions of Wilkinson’s Theory, which states that income inequality is playing an important role in health differentials and health is affected more by income inequality in areas with large population. Kondo et al. (2012) studied the role of population size on income inequality and health. According to their results, average population, which is greater than 24 million, tended to be a stronger association between income inequality and poor health compared to smaller regions with smaller 820.000 population.

3.12. The Studies About the Factors That Affect by Gini coefficient

3.12.1. Mortality and Suicide Rate

Muller examined the multiple regression analysis of education, income inequality and mortality. He examined the years 1989 and 1990 in United States.

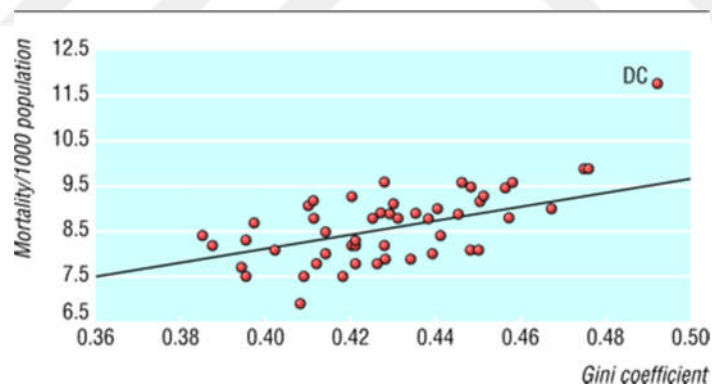


Figure 3.3. The positive relation between Gini coefficient and Mortality

Source: Age adjusted death rates by Gini coefficient for the 50 US states and the District of Columbia (DC), 1989-90 ($y=1.831+15.705 \times x$; $R^2=0.24$; weighted regression). (Data sources US Public Health Service¹⁵ and US Census Bureau¹⁶) (Muller, 2001).

According to his study, the Gini coefficient and mortality rate have a positive relationship. The District of Columbia was an outlier. The District of Columbia had a

much higher death ratio than expected, and regression coefficients show that a 0.1 increase in the Gini coefficient was related to an increase of 1.6 deaths per 1000 population which is shown in the axis.

Andres (2016) examined income inequality, unemployment and suicide. He used 15 European countries between 1970 to 1998 and according to his results economic growth, fertility rate and alcohol consumption have a significant effect on suicide rate.



4. CHAPTER PREVIOUS STUDIES FOR TÜRKİYE and OTHER COUNTRIES

According to some economists, income inequality is the main condition for economic improvement (Filiztekin, Çetin,2010). According to Kuznet, developing countries, in the process of transitioning from an agricultural economy to an industrial economy, could encounter a high degree of income inequality, but it was forecasted that this would disappear in the long run (Filiztekin, Çetin, 2010). There have been several studies on income inequality; Duygan and Güner examined it in 2006, and in these studies, education level and other demographic changes were considered (Filiztekin, Çetin,2010). The table below shows the Gini coefficient in different years of Türkiye.

Table 4.1. The Findings: Income Equality of Türkiye (Household Income Distribution by Quantile and Gini Coefficient)

Year	1963	1968	1973	1978	1983	1986	1987	1994	2002	2003
I. Slice (Lowest 20%)	4.5	3	3.5	2.9	2.7	3.9	5.2	4.9	5.3	6
II. Slice	8.5	7	8	7.4	7	8.4	9.6	8.6	9.8	10.3
III. Slice	11.5	10	12.5	13	12.6	12.6	14.1	12.6	14	14.5
IV. Slice	18.5	20	19.5	22.1	21.9	19.2	21.2	19	20.8	20.9
V. Slice (Top 20%)	57	60	56.5	54.7	55.8	55.9	49.9	54.9	50.1	48.3
Gini Coefficient	0.55	0.56	0.51	0.51	0.52	0.5	0.43	0.49	0.46	0.42

Source:(a) 1963 - Çavuşoğlu & Hamurdan, Income distribution research (Gelir dağılımı araştırması) 1963, Ankara, 1966. (b) 1968 - Bulutay, Timur & Ersel, Türkiye income distribution (Türkiye gelir dağılımı), Ankara, 1971. (c) 1973 - DPT, Income distribution (Gelir dağılımı) 1973, Ankara, 1976. (d) 1978 - Celasun, M., Income Distribution and Domestic Terms of Trade in Turkey, 1986. (e) 1983 - Celasun, M., Income Distribution and Domestic Terms of Trade in Türkiye, 1986. (f)

1986 - Esmer, Fişek & Kalaycıoğlu, Socio-Economic Priorities in Türkiye (Türkiye’de Sosyo-Ekonomik Öncelikler), Research Series on Household Income, Expenditures and Socioeconomic Needs (Hane Gelirleri, Harcamaları ve Sosyoekonomik İhtiyaçlar Üzerine Araştırma Dizisi), TUSIAD, İstanbul, 1986. (g) 1987 - DİE, 1987 Income Distribution (Gelir dağılımı), Ankara, 1990. (h) 1994 - DİE, 1994 Household income distribution survey results (Hane halkı gelir dağılımı anketi sonuçları), Ankara, 1996. (i, j) 2002, 2003 - Duygan & Güner, Income and Consumption Inequality in Turkey: What role does education play? 2006.

Table 4.2. Selected Countries' Gini coefficients and GDP Per Capita (2008)

Country	Gini coefficient	GDP Per Capita (PPP, USD)
Japan	24.9	31,267
Czech Republic	25.4	20,538
Hungary	26.9	17,887
Germany	28.3	29,461
Austria	29.1	33,700
Bulgaria	29.2	9,032
South Korea	31.6	22,029
France	32.7	30,386
Switzerland	33.7	35,633
Greece	34.3	23,381
Egypt	34.4	4,337
Spain	34.7	27,169
Australia	35.2	31,794
United Kingdom	36	33,238
Italy	36	28,529
India	36.8	3,452
Russia	39.9	10,845
United States	40.8	41,890
Iran	43	7,968
Turkey	43.6	8,407
Mexico	46.1	10,751
China	46.9	6,757
Malaysia	49.2	10,882
Argentina	51.3	14,280
Brazil	57	8,402

Source: Filiztekin, Çetin,(2010) from UNDP (United Nations Development Programme)

TUSIAD's data was used to calculate in Gini coefficient in the Table 4.2. The data from 2003 employed to investigate income inequality by spatial and as shown in Table 4.2, Türkiye's Gini coefficient shows high income inequality compared to other given countries in 2018 (Filiztekin, Çetin,2010).

It is important to compare Türkiye's place in the Gini Index with other countries. The OECD (Organisation for Economic Co-operation and Development) has listed the Gini coefficient of Türkiye and other countries for the year 2021. The lowest Gini coefficient was observed in the Slovak Republic with a value of 0.2.

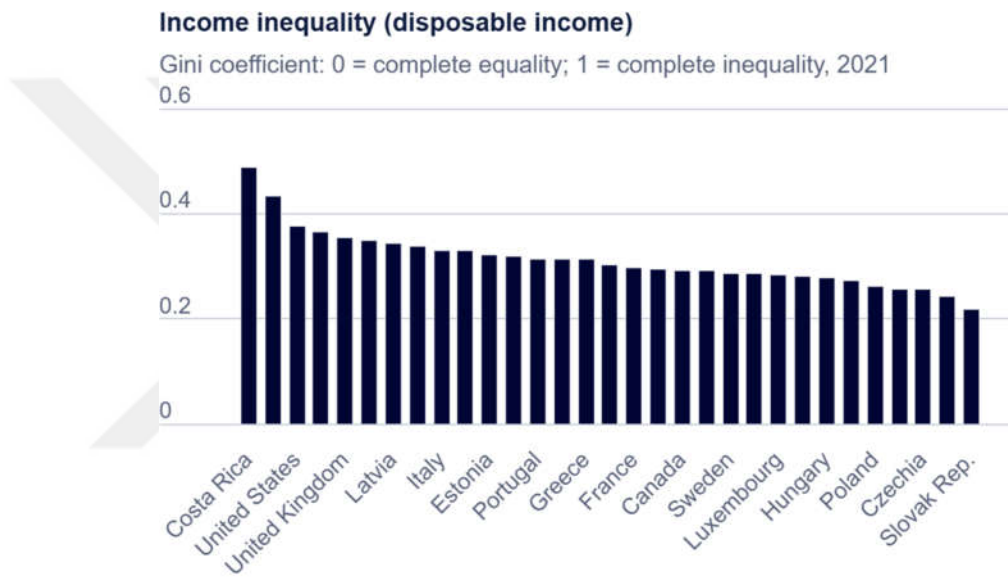


Figure 4.1. Income inequality indicators

Source: OECD

In Figure 4.1, Türkiye is between Costa Rica and the United States, with a Gini coefficient of 0.4. In 2021, Türkiye was one of the countries with the highest income inequality. Equality is important for ensuring equal rights and opportunities, and decreasing inequality contributes to sustainability for any society (European Union, n.d.). Inequality can create criminal environments and can cause social collapse also it is an obstacle for economic growth at the same time (Kayıkçı,2019). Understanding the reasons behind income inequality in Türkiye may reduce

inequalities and it will affect life standards in Türkiye. The Gini coefficient of Türkiye was examined from 2014 to 2023 as listed in Table 4.3.

Table 4.3. The Gini coefficient of Türkiye

Survey Year	Income Reference Year	P80/P20 Ratio	P90/P10 Ratio	Gini coefficient	Gini coefficient (Excluding Social Transfers)	Gini coefficient (Excluding Pension and All Social Transfers)
2015	2014	7.6	13.3	0.397	0.454	0.406
2016	2015	7.7	13.6	0.404	0.465	0.412
2017	2016	7.5	13.4	0.405	0.468	0.414
2018	2017	7.8	13.7	0.408	0.473	0.417
2019	2018	7.4	13	0.395	0.463	0.405
2020	2019	8	14.6	0.401	0.47	0.42
2021	2020	7.6	13.7	0.415	0.482	0.419
2022	2021	7.9	14.2	0.42	0.487	0.423
2023	2022	7.9	14.8	0.42	0.488	0.423
2024	2023	7.7	13.3	0.413	0.476	0.423

Source: <https://data.tuik.gov.tr/>

In Table 4.3, the Gini coefficient of Türkiye shows a tendency to increase from 2014 to 2023. Since income inequality is crucial for a country's economic growth, the underlying reasons must be investigated. According to Kuznets, there is a U-shaped relationship, meaning that in the early stages of development, income inequality increases as the wealthy benefit, and then it begins to decline. In 1965, Williamson applied the U-shaped relationship to regional unequal development stemming from natural resource contributions. Most studies on regional income inequality remain exploratory (Rey, 2004). According to Rey, it is important to focus on regional boundaries and the geographic unit level, and according to Baker and Grosh (1994), targeted policies are essential to reduce regional income inequality.

5. CHAPTER DATA COLLECTION

5.1. Data Description

The data in the Table 5.1 were taken from TURKSTAT. These data were used in map analysis, Ordinary Least Squares (OLS) Model, Spatial Lag Model and Standard Error Model (SEM). In GDP analysis, the data were calculated from ESA standards. The data and explanations used in this study are given in the table below.

Table 5.1. Data Names and Explanations

Data Name	Explanation	Source
Gini Index	In the calculation process of the Gini coefficient, household disposable income was calculated after deducting the taxes paid in the income reference period and regular transfers made to other households or individuals from the total annual income of the household and individuals (Turkstat, 2024)	TURKSTAT
Pareto Index	P80/20	TURKSTAT
GDP	Current prices, 1000 TRY	TURKSTAT
GDP Shares	Every variable's GDP share was calculated as its share divided by the total GDP in that year, and the data set was based on the ESA 2010 system	TURKSTAT
Unemployment rate	Persons aged 15 and over Unemployment Rate = (Number of Unemployed / Active Labour Force) X 100	TURKSTAT
Poverty rate	Share of households with income below 60% of the median	TURKSTAT
R&D Share	Ratio of research and development expenditures to GDP	TURKSTAT
Gender Parity	Mean years of schooling for females / Mean years of schooling for males	TURKSTAT
Female Employment Ratio	Share of female employment in Agriculture, Industry and Services	TURKSTAT
Consumer Price Index (CPI)	General	TURKSTAT
Mortality Rate	Crude death rate (deaths per thousand population)	TURKSTAT
Migration	Net Migration	TURKSTAT
Population	in thousands	TURKSTAT
Export	General Export	TURKSTAT
Import	General Import	TURKSTAT
Net Export	General Export-General Import	calculated by the author

Source: Created by author

5.2. ESA 2010/NA 10 Classification

The ESA 2010 GDP calculation system consists of transfers into the economy at the NUTS 2 level. It is in the segmentation of GDP shares by workplaces.

ESA 2010 is the implementation of NACE Rev. 2 at A21 with more details. Due to the compatibility of Türkiye's data with ESA, Türkiye's GDP data in dataset are counted by this method (EUROSTAT, TURKSTAT, ESMS, n.d.). ESA 2010 is separated into 4 fundamental distinctions:

- (a) "non-financial corporations
- (b) financial corporations
- (c) general government
- (d) households
- (e) non-profit institutions serving households." (Eurostat).

These 5 sectors represent the total domestic economy of Türkiye (EUROSTAT, 2017).

Table 5.2. Distinction of Levels by Regions

Level	Name	Regions
NUTS Level 1	Regions	12
NUTS Level 2	Sub-regions	26
NUTS Level 3	Provinces	81

Source: EUROSTAT

GDP for the total economy based on ESA 10 was obtained from TURKSTAT and the dataset was calculated by the form of ESA 2010. In table 5.3. lists the descriptions of the sections by category.

Table 5.3. A*10 classification of industries A*10 Seq. No NACE Rev. 2 Sections
Description

1. A:	Agriculture, forestry and fishing
2. B, C, D and E:	Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management and remediation activities
3. F:	Construction
4. G, H and I:	Wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities
5. J:	Information and communication
6. K:	Financial and insurance activities
7. L:	Real estate activities
8. M and N:	Professional, scientific and technical activities; administrative and support service activities
9. O, P, and Q:	Public administration and defence; compulsory social security; education; human health and social work activities
10. R, S, T and U:	Arts, entertainment and recreation; other service activities; activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; activities of extraterritorial organisations and bodies

Source: EUROSTAT



6. CHAPTER: METHODOLOGY

6.1. ESDA Analysis in GeoDa

Spatial data analysis has been rapidly developed, Haining criticised it in the late 1980s because the lack of such tools was one of the main concerns for GIS researchers and thus main focus shifted to focus on conceptual issues such as how to integrate spatial statistical methods and in a GIS environment; these issues were debated among Anselin and Getis (1992), Goodchild et al. (1992), Fisher and Nijkamp (1993), Fotheringham and Rogerson (1993,1994), Fisher et al. (1996) and Fisher and Getis (1997), However today because of development open source software tools, spatial data analysis is available (Anselin et al., 2009).

Anselin explains that the basic concept of GeoDa is familiar with the Geographic Information System (GIS) concept and is based on the knowledge of basic statistical principles and fundamental spatial statistics. While Exploratory Data Analysis (EDA) examines the distribution of patterns and non-spatial data, Exploratory Spatial Data Analysis (ESDA) extends EDA by considering the spatial dimension of data and creates spatial patterns, clusters and outliers which can be seen in the map. The GeoDa uses several techniques by ESDA such as; Moran's I which was developed by Patrick Alfred Pierce Moran, detecting similar values and clustering them and also shows global spatial autocorrelation, Local Moran's I which extends Global Moran's I and concerning local spatial analysis, Local Indicators of Spatial Association (LISA) detects local spatial clusters and shows the outliers in the graph, Getis-Ord G identifies hot and cold spots and shows them as clusters, Spatial Lag and Spatial Error Model examine the level of spatial dependencies and the cluster maps show high-high, low-low and outlier such as low-high or high-low regions in the map. Lee's L statistic ranges from -1 to 1 and is likely similar to a correlation coefficient, however the spatial autocorrelation of the two variables, if they are close to 1 indicate that the variables are highly positively correlated which means when one value is high, the other tends to be high as well in that case each variable has high spatial autocorrelation but if the values close to -1 indicate that the variables are highly negatively correlated when one value is high, the other tends to be low and that means each variable has high spatial autocorrelation (ArcGIS , n.d.).

6.2. Workflow of GeoDa

GeoDA is generally used for a certain country and local maps. For the broader concepts Python can be use. Python and GeoDA's workflow are similar enough to understand their fundamental concept is the same. The Figure 6.1. below, shows the workflow of Matplotlib's output data. Rather than having the same process, in GeoDa, the files in the shape format can be matched with Nuts 2 level's value. The process requires creating a spatial weight matrix, such as Queen Contiguity, which shows the outputs as a map. The early versions of GeoDa were based on the MapObjects and it used libraries from Environmental Systems Research Institute (ESRI) but since 2006 it is a full open source which uses WxWidgets library and different from Geographic Information Systems (GIS), it creates point layers from coordinates and can be used in the cartographic projections by opportunity to create different spatial weight matrices (Anselin, 2021).



Figure 6.1. The Workflow Diagram of Geospatial Data in Python

Source: https://geodacenter.github.io/pygeoda/esda_geopandas.html/

GeoDa on Github

6.3. Creating Spatial Weight Matrix in GeoDa

Depending on data, the spatial modelling can be varying and depends on the modelling approach; Geographically Weighted Regression (GWR), Geographically Weighted Poisson Regression (GWPR), Logistic Geographically Weighted Regression (GWLRL), Space-Time Autoregressive (STAR) and Generalized Space-Time Autoregressive (GSTAR) are one of the examples of modelling depends on the search aim (Scolastika et al., 2017).

In Geo-da, the system creates a neighbour structure matrix. According to Anselin while creating a spatial weight matrix there is a value for given whether they are neighbour or not.

$$W = \begin{vmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \dots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nn} \end{vmatrix} \quad (6.1)$$

Weights show the structure of neighbour between the observation in $n \times n$, and w_{ij} is the matrix of spatial weights. if i and j are neighbours, w_{ij} is not zero but if i and j are not neighbours, w_{ij} is zero in that case. Anselin shows the binary relations by using 1 and 0. If j is the spatial unit, j is a possible neighbour and j is not equal to i ($j \neq i$), then w_{ij} value is 1.

According to binary zero-one weights, the row standardisation mechanism takes the weights, which are “ w_{ij} ” and divides them by the sum row :

$$w_{ij(s)} = w_{ij} / \sum_j w_{ij} \quad (6.2)$$

Here, it is calculated for each row's sum of the row standardised weights equal to 1 and the number of observations “ n ” equal to:

$$S_0 = \sum_i \sum_j w_{ij} \quad (6.3)$$

And they are the sum of all weights.

6.4. Queen Contiguity

Contiguity term refers to two spatial units that share a common border with non-zero length and while rock contiguity refers to only a common edge between these two

spatial units, the queen contiguity is a border term and includes a common edge or common vertex (ArcGIS, nd) and also (Anselin, 2020).

In this research, while creating a spatial weight matrix, after the processes of loading the Gal file (according to Anselin's explanation the file that consists of each observation, the number of neighbours and also the identifiers), the queen contiguity was created. The queen contiguity number is related to the number of contiguity, and selecting one refers to having clearer contiguity and borders of them.

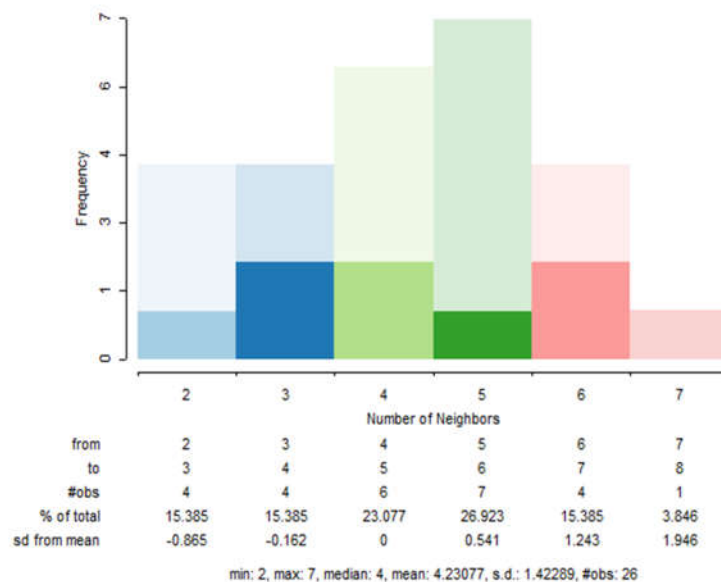


Figure 6.2. Histogram of Queen Contiguity

Source: Created by author

Figure 6.2. corresponds to the Queen Contiguity histogram. The number of the most repeated contiguity is 26.923 %, and the number is 5. The minimum number of contiguity is 2, while the maximum number of contiguity is 7.

6.5. Borders of Contiguity

The selection of contiguities and the reference contiguities are shown on the maps of Türkiye below. The white borders are neighbours of cluster provinces, and certain samples are also shown.

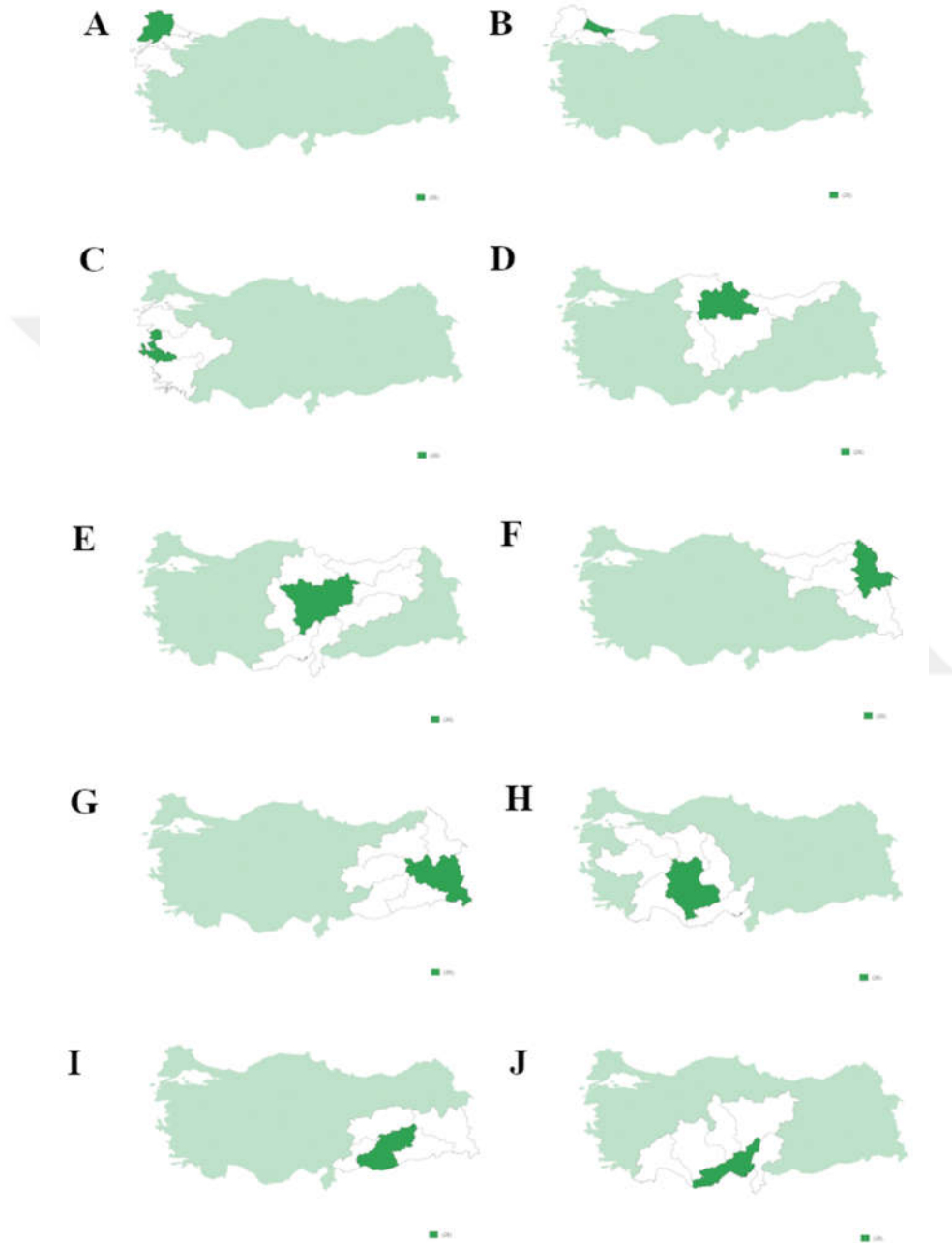


Figure 6.3 TR21: Tekirdağ, Edirne, Kırklareli (A); TR10: İstanbul (B); TR31: İzmir (C); TR83: Samsun, Tokat, Çorum, Amasya (D); TR72: Kayseri, Sivas, Yozgat (E); TRA2: Ağrı, Kars, Iğdır, Ardahan (F); TRB2: Van, Muş, Bitlis, Hakkari (G); TR52: Konya, Karaman (H); TRC2: Şanlıurfa, Diyarbakır (I); TR62: Adana, Mersin (J)

Source: Created by author

6.6. Connectivity Graph of Türkiye

In Figure 6.4., the provinces of Türkiye's visible corners and edges can be seen as a whole as lines.

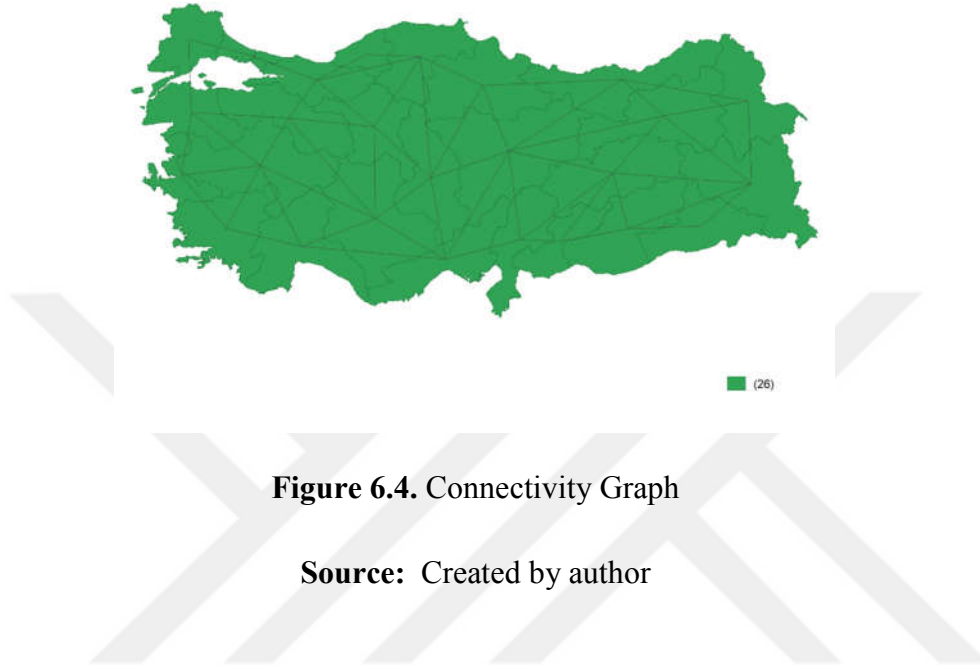


Figure 6.4. Connectivity Graph

Source: Created by author

6.7. Getis Map Hot-Spot Analysis

$$G_i = \frac{\sum_{j \neq i} W_{ij} X_j}{\sum_{j \neq i} X_j} \quad (6.4)$$

$$G_{i*} = \frac{\sum_j W_{ij} X_j}{\sum_j X_j} \quad (6.5)$$

In equation 6.4, X_j value is a variable of the observed region, W_{ij} is a spatial weight, and if W_{ij} is a neighbour, the value is equal to 1, and otherwise it is 0. This equation calculates the relative spatial weighted average. It means if the G_i value is high, the neighbouring regions have relatively high values.

Equation 6.5 consists of all regions and is especially used in global comparative spatial analysis.

6.8. Lisa Principle

Global Spatial Autocorrelation statistics such as Moran's I cannot provide a locational spatial pattern although they were designed to reject the null hypothesis of spatial randomness and the Lisa Principle was suggested for this situation (Anselin,2020). Moran was the first one who present the measurement of spatial autocorrelation and Moran's Index is based on the similarity between given features depending on feature location and the values are shown under any certain feature similarity (Scolastika et al.,2017).

Lisa has 2 fundamental properties. First one is: it provides a significance test for each location statistically, and the second one is it shows how the sum of the local statistics relate to global statistics, which correspond to them (Anselin,2020).

$$\sum_i \sum_j g_{ij} \quad (6.6)$$

Equation 6.6 is the expression of the most global statistic autocorrelation, while the local one is expressed as:

$$\sum_j g_{ij} \quad (6.7)$$

In equation 6.7, in Anselin's explanation, i represents each location's observation, j is the set of locations, and the sum over j, in other words, for all j, obtains related patterns where $f(x_i, x_j)$ measures the characteristic similarity between a pair of observations and spatial closeness.

$$\sum_j w_{ij} f(x_i, x_j) \quad (6.8)$$

In equation 6.8, w_{ij} is the spatial weight, and the whole equation is a generic composition of the spatial association's local index (Anselin,2020).

6.9. Global Moran

Global Moran is one of the most common indicators for spatial autocorrelation, and in Anselin's Geoda, Local Moran I is derived from Global Moran I.

$$I = \frac{\sum_i \sum_j w_{ij} z_i \cdot z_j / S_0}{\sum_i z_i^2 / n} \quad (6.9)$$

Equation 6.9, n represents the number of observations, i is the observation at the location i , w_{ij} are the elements of the spatial weight matrix, z_i equals to $x_i - \bar{x}$ (x 's mean variable).

$$S_0 = \sum_i \sum_j w_{ij} \quad (6.10)$$

In equation 6.10, S_0 is the sum of all weights. Moran's Index shows the value between 1 and -1, and positive values close to +1 show spatial clustering while negative values close to -1 show spatial disintegration (Anselin, 1995; Suryowati et al., 2018).

6.10. Local Moran I

As mentioned above, the Local Moran I statistic, which identifies local clusters and outliers, was proposed in 1995 (Anselin, 2020).

Since the sum of all weights equals the number of observations in a row, the standardised weight circumstance equals:

$$S_0 = \sum_i \sum_j w_{ij} \quad (6.11)$$

In the Getis Map, by measuring statistically significant areas and using hot-spot analysis, Lisa analyses low-high and high-low measurements and corresponds locational abnormalities.

While studying with Local Moran I, there is a prioritised situation that the neighbourhood relations take into account. Local Moran I has 999 permutations with each observation. We have a 26-regional Nuts 2 system and 999 permutations, with each region being observed.

6.11. Meaning of Indicators and Spatial Outliers

The clusters are categorised into 4 sections in the Moran scatter plot, and this system works in the four quadrants of the plot where the categories are Low-Low, Low-High, High-Low and High-High.

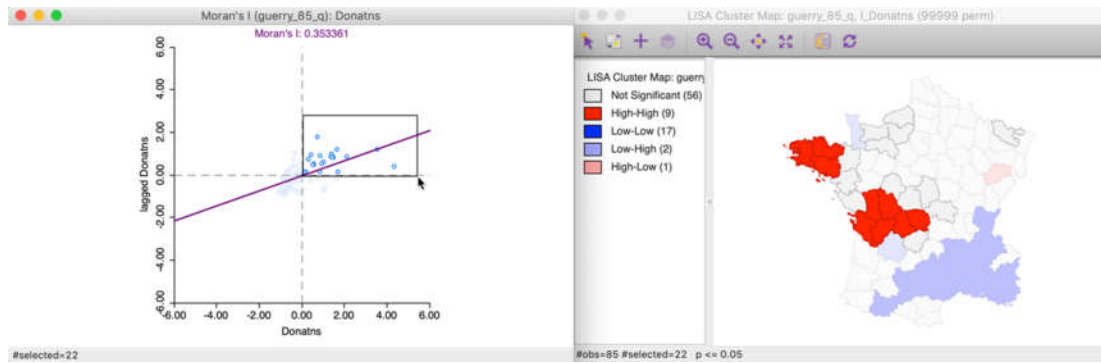


Figure 6.5. The red cluster's Moran's I Graph and Map

Source: Geoda /LISA and Local Moran

The red areas are created by the Moran's I scatter plot which is the area of little blue points in the graph. They represent a High-High Cluster (Anselin,2020).

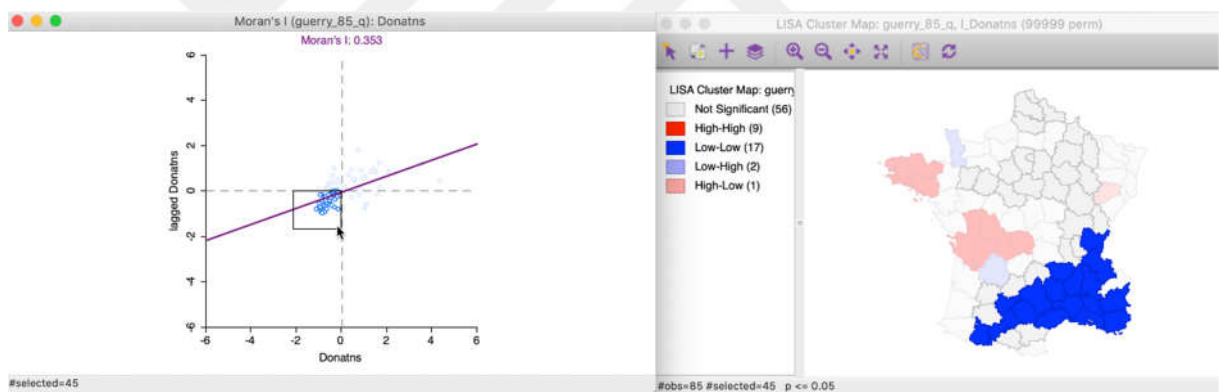


Figure 6.6. The blue cluster's Moran's I Graph and Map

Source: Geoda/LISA and Local Moran

In Anselin's explanation, the blue areas belong to the Low-Low Cluster, which is created by the left quadrant.

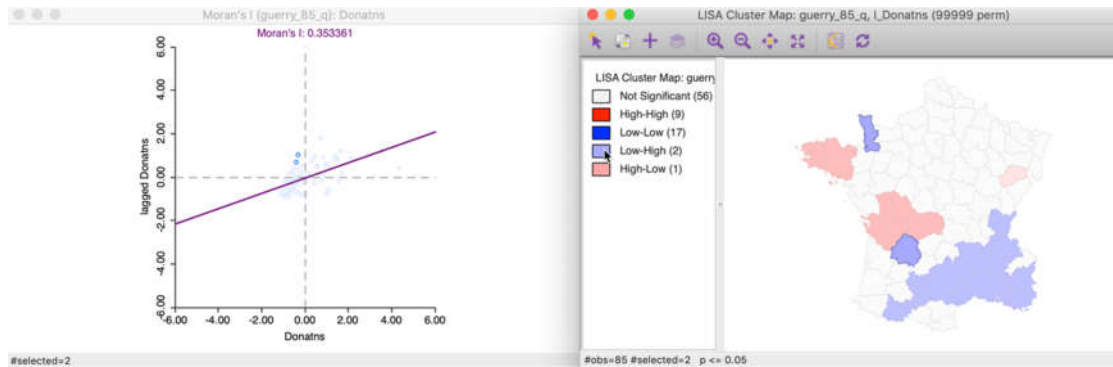


Figure 6.7. The spatial outlier example (the left point)

Source: Geoda/LISA and Local Moran

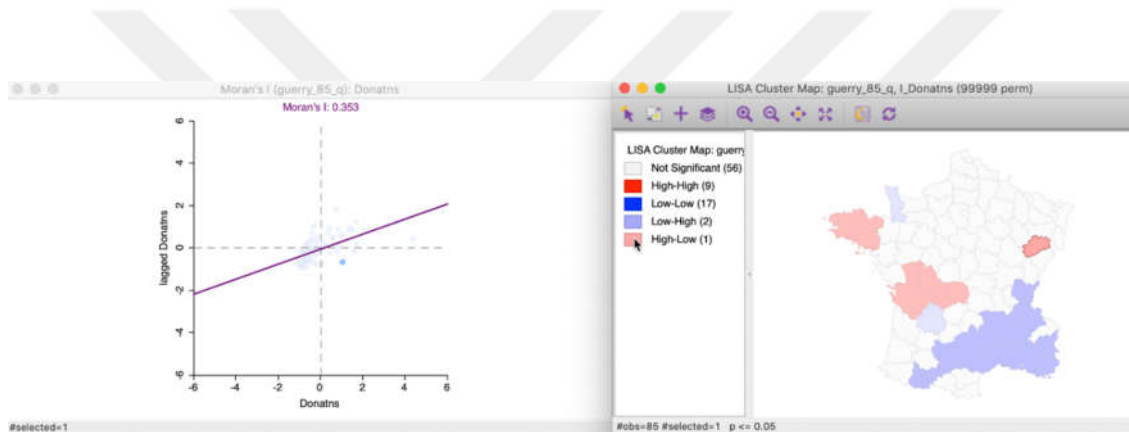


Figure 6.8. The spatial outlier example (the right point)

Source: Geoda/LISA and Local Moran

In Anselin's explanation, this can be a significant outlier, which is in the one small point in the right quadrant in Figure 6.8, and another possible spatial outlier is in Figure 6.7. left quadrant's small point. Grey areas are statistically not significant areas. High-High clusters show the regions which have a high Gini coefficient, and their neighbours also have a high Gini coefficient. In a High-High LISA clustered situation, there is a strong relation to having a high level of income inequality. Low-low clusters show the low Gini coefficient, and also their neighbours have the low Gini coefficient. In a Low-Low LISA clustered situation, there is a strong association with having a low level of income inequality. Low-High clusters show there is a low Gini coefficient and are surrounded by neighbours which have a high Gini

coefficient value, indicating negative spatial correlation because while the observed region has a low Gini, its neighbours have a high Gini. High-low clusters show there is a reverse situation with the Low-high clusters; the observed region has a high Gini coefficient while its neighbours have a low Gini, and this situation also reflects the negative spatial correlation.

6.12. Bivariate Analysis

Bivariate Moran Scatter Plot

It is a plot with a variable on the x-axis and spatial lag on the y-axis in the bivariate context. The biggest difference is that it measures a given variable concerning its neighbour's different variables (Anselin, 2020).

Moran's I is coming from the equation:

$$I_B = \frac{\sum_i (\sum_j w_{ij} y_j \times x_i)}{\sum_i x_i^2} \quad (6.12)$$

A value at t and contiguous in a previous time period's correlation shown as:

$$I_T = \frac{\sum_i (\sum_j w_{ij} z_{j,t-1} \times x_{i,t})}{\sum_i x_{i,t}^2} \quad (6.13)$$

Also, there can be a relation between the value at a previous time period, which is z_{t-1} , to its neighbours in the future time period, which is $\sum_j w_{ij} z_t$:

$$I_T = \frac{\sum_i (\sum_j w_{ij} z_{j,t} \times z_{i,t-1})}{\sum_i z_{i,t-1}^2} \quad (6.14)$$

Linear regression is used to estimate the bivariate Moran's I:

$$\sum_j w_{ij} z_{j,t-1} = \beta_{3,z_{i,t}} + u_i \quad (6.15)$$

β_3 is the correct estimation of the spatial correlation between past value of neighbours and the present value of the observed region.

6.13. Equations Framework for OLS, SAR and SEM Models

6.13.1. OLS Equation

Classic regression model's equation:

$$X\beta = \beta_1X_1 + \beta_2X_2 + \dots + \beta_kX_k \quad (6.16)$$

$X_1, X_2, \dots, X_k$ are the independent variables were used in this model estimation and correspond to gini2020 (previous years' Gini coefficient), agrif_2021 (agriculture, forestry and fishing shares in GDP in 2021), cons2021 (construction shares in GDP in 2021), info2021 (information and communication share in GDP in 2021), finan2021 (financial and insurance activities shares in GDP in 2021), ARGER_2021 (research & development shares in GDP in 2021), respectively and $X\beta$ is regional Gini coefficient.

$$y = X\beta + \varepsilon \quad (6.17)$$

X is the independent variables matrix that contains all the independent variables used in Equation (6.16)

6.13.2. Spatial Lag Model (SAR) Equation

$$y = \rho Wy + X\beta + \varepsilon \quad (6.18)$$

Here, ρ is the spatial autoregressive coefficient, and W is the spatial weight matrix that captures the influence of neighboring regions on the dependent variable.

6.13.3. Spatial Error Model (SEM) Equation

$$y = X\beta + u, \quad u = \lambda Wu + \xi \quad (6.19)$$

In this model, spatial dependence is modelled in the error term instead of the dependent variable. λ is the spatial error coefficient. Here, u is the error component that shows the spatial dependence of the errors (residuals), λ is the spatial error dependence coefficient, W is the spatial weight matrix (queen contiguity), and ξ is the white noise errors.

7. CHAPTER QUANTILE and BIVARIATE ANALYSIS

7.1. Regional Gini Coefficient of Türkiye's Quantile Map

A quantile map is based on the same number of observations, which are called quantiles after and they are sorted into groups (Anselin,2020). Türkiye's Gini coefficient quantile map has five quantiles, meaning five categories in which the Gini coefficient value is divided. That quantile map represents Gini coefficients according to regional distribution. In the literature review, as mentioned, the Gini coefficient is the measurement of income inequality. The Gini coefficient was examined for 10 years, from 2014 to 2023, and the results are shown. The value of the Gini coefficient is 0 to 1, where 0 means equal income distribution, while 1 represents the maximum inequality distribution of income. In this quantile map, light colours represent lower income inequality, and darker colour regions represent income inequality that is more intense. In 2014, Southeastern and Southern Regions; TR61 (Antalya, Isparta and Burdur); TR52 (Konya, Karaman); TR63 (Hatay, Kahramanmaraş, Osmaniye); TRC2 (Şanlıurfa, Diyarbakır) and TRA1 (Erzurum, Erzincan and Bayburt) had highest level of Gini coefficient, indicating highest income inequality, on the other hand, the lowest level of Gini coefficient belonged to Central Anatolia and Black Sea Region, corresponding to TR42 (Kocaeli, Sakarya, Düzce, Bolu, Yalova); TR81 (Zonguldak; TR90 Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane) and TR71(Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir). The reason for the income inequality difference across regions may have been due to the sectors that developed in specific regions. After the year 2015, Istanbul had consistently high income inequality. In 2021, the highest income inequality belonged to TR52 (Konya, Karaman); TR62 (Adana, Mersin); TR83 (Samsun, Tokat, Çorum, Amasya) and TRA2 (Ağrı, Kars, Iğdır, Ardahan).

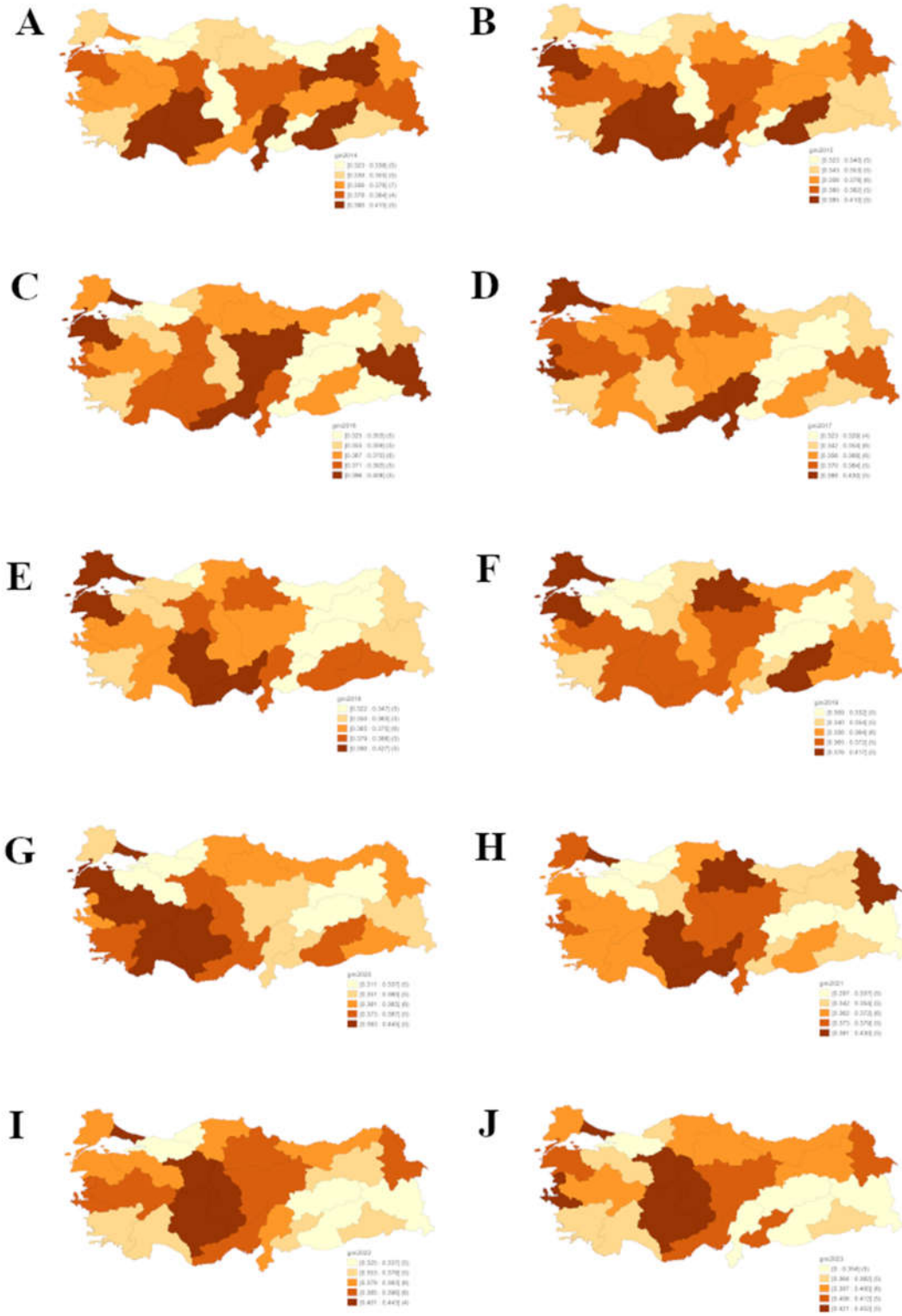


Figure 7.1. The Gini Coefficient Quantile Map of Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

After 2021, darker red areas exhibited increasing stability for some regions in terms of the Gini coefficient, and TR51 (Ankara) was added to the map of highest-income inequality clusters. In 2023, TR31 (Izmir) was also added to the map of highest-income inequality clusters.

This may have been caused by socio-economic structure, high urbanisation and population of the province. The figure below represents a population quantile map for 2023. TR51(Ankara) and TR31(Izmir) were one of the highest population provinces in Türkiye.

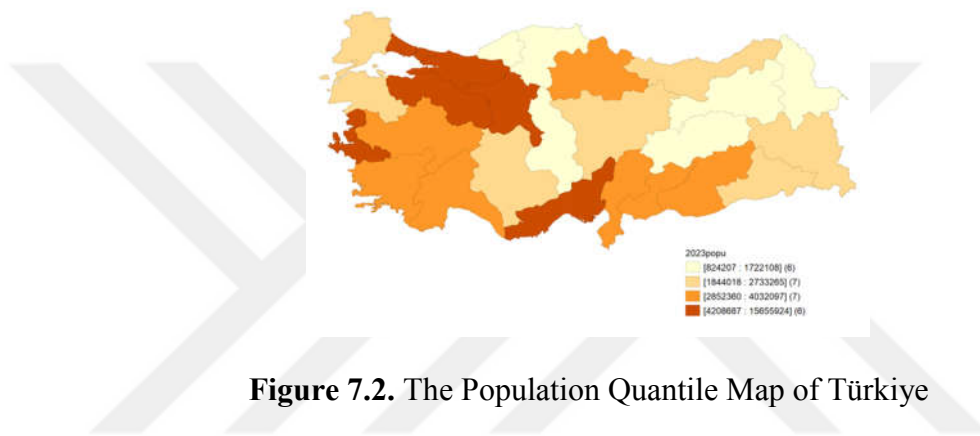


Figure 7.2. The Population Quantile Map of Türkiye

Source: Created by author using data from TURKSTAT

After examining the quantile map, the Getis maps were reviewed to identify statistically significant clusters. Getis-Ord Gi* Map is the result of hotspot analysis.

7.2. Gini Coefficient Getis-Ord-Gi* Maps of Türkiye

Getis-Ord Gi* map is a significance map, and it helps us to see details in econometrically the importance of the different locations (Anselin,2020). The Getis-Ord Gi* map is a hotspot analysis map. Anselin noted that Getis-Ord Gi* map does not always, but generally, shows the same areas because the setting involves 999 permutations where the point's p value is 0.05. The significant areas have a p-value is 0.05 or less. There is also a significance test representing significant areas whose p-value is 0.05. When the value is greater than the mean or its standardised z value is

a positive value, the Cluster is High-High, indicating hot spot one, and the colour is red (Anselin,2020).

The 10-year Getis-Ord Gi* Gini coefficient Map of Türkiye, shown in Figure 7.3. below, corresponds to the years between 2014 and 2023.

In 2014, the High-value cluster (hot spot) corresponded to the TRB1 NUTS 2 region code, which includes the cities of Malatya, Elazığ, Bingöl, and Tunceli. They had a high Gini coefficient values, indicating that income inequality was spatially concentrated in the TRB1 region and its surrounding areas. The blue cluster corresponded to TR82, which includes the cities of Kastamonu, Çankırı and Sinop.

The cluster exhibited a low Gini coefficient in 2014, and it had a low income inequality, was surrounded by neighbours with similarly low values. In other words, there was a spatial concentration of low-income inequality. Figure 7.3. (B) shows the Getis map of the year 2015. There was no red area where their value was significantly high. The low Gini coefficient clusters corresponded to TR82 (Kastamonu and Çankırı); TRC2 (Şanlıurfa and Diyarbakır). Their Gini coefficient were low, which means they had low income inequality. There was an indication of improvement in income inequality at the NUTS 2 level. Because in 2014 TRB1 region had a high level of income inequality, and it was disseminated in 2015. Their significance p-values were 0.05 or lower in the same areas. as the Getis Map corresponds, statistically significant clusters.

Figure 7.3. (C) shows the Getis map of the year 2016 Gini values. The red cluster corresponded to TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir). This cluster had a high Gini coefficient, indicating high income inequality and was surrounded by neighbours with high values, however the blue cluster had the reverse. The blue cluster corresponded to TRB2 (Van, Muş, Bitlis, Hakkari). In 2017, the clustered areas appear to have expanded. This time, the red areas corresponded to TR21 (Tekirdağ, Edirne, Kırklareli) and TR22 (Balıkesir, Çanakkale), respectively. The blue clusters, TRC2 (Şanlıurfa, Diyarbakır) and TRB2 (Van, Muş, Bitlis, Hakkari), had low Gini coefficients, indicating low income inequality and were surrounded by neighbours, along with similarly low values. TRC2 region (Şanlıurfa and Diyarbakır) was in the blue cluster, just as been in the previous year. In 2018, the blue clusters expanded significantly in Figure 7.3. (E). These blue clusters exhibited a low Gini

coefficient and were surrounded by neighbours with similarly low values, indicating spatial clusters of low income inequality.

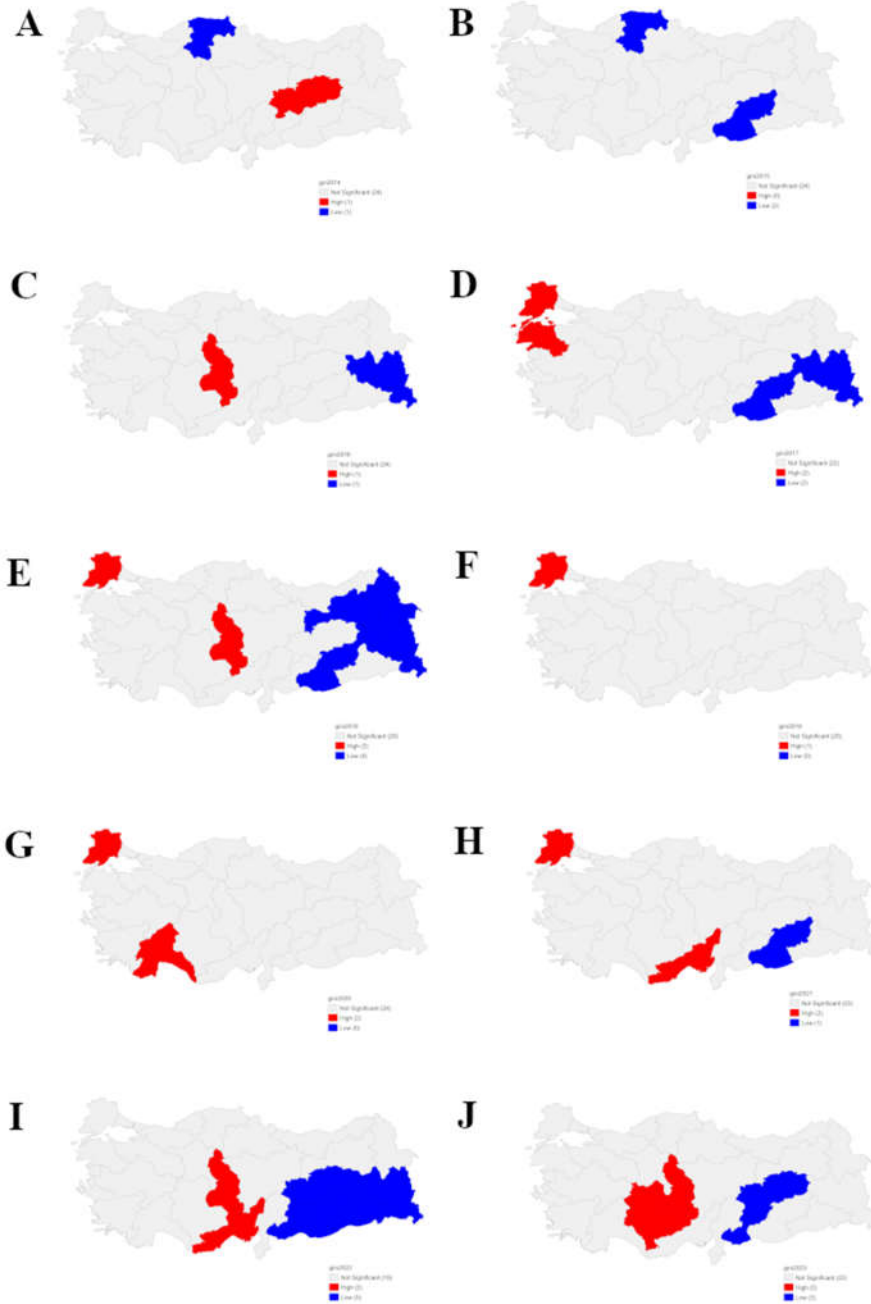


Figure 7.3. The Gini Coefficient Getis Map of Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

Although they did not appear on the blue region map, they may have contributed to the formation of these clusters as blue through spatial effects. This interaction can be examined more effectively by using the LISA cluster map, which considers autocorrelation patterns as the basis for neighbourhood relations.

The red clusters corresponded to TR21 (Tekirdağ, Edirne, Kırklareli) and TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir). TR21 exhibited the same clustering tendency of a high Gini coefficient as in the previous year.

In 2019, there was no blue area while there still existed a red one. This red cluster corresponded to the TR21 (Tekirdağ, Edirne, Kırklareli).

In 2020, there was no blue clustered region. According to Bayar et al.'s findings (2023), the COVID-19 pandemic has caused income inequality to increase. In Figure 7.3. (G), there was another red region that has occurred. This red region corresponded to TR61 (Antalya, Isparta, Burdur).

While TR61 remained the same in Figure 7.3 (H) in the year 2021, it disappeared in Figure 7.3. (I), which shows the year 2022 but in Figure 7.3. (I), the clusters were expanded. The red regions belonged to TR62 (Adana, Mersin) and TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir). In 2022, the blue regions were expanded more than the red regions. The blue clusters corresponded to TRC1, TRB1, TRC2, TRC3, and TRB2 regions.

In 2023, another red cluster corresponded to TR52 (Konya and Karaman). The blue clusters were diminished. One of the possible reasons might have been the earthquake that occurred in 2023 in the Eastern Anatolian Region.

7.3. Lisa Analysis of the Gini Coefficient

While Getis-Ord G_i^* indicates spatial concentrations, LISA is capable of indicating spatial outliers based on neighbourhood relationships. In the LISA map, High-Low and Low-High clusters can be seen. These analyses were observed by the Queen matrix, and in Figure 7.4. (A) there was no High-High or High-Low cluster; however, Low-Low and Low-High clusters were observed. Low-high cluster corresponded to TRB1 (Malatya, Elazığ, Bingöl, and Tunceli). While these provinces had a low Gini coefficient, their neighbours had a high Gini coefficient in 2014. Low-low cluster corresponded to TR82; (Kastamonu, Çankırı and Sinop). While

these provinces had low Gini coefficients, their neighbours also had low Gini coefficients.

In Figure 7.4. (B), The Low-Low cluster corresponded to TR82 (Kastamonu, Çankırı, Sinop). They had low-income inequality, and they were also surrounded by low-income inequality neighbours, even though they were not blue on the map. For example, Sinop's neighbours are Kastamonu and Samsun; Kastamonu's neighbours are Sinop, Çankırı, Karabük and Bartın; Çankırı shares a border with Kastamonu, Ankara, Kırıkkale and Bolu. These regions also had relatively low income inequality, but they were not classified as blue because they were not statistically significant to be part of a blue cluster. When examined in detail, for example, Zonguldak has a coal-mining industry and Ankara, on the other hand, is urbanised compared to other border cities. The High-Low cluster was observed, which corresponded to TRC2 (Şanlıurfa and Diyarbakır). These provinces had a high Gini while their neighbours had a low Gini coefficient.

In 2016, 2 Low-high clusters were observed. TR21 (Tekirdağ, Edirne, Kırklareli); TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir). These clusters' Gini coefficients were low, whereas their neighbours' were high. Istanbul, for example, had a high Gini coefficient because of sharing a border with TR21. There might have been countable reasons behind this situation, such as immigration, population density.

In 2017, as shown in Figure 7.4. (D), the red High-High clusters and High-Low clusters were observed. The first High-High cluster corresponded to TR21 (Tekirdağ, Edirne, Kırklareli), with its neighbouring city being Istanbul. These areas exhibited high income inequality, and another High-High red cluster, corresponding to TR22 (Balıkesir, Çanakkale), shares borders with Bursa, Kütahya, Manisa, and Izmir. Both red clusters demonstrated a significant level of income inequality, surrounded by neighbouring regions with similarly high income inequality. On the map, unlike previous years, two High-Low clusters were observed, corresponding to TRB2 (Van, Muş, Bitlis, Hakkari) and TRC2 (Şanlıurfa, Diyarbakır). These clusters exhibited high Gini coefficients and high income inequality, while their bordering provinces had low Gini coefficients and low income inequality.

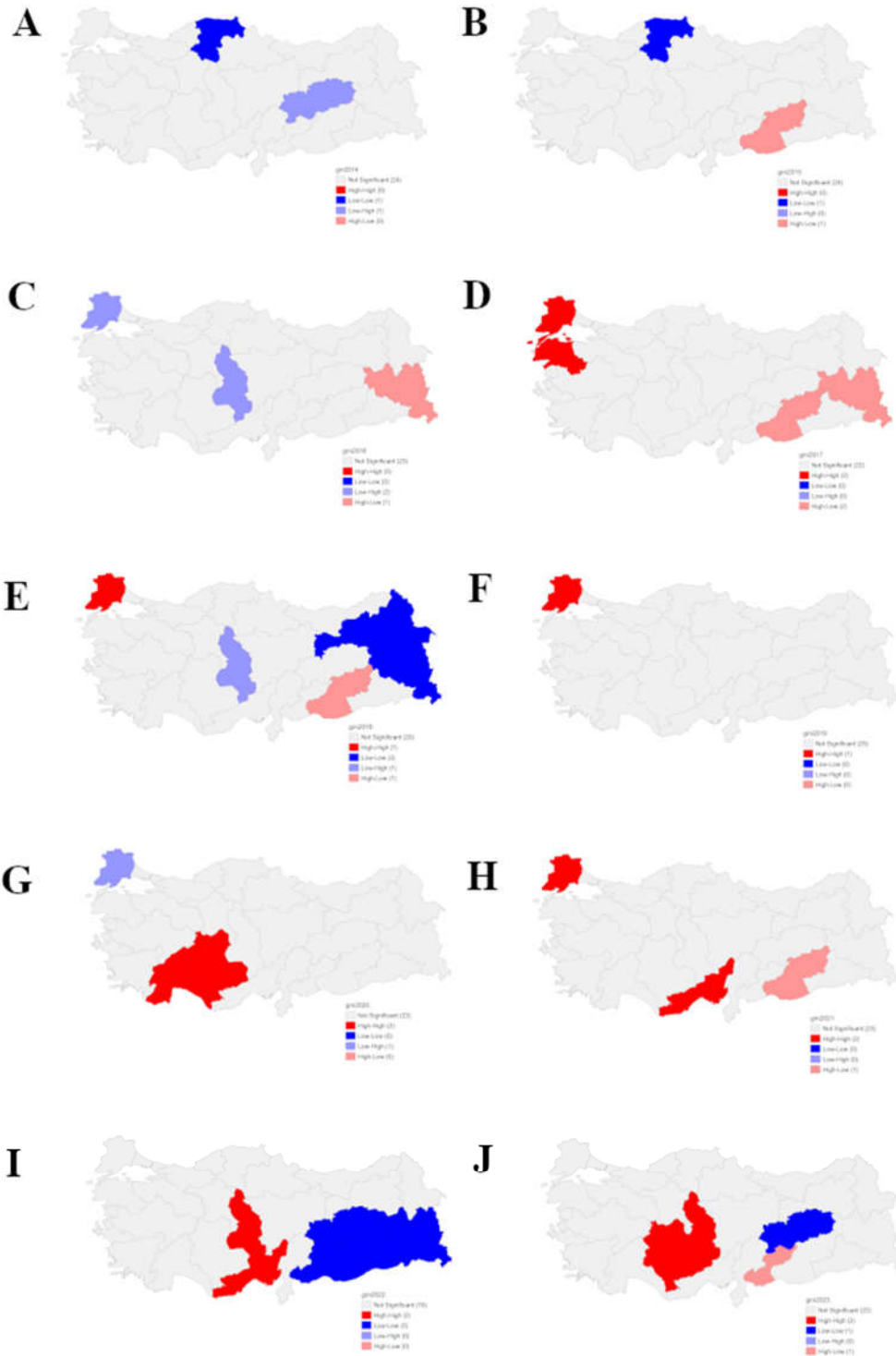


Figure 7.4. The Gini Coefficient Lisa Map of Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

In 2018, Figure 7.4. (E) illustrated a Low-High cluster corresponding to TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir). While these provinces experienced low income inequality, their borders exhibited high income inequality, specifically with Yozgat and Çorum marking the boundaries. The Low-Low cluster expanded across TRA2 (Ağrı, Kars, Iğdır, Ardahan), TRA1 (Erzurum, Erzincan, Bayburt), and TRB2 (Van, Muş, Bitlis, Hakkari). No significant blue cluster was observed in 2019. However, the high-high cluster persisted in the same province as in previous years. TR21 (Tekirdağ, Edirne, Kırklareli) turned into a Low-high cluster in Figure 7.4. (G). High-high clusters corresponded to TR61 (Antalya, Isparta, Burdur) and TR52 (Konya, and Karaman), respectively. These provinces had a high Gini coefficient, and their neighbours had high Gini coefficients. In 2020, the COVID-19 pandemic occurred. The COVID-19 pandemic increased various forms of economic inequality and also wealth (Murshed, 2022). Not until 2020, Türkiye had a High-high cluster which covers multiple provinces simultaneously in a stable condition that would keep the position for the next years. The pandemic's effect on Türkiye's income inequality cannot be deniable, and it is visible in Geoda's Lisa Map: Figure 7.4. (H), Figure 7.4. (I) and Figure 7.4. (J) which show the years 2021, 2022 and 2023 respectively. In Figure 7.4. (H), the High-high cluster corresponded to TR62 (Adana, Mersin). In the Figure 7.4. (I), in addition to Adana and Mersin provinces, TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir) was also added. In Figure 7.4. (J) Red clusters corresponded to TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir) and TR52 (Konya and Karaman). To investigate and understand the multiple reasons behind the increase or decrease in income inequality, bivariate analysis can be a useful tool for examining the spatial association between two variables. The Spatial Spill-Over Theory can explain spatial dependence in bivariate analysis. According to Li and Li (2018) the spill-over effects of China's regional economic growth gaining interest. Carrington (2008) applied spatial econometrics and found that the regional locations role of evolution not only depends on its own qualifications but also those of the regions that shaped the neighbourhood. Liu and Liu (2019) examined spatial spill-over effect on the damage of global environment. According to their finding carbon emissions had significant spatial spill-over effect among provinces and the other factors such as technology and population, had different spatial interactive effects on emissions. Also Dual Sector

Model can explain in the development process, how each country is at a different point, and it contributes to the Structural Change Theory (Sarah, 2012). Lewis Structural Change Theory can explain the developing country 's transition between two sector and also called Dual Economic Theory and it is deriving from the theory of Structural Change Theories, which explains underdeveloped economies transformation from traditional agriculture to a more modern industrial, manufactured and service economy (Agbenyo, 2020). Chen et al. (2009) examined the Dual Sector Model, how population affects income disparity. According to their findings urban population ratio contributes to the income disparity.

7.4. The Gender Parity Quantile Analysis of Türkiye

The gender parity map of Türkiye was examined from 2014 to 2023 and it is shown in Figure 7.5. Over the past ten years, there has been no significant change. Izmir, Aydın, Denizli, Tekirdağ, Edirne, and Kırklareli have consistently shown the smallest gap between female and male mean education levels. In contrast, regions such as Ağrı, Kars, Iğdır, Ardahan, Van, Muş, Bitlis, and Hakkari have remained the areas with the greatest disparity in mean education levels between females and males.

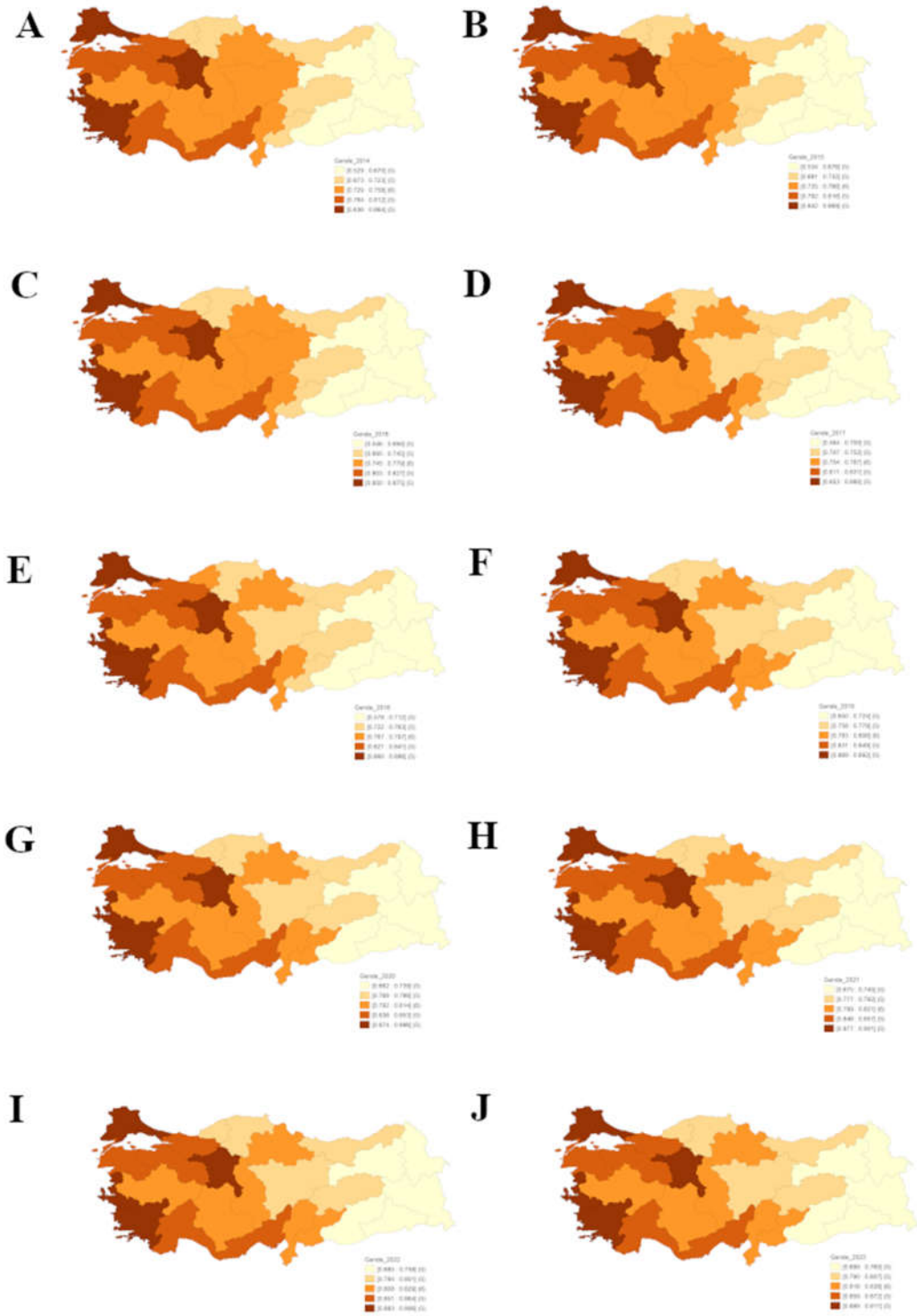


Figure 7.5. Gender Parity Quantile Map in Türkiye for the years: 2014 (A),2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

7.5. Bivariate Analysis of Gini Coefficient and Gender Parity

In Figure 7.6, the x-axis corresponded to the Gini coefficient, and the y-axis corresponded to gender parity. Since this is slightly different from other regression analyses, it allows us to observe relationships even if the axes are swapped. If the x-axis corresponds to the Gini coefficient, it indicates how the spatial clustering of inequality relates to gender parity across regions. In other words, income inequality exhibits spatial patterns alongside gender parity. Red clusters indicate high Gini coefficients and are surrounded by neighbours with a high gender parity ratio, referred to as High-High. The light blue clusters represent Low-High, denote areas where the Gini coefficient is low while being surrounded by neighbours with high gender parity. In the Light-Red (High-Low) clusters, the Gini coefficient is high but is surrounded by neighbours with low gender parity, and the Blue clusters represent areas where both the Gini coefficient and the surrounding neighbours' gender parity are low. High Gini and low gender parity areas suggest that high income inequality is linked to a lower educational level for women in other regions. In red areas, however, income inequality did not hinder female education in the surrounding regions. If the Gini is low and the neighbouring regions' gender parity is high, it reflects the balanced effect of better educational levels for women. These areas were represented in light blue and corresponded to TR21 (Tekirdağ, Edirne, Kırklareli), TR41 (Bursa, Eskişehir, Bilecik), and TR32 (Aydın, Denizli, Muğla) in 2014, as shown in Figure 7.6 (A). To analyse the spatial pattern between income inequality and gender parity in-depth, the study was conducted between 2014 and 2023. In 2015, in Figure 7.6 (B). High Gini coefficient clusters were surrounded by regions with low gender parity and their colour marked by light red; in these clusters, high income inequality was linked to the surrounded regions' low educational level of women and it is important to examine these clusters: TRA1 (Erzurum, Erzincan, Bayburt); TRA2 (Ağrı, Kars, Iğdır, Ardahan) and TRC2 (Şanlıurfa and Diyarbakır). In 2016, the Western Aegean Regions were in a High-High cluster; they had a high Gini coefficient, high income inequality, and were surrounded by high gender parity regions. Low-low areas corresponded to Eastern Anatolia; they had low income inequality and were surrounded by low gender parity regions. In 2017, some of the low-income inequality clusters with high-gender-parity surrounding regions turned into high-income inequality clusters with high-gender-parity surrounding regions.

Some of the blue clusters turned into High-Low clusters. In 2018, the High-High clusters corresponded to TR21 (Tekirdağ, Edirne and Kırklareli) and TR22 (Balıkesir and Çanakkale). Eastern Anatolia was marked by a Low-low cluster. They exhibited low income inequality and were surrounded by neighbours with similarly low gender parity. The reason for this is possibly caused by welfare policies, transfer taxes or sector distribution. The map of Gini and Gender parity started to become as a red cluster in Western regions, in high-high clusters, whereas Eastern regions were in low-low clusters. High income inequality is spatially associated with high female education level. One of the reasons for that might be is when the female's education level increases, the wages also increase, or they do not prefer to work for low payments anymore, which can be explained by the income effect. According to Human Capital Theory (HCT), when women invest in education, it increases the parity ratio; however, if income inequality among other groups rises, the Gini coefficient remains high. In this case, the situation observed here suggests that theories such as human capital do not always yield expected results. By presenting education as an “investment” that provides returns for individuals in terms of financial gain and for the state in terms of employment and economic growth, HCT offers an interesting model for the neoliberal management of public education (Gillies, 2015).

Human capital theory focuses on the female workforce within the neo-classical marginality approach. According to this theory, women are less qualified and less trained than men, which leads to them earning lower wages. Human capital theory argues that removing inequality between women and men and enabling women to participate in the economy fully can only be achieved through development and industrialization (Levent & Aydın, 2021).

Spatial interaction modelling has become a key branch of modern human geographic modelling literature and also the spatial interaction models demonstrate how various locations are functionally connected. (Rey, 2001).

In 2020, a Pandemic occurred. Eastern Anatolia was marked by a blue cluster (Low-Low). They exhibited a low Gini coefficient and were surrounded by neighbours with low female gender parity. Western Region was marked by a red cluster (High-

High): they exhibited a high Gini coefficient and were surrounded by neighbours with similarly high gender parity.

In 2021, clustered regions colour remained mostly the same, but at this time, the Marmara region was marked by red. TR21 (Tekirdağ, Edirne and Kırklareli) exhibited a high Gini coefficient, while one of the neighbours, Istanbul, had a high gender parity. In 2022, TR32 (Aydın, Denizli and Muğla) turned into a Low-High cluster, which means that when they had a low Gini coefficient, their neighbour had high gender parity.

After 2018, most of the red and blue areas were clustered in certain regions. Although income equality was high, the neighbour regions' gender parity was high in the West Region provinces; on the other hand, even with the low income inequality, the neighbour regions' gender parity was low in the East Region provinces. This is because the general poverty and low level of education in the Eastern Region, as well as the low participation of women in the workforce, may mask inequality, which may be consistent with the theory of invisible labor. The founders of the Marxist economic approach, which defines women as a secret labour in the labour market, are K. Marx and F. Engels (Kaplan, 2009: 8); according to Marxist theory, economic approaches based on criticisms of capitalism regard women as engaging in secret labour in the economy (Akansel, 2004: 39), and the Marxist approach explains that men are considered bourgeois and women are seen as part of the proletariat within the family. therefore, the reserve army approach was developed within this scope, whereby this reserve army of labour comes into play in the face of fluctuations in the economy so based on this, women are also included in the group of the secret reserve army of labour (Özmen, 2011: 32) (Levent, Aydın, 2021). An agricultural economy, on the other hand, may limit women's education, which is consistent with Lewis's dual sector theory. In this case, sectors such as agriculture would result in similar income distributions, but this would not indicate prosperity.

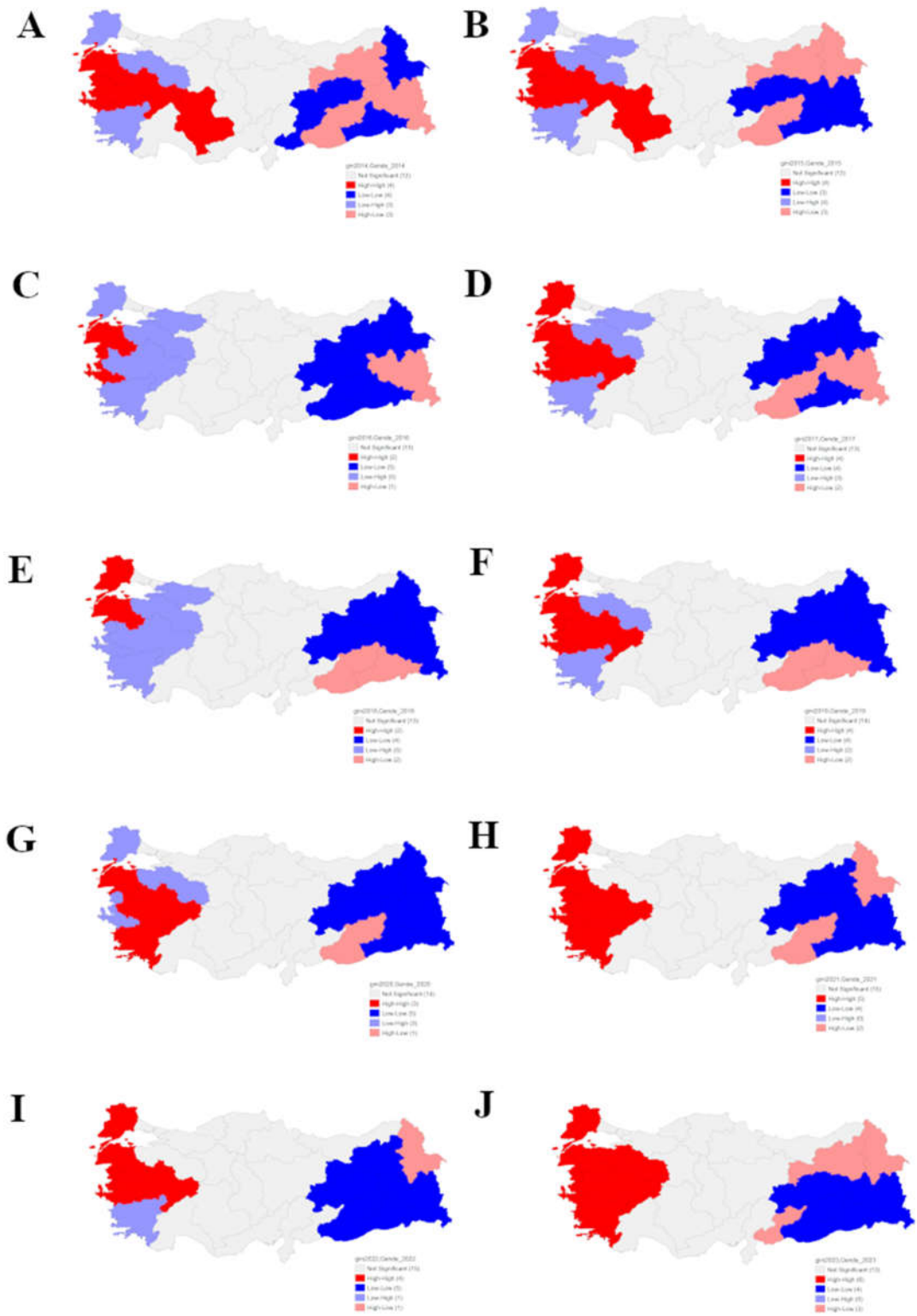


Figure 7.6. Bivariate Map of Gini Coefficient and Gender Parity in Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

But some regions in the East, for example, TRA1 (Erzurum, Erzincan and Bayburt), were marked as a High-low, which means while it exhibited a high income inequality, it was surrounded by neighbours with low gender parity. In the analyses of Quantile and Bivariate, it was observed that in areas such as Izmir and Tekirdağ, particularly in the last three years of 2021, 2022, and 2023, where both female education and income inequality were high, income inequality was also high in neighboring regions.

This indicates that in regions exhibiting this pattern, spatially clustered higher female education alone is not enough to lower income inequality.

Positive spatial autocorrelation means that geographically close values of a variable tend to be similar on the map: high values tend to be found near high values, middle values tend to be found near middle values, and low values tend to be found near low values (Li Li et al., 2011). If the x-axis corresponds to gender parity, then the map would be in 2014:

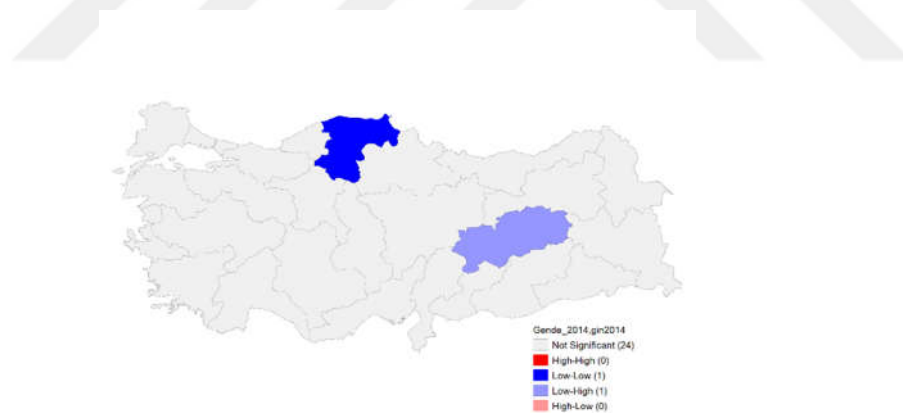


Figure 7.7. Bivariate Map of Gender Parity and Gini Coefficient in Türkiye, 2014. (The Gender Parity corresponds the x axis and Gini Coefficient corresponds to y axis)

Source: Created by author using data from TURKSTAT

In Figure 7.7, the significant clusters disappeared, so less spatial paternal relation was observed. In the previous map, when the x-axis corresponds to the Gini coefficient, there were stronger clustering patterns, and it helps us to comprehend

that income inequality is structured spatially to gender parity. Now, since the axes were swapped, it can be seen, it might not be perfectly linear, and in the previous map, some clusters had stronger spatial autocorrelation, but in the reverse direction, it gets weaker. Low-low cluster means there is low gender parity, and it is surrounded by regions with low income inequality might be caused by governmental welfare policies or the fishing line business in the cluster TR82 (Kastamonu, Çankırı and Sinop). However, light blue shows that lower female educational level is associated with other surrounding regions higher income inequality, and these provinces are: Malatya, Elazığ, Bingöl and Tunceli.

7.6. Quantile Analysis of Female Employment Ratio

This map shows the highest female labor force participation ratios in clusters of cities like Istanbul, Kocaeli, Sakarya, Bursa, and Eskişehir.

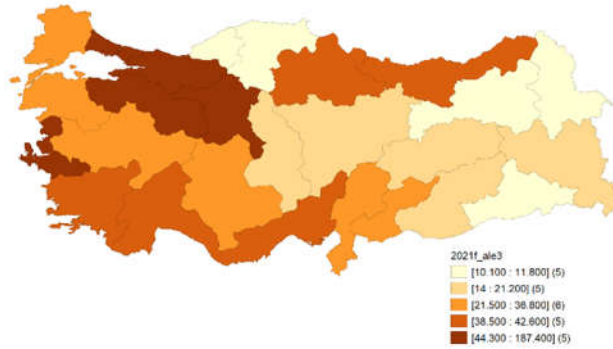


Figure 7.8. Quantile Map of Female Employment Ratio in 2021

Source: Created by author using data from TURKSTAT

7.7. The Bivariate Analysis of Female Employment Ratio

Eastern Anatolia exhibited a low Gini coefficient and was surrounded by neighbours with similarly low female participation. The Marmara Region (TR21) exhibited a high Gini coefficient and was surrounded by neighbours with similarly high female participation in 3 sectors; however, the cluster TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova) exhibited a low Gini coefficient and was surrounded by neighbours with high female participation. TRC2 (Şanlıurfa and Diyarbakır) exhibited a high Gini coefficient and was surrounded by neighbours with low female participation by indicating a negative spatial autocorrelation.

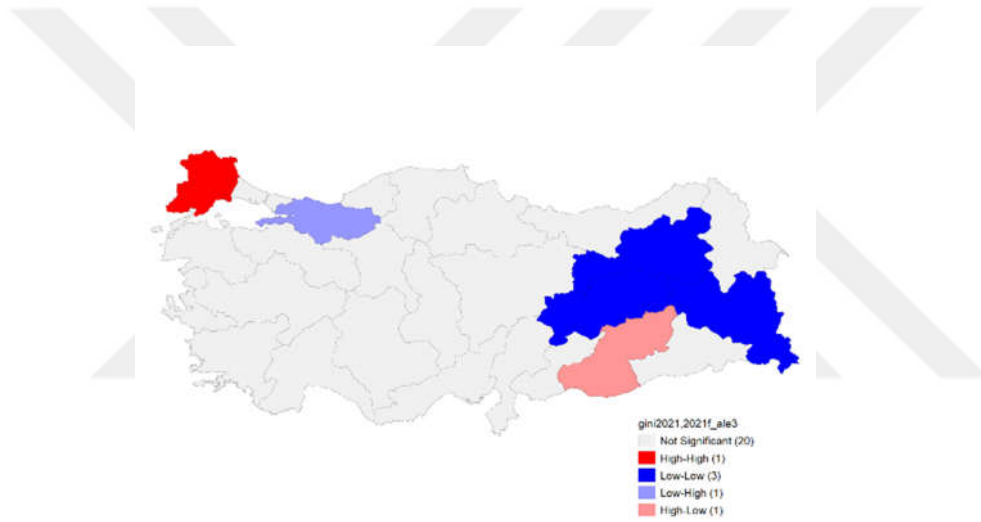


Figure 7.9. Bivariate Map of Gini Coefficient and Female Employment Ratio for Agriculture, Industry and Services in 2021

Source: Created by author using data from TURKSTAT

As indicated by the bivariate analysis, cities such as Kocaeli, Sakarya, and Düzce exhibit low income inequality, while female employment is high in both their surrounding regions and within them. This suggests that female employment may have contributed to reducing inequality. The quantile map shows that female employment is especially high in the observed area.

7.8. The Quantile Analysis of Research & Development

In 2021, clusters formed by cities such as Kocaeli, Sakarya, Düzce, Ankara, Kastamonu, Erzurum, and Çankırı had much higher research and development expenditure shares compared to other regions.

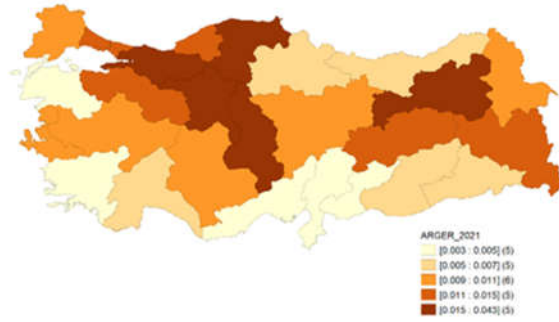


Figure 7.10. Quantile Map of Research & Development Shares in 2021

Source: Created by author using data from TURKSTAT

7.9. Bivariate Analysis of Gini Coefficient and Research & Development

The Figure 7.11. shows bivariate analysis of research and development (1000 Turkish Lira per person) expenses and Gini coefficient in 2021.

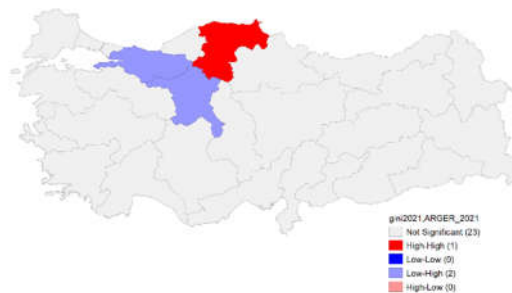


Figure 7.11. Bivariate Map of Gini Coefficient and Research & Development Expenditures in GDP, 2021

Source: Created by author using data from TURKSTAT

High-High cluster corresponded to TR82 (Kastamonu, Çankırı and Sinop). The Low-High cluster corresponded to TR42 (Kocaeli, Sakarya, Düzce, Bolu and Ankara). The map shows the Research and Development expenses ratio in GDP. TR82 (Kastamonu, Çankırı and Sinop) exhibited a high Gini coefficient, and also were surrounded by high research and development expenses shares regions, but TR42 (Kocaeli, Sakarya, Düzce, Bolu, Yalova); TR51 (Ankara); these Low-High clusters refer to that they exhibited low income inequality and were surrounded by regions with high shares of research and development expenditures in GDP.

Ankara could be an indication of Knowledge Spillover Theory because like Kocaeli, the research shares were high in themselves compared to other regions and it shows low inequality with high share expense neighbours. Audretsch and Feldman (2004) mentioned that knowledge production has a spatial dimension, which is related to knowledge Spillover Theory.

7.10. The Quantile Analysis of Unemployment Rate

Türkiye's unemployment rates, which encompass the unemployment of individuals aged 15 and above, were analysed using bivariate analysis from 2014 to 2023.

Although the Eastern Anatolia Region has experienced high unemployment in recent years, the Black Sea Region has lower unemployment rates in this regard. In fact, the Eastern Anatolia Region was included in the Southeastern Anatolia Region among those experiencing high inequality in 2022 and 2023.

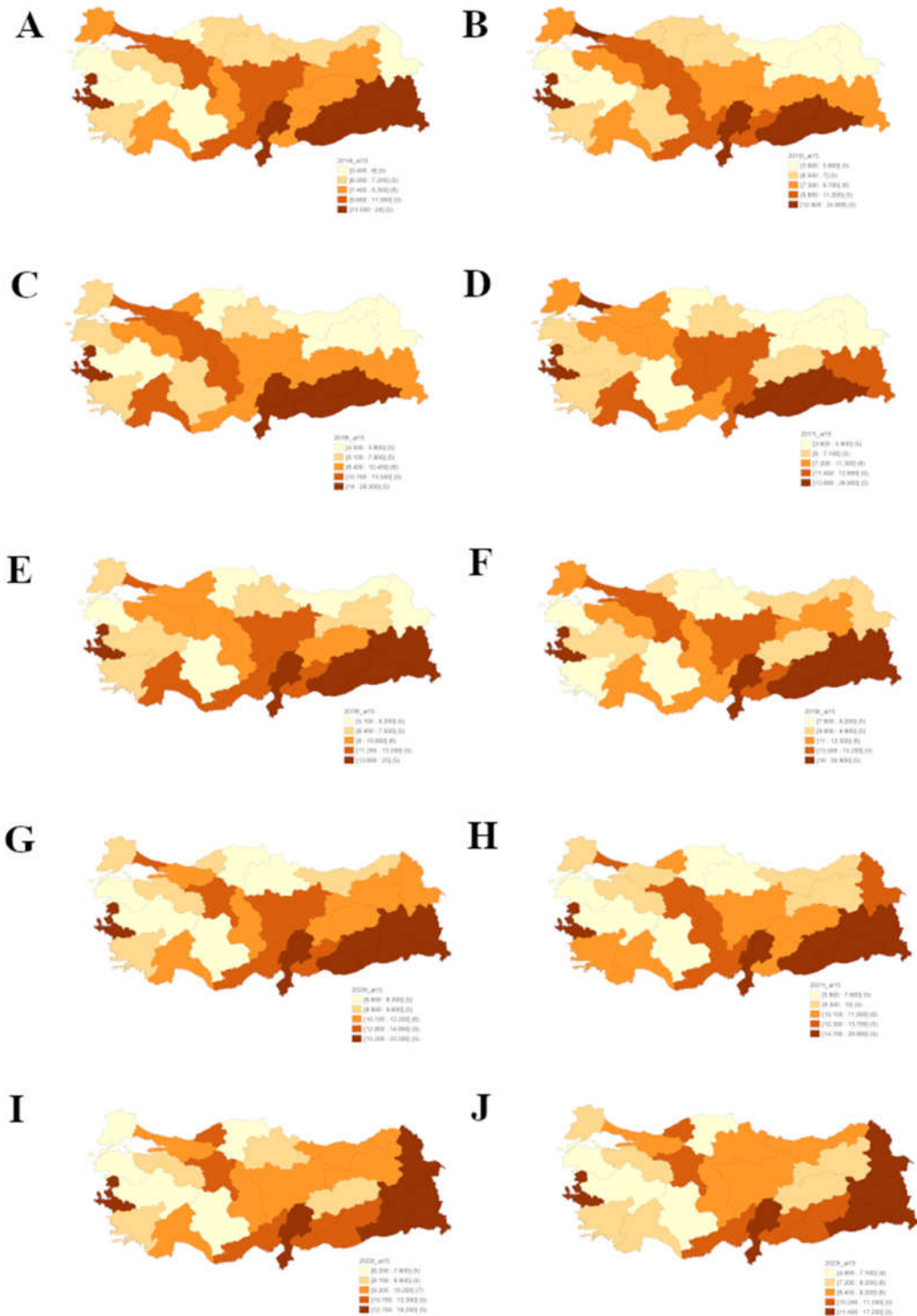


Figure 7.12. Quantile Map of Unemployment Rate for the years: 2014 (A),2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

7.11. Bivariate Analysis of Unemployment Rate

Türkiye's unemployment rates, which include the unemployment of people who are older than 15 years, were examined by using bivariate analysis from 2014 to 2023. To see how income inequality is related to the unemployment rate across regions, a bivariate analysis was done. The data set is based on disposable income, and since disposable income is calculated by deduction of governmental social transfers such as pensions, social assistance, and unemployment benefits, the results should be interpreted with this point.

The red clusters indicate a high Gini coefficient, while their neighbours experience a high unemployment rate. In these red clusters, income inequality worsens due to structural issues in the labour market. One potential cause for these red areas could be that income inequality rises because the unemployed cannot receive payments or are unable to find jobs in nearby areas, which aligns with existing literature. Conversely, the light blue regions, known as Low-High clusters, exhibit low income inequality, yet their neighbours had a high unemployment rate; one possible reason for this may be the social benefits that have been government-provided social benefits and transfers by the government.

In 2014, Izmir province had a high Gini coefficient and was surrounded by neighbours with low unemployment rates, which means that most people were employed. However, income inequality remained high in Izmir in 2014. It can be explained by Krugman's New Economic Geography explanation. According to Krugman (1999), land can produce a process of self-organisation in which symmetrical locations take on very different economic roles, and they argue for geographical patterns of division of the world into industrial and developing countries, the emergence of regional inequality in developing countries, and the emergence of giant urban centers. Krugman says in the centre place, there can be high differences while nearby places have homogeneity.

In 2015, TR90 (Trabzon, Ordu, Giresun, Rize, Artvin and Gümüşhane) were clustered as a Low-Low. They had a tendency to have a low Gini coefficient while their neighbour had a low unemployment rate.

In 2016, the blue clusters were expanded. TRA1 (Erzurum, Erzincan, Bayburt) and TRA2 (Ağrı, Kars, Iğdır and Ardahan) were in the Low-Low cluster.

In 2017, only one cluster was red and corresponded to TRC2 (Şanlıurfa, Diyarbakır). The cluster tended to have a high Gini coefficient while its neighbours had a high unemployment rate.

In 2018, in addition to TRC2, TRC3 (Mardin, Batman, Şırnak and Siirt) tended to have a high Gini coefficient while their neighbours had a high unemployment rate.

In 2019 Izmir province cluster was changed to high-low colour, but in the Western Region, there was no apparent cluster. In the Figure 7.13. (E, F, G, H), a similar pattern was observed in the South-eastern Anatolia Region in 2018, 2019, 2020 and 2021, respectively. TRB2 (Van, Muş, Bitlis and Hakkari) exhibited a low Gini coefficient and was surrounded by regions with a high unemployment rate.

It might be caused by the agricultural economic structure for the TRB2 cluster. The stability of inequality in some clusters could create nearby environments with higher unemployment rates. In the quantile map, these regions and their neighbours showed high unemployment rates. The stability of inequality in certain clusters might foster nearby environments with elevated unemployment. In the quantile map, these regions and their neighbours show high unemployment rates.

In 2020, the Pandemic changed policies and regulations, and the effects of these events were expected to be seen in the years after 2020. In 2021, one of the blue clusters corresponded to TR41 (Bursa, Eskişehir, Bilecik) and the other one was TR81 (Zonguldak). They tended to have a low Gini coefficient while their neighbour had a low unemployment rate.

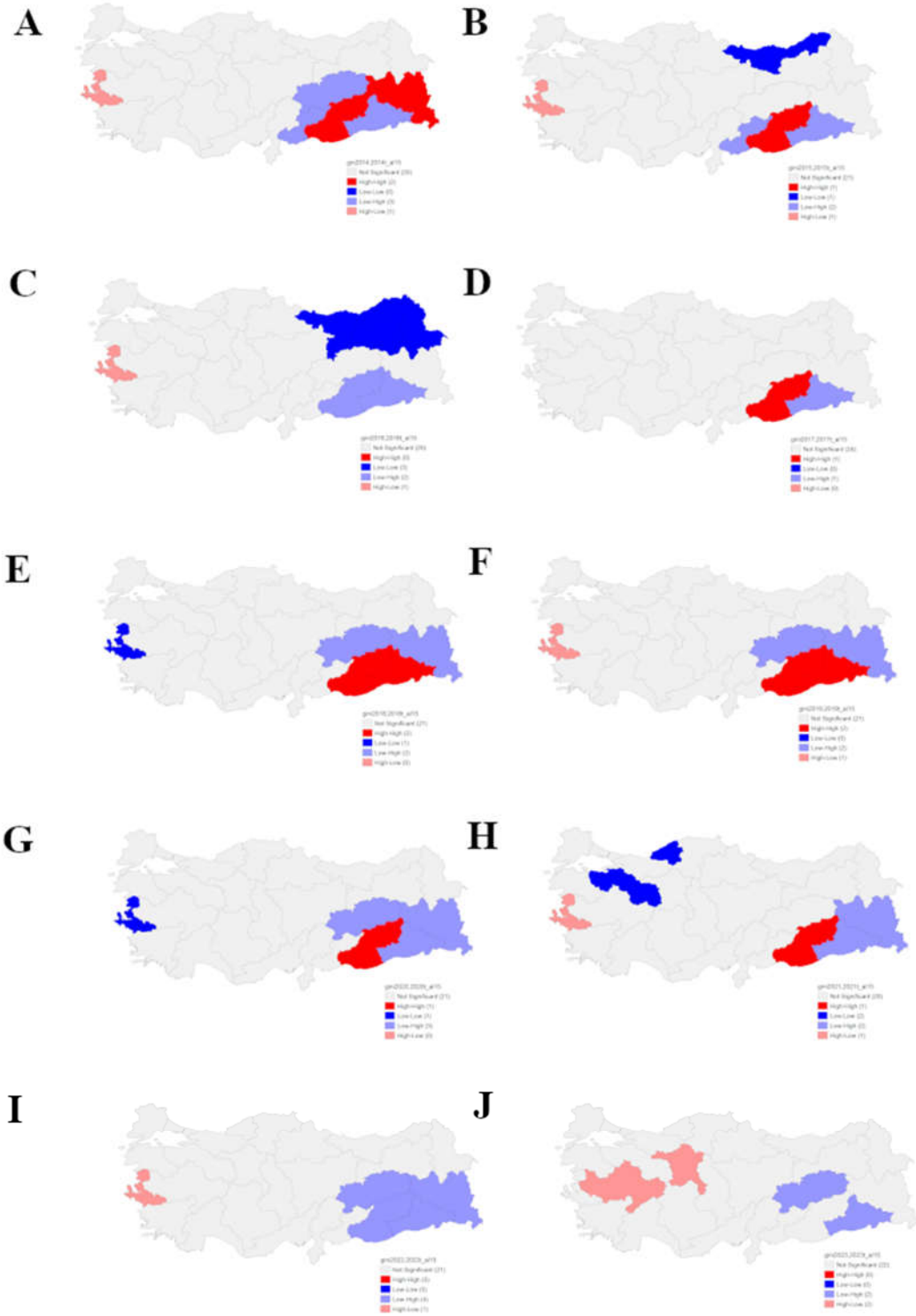


Figure 7.13. Bivariate Map of Gini Coefficient and Unemployment Rate in Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

There were no apparent red and blue clusters in 2022. Most of South-eastern Anatolia corresponds to the Low-High cluster.

In 2023, high-low clusters corresponded to TR33 (Manisa, Afyon, Kütahya and Uşak) and TR51 (Ankara). They were in an outlier cluster in 2023; while they tended to have a high Gini coefficient, their neighbours had a low unemployment rate.

7.12. The Quantile Analysis of Consumer Price Index in Türkiye

Türkiye's consumer price index from 2014 to 2021 was analyzed and especially in 2020 and 2021 the Eastern Black Sea region had the highest consumer price index compared to other regions.



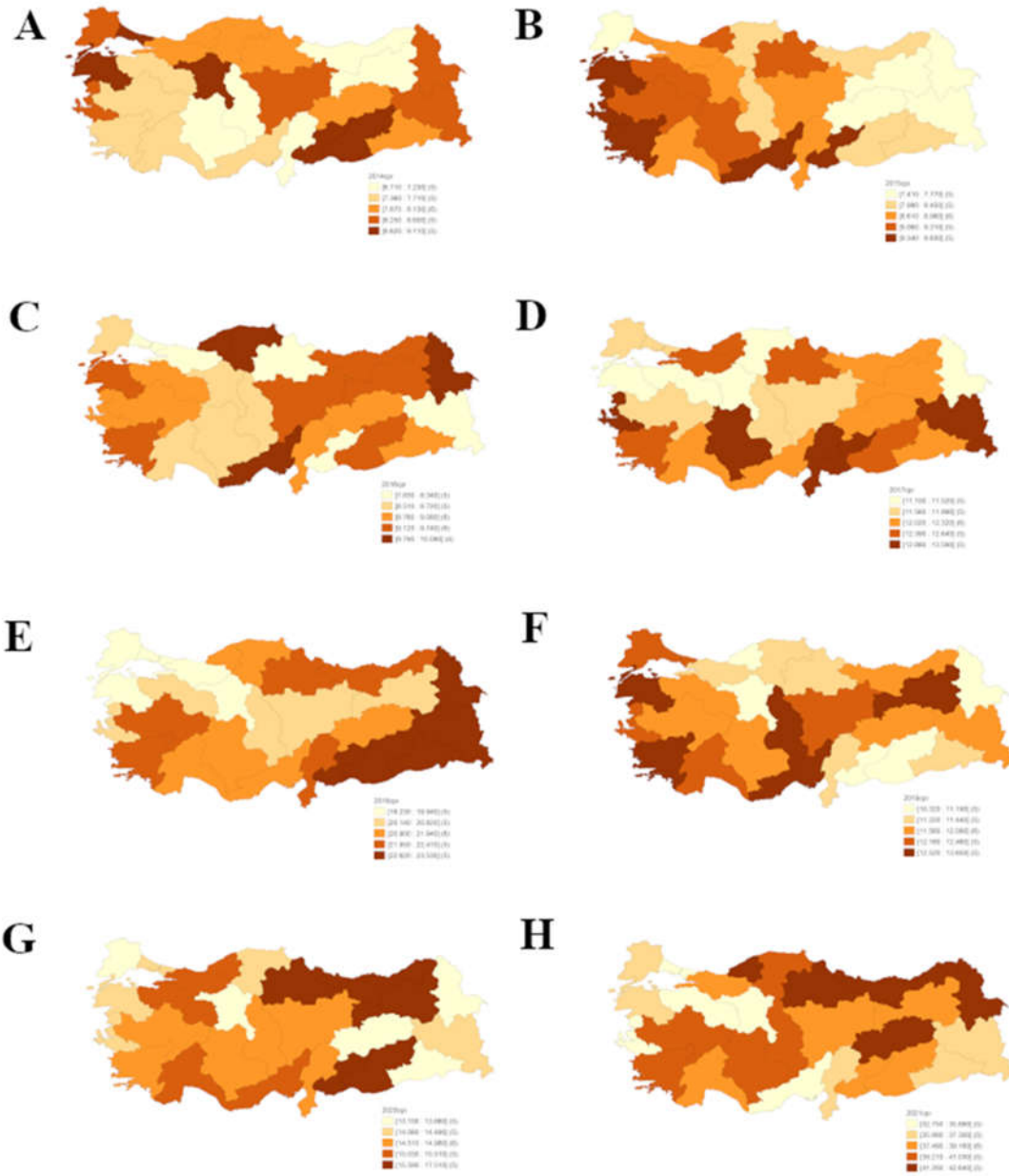


Figure 7.14. Quantile Map of Consumer Price Index for the years: 2014 (A),2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H).

Source: Created by author using data from TURKSTAT

7.13. Bivariate Analysis of Gini Coefficient and Consumer Price Index

In 2014, there were two Low-High clusters corresponding to TR21 (Tekirdağ, Edirne and Kırklareli) and TRC3 (Mardin, Batman, Şırnak and Siirt). These clusters exhibited low Gini coefficient and were surrounded by neighbours with high consumer price index. This means even they had low income inequality their neighbours cost of living was expensive in 2014. There were four High-Low clusters corresponding to TR51 (Ankara); TR72 (Kayseri, Sivas and Yozgat); TR62 (Adana, Mersin) and TR61 (Antalya, Isparta and Burdur). These clusters exhibited a high Gini coefficient and were surrounded by neighbours with a low consumer price index. It is consistent with Krugman's explanation for New Economic Geography. In the central places such as Ankara, Kayseri and Sivas, an increase in the high-income groups could increase income inequality, while the surrounding regions' price pressure may have been remained at a low level and Krugman's view is the most promise for understanding spatial aspects of urbanization (Dymski, 1996). In 2015, there were three High-High clusters corresponding to TR31 (Izmir); TR33 (Manisa, Afyon, Kütahya and Uşak); TR61 (Antalya, Isparta and Burdur). These clusters exhibited a High Gini coefficient and were surrounded by neighbours with a high consumer price index. The Low-High cluster corresponded to TR32 (Aydın, Denizli and Muğla). That cluster exhibited a low Gini coefficient and was surrounded by neighbours with a high consumer price index. There were three High-Low clusters: TRA1 (Erzurum, Erzincan and Bayburt); TRA2 (Ağrı, Kars, Iğdır and Ardahan); and TRC2 (Şanlıurfa, Diyarbakır). These clusters exhibited a high Gini coefficient and were surrounded by neighbours with a low consumer price index. There was only one Low-Low cluster that belonged to TRB2 (Van, Muş, Bitlis and Hakkari). This cluster exhibited a low Gini coefficient and was surrounded by neighbours with a low consumer price index. The TRB2 region is one of the less developed regions in Türkiye; the Gini coefficient indicated a low level, but it does not necessarily mean a social welfare; it can be explained by the population in that region had a low level of income in 2015.

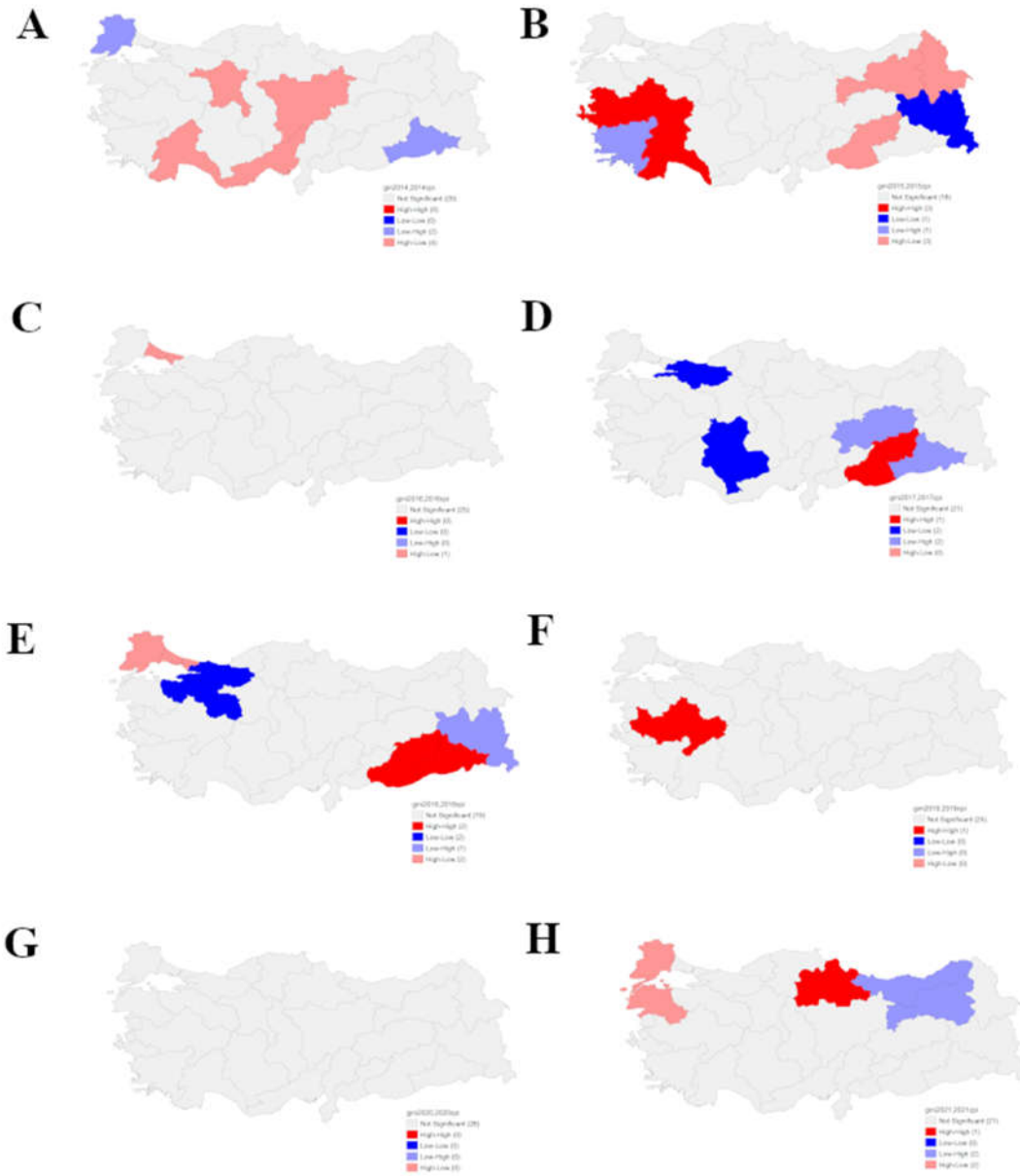


Figure 7.15. Bivariate Map of Gini Coefficient and Consumer Price Index in Türkiye for the years 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H).

Source: Created by author using data from TURKSTAT

Also, the market demand could be affected, and it could decrease the consumer price index. Gini coefficient data reflected after the transfer payments, so a low Gini coefficient could be an indication of the results of social transfers.

There was only one cluster corresponding to TR10 (Istanbul) in 2016. High-Low cluster refers to a High Gini coefficient tends to be high with a neighbour's low consumer price index.

There were two Low-Low clusters corresponding to TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova) and TR52 (Konya, Karaman) in 2017. These clusters exhibited a low Gini coefficient and were surrounded by neighbours with a low consumer price index. The red cluster corresponded to TRC2 (Şanlıurfa, Diyarbakır), and this cluster's Gini coefficient was spatially positively correlated to the neighbour's high consumer price index in 2017.

The blue clusters corresponded to TR41 (Bursa, Eskişehir and Bilecik) and TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova) in 2018, and the red clusters corresponded to TRC2 (Şanlıurfa, Diyarbakır) and TRC3 (Mardin, Batman, Şırnak and Siirt).

The red cluster such as TRC2 (Şanlıurfa, Diyarbakır) can reflect the surrounding places inflationary pressures might drive economic disparities in observed clusters.

In 2019, there was only one red cluster corresponding to TR33 (Manisa, Afyon, Kütahya and Uşak).

There wasn't any significant region in 2020, and this might be caused by the COVID-19 Pandemic.

After the COVID-19 Pandemic, in 2021, the red cluster corresponded to TR83 (Samsun, Tokat, Çorum and Amasya). This cluster's high Gini coefficient tended to be high along with its neighbour's high consumer price index.

When analyzing both the quantile map and the bivariate map, especially for 2021, Samsun, Tokat, Çorum, and Amasya display the highest CPI values. Although their inequality is significant, the neighboring areas also tend to have a high cost of living which indicates a clustering of high living costs and inequality.

7.14. Quantile Analysis of Poverty Rate in Türkiye

During ten years, the poverty rate data showed that Izmir was one of the clusters with the highest values, except in the years 2017 and 2023.

In 2023, clusters formed by cities such as Kastamonu, Çankırı, Sinop, Samsun, Tokat, Kayseri, Sivas, Yozgat show high poverty rates.

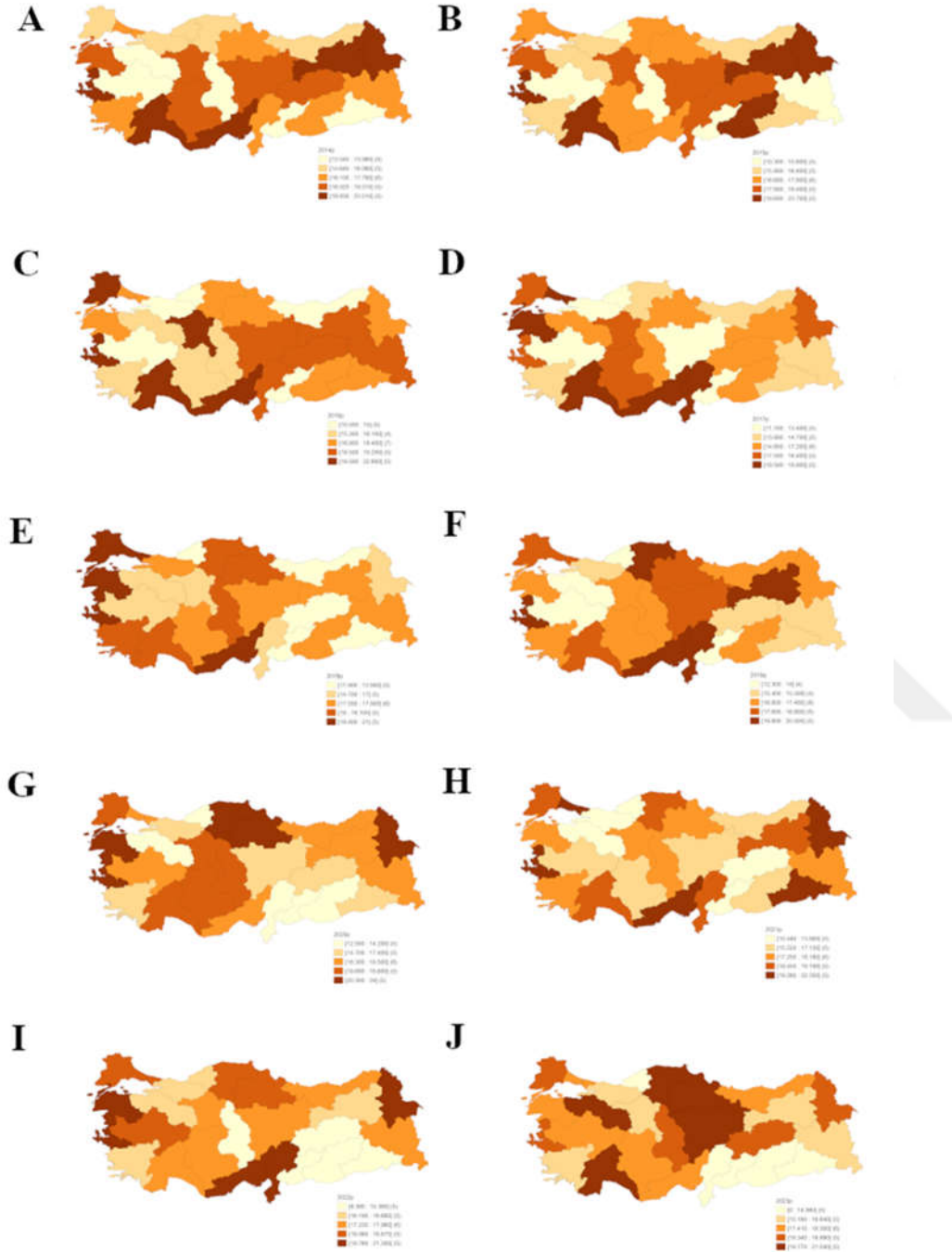


Figure 7.16. Quantile Map of Poverty Rate in Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

7.15. Bivariate Analysis of the Gini Coefficient and Poverty Rate

Since previous studies suggest a bidirectional relationship between poverty rate and income inequality, I conducted two separate bivariate spatial analyses by using the Gini coefficient as the independent variable (x-axis) and poverty rate as the dependent variable (y-axis), and the second one positions reversed. In this way, it allowed us to see the spatial correlation pattern from both perspectives.

In 2014, the High-Low cluster corresponded to Ankara; it exhibited a high Gini coefficient and was surrounded by neighbours with a low poverty rate. This can be explained by the Core-Periphery Theory, which states that resources cannot be distributed equally and nearby areas may have less economic diversity and tend to be more homogeneous such as having a low poverty rate. The rationalisation of sectors in the processing can account for this periphery development. The combined effect of factors here referred to as the environmental syndrome, results in differences in welfare and regional differentiation within the economy as a whole (Tykkyläinen, Markku, 1988).

The Low-High cluster corresponded to TR90 (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane). This cluster showed a low Gini coefficient and was neighbouring areas with a high poverty rate. The Eastern Black Sea Region has significant tea production and may indicate low income inequality and a low Gini. In 2017 and 2018, TR21 (Tekirdağ, Edirne, and Kırklareli) was positioned in the same cluster as red. The cluster exhibited a high Gini coefficient and was surrounded by neighbours with high poverty rates. TR21 is a region where industry and agriculture coexist, which seems developed but contains inequality. High-income groups may have formed due to being an industrial and port city. Internal migration and rural areas in neighbouring regions may have contributed to poverty however, in the quantile map, most rural areas clustered as low poverty, especially in 2020, 2021, and 2022. From this perspective, it is evident that this view is not valid for some rural areas of Türkiye.

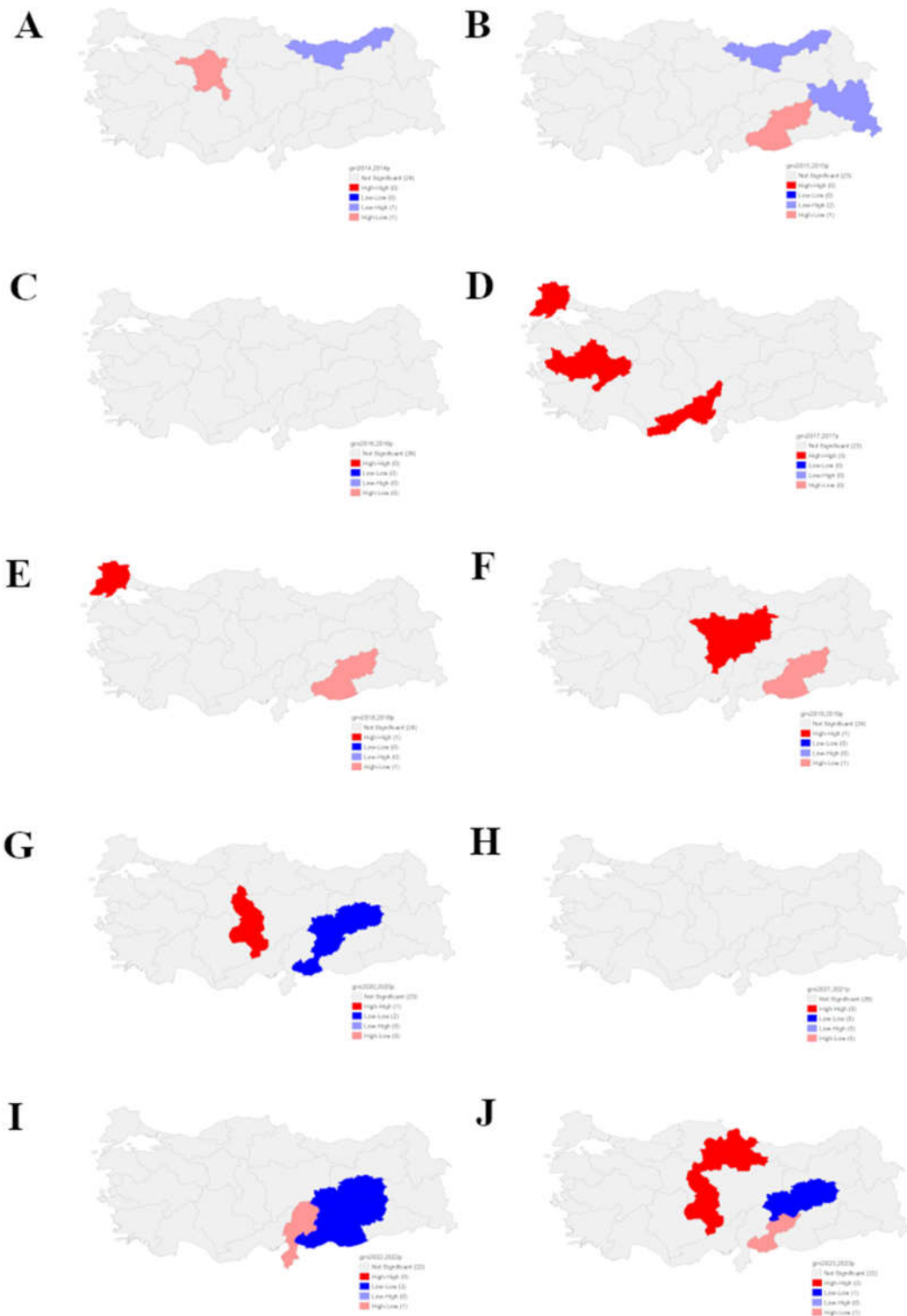


Figure 7.17. Bivariate Map of Gini Coefficient and Poverty Rate in Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J) (On the x axis Gini coefficient, on the y axis Poverty Rate.)

Source: Created by author using data from TURKSTAT

In 2020, the blue clusters corresponded to TRB1 (Malatya, Elazığ, Bingöl, Tunceli) and TRC1 (Gaziantep, Adıyaman and Kilis). These clusters exhibited a low Gini coefficient and were surrounded by neighbours with a low poverty rate.

In 2023, the red clusters corresponded to TR83 (Samsun, Tokat, Çorum, Amasya) and TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir). These clusters high Gini coefficient tended to be high along with their neighbours' high poverty rate. This pattern might be explained by Dual Sector Development Theory, and post-pandemic economic shocks could create widening income gaps.

When both the quantile map and the bivariate map are examined in 2023, the cluster formed by the cities of Samsun, Tokat, Çorum, and Amasya indicates high poverty within itself, while its inequality remains high, coupled with high poverty in the surrounding regions. This situation suggests that there may be a spatial relation between inequality and poverty in this area.

7.16. Bivariate Analysis of Poverty Rate and Gini Coefficient in Türkiye

There were one red and one blue cluster in 2014. The blue cluster corresponded to TR82 (Kastamonu, Çankırı and Sinop). The blue cluster poverty rate tended to be low, along with its neighbours' low Gini coefficient in 2014.

The fact that this region is predominantly rural and agricultural may lead to low income inequality and about Lewis's dual sector theory, since these regions cannot transition to industry, inequality may remain low, but this may be due to lack of development and the poverty rate may be low because families provide for themselves.

The red cluster, which corresponds to TRB1 (Malatya, Elazığ, Bingöl and Tunceli) and was marked as High-High. Their poverty rate tended to be high, along with their neighbours' high Gini coefficient in 2014.

There were no apparent red or blue clusters in 2015. The High-low clusters corresponded to TR82 (Kastamonu, Çankırı, Sinop) and TRC2 (Şanlıurfa and Diyarbakır). These clusters exhibited a high poverty rate and were surrounded by neighbours with low Gini coefficients.

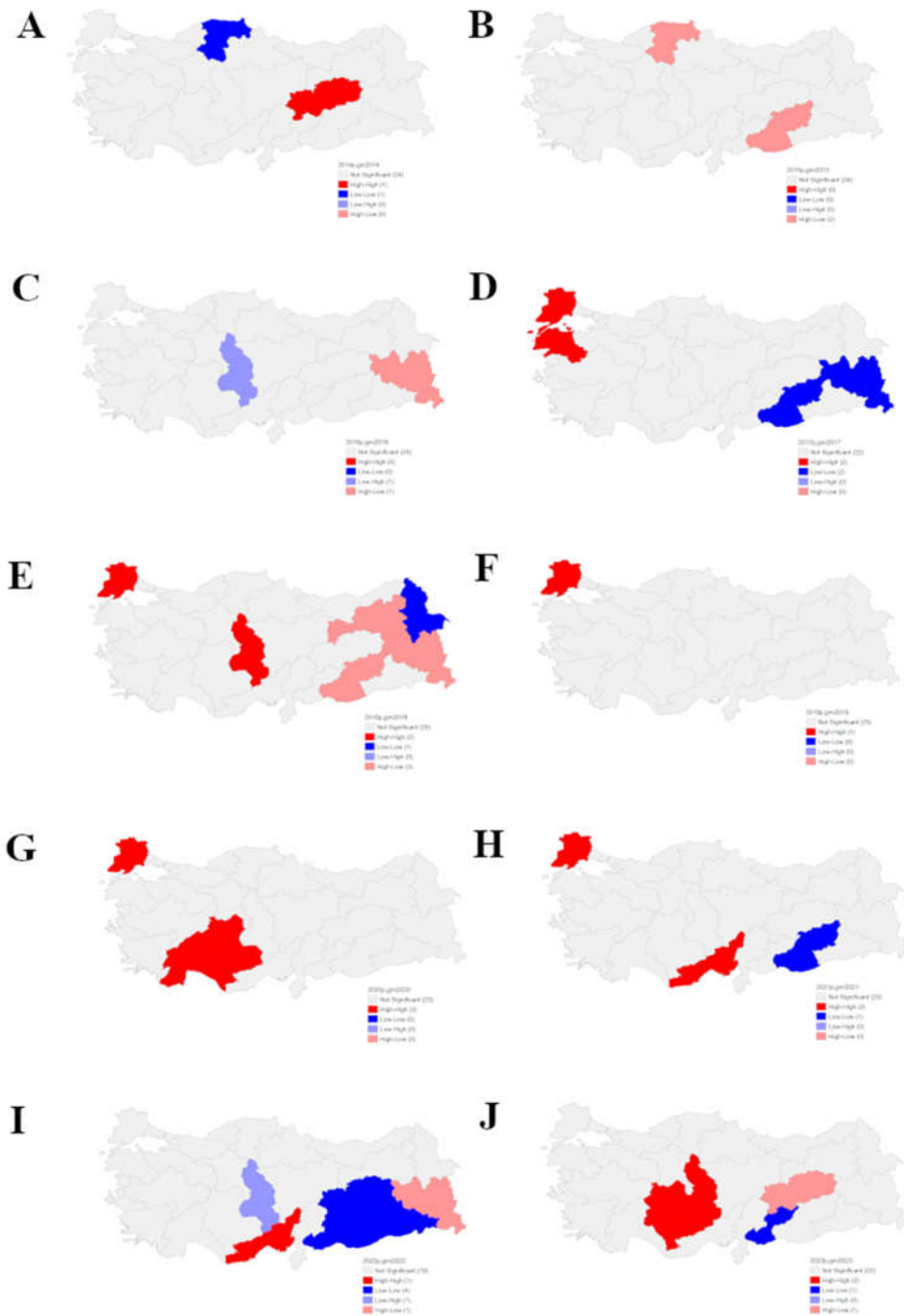


Figure 7.18. The Poverty Rate Bivariate Map of Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J) (On the x axis Poverty Rate, on the y axis Gini coefficient.)

Source: Created by author using data from TURKSTAT

This may be due to absolute poverty in these regions, but the difference between rich and poor may be relatively less in their surroundings, and in this case, their neighboring regions may exhibit a more equally distributed income structure.

In 2016, there was no apparent blue or red cluster. One cluster was marked as Low-High, and the other cluster was High-Low. Low-High Cluster corresponded to TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir). Their low poverty rate tended to be low, along with their neighbours' high Gini coefficient. The High-Low cluster corresponded to TRB2 (Van, Muş, Bitlis and Hakkari). The cluster's high poverty rate tended to be high along with neighbours' low Gini coefficient.

In 2017, TR21 High-High clusters corresponded to TR21 (Tekirdağ, Edirne and Kırklareli); TR22 (Balıkesir and Çanakkale), which means high poverty rate region was clustered by the regions with high Gini coefficient, there was a positive spatial correlation between poverty rate and income inequality.

These regions were considered relatively developed when compared to Türkiye and income differences may have been occurred and consistent with Relative Deprivation Theory which may make poverty more visible.

On the other hand, TRB2 (Van, Muş, Bitlis, Hakkari); TRC2 (Şanlıurfa, Diyarbakır) had a low poverty rate along with low income inequality neighbours.

In 2018, TRA1 (Erzurum, Erzincan, Bayburt); TRB2 (Van, Muş, Bitlis, Hakkari) and TRC2 (Şanlıurfa, Diyarbakır) were marked as High-Low. Their poverty rate tended to be high, along with their neighbours' low Gini coefficient in 2018. But in the Eastern part of Türkiye, there was also a blue cluster corresponding to TRA2 (Ağrı, Kars, Iğdır and Ardahan). That blue cluster's poverty rate tended to be low along with neighbours' low Gini coefficient in 2018. 2 red clusters corresponded to TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir); TR21 (Tekirdağ, Edirne and Kırklareli). These red clusters exhibited a high poverty rate and were surrounded by neighbours with a high Gini coefficient in 2018.

In 2019, there was only one red cluster, which corresponds to TR21 (Tekirdağ, Edirne and Kırklareli). That red cluster's high poverty rate was positively spatially correlated with its neighbours' High Gini coefficient.

In 2020, red clusters were expanded through 3 regions. TR61 (Antalya, Isparta, Burdur); TR52 (Konya, Karaman); TR21 (Tekirdağ, Edirne and Kırklareli). Their high poverty rate was positively spatially correlated with their neighbours' High Gini coefficient in 2020.

The red clusters decreased to two in 2021. One was the same as TR21, the other one corresponded to TR62 (Adana and Mersin). The blue cluster corresponded to TRC2 (Şanlıurfa and Diyarbakır). The blue regions' low poverty rate tended to be low, along with their neighbours' low Gini coefficient in 2021.

In 2022, there were 4 Low-Low clusters corresponding to TRB1 (Malatya, Elazığ, Bingöl, Tunceli); TRC1 (Gaziantep, Adıyaman, Kilis); TRC2 (Şanlıurfa, Diyarbakır); TRC3 (Mardin, Batman, Şırnak and Siirt). Their low poverty rate tended to be low, along with their neighbours' low Gini coefficient in 2022. There were also one Low-High, one High-Low and one High-High cluster. Low-High corresponded to TR71; its low poverty rate tended to be low along with its neighbours' high Gini coefficient, and High-Low cluster corresponded to TRB2; its high poverty rate tended to be high along with its neighbours' low Gini coefficient. These High-Low and Low-High clusters were negatively spatially correlated. The red region corresponded to TR62 (Adana and Mersin). That red cluster's high poverty rate was positively spatially correlated to its neighbours' high Gini coefficient in 2022.

The red clusters increased to two clusters in 2023, corresponding to TR52 (Konya, Karaman); TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir). Their high poverty rate was positively spatially correlated to their neighbours' high Gini coefficient in 2023.

7.17. Analysis of Gini Coefficient and Trade Openness in Türkiye

7.17.1. Quantile Analysis of Net Export

In 2021, clusters formed by cities such as İzmir, Aydın, Denizli, Muğla, Konya, Karaman, Bursa, Eskişehir, Bilecik, Hatay, Kahramanmaraş, Osmaniye and they were regions with high net export value.

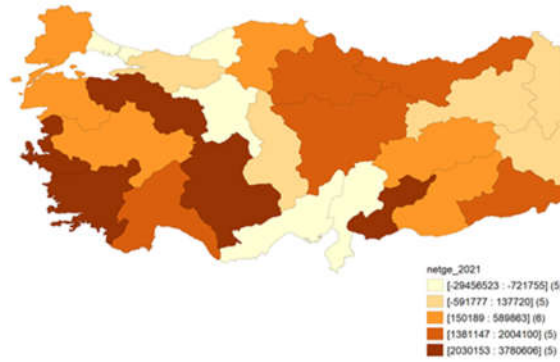


Figure 7.19. Quantile Map of Net Export in 2021

Source: Created by author using data from TURKSTAT

7.17.2. Bivariate Analysis of Gini Coefficient and Net Export

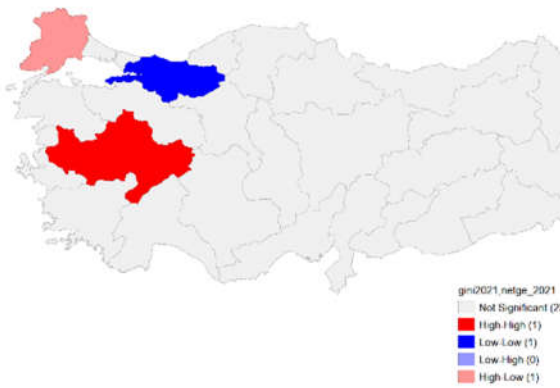


Figure 7.20. The Bivariate Gini Coefficient Map of Net Export in 2021

Source: Created by author using data from TURKSTAT

The High-High Cluster corresponded to TR33 (Manisa, Afyon, Kütahya, Uşak). This red cluster's Gini coefficient tended to be high, along with neighbours' high net export value in 2021. These areas were consistent with the Heckscher-Ohlin theory. According to this theory, regions concentrate on the factors of production they have in abundance; for example, if they are capital-intensive, they produce capital intensively. While capital owners earn a lot, the labor force may not share this income, thus creating income inequality. This may explain why capital-intensive regions experience high income inequality, but when we look at spatial

autocorrelation, it can be argued that the region with high inequality may be affected by labor movements of neighboring regions or regional externalities, which is consistent with the positive spatial correlation obtained by LISA analysis.

The blue cluster corresponded to TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova). This cluster's low Gini coefficient tended to be low along with neighbours' low net export values.

This pattern may reflect a relatively balanced economy and low income inequality might be associated with less exposure to export trade structural shift. When the bivariate and quantile maps are examined together, it is evident that the cluster formed by the cities of Manisa, Afyon, Kütahya, and Uşak does not have significantly high exports but displays spatial clustering with its surroundings. This suggests that this region may be limited in terms of export value.

7.17.3. Quantile Analysis of Export

The export map was analyzed to understand the impact of imports better. For example, although the cluster of cities including Kocaeli, Sakarya, Düzce, Bolu, and Yalova shows high export levels, the fact that it did not reflect in net exports to show the effect of high imports.

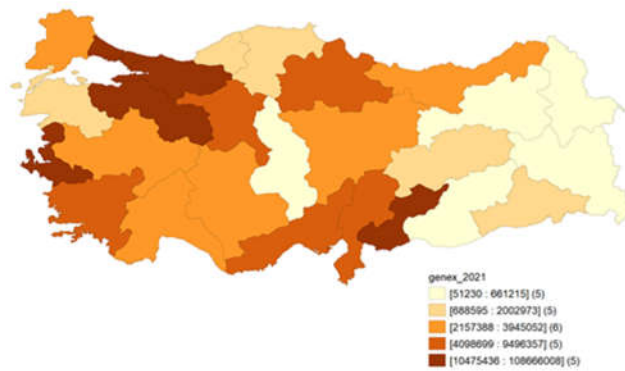


Figure 7.21. Quantile Map of Export in 2021

Source: Created by author using data from TURKSTAT

7.17.4. Bivariate Analysis of Gini Coefficient and Export

In 2021, the blue clusters corresponded to TRA1, TRB2 and TRC3. They were mostly positioned in the Eastern part of Türkiye. They exhibited a low Gini coefficient and were surrounded by neighbours with low export.

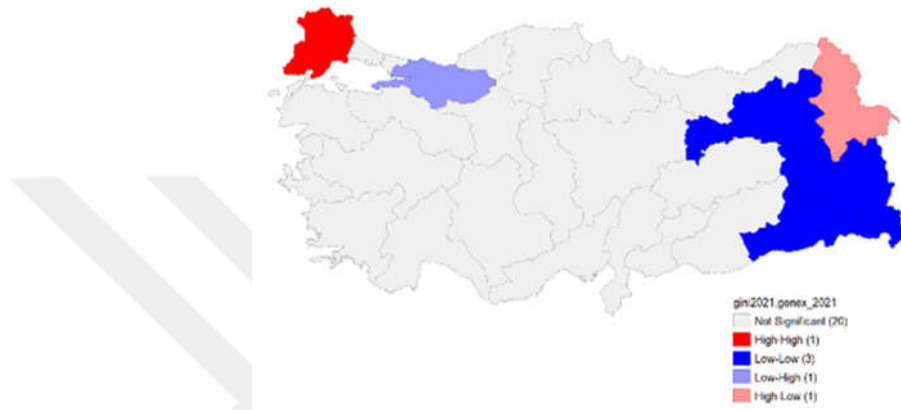


Figure 7.22. The Bivariate Map of Gini Coefficient and Export in 2021

Source: Created by author using data from TURKSTAT

The blue cluster spatially represents the region with low exports, while also showing low income inequality in the regions with this structure but the change in regions and clusters in the previous net export map might reflect that imports can play a key role in shaping the spatial pattern.

7.17.5. Quantile Analysis of Import

When analysing the cluster consisting of Kocaeli, Sakarya, Düzce, Bolu, and Yalova cities together with bivariate and quantile data in 2021, both the cluster itself and its surrounding regions exhibit high trade activity. Since its low inequality trend aligns with a high level of imports from nearby areas, and given its significant imports in the same year, it can be concluded that high import integration here contributes to reducing income inequality locally.

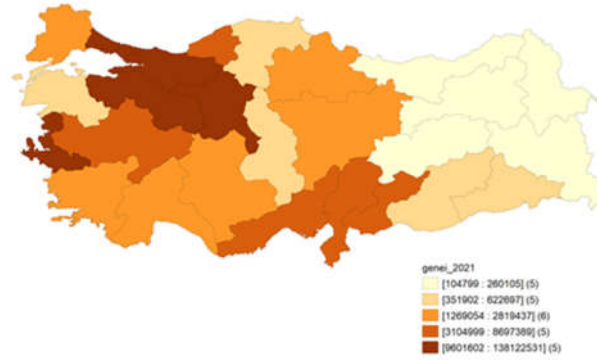


Figure 7.23. Quantile Map of Import in 2021

Source: Created by author using data from TURKSTAT

7.17.6. Bivariate Analysis of Gini Coefficient and Import

The blue clusters corresponded to TR90, TRA1, and TRB2 in 2021. These clusters exhibited a low Gini coefficient and were surrounded by neighbours with low import values. In this map, the TR21 region appears red in both export and import maps but changes to light red in the previous net export map. This might indicate that foreign trade was being balanced by high import volumes, as seen in the quantile map.

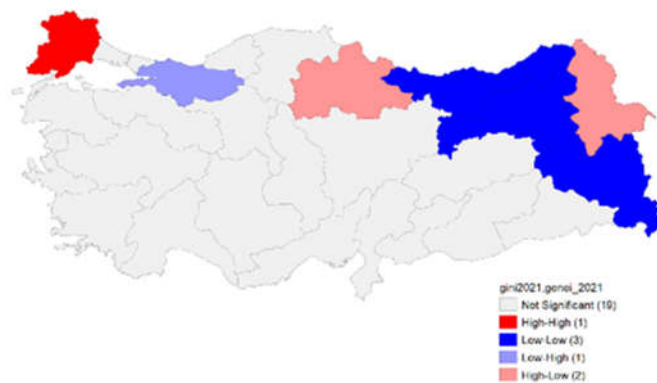


Figure 7.24. The Bivariate Map of Gini Coefficient and Import in 2021

Source: Created by author using data from TURKSTAT

7.18. GDP Shares Quantile and Bivariate Analysis

7.18.1. Quantile Analysis of Agriculture, Forestry and Fishing Shares in GDP

The cluster comprising Konya, Karaman, Ağrı, Kars, Iğdır, and Ardahan was the one with the highest agriculture, forestry and fishing shares in GDP in both 2014 and 2021.

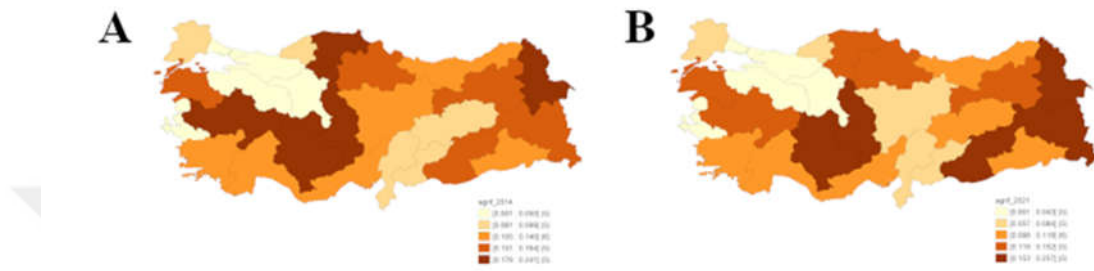


Figure 7.25. Quantile Map of Agriculture, Forestry and Fishing Shares in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.2. Bivariate Analysis of Agriculture, Forestry and Fishing Shares in GDP

In 2014, the High-High cluster corresponded to TRB2 (Van, Muş, Bitlis and Hakkari). This red cluster exhibited a high Gini coefficient and was surrounded by neighbours with high share of agriculture, forestry and fishing in GDP in 2014. Both P80/20 Gini and other Gini coefficient results are shown. It is very important to see here that although agriculture is generally seen as a factor that ensures homogeneous income distribution, this may not always be the case. The reason for such a pattern in 2014 may be due to the low contribution value of agriculture in that period, or another reason may be that the high agricultural rate of the neighbors created indirect pressure on the observed region by creating lower industrialization and as in the seen in the industry quantile map, Eastern Anatolia is clustered as low industry shares.

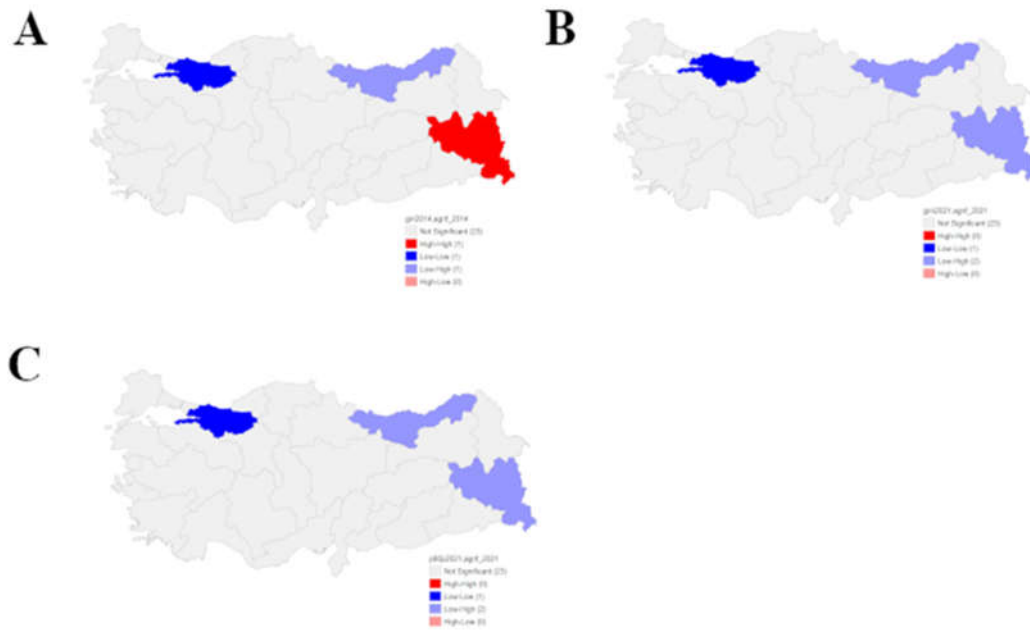


Figure 7.26. Agriculture, Forestry and Fishing Shares Bivariate Map, 2014 (A), 2021 (B), Gini P80/20 (2021) (C).

Source: Created by author using data from TURKSTAT

Blue cluster corresponded to TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova). This blue cluster exhibited a low Gini coefficient and was surrounded by neighbours with low share of agriculture, forestry and fishing in GDP.

In 2021, there were 2 Low-High clusters, which corresponded to TR90 (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane) and TRB2 (Van, Muş, Bitlis, Hakkari). These clusters' Gini coefficient tended to be low along with their neighbours' high GDP shares of agriculture, forestry and fishing. This may be due to neighbors with strong agricultural economies supporting low inequality.

As seen in Figure 7.26, the usage of p80/20 did not change the results significantly in this bivariate analysis of GDP shares in 2021.

7.18.3. The Quantile Analysis of Industry Shares in GDP

The regions with high industrial shares are the clusters formed by the cities of Kocaeli, Sakarya, Düzce, Bolu, Yalova, Tekirdağ, Edirne, Kırklareli, Gaziantep, Adıyaman, Kilis, which remained unchanged in 2014 and 2021.

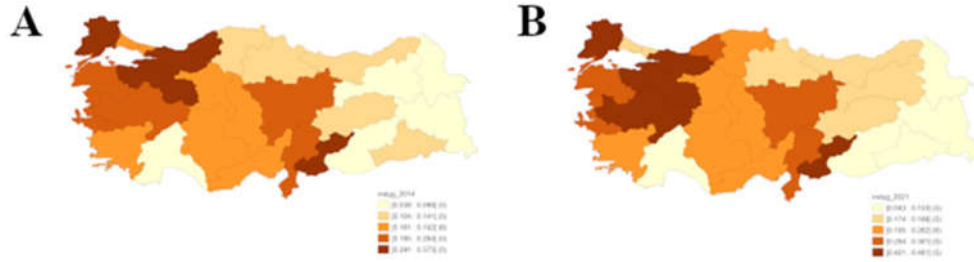


Figure 7.27. Quantile Map of Industry Shares in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.4. Bivariate Analysis of Industry Shares in GDP

There were three Low-Low clusters in 2014, corresponding to TR90 (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane); TRA2 (Ağrı, Kars, Iğdır, Ardahan) and TRC3 (Mardin, Batman, Şırnak and Siirt). The blue clusters' Gini coefficient tended to be low, along with neighbours' low share of industry in GDP. This type of spatial pattern may reflect Kuznets' theory of low inequality at the beginning of the Industrial Revolution.

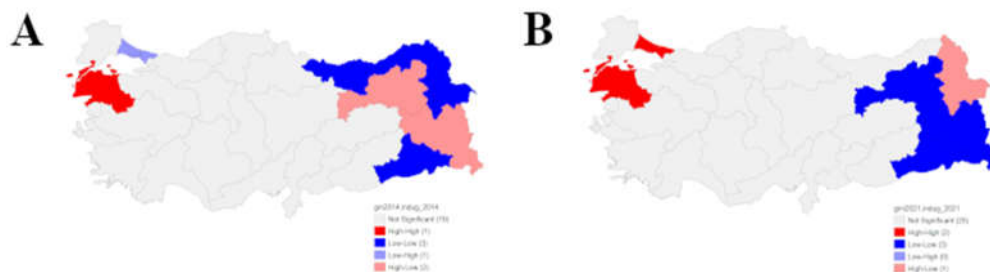


Figure 7.28. Industry Expanses Shares Bivariate Map; 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

However, red clusters corresponded to TR22 (Balıkesir, Çanakkale), and their Gini coefficient tended to be high, with neighbours exhibiting a high share of industry in GDP. The high-low areas corresponded to TRA1 (Erzurum, Erzincan, Bayburt) and TRB2 (Van, Muş, Bitlis, Hakkari). Their Gini coefficient was also generally high, along with their neighbours' low industry shares in GDP in 2014. This may be because, although industrial investments were low in these regions as seen in the quantile map, the presence of government employees and similar income groups may have contributed to greater income disparities. This could actually be due to the fact that these regions are still passing through the industrialisation phase, as suggested by Kuznets' theory because these areas turned blue in 2021. This explains why inequality has decreased and it has been observed on the quantile map that some eastern regions have shifted into higher industrial share clusters. In 2021, the blue clusters expanded across TRA1 (Erzurum, Erzincan, Bayburt), TRB2 (Van, Muş, Bitlis, Hakkari), and TRC3 (Mardin, Batman, Şırnak, and Siirt). One red cluster was added to the map, representing TR10 (Istanbul). Istanbul's Gini coefficient tended to be high, with its neighbours exhibiting high industry shares in GDP in 2021.

7.18.5. Quantile Analysis of Manufacturing Shares in GDP

The quantile map of manufacturing shares for 2014 and 2021 has remained mostly unchanged.

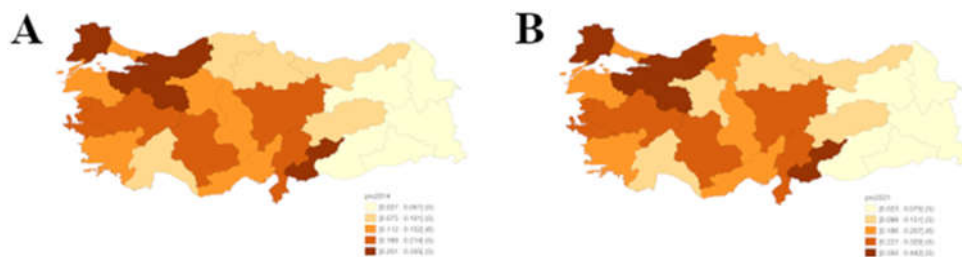


Figure 7.29. Quantile Map of Manufacturing Shares in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.6. Bivariate Analysis of Manufacturing Shares in GDP

The manufacturing GDP shares in the 2014 bivariate map were identical to industry shares in GDP for that year's bivariate map. However, in 2021, it was not the same as the industry share of GDP map. TR90 (Samsun, Ordu, Giresun, Rize, Artvin and Gümüşhane) was added to the blue cluster. TRA2 (Ağrı, Kars, Iğdır and Ardahan) was included in a High-Low cluster. This cluster's high Gini coefficient tended to be high along with its neighbours' low manufacturing shares in GDP. In fact, a situation may have arisen here due to the industry sector although manufacturing did not change in Eastern Anatolia on the Quantile map in 2021. It may have been affected by the development of the industry sector. In the quantile map for both years 2014 and 2021, the industry shares of the Eastern Anatolia region formed the lowest share cluster.

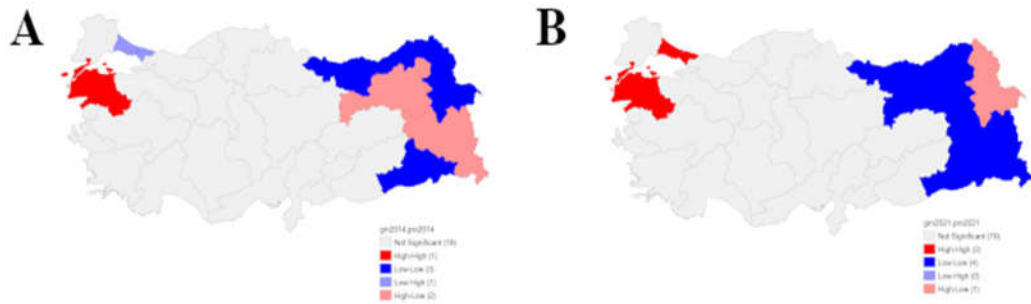


Figure 7.30. Bivariate Map of Manufacturing Shares in GDP in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

7.18.7. Quantile Analysis of Construction Shares in GDP

For both years 2014 and 2021, the clusters shaped by Ankara, Malatya, Elazığ, Bingöl, and Tunceli provinces were the clusters with the highest construction shares.

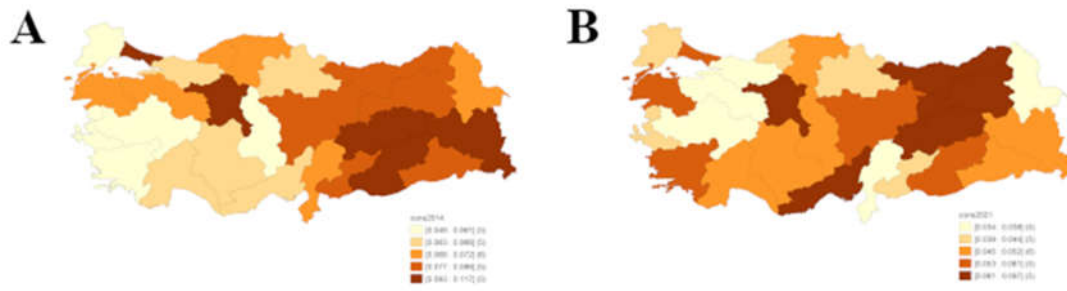


Figure 7.31. Quantile Map of Construction Shares in GDP, 2014 (A), 2021 (B)

Source: Created by author using data from TURKSTAT

7.18.8. Bivariate Analysis of Construction Shares in GDP

The red clusters corresponded to East in 2014. This shows that mostly construction shares were incurred in the East of Türkiye. The red clusters corresponded to TRA1 (Erzurum, Erzincan, Bayburt); TRB2 (Van, Muş, Bitlis, Hakkari) and TRC2 (Şanlıurfa and Diyarbakır). The red clusters' Gini coefficient tended to be high, along with neighbours' high construction shares in GDP in 2014.

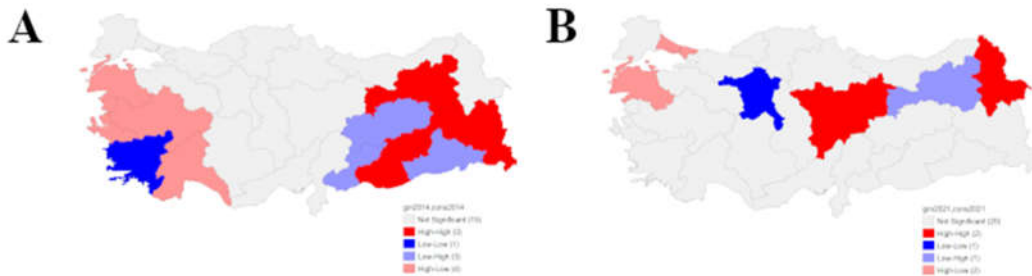


Figure 7.32. Construction Shares in GDP Bivariate Map in 2014 (A) and 2021(B)

Source: Created by author using data from TURKSTAT

Here, the clusters in red in Eastern Anatolia in the bivariate, as observed in the quantile map, construction shares are relatively much more concentrated either within themselves or in their surroundings. Here, it can be said that construction shares have an effect that increases spatial inequality. The reason for this may be that, just as women's labor creates an invisible army, the construction sector also creates an invisible army of workers and causes inequality.

The blue map corresponded to TR32 (Aydın, Denizli and Muğla), and the cluster's Gini coefficient tended to be low along with neighbours' low construction shares in 2014. There were also four High-Low clusters belonging to TR22 (Balıkesir, Çanakkale); TR31 (Izmir); TR33 (Manisa, Afyon, Kütahya, Uşak) and TR61 (Antalya, Isparta and Burdur). These clusters' Gini coefficients tended to be high, along with neighbours' low construction shares in 2014. This situation may also reflect structural differences that occur as a result of relatively rich and developed areas being surrounded by less developed areas that do not receive much investment in construction and as a result low construction spending in neighboring areas may have limited infrastructure there.

In 2021, the map of the bivariate spatial association between the Gini coefficient and construction share in GDP mostly changed compared to 2014. Two red clusters corresponded to TR72 (Kayseri, Sivas, Yozgat); TRA2 (Ağrı, Kars, Iğdır and Ardahan). These clusters' Gini coefficient was positively spatially related to their neighbours' high construction share in 2021. This situation may have been due to the construction sector creating short-term jobs rather than employment. The middle region of them corresponded to TRA1 (Erzurum, Erzincan and Bayburt) and was marked as a Low-High. The cluster's Gini coefficient tended to be low, along with their neighbours' high construction in GDP. It has also been observed that it is one of the clusters with the highest construction shares on the quantile map. Blue cluster corresponded to TR51 (Ankara) and its Gini coefficient tended to be low, along with its neighbours' low construction share in 2021. However, on the quantile map Ankara's construction share formed the high share cluster group. The two High-Low clusters corresponded to TR22 (Balıkesir, Çanakkale) and TR10 (Istanbul). These clusters' Gini coefficient tended to be high, along with their neighbours' low construction share in GDP.

7.18.9. Quantile Analysis of Service Share in GDP

In the quantile map, the cities that formed the clusters with the highest service sector shares in 2014 and 2021 were Istanbul, Izmir, Antalya, Isparta, Burdur, Adana, Mersin, Mardin, Batman, Şırnak, and Siirt.

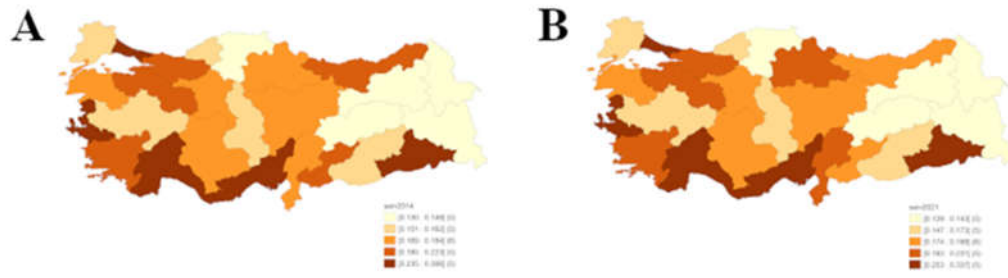


Figure 7.33. Quantile Map of Service Shares in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.10. Bivariate Analysis of Service Share in GDP

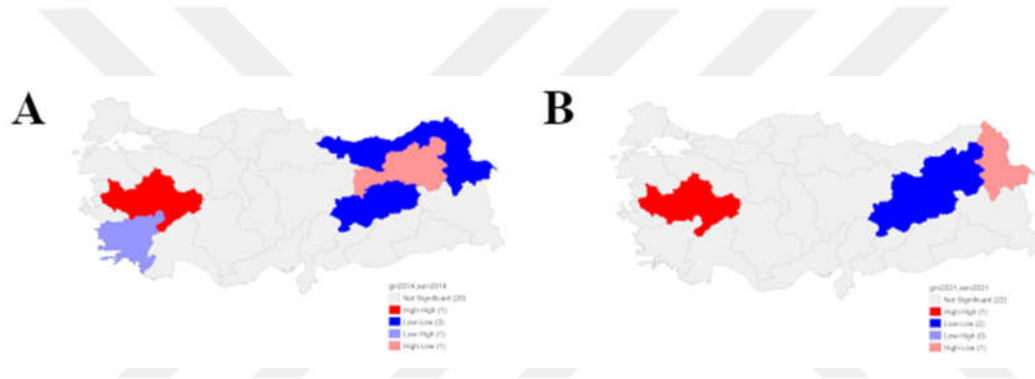


Figure 7.34. Service Share in GDP Bivariate Map in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

In 2014, the blue clusters corresponded to TR90 (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane); TRA2 (Ağrı, Kars, Iğdır, Ardahan) and TRB1 (Malatya, Elazığ, Bingöl, Tunceli). These Low-Low clusters' Gini coefficients tended to be low, along with neighbours' low service share in GDP in 2014. The service sector may have created a high-income segment, and the small size of this segment may have created a pattern with the low inequality observed in the region. The red cluster corresponded to TR33 (Manisa, Afyon, Kütahya and Uşak). The red cluster's Gini coefficient tended to be high, along with neighbours' high service share in GDP in 2014. The Low-High cluster corresponded to TR32 (Aydın, Denizli and Muğla). The Low-High clusters' Gini coefficient tended to be low, along with neighbours' high service share in GDP in 2014. This situation may have been due to the homogeneity of tourism revenues being spread more widely in these regions. The High-Low

cluster corresponded to TRA1 (Erzurum, Erzincan and Bayburt). The High-Low clusters' Gini coefficient tended to be high along with their neighbours' low service shares in GDP in 2014. This situation may have reflected a pattern where some investments made in the observed region enriched some segments, while the service sector in the neighboring regions did not develop and also it did not develop similarly as seen in the quantile map.

In 2021, the TR33 (Manisa, Afyon, Kütahya, Uşak) cluster's provinces' Gini coefficient tended to be high, along with neighbours' high service share in GDP. There were two blue clusters, which corresponded to TRA1 (Erzurum, Erzincan, Bayburt) and TRB1 (Malatya, Elazığ, Bingöl and Tunceli). These clusters' Gini coefficients tended to be low, along with neighbours' low service share in GDP in 2021. There was one High-Low cluster which corresponded to TRA2 (Ağrı, Kars, Iğdır and Ardahan). That cluster's Gini coefficient tended to be high, along with neighbours' low service shares in GDP.

7.18.11. Quantile Analysis of Information and Communication Shares in GDP

In the quantile map, the cities that formed the clusters with the highest information and communication shares in both 2014 and 2021 were Istanbul, Izmir, Ankara, Erzurum, Erzincan, and Bayburt.

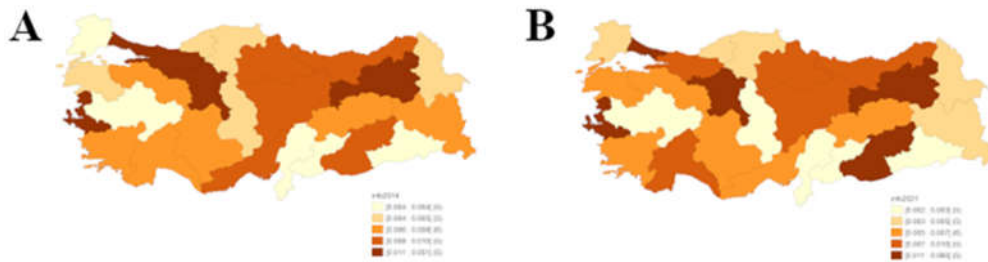


Figure 7.35. Quantile Map of Information and Communication Shares in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.12. Bivariate Analysis of the Share of Information and Communication in GDP

There was only one Low-High cluster, which belonged to TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova). The cluster's Gini coefficient tended to be low, along with neighbours' high information and communication share in GDP. On the quantile map, it is seen that one of the neighbors' is Istanbul. At the same time, it was observed that this cluster has one of the highest share rates in the observed region. This pattern suggests that high technology shares both within and within the peripheral regions create a spatial pattern with low inequality in the observed region.

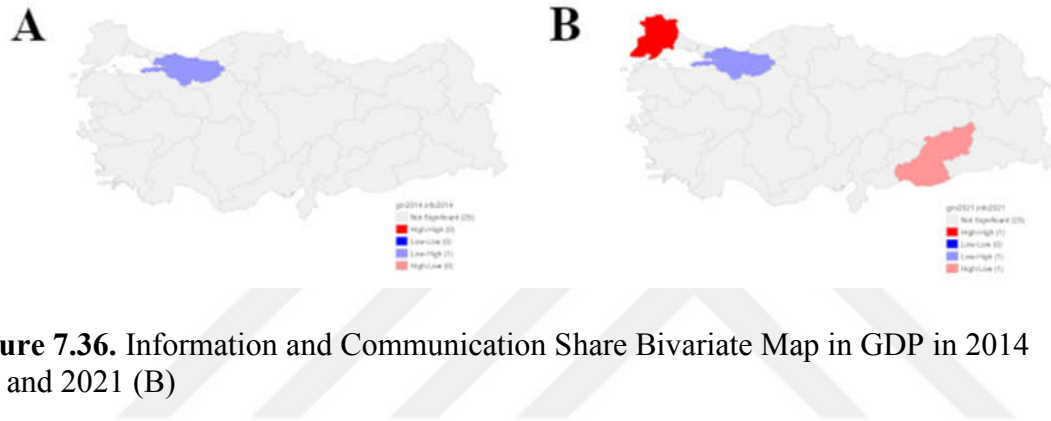


Figure 7.36. Information and Communication Share Bivariate Map in GDP in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

This situation may be due to the industry-based structure of the region suppressing the inequality within itself, together with the neighborhood effect observed in the region, while the information and communication sector shares of its neighbors created a limited segment with high income.

In 2021, one High-High and one High-Low cluster were added to the map. The High-Low cluster corresponded to TRC2 (Şanlıurfa and Diyarbakır). The cluster's Gini coefficient tended to be high, along with neighbours' low information and communication share in GDP. The red cluster corresponded to TR21 (Tekirdağ, Edirne and Kırklareli), and the clusters' Gini coefficient tended to be high along with neighbours' high information and communication share in 2021. On the quantile map one of the neighbor was Istanbul.

7.18.13. Quantile Analysis of Financial and Insurance Activities Shares in GDP

In the quantile map, the provinces with the highest share clusters in financial and insurance sectors in both years were Istanbul, Izmir, Ankara, Samsun, Tokat, Corum, and Amasya.

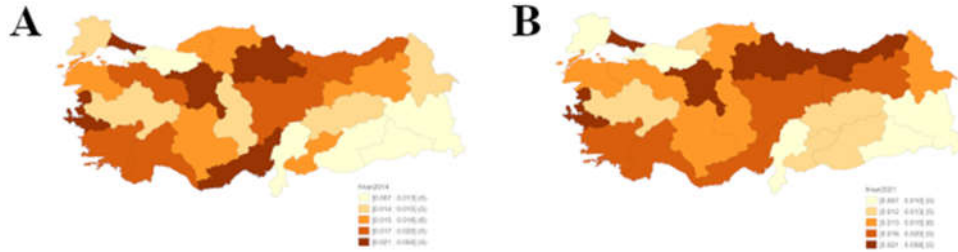


Figure 7.37. Quantile Map of Financial and Insurance Activities' Shares in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.14. Bivariate Analysis of Financial and Insurance Activities Shares in GDP

There were a total of three clusters of Low-Low corresponding to TRB1 (Malatya, Elazığ, Bingöl, Tunceli); TRC1 (Gaziantep, Adıyaman, Kilis) and TRC3 (Mardin, Batman, Şırnak and Siirt). These Low-Low clusters' Gini coefficients tended to be low, along with neighbours' low share of financial and insurance activities in GDP in 2014. This spatial pattern may have been caused by the underdevelopment of finance and insurance companies in the observed regions, which may have suppressed the emergence of a high-income class, resulting in a relatively homogeneous distribution of income. It was observed on the quantile map that the Eastern Anatolia region and its surroundings showed low share clusters.

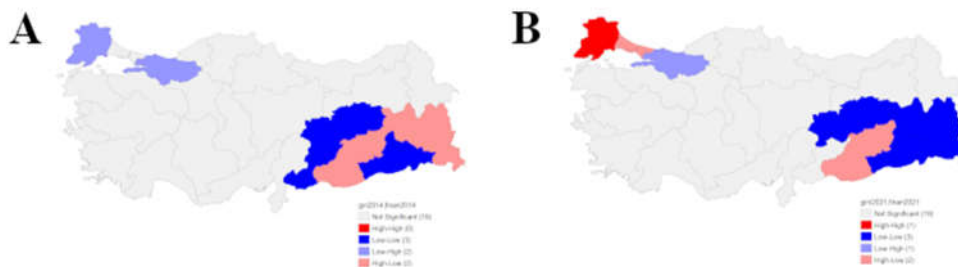


Figure 7.38. Financial and Insurance Activities Shares Bivariate Map in GDP in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

On the other hand, there were a total of two High-Low clusters corresponding to TRC2 (Şanlıurfa, Diyarbakır) and TRB2 (Van, Muş, Bitlis and Hakkari). These High-Low clusters' high Gini coefficients tended to be high along with their neighbours' low share of financial and insurance activities in GDP in 2014. This spatial association may have been caused by TRC2 and TRB2 regions may have had heavy public transfers, while surrounding regions reflected underdeveloped financial infrastructure and this pattern was driven by structural instabilities. There were two Low-High clusters corresponding to TR21 (Tekirdağ, Edirne, Kırklareli) and TR42 (Kocaeli, Sakarya, Düzce, Bolu, Yalova). These clusters' Gini coefficient tended to be low, along with neighbours' high share of financial and insurance activities in GDP in 2014. However, the interesting thing as observed on the quantile map, these clusters form regions with a low share.

In 2021, TR21 (Tekirdağ, Edirne, Kırklareli) turned into a High-High cluster. The cluster exhibited a high Gini coefficient and was surrounded by neighbours with a high share of financial and insurance activities in GDP. There were a total of two High-Low clusters corresponding to TR10 (Istanbul) and TRC2 (Şanlıurfa and Diyarbakır). These clusters' Gini coefficient tended to be high, along with neighbours' low share of financial and insurance activities in GDP in 2021. The Low-Low clusters corresponded to TRB1 (Malatya, Elazığ, Bingöl, Tunceli); TRB2 (Van, Muş, Bitlis, Hakkari) and TRC3 (Mardin, Batman, Şırnak and Siirt). These clusters' Gini coefficients tended to be low, along with neighbours' low share of financial and insurance activities in GDP in 2021.

7.18.15. Quantile Analysis of Real Estate Activities Shares in GDP

The cities with the highest real estate share clusters in both years were Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane, Malatya, Elazığ, Bingöl, and Tunceli.

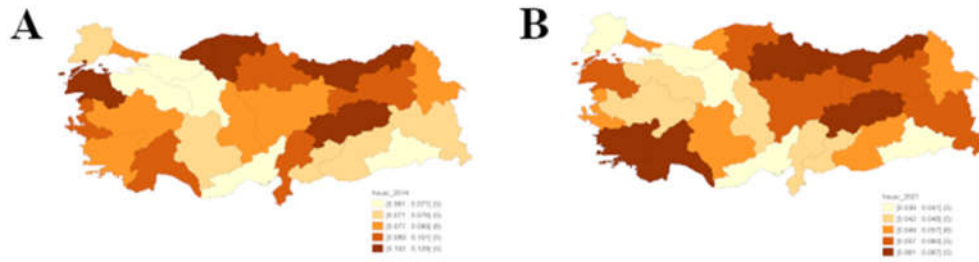


Figure 7.39. Quantile Map of Shares of Real Estate Activities in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.16. Real Estate Activities Shares in GDP

In 2014, the High-High cluster corresponded to TR72 (Kayseri, Sivas and Yozgat). This cluster's Gini coefficient tended to be high, along with neighbours' high share of real estate activities and observed region generally formed average share clusters on the quantile map.

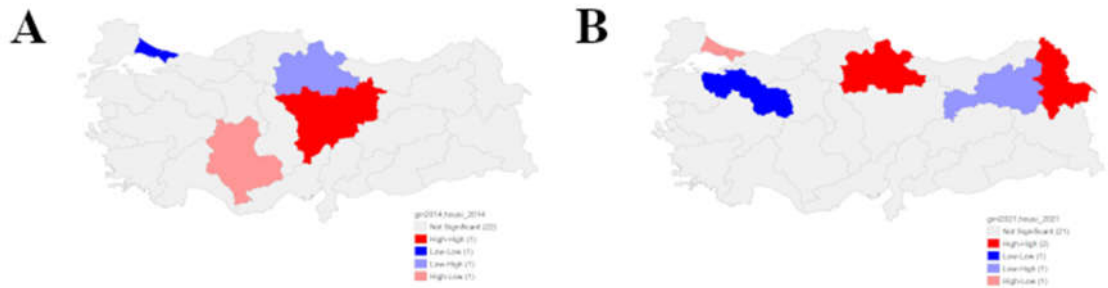


Figure 7.40. Bivariate Map of Shares of Real Estate Activities in GDP for 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

This High-High spatial pattern can be explained by wealth concentration in real estate, where capital-intensive activities such as property ownership represent a small fraction of the population. Consequently, the increasing shares of real estate-related GDP may have reflected a rise in wealth-based inequality in the region and its neighbors.

The blue Low-Low cluster corresponded to TR10 (Istanbul). The Gini coefficient of Istanbul tended to be low, along with neighbours' high share of real estate activities in GDP. The Low-High cluster corresponded to TR83 (Samsun, Tokat, Çorum and Amasya). This cluster's Gini coefficient tended to be low, along with neighbours' high share of real estate activities in GDP in 2014. The High-Low cluster corresponded to TR52 (Konya and Karaman); this cluster's Gini coefficient tended to be high, along with neighbours' low share of real estate activities in GDP in 2014.

In 2021, there were two High-High clusters corresponding to TR83 (Samsun, Tokat, Çorum, Amasya) and TRA2 (Ağrı, Kars, Iğdır and Ardahan). These clusters' Gini coefficients tended to be high with neighbours' high real estate activities shares in GDP in 2021. The Low-Low cluster corresponded to TR41 (Bursa, Eskişehir and Bilecik). This cluster's Gini coefficient tended to be low with neighbours' low estate activities shares in GDP in 2021. The High-Low cluster corresponded to TR10 (Istanbul) and its Gini coefficient tended to be high with its neighbours' low real estate activities share in GDP in 2021. The Low-High cluster corresponded to TRA1 (Erzurum, Erzincan and Bayburt). This clusters' Gini coefficient tended to be low with neighbours' high real estate activities shares in GDP in 2021. The reason for this pattern may have been caused by that while land prices or housing investments increased in neighboring areas and such investments remained limited in the observed region, which may have led to a more homogeneous income distribution in this region.

7.18.17. Quantile Analysis of Professional Administrative and Support Service Activities Shares

The cities that formed the clusters with the highest shares of professional administrative and support services in 2014 and 2021 were Istanbul, Izmir, Ankara, Antalya, Isparta, and Burdur.

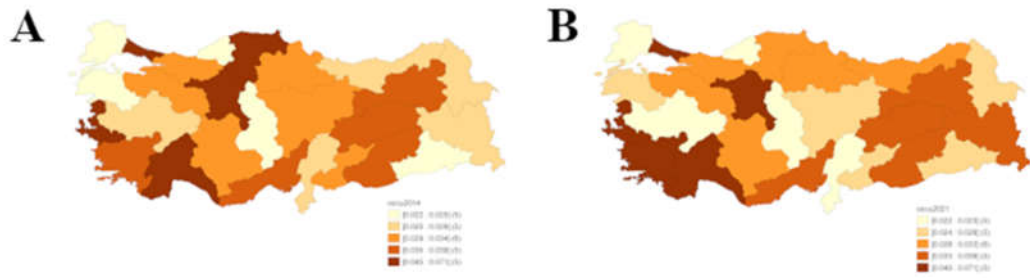


Figure 7.41. Quantile Map of Shares of Professional Administrative and Support Activities in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.18. Bivariate Analysis of the Shares of Professional, Administrative, and Support Service Activities in GDP

There was only one cluster belonging to Low-High TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova) and this cluster's Gini coefficient tended to be low, along with neighbours' high professional administrative and support service activities share in GDP in 2014. This Low-High spatial association may have been caused by relatively equal income distribution in TR42, with a dominance of industrial and public employment, and with potentially moderate wage differentials. In contrast, neighboring regions, such as Ankara in particular, may have hosted a variety of professional and administrative service activities that include both high-income and low-income occupations, which contribute to greater income inequality.

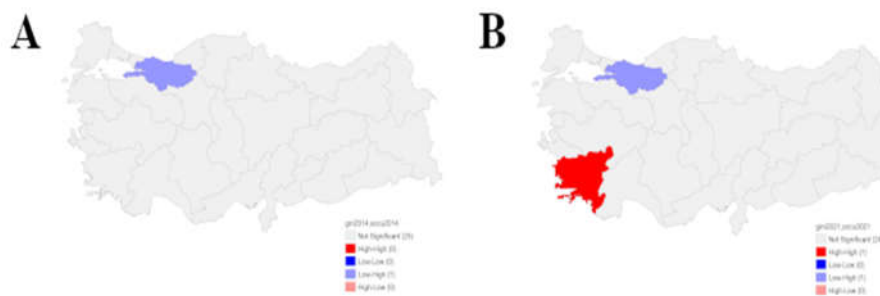


Figure 7.42. Professional Administrative and Support Service Activities Shares Bivariate Map in GDP in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

In 2021, there was also a High-High cluster belonging to TR32 (Aydın, Denizli and Muğla). This cluster's Gini coefficient tended to be high, along with neighbours' high professional administrative and support service activities share in GDP.

7.18.19. Quantile Analysis of Shares in GDP for Public Administration, Education, Human Health and Social Work Activities

High proportions in public administration, education, human health, and social work activities were observed particularly in the Eastern Anatolia region in 2014 and 2021. In Western Türkiye, this average share was considerably lower, as shown in the quantile map.

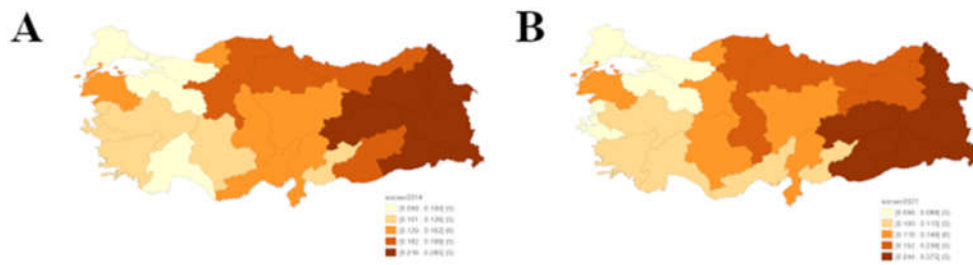


Figure 7.43. Quantile Map of the Shares of Public Administration, Education, Human Health and Social Work Activities in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.20. Bivariate Analysis of the Share of GDP in Public Administration, Education, Human Health and Social Work Activities

In 2014, the blue clusters corresponded to TR21 (Tekirdağ, Edirne, Kırklareli) and TR32 (Aydın, Denizli and Muğla). These clusters' Gini coefficient tended to be low, along with neighbours' low public administration, education, human health and social work activities shares in GDP. Even if expenditures on services such as public

administration, education and health were low in neighbouring regions, tourism in places such as Aydın, Denizli and Muğla, and the industrial sector in provinces such as Tekirdağ and Edirne may have provided a more homogeneous income distribution. This pattern may indicate that income inequality does not have to be high, especially if public expenditures remain low. On the quantile map, clustering of regions with low spending was generally observed in the Western part of the country.

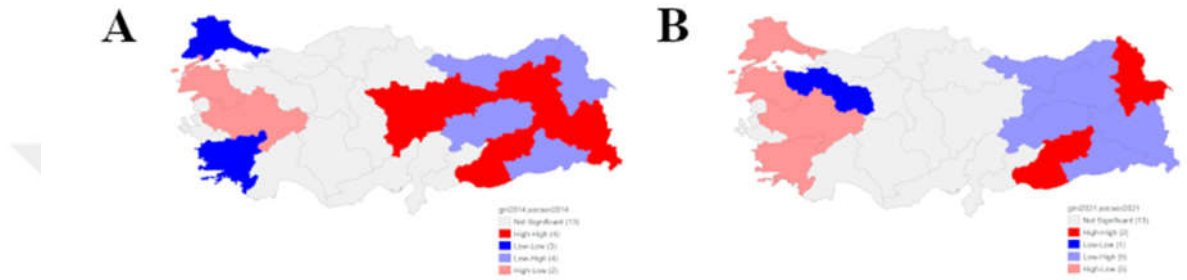


Figure 7.44. Public Administration, Education, Human Health and Social Work Activities Shares Bivariate Map in GDP in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

The High-High clusters corresponded to: TR72 (Kayseri, Sivas, Yozgat); TRA1 (Erzurum, Erzincan, Bayburt); TRB2 (Van, Muş, Bitlis, Hakkari) and TRC2 (Şanlıurfa and Diyarbakır). These clusters' Gini coefficient tended to be high along with neighbours' high public administration, education, human health and social work activities shares in GDP in 2014. The High-Low cluster corresponded to TR22 (Balıkesir, Çanakkale) and TR33 (Manisa, Afyon, Kütahya and Uşak). These clusters' Gini coefficient tended to be high along with neighbours' low public administration, education, human health and social work activities shares in GDP in 2014. The Low-High clusters corresponded to TR90 (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane); TRA2 (Ağrı, Kars, Iğdır, Ardahan); TRB1 (Malatya, Elazığ, Bingöl, Tunceli) and TRC3 (Mardin, Batman, Şırnak and Siirt). These clusters' Gini coefficient tended to be low, along with neighbours' high public administration, education, human health and social work activities shares in GDP in 2014.

In 2021, the red clusters corresponded to TRA2 (Ağrı, Kars, Iğdır, Ardahan) and TRC2 (Şanlıurfa and Diyarbakır). These clusters' Gini coefficient tended to be high along with neighbours' high public administration, education, human health and social work activities shares in GDP. This pattern may indicate structural inequalities in terms of public expenditures and the distribution of benefits from these expenditures. Here, the spatial spillover effect may indicate that the effect of an expenditure item in the neighboring region may have a similar effect in the observed region. When examining the quantile map, it is clear that this regional cluster also in a high share class in 2021. This implies although high spending, efforts may still be insufficient to reduce inequality. However, an analysis of both the bivariate and the 2021 quantile maps shows that public administration, education, and health shares were generally high in Eastern Anatolia and this pattern tended to reduce inequality. In this context, it can be argued that these shares may have the potential to decrease income inequality in this region.

TRA1 (Erzurum, Erzincan, Bayburt) and TRB2 (Van, Muş, Bitlis, Hakkari) turned into Low-High clusters; These clusters' Gini coefficient tended to be low along with neighbours' high public administration, education, human health and social work activities shares in GDP in 2021. TR21 (Tekirdağ, Edirne, Kırklareli); TR22 (Balıkesir, Çanakkale); TR33 (Manisa, Afyon, Kütahya and Uşak) and TR32 (Aydın, Denizli and Muğla) corresponded to High-Low clusters in 2021. These clusters' Gini coefficient tended to be high along with neighbours' low public administration, education, human health and social work activities shares in GDP.

7.18.21.Quantile Analysis of Shares in GDP for Other Service Activities

In the quantile map, Türkiye as a whole, observed shares in the Eastern Anatolia Region changed from lowest one to average one in 2021.

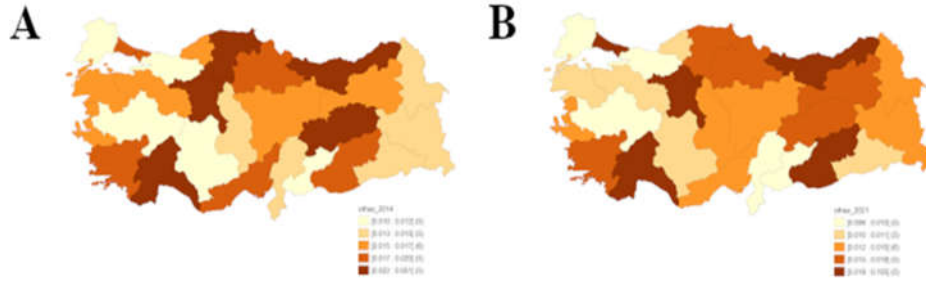


Figure 7.45. Quantile Map of the Shares of Other Service Activities in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.22.Bivariate Analysis of Shares in GDP for Other Service Activities

There were no multiple grouped clusters; the Low-Low cluster corresponded to TR10 (Istanbul). Its Gini coefficient tended to be low, along with the neighbour's low share of other service activities in GDP in the year 2014.

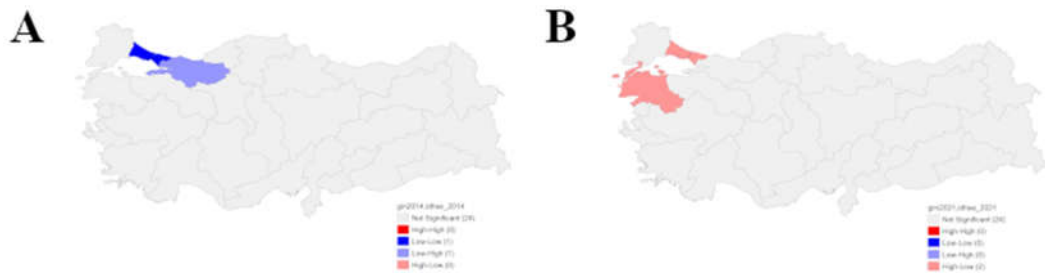


Figure 7.46. Other Service Activities Shares in GDP Bivariate Map in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

The Low-High cluster corresponded to TR41 (Kocaeli, Sakarya, Düzce, Bolu and Yalova). This cluster's Gini coefficient tended to be low, along with neighbours' high share of other service activities in GDP.

There were two High-Low clusters in 2021 corresponding to TR10 (Istanbul) and TR41 (Bursa, Eskişehir and Bilecik). These clusters' Gini coefficient tended to be high, along with neighbours' low share of other service activities' in GDP.

On the quantile map although it was above Istanbul's average for other service shares in 2021, it became one of the clusters with the highest shares in 2021.

7.18.23. Quantile Analysis of Sectoral Total Shares in GDP

Bivariate maps of the sectoral total map show the same color across all of Türkiye due to the uniform distribution of the data.

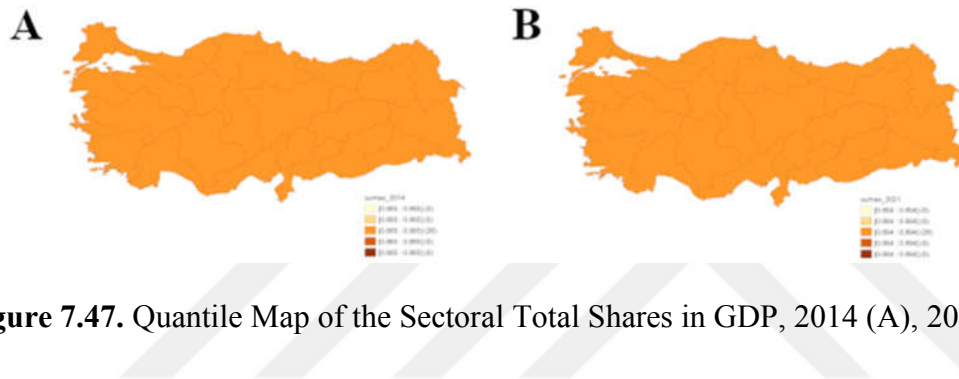


Figure 7.47. Quantile Map of the Sectoral Total Shares in GDP, 2014 (A), 2021 (B).

Source: Created by author using data from TURKSTAT

7.18.24. Bivariate Analysis of Sectoral Total Shares in GDP

The map shows sectoral total shares in GDP in the year 2014. The blue areas, Low-Low clusters, exhibited a low Gini coefficient and were surrounded by neighbours with a low share of sectoral total in GDP. However, the High-Low clusters show that their Gini coefficient tended to be high along with neighbours' low share of sectoral total in GDP. In 2021, some of the blue clusters transformed into High-Low clusters, while others shifted to Low-Low clusters.

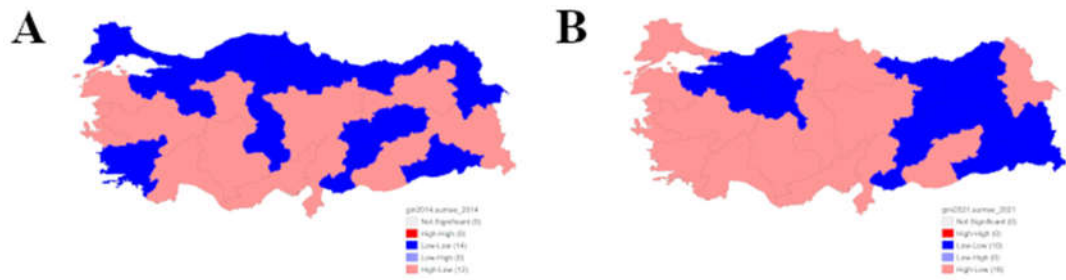


Figure 7.48. Bivariate Map of Sectoral Total Shares in GDP in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

The Black Sea Region transitioned into a High-Low cluster, whereas the Eastern Region became a Low-Low cluster in 2021. The High-Low pattern may suggest that spending and investment in neighbouring areas did not alleviate inequality in the observed region. When examining the quantile map, although there was a uniform distribution of shares across all regions, light red clusters have appeared. This may actually demonstrate why economic policies require different regional approaches. Because even with equal share levels, the pattern of income inequality within regions varies.

7.18.25. Quantile Analysis of Taxes in GDP

Bivariate maps of the taxes map have shown the same color for all of Türkiye due to the homogeneous distribution of the data.

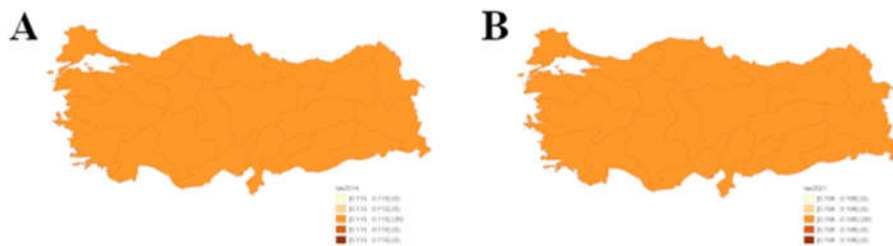


Figure 7.49. Quantile Map of the Tax Shares in GDP, 2014 (A), 2021 (B)

Source: Created by author using data from TURKSTAT

7.18.26. Bivariate Analysis of Taxes in GDP

The red areas show their high Gini coefficient was positively spatially related to neighbours' high taxes-subsidies share in GDP, the Low-High cluster which belonged to 14 regions show their Gini coefficient tended to be low with neighbours' high taxes-subsidies share in GDP in the year 2014.

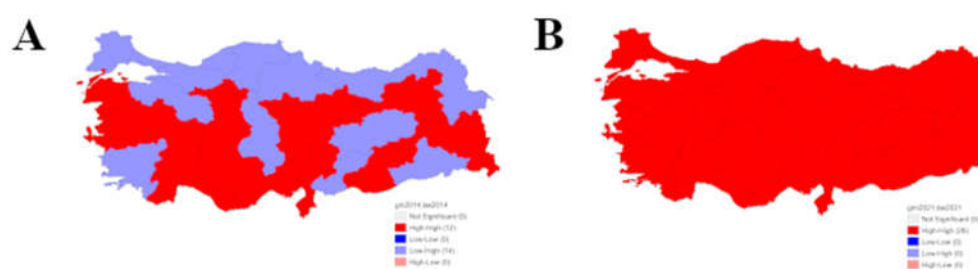


Figure 7.50. Taxes-subsidies Shares in GDP in 2014 (A) and 2021 (B)

Source: Created by author using data from TURKSTAT

In 2021, 26 regions were classified as red. Their high Gini coefficient was positively spatially correlated with neighbouring regions' high share of taxes and subsidies in GDP. It may have been evident that in 2021, income inequality has spread throughout Türkiye, influenced by high tax subsidies in neighbouring regions, and has become more pronounced, indicating a stronger positive spatial relationship. According to Günel's (2019) findings the tax system distorts income distribution and has become one of the most important obstacles to the fight against poverty in Türkiye. When examining the quantile map, it is clear that taxes remained at the average value across all regions by maintaining their homogeneity in both 2014 and 2021. However different patterns formed by the areas has shown significant changes. In 2021, all regions showed a high tax pattern in their surrounding areas, characterised by high inequality.

7.19. Quantile Analysis of Net Migration Between

During 10 years, the cluster structure on the quantile map of Türkiye generally has shown that the Western Region forms clusters with a higher average net migration than Eastern Anatolia. An additional point for 2023 is the Eastern Black Sea Region formed the clusters with the highest net migration value. Istanbul has become one of the clusters with low immigration over the past four years.



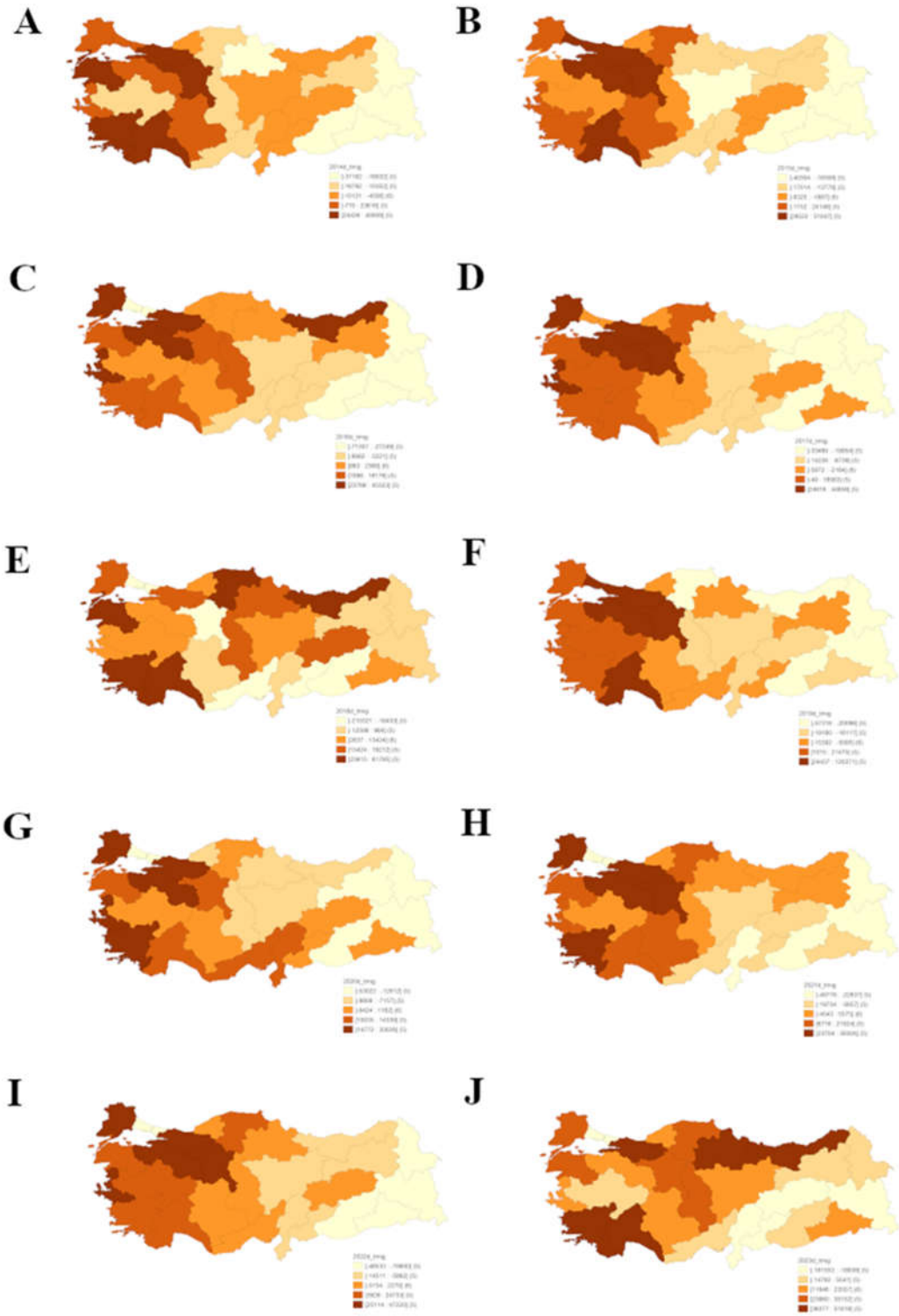


Figure 7.51. Quantile Map of Net Migration in Türkiye for the years: 2014 (A),2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

7.20. Bivariate Analysis of Net Migration

In 2014, the red clusters corresponded to TR22 (Balıkesir, Çanakkale) and TR33 (Manisa, Afyon, Kütahya and Uşak). These red clustered regions' Gini coefficient tended to be high along with their neighbours' high net migration. İzmir province, for example, had high net migration and shares a border with the TR33 region. Mostly East regions clustered as blue, which corresponds to TR90 (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane); TRA2 (Ağrı, Kars, Iğdır, Ardahan); TRB1 (Malatya, Elazığ, Bingöl, Tunceli) and TRC3 (Mardin, Batman, Şırnak and Siirt). The blue cluster's Gini coefficient tended to be low along with their neighbours' net migration. The red clusters were expanded in 2015 through TR10 (Istanbul); TR22 (Balıkesir, Çanakkale); TR33 (Manisa, Afyon, Kütahya, Uşak) and TR52 (Konya and Karaman). These clusters exhibited a high Gini coefficient and were surrounded by neighbours with a high migration. In addition to 2014's blue cluster regions, TRB2 (Van, Muş, Bitlis and Hakkari) was added. In 2016, there were not as many intense red areas as in 2015, but the Eastern part of Türkiye was mostly blue. Their Gini coefficient tended to be low, along with their neighbours' low net migration. In 2017, the blue clusters were expanded through the Eastern Black Sea region. TR90 (Trabzon, Ordu, Giresun, Rize, Artvin and Gümüşhane); TRA1 (Erzurum, Erzincan and Bayburt) and TRA2 (Ağrı, Kars, Iğdır and Ardahan). Only one region was red in 2018, and this region belonged to TR83 (Samsun, Tokat, Çorum and Amasya). This region's high Gini coefficient was associated with high net migration in neighbouring regions. In 2019, the High-Low cluster belonged to two regions: TR83 (Samsun, Tokat, Çorum, Amasya) and TR72 (Kayseri, Sivas and Yozgat). These clusters' Gini coefficient was associated with their neighbours' low net migration. In 2020, TR21 (Tekirdağ, Edirne and Kırklareli) was in the blue cluster. This blue cluster's Gini coefficient tended to be low along with their neighbours' low net migration but it was the Pandemic year, and there were some regulations and restrictions. In 2021, the map turned mostly red areas which belonged to the Western part of Türkiye and blue clusters corresponded to the Eastern part of Türkiye. Western part of Türkiye's net migration was relatively high compared to the Eastern part of Türkiye. They were consistent with the literature studies explanations about high migration rate increases high income inequality. According to Spatial Spill-

Over Theory, big events can affect their neighbours (Atikah, Rahardjo, 2021), such as migration.

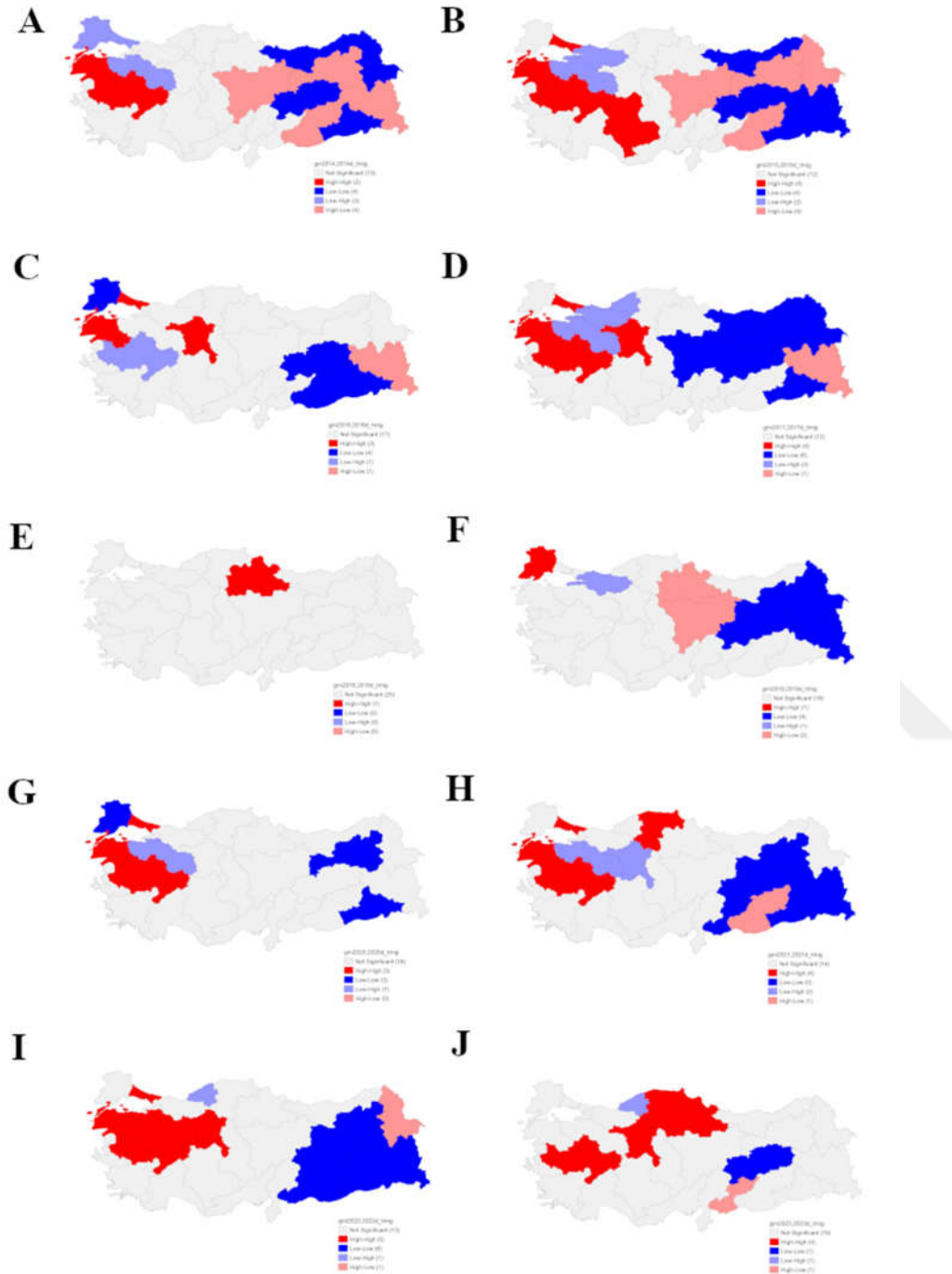


Figure 7.52. The Net Migration Bivariate Map of Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

The reason why the spill-over effect is emphasized here is that clusters covering distinct and large areas were observed. So the red areas may have shown that the observed clusters' high Gini coefficient was associated with the surrounding region's high migration. The Low High clusters of 2021 turned into red clusters in 2022. Mostly in the Western part of Türkiye's Gini coefficient tended to be high along with their neighbours' high net migration. Also, mostly in the Eastern part of Türkiye's Gini coefficient tended to be low with their neighbours' low net migration. In 2023, some of the Black Sea provinces were in the red cluster, which belonged to TR82 (Kastamonu, Çankırı, Sinop); TR83 (Samsun, Tokat, Çorum, Amasya) and in the inlands of Anatolia, the one which TR51 (Ankara) and the Western part of Türkiye, those TR33 (Manisa, Afyon, Kütahya and Uşak). These clusters' Gini coefficients tended to be high, along with their neighbours' high net migration.

7.21. Quantile Analysis of the Population

The cities in the clusters with the highest population density during 10 years were Ankara, Izmir, Istanbul, Bursa, Eskişehir, and Bilecik. There was no high population cluster in Eastern Anatolia. Another interesting finding is although the Edirne, Tekirdağ, Kırklareli cluster had the highest net migration density its population remained below the average for nearly 10 years.

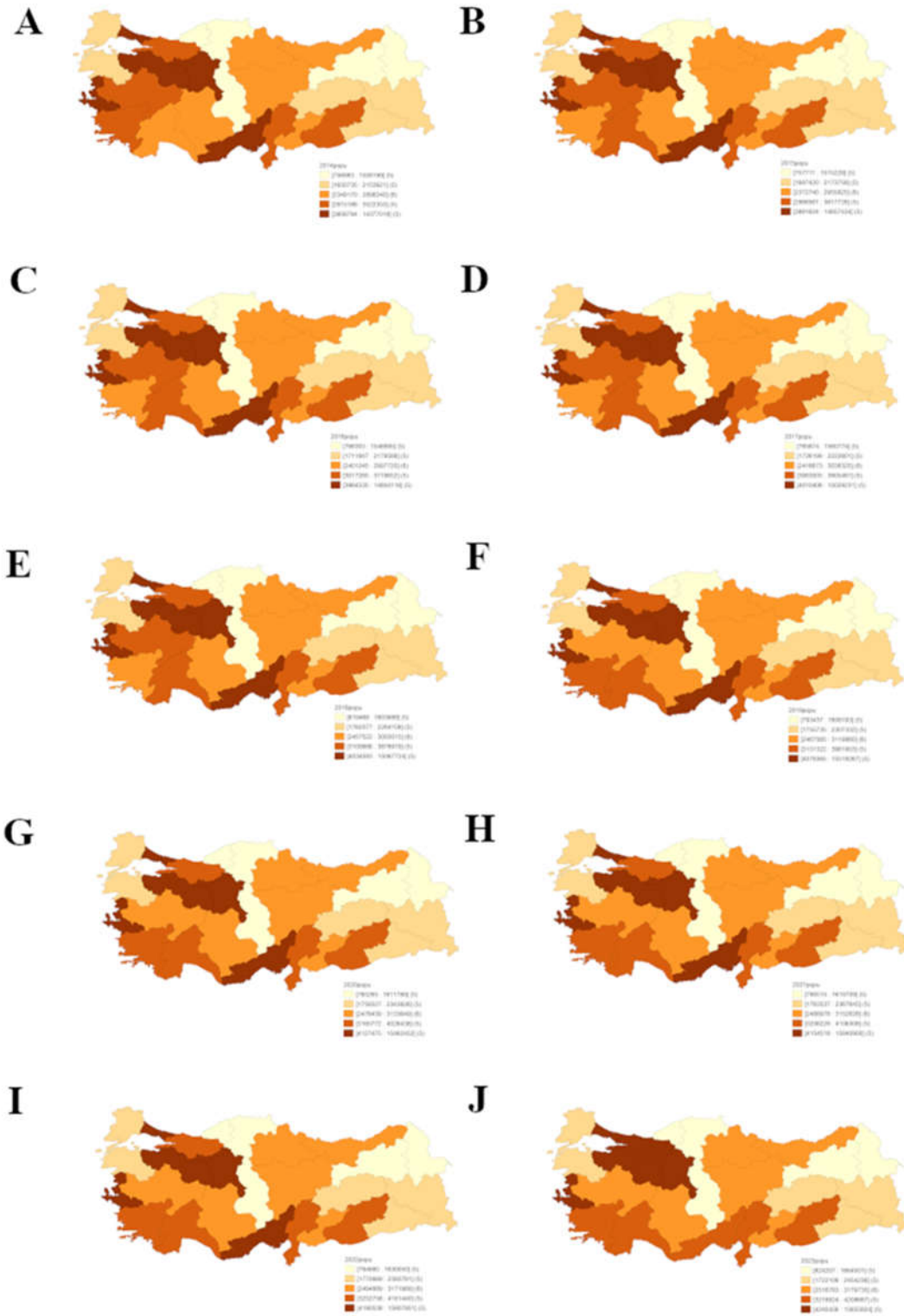


Figure 7.53. Quantile Map of Population in Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

7.22. Bivariate Analysis of Population

There was no apparent cluster of red or blue in 2014. However, TR21 (Tekirdağ, Edirne, Kırklareli) tended to have a low Gini coefficient while their neighbours had high population and one of which was Istanbul. In 2015, the map did not change and remained the same as the previous year. The High-low cluster corresponded to TRA1 (Erzurum, Erzincan and Bayburt). While they tended to have a high Gini coefficient, their neighbour had a low population. The blue cluster corresponded to TRA1 (Erzurum, Erzincan and Bayburt) and they turned into a blue cluster in 2016. While they tended to have a low Gini coefficient, their neighbour had a low population. In 2017, one red cluster corresponded to TR21 (Tekirdağ, Edirne and Kırklareli), and they tended to have a high Gini coefficient along with their neighbours' high population, and that might be caused by Istanbul's population. The 2018 map was identical to the 2019 map. A blue cluster remained unchanged, comprising the provinces of Erzurum, Erzincan, and Bayburt. In 2020, the red cluster region turned into a Low-High cluster. In this cluster, the low Gini coefficient tended to be low along with neighbours' high population, and this neighbours' high population might be caused by Istanbul. In 2021, after the Pandemic, TR21 (Tekirdağ, Edirne and Kırklareli) exhibited a high Gini coefficient and was surrounded by neighbours with high population. The Low-High clustered provinces are Kocaeli, Sakarya, Düzce, Bolu, and Yalova's Gini coefficients tended to be high with their neighbours' high population, and one of the neighbours of this cluster is also Istanbul. This map of 2022 did not change and the same with the previous one in 2021. In 2023, the High-Low clustered were expanded to the regions through TR90 (Trabzon, Ordu, Giresun, Rize, Artvin and Gümüşhane); TRA1 (Erzurum, Erzincan and Bayburt). Their Gini coefficient tended to be high with their neighbour populations' low. When looking at the quantile map they also had an average population cluster.

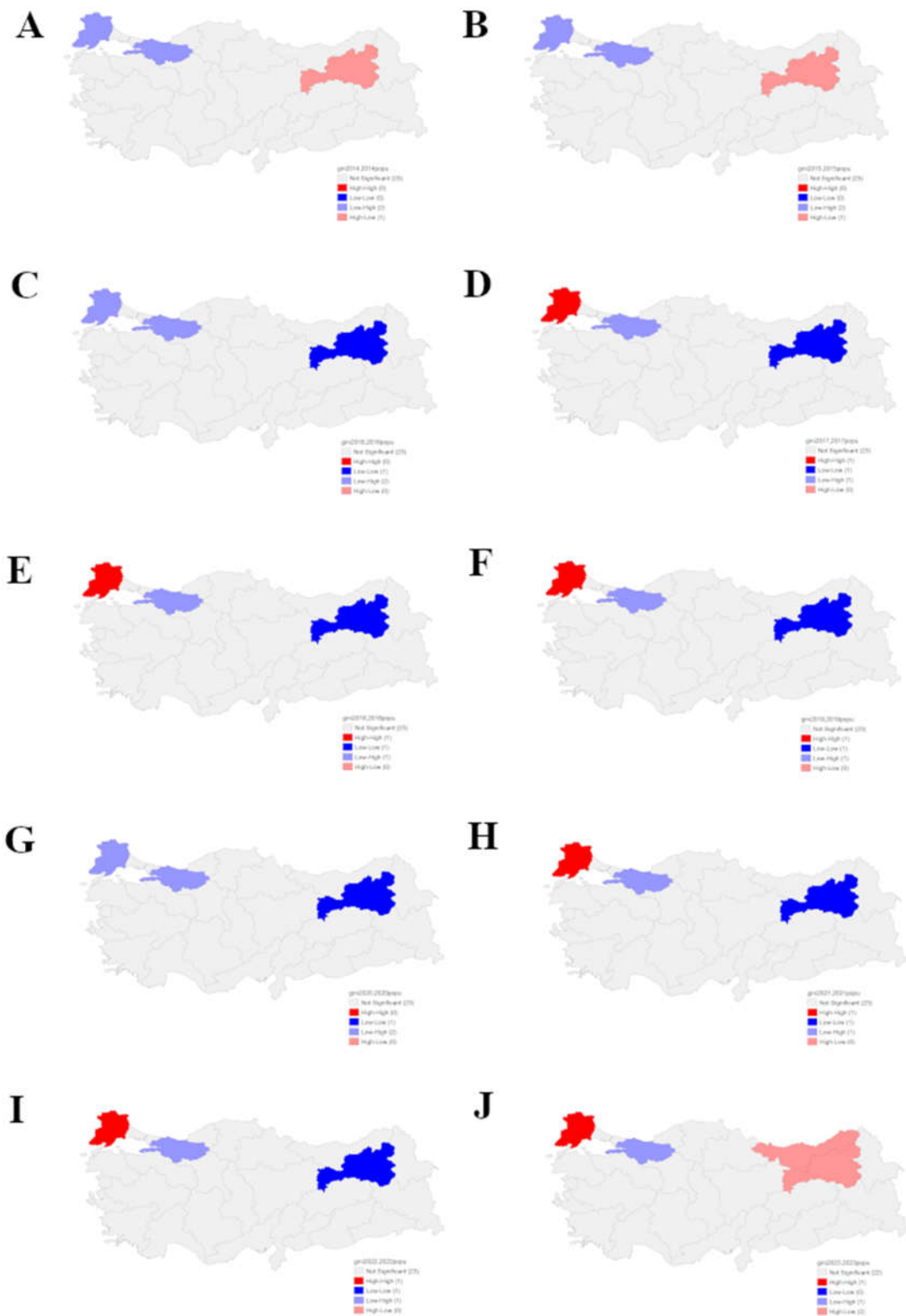


Figure 7.54. The Population Bivariate Map of Türkiye for the years: 2014 (A), 2015 (B), 2016 (C), 2017 (D), 2018 (E), 2019 (F), 2020 (G), 2021 (H), 2022 (I), 2023 (J)

Source: Created by author using data from TURKSTAT

7.23. Quantile Analysis of the Mortality Rate

On the quantile map, the regions with the highest death rates were the Black Sea. Due to the earthquake that occurred in Hatay in 2023, it is seen that this region had the highest death rate.

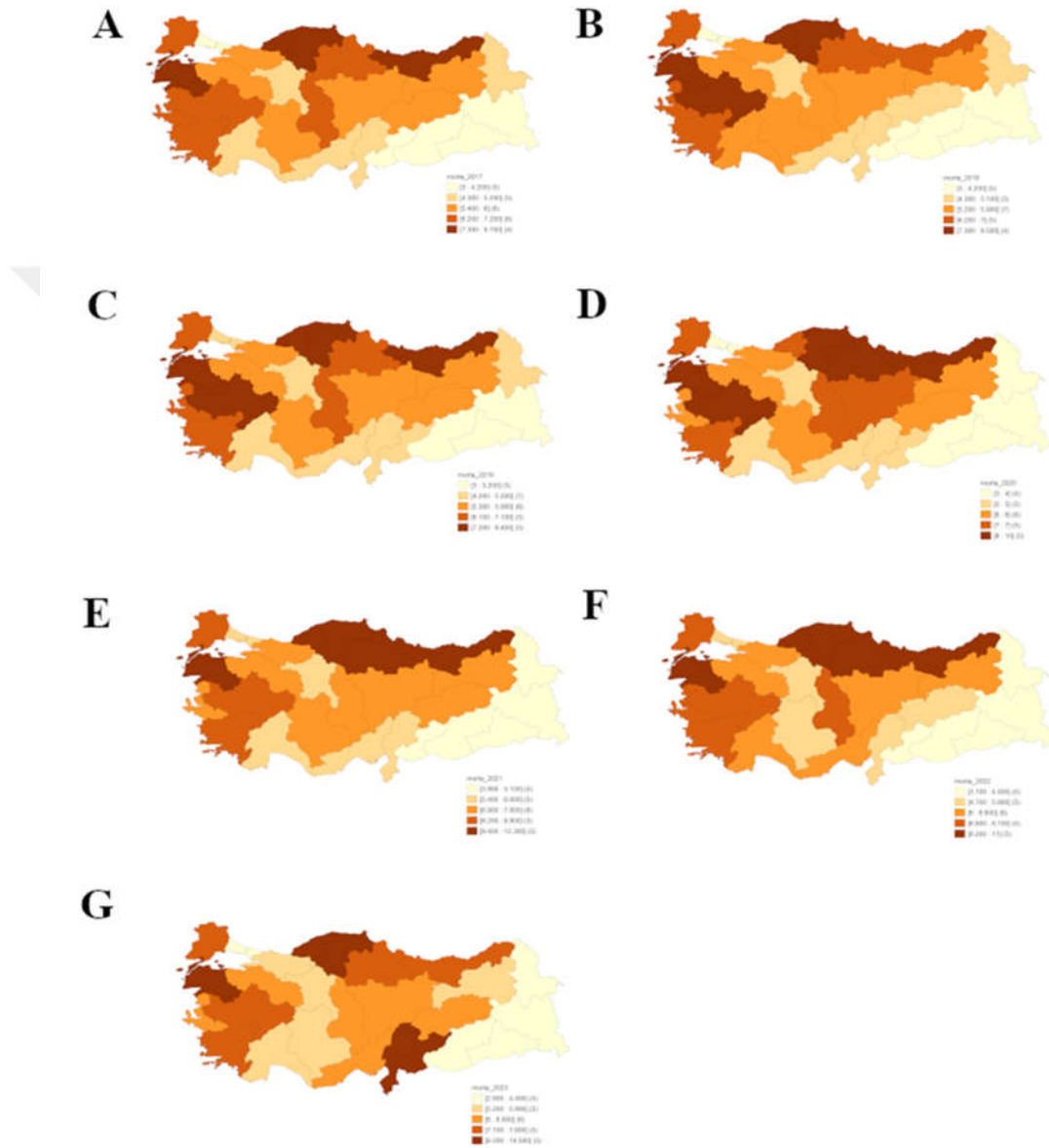


Figure 7.55. Quantile Map of Mortality Rate in Türkiye for the years: 2017 (A), 2018 (B), 2019 (C), 2020 (D), 2021 (E), 2022 (F), 2023 (G).

Source: Created by author using data from TURKSTAT

7.24. Bivariate Analysis of Mortality Rate

In 2017, the red areas belonged to TR22 (Balıkesir, Çanakkale) and TR21 (Tekirdağ, Edirne and Kırklareli). Their high mortality rate tended to be high along with their neighbours' high Gini coefficient and the blue regions belonged to TRB2 (Van, Muş, Bitlis and Hakkari) and TRC2 (Şanlıurfa and Diyarbakır). These clusters low mortality rate were tended to be low with their neighbours' low Gini coefficient. In 2018, the red areas belonged to TR21 (Tekirdağ, Edirne and Kırklareli) and TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir), and the blue areas belonged to TRA1 (Erzurum, Erzincan and Bayburt), TRA2 (Ağrı, Kars, Iğdır and Ardahan), TRB2 (Van, Muş, Bitlis and Hakkari), and TRC2 (Şanlıurfa and Diyarbakır). There was only one red cluster in 2019, which corresponds to TR21 (Tekirdağ, Edirne and Kırklareli). In 2020, the red clusters belonged to TR21 (Tekirdağ, Edirne and Kırklareli), TR31 (Izmir), TR41 (Bursa, Eskişehir and Bilecik), TR42 (Kocaeli, Sakarya, Düzce, Bolu and Yalova), TR52 (Konya, Karaman), TRA1 (Erzurum, Erzincan and Bayburt) and TRB1 (Malatya, Elazığ, Bingöl and Tunceli). There was only one Low-High cluster, which belonged to TR61 (Antalya, Isparta and Burdur). TR61's mortality rate tended to be low with neighbours' high Gini coefficient. In 2021, there was only one Low-High cluster, which belonged to TR62 (Adana and Mersin). In 2022, the blue clusters belonged to TRB1 (Malatya, Elazığ, Bingöl and Tunceli); TRB2 (Van, Muş, Bitlis and Hakkari), TRC2 (Şanlıurfa and Diyarbakır), TRC3 (Mardin, Batman, Şırnak and Siirt) and TRC1 (Gaziantep, Adıyaman and Kilis). The red cluster belonged to TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir). In 2023, the Low-High clusters belonged to TR52 (Konya and Karaman) and TR71 (Kırıkkale, Aksaray, Niğde, Nevşehir and Kırşehir). These clusters' mortality rate tended to be low with neighbours' high Gini coefficient. While the TR71 cluster was red in 2022, income inequality continued in neighboring regions, creating a Low-High pattern in 2023. This could be due to new hospitals opening or innovations in healthcare. Additionally, this pattern may also indicate that the observed region benefits from health expenditures in neighboring regions because on the quantile map health shares appear to be much higher in the surroundings of the observed region than in the observed region.

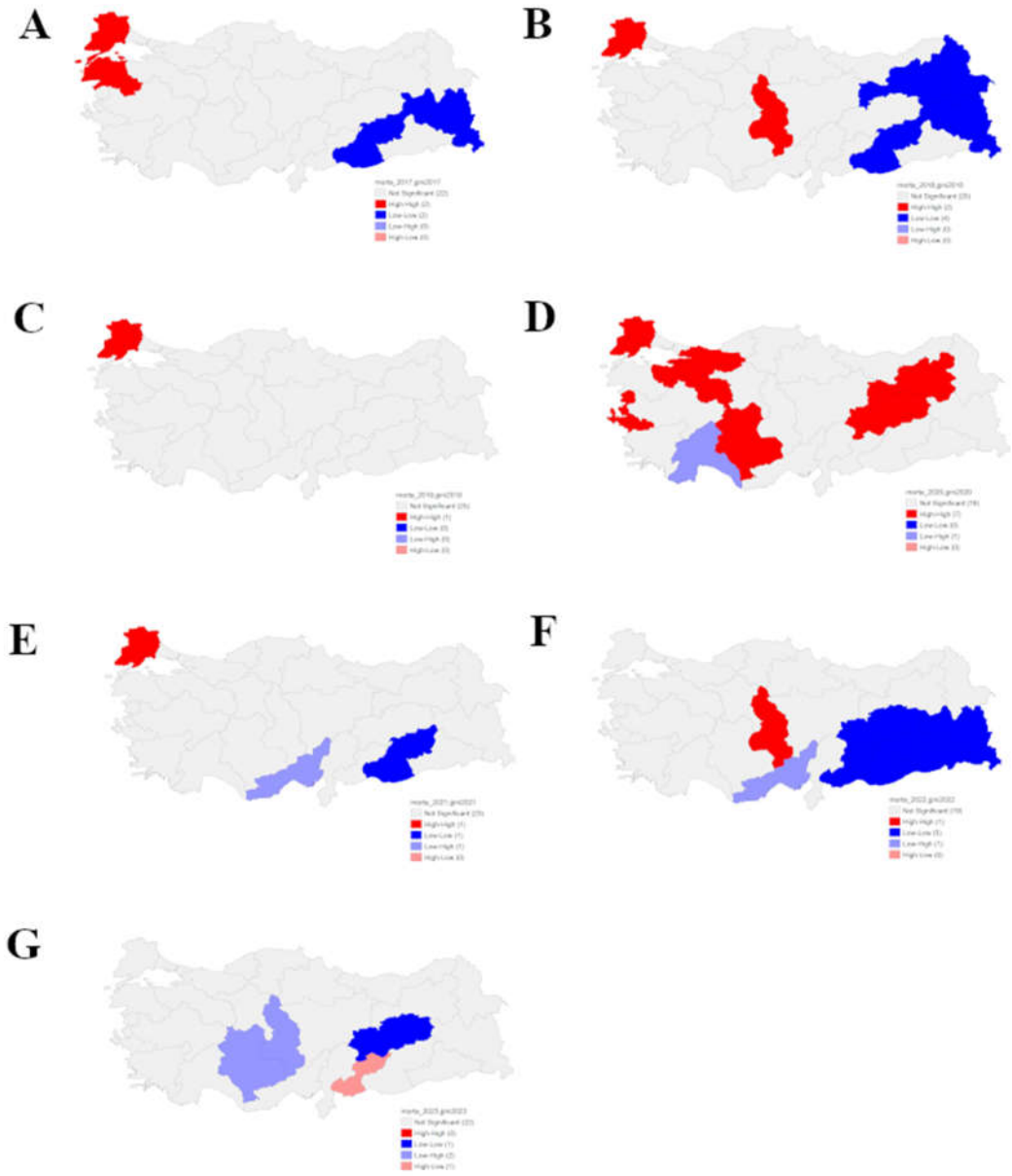


Figure 7.56. The Mortality Rate Bivariate Map of Türkiye for the years: 2017 (A), 2018 (B), 2019 (C), 2020 (D), 2021 (E), 2022 (F), 2023 (G) (on the x axis mortality rate, on the y axis Gini Coefficient)

Source: Created by author using data from TURKSTAT



8. CHAPTER SAR, SEM OLS Model Results

The result is summarized in the following equation. When all OLS, SAR, and SEM results are reviewed, the significant test at the p-value indicates that the SAR model is preferred. Since the SAR value is positive and its coefficient is 0.430, a positive spatial relationship exists between regions and income inequality. In other words, income inequality influences not only its region but also neighboring regions.

Equation of the SAR model results:

$$\text{Gini 2021} = 0.430 * W \text{ gini2021} + 0.134 + 0.286 * \text{gini2020} + 0.123 * \text{agrif 2021} - 0.784 * \text{cons2021} + 1.460 * \text{info2021} - 1.776 * \text{ARGER 2021} + \epsilon \quad (8.1)$$

Here, the regional 2021 Gini index increased by 0.430 units, along with the Gini weight of neighbors in 2021, while the 2020 Gini index rose by 0.286 units. Shares of agriculture, forestry, and fishing in GDP in 2021 increased by 0.123 units, whereas construction shares in GDP in 2021 declined by 0.784 units. Information and communication shares in GDP in 2021 increased by 1.460 units. Research and development shares in GDP in 2021 reduced regional income inequality by 1.776 units. It is also observed that the smallest AIC value belongs to the SAR test. The results of other models are also shown in the table below.

Table 8.1. Estimation Results for Spatial Lag Model, Ordinary Least Squares (OLS) and Spatial Error Model (SEM)

Variable	OLS Coefficient (SE)	Spatial Lag Coefficient (SE)	Spatial Error Coefficient (SE)
Constant	0.248 (0.051) ***	0.134 (0.048) **	0.256 (0.041) ***
gini2020	0.393 (0.154) *	0.286 (0.115) *	0.372 (0.124) **
agrif_2021	0.058 (0.084)	0.123 (0.061) *	0.106 (0.065)
cons2021	-0.755 (0.210) **	-0.784 (0.147) ***	-0.673 (0.145) ***
serv2021	-0.032 (0.078)	-0.043 (0.055)	-0.014 (0.060)
info2021	0.780 (0.636)	1.460 (0.477) **	1.111 (0.479) *
finan2021	1.585 (0.982)	1.177 (0.687) †	0.231 (0.780)
2021f_ale3	-0.00033 (0.00030)	-0.00033 (0.00021)	-0.00012 (0.00021)
ARGER_2021	-1.272 (0.652) †	-1.776 (0.472) ***	-1.443 (0.556) **
Spatial Coef.	-	0.430 (0.129) ***	0.549 (0.185) **
R ²	0.813	0.861	0.840
Log-Likelihood	80.53	83.69	81.41
AIC	-143.07	-147.37	-144.83
Heteroskedasticity (BP test)	p = .744	p = .418	p = .827
Spatial Dependence (LR test)	p = .042 (Lag significant)	p = .012 (Lag significant)	p = .185 (Not significant)

Source: Created by author using data from TURKSTAT

(† p < 0.10, * p < 0.05, ** p < 0.01, *** < 0.001; SE represents Standard Error, AIC represents Akaike Information Criterion, p value greater than 0.05 meaning there is no heteroscedasticity, in the spatial lag model p < 0.05 is significant, gini2020 (previous years' Gini coefficient), agrif 2021 (agriculture, forestry and fishing shares in GDP in 2021), cons2021 (construction shares in GDP in 2021), serv2021 (service share in GDP in 2021), info2021 (information and communication share in GDP in 2021), finan2021 (financial and insurance activities shares in GDP in 2021), occu2021 (professional administrative and support service activities shares in GDP in 2021, 2021f_ale3 (female employment ratio for agriculture, industry and services in 2021), ARGER 2021 (research & development shares in GDP in 2021)

9. CHAPTER DISCUSSION, CONCLUSION and FUTURE WORK

This study emphasizes the significance of considering regional disparities while examining the factors that affect income inequality and when these factors are ignored, it has been observed in literature reviews how a country becomes poorer and its crime rates increase accordingly. At the same time, the observation that an increase in income inequality in one region leads to higher income inequality elsewhere emphasizes the urgency of regional planning for economic policies.

A region has been analyzed by using maps to examine how it reflects various inequality patterns associated with factors influencing income disparity. When developing modern economic policies, considering regional disparities is essential to improve the effectiveness of future research. As seen in the results of the SAR test model, the variable that most affects and simultaneously reduces regional income inequality is the share of research and development in GDP. Since the share of research and development expenditures in GDP significantly reduces regional income inequality, further increasing this share can be included in the planning for the coming years. Tax rates can be reduced, particularly to encourage research and development.

The fact that the construction sector shares also reduce regional income inequality suggests that economic policies should be aimed in this direction. Improvements in the construction sector and more protective planning for workers' rights can further increase its effectiveness. The government must increase construction safety when implementing policies, and the transition from an irregular to a regular income structure must be implemented. Indeed, the development of this sector after the 2023 earthquake in our country is crucial.

Another finding is that agriculture, forestry and fishing GDP shares in 2021 increased regional income inequality. While this study suggests that the shares of agriculture, forestry, and fishing do not increase inequality as much as the share of

information and communication, they should be planned to reduce income inequality, and policies should be implemented accordingly.

The regional effects of tax policies are illustrated in the maps, indicating that regional tax policies should also be developed. Particularly, the fact that regions create a different pattern of inequality in the distribution of homogeneous taxation may encourage the state to take this situation into account when organizing its fiscal policies. Additionally, the study emphasized that the variable most likely to increase regional income inequality may be financial shares, as it is not fully significant in the significance test but falls within an observable range. One of the most essential requirement should be in improvements of information and communication sector to reduce inequality rather than increase it, by taking advantage of this technology since its' share in GDP is one of the main factor of increasing inequality.

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APPENDIX

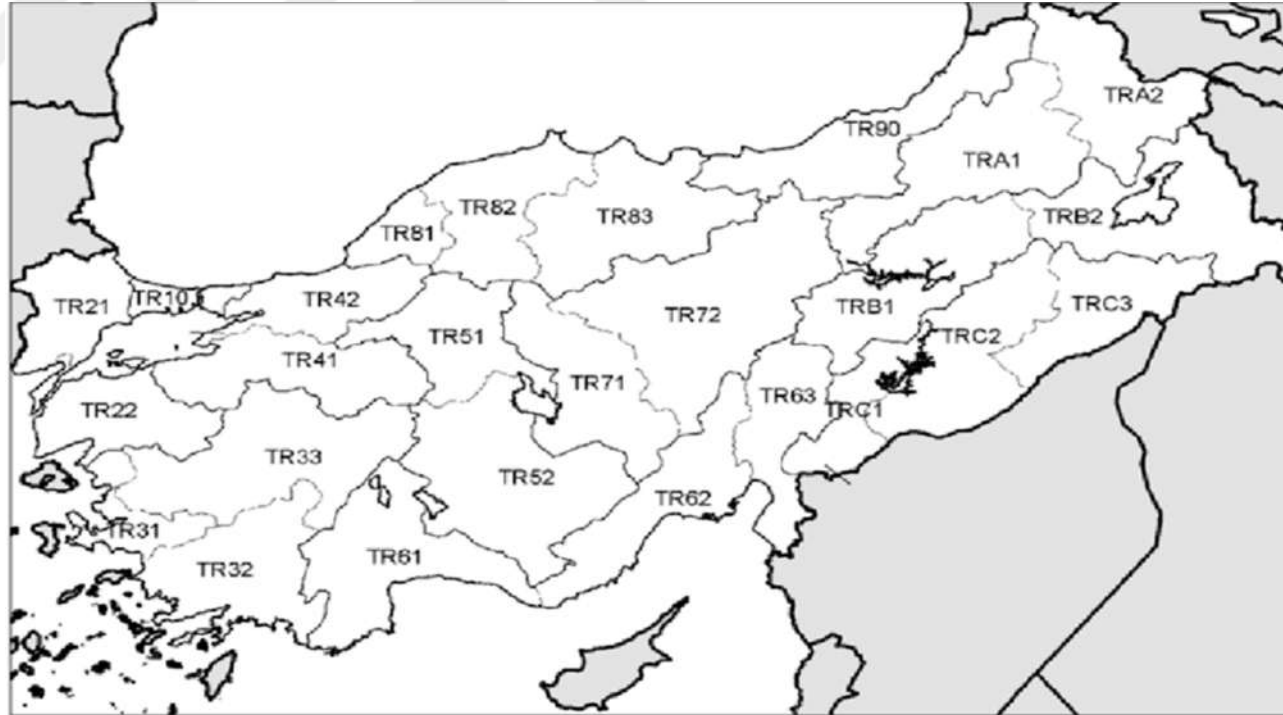
PROVINCES and PROVINCES NUTS-2 CODES

Provinces Name and Nuts-2 Codes

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

Source: Edited from TURKSTAT

THE MAP OF TÜRKİYE BY NUTS 2 CODE



Provinces Nuts-2 Codes in the Türkiye Map

Source: Researchgate/ Nuts 2 Level of Türkiye