Spatial Effects of Electricity Consumption on Air Pollution in Türkiye at Provincial Level

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ABSTRACT

This study investigates the effect of electricity consumption on air pollution in Türkiye at the provincial level through spatial analyses. Using SO_2 and PM_{10} measurements as indicators of air pollution, this study incorporates income, population density, and electricity consumption as explanatory variables. The direct and indirect effects of economic factors are analyzed using a spatial Durbin model on annual data from 2008 to 2021. Our results provide strong evidence of spillovers from both air pollution and economic determinants in neighboring provinces. Electricity consumption has a significant positive direct effect on air pollution. Foremost, a 1% increase in electricity consumption results in a 0.57% rise in SO_2 levels and a 0.16% rise in PM_{10} levels within the province. Additionally, it causes a 1.1% rise in PM_{10} levels in neighboring provinces due to spillover effects. In conclusion, our recommendations involve boosting incentives for renewables to mitigate the impact of electricity consumption on air pollution. Furthermore, the upcoming establishment of a mandatory carbon market in Türkiye necessitates spatial considerations in carbon pricing, especially in high-pollution clusters.

Key words: *Air Pollution, Electricity Consumption, Spatial Durbin Model, Environmental Kuznets Curve, Türkiye*

JEL Codes: C23, Q53, Q58

1. INTRODUCTION

In addition to the economic and social factors surrounding and shaping economic growth, we are experiencing a period in which environmental factors also strengthen their influence on our lives. While the effects of climate change are becoming increasingly evident, the understanding that nature exists to serve humanity is being replaced by sustainable approaches. Although the concept of sustainability was met with the Brundtland Report in 1987, the energy need for growth and the environmental degradation caused by energy usage have been discussed since the Club of Rome was met in 1968.

The most common study area concerning the relationship between economic growth and environmental degradation is the Environmental Kuznets Curve (EKC). In theory, the main idea is that environmental degradation increases through the use of more resources in the first

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stage of growth. However, environmental awareness and implementing environmentally friendly policies and technologies in the later stages of growth reverse the degradation process and lead to environmental improvement. The impact of growth on the environment is linked to resource usage. For this reason, it is expected to get more efficient outputs when the environmental issues are addressed together with energy. At this point, electricity, as the most common energy carrier, can be considered as representative of energy. Electricity is also highly representative in terms of the diversity of energy sources from which it is generated. When examining environmental degradation, growth, and energy consumption relationships, population is another important factor that should be considered.

This study aims to examine the impact of electricity consumption on air pollution in Türkiye at the provincial level by conducting spatial analyses. In this framework, measurements of sulfur dioxide (SO_2) and particulate matter (PM_{10}) are considered representative of air pollution. Income and population density are other economic determinants examined for this purpose. Pollution spillovers are also investigated in this study. Spatial analyses allow us to learn the role of neighboring provinces in transmitting pollution. Our study focuses on Türkiye, a developing country and one of the largest trading partners of the European Union (EU), where combating climate change and reducing greenhouse gas emissions are important issues.

This study makes two important contributions to existing literature. First, we examine the economic determinants of air pollution in Türkiye, considering the pollution spillover among provinces. To achieve this, a spatial analysis is conducted. Few studies have examined the impact of economic factors on air pollution at the provincial level in Türkiye using spatial panel data models (Çatık et al., 2016; Tuzcu and Usupbeyli, 2018; Yildirim et al., 2021; Karahasan and Pınar, 2022). Although spatial modeling is utilized in these studies, the direct and indirect effects of the determinants are not investigated. This study aims to contribute to the literature by presenting the marginal effects of the determinants of air pollution by investigating their direct and indirect effects. Second, the analysis mainly investigates the impact of electricity consumption, an important component of energy consumption, on environmental degradation. For this purpose, two pollution indicators, SO_2 and PM_{10}, are used in the analysis.

The rest of the study is organized as follows. The related literature is provided in Section 2. Section 3 describes our econometric approach. Section 4 describes the data used in this study. Models and empirical findings are evaluated in Section 5. Finally, Section 6 presents the results of the study along with recommendations.

2. LITERATURE REVIEW

Based on the perspective that energy demand, emerges from the growth and environmental degradation, arising from energy usage, Grossman and Krueger, (1991,1995) have been pioneering studies in this field. In both studies, Grossman and Krueger determine that the per capita income increase at low-income levels leads to an increase in environmental degradation, whereas the per capita income increase at high-income levels leads to an improvement in environmental indicators, which implies the EKC. Similarly, Panayotou (1993, 1997) and Selden and Song (1994) confirm the EKC in their studies. Other studies examine the EKC hypothesis by taking into account various economic variables, such as the spatial intensity of economic activity (Kaufmann et al., 1998), as well as socioeconomic explanatory variables such as literacy rate, civil rights, Gini coefficient, urbanization, and income (Torras and Boyce, 1998).

Air pollution and income relationships have been extensively studied using spatial modeling in the literature. Maddison (2006) examines SO_2 and NO_x emissions along with per capita income for 135 countries and finds that emissions in neighboring countries significantly influenced each other. Additionally, geographic proximity to high-income countries is also associated with reduced per capita NO_x emissions. Similarly, Shahnazi and Shabani (2021) and Wu et al. (2022) examine the spatial impact of CO_2 emissions across EU countries. They find that pollution levels in one country are influenced by emissions in neighboring countries, highlighting the transboundary nature of environmental challenges. Both studies also support the EKC hypothesis. In other similar country-level studies, Hosseini and Kaneko (2013) and Li and Lv (2021) both confirm the EKC hypothesis, while Balado-Naves et al. (2018) find no evidence supporting it.

Besides per capita income, Fong et al. (2020) incorporate independent variables such as urban population ratio, share of renewable energy, service sector, primary energy intensity, and foreign direct investments into spatial models, alongside SO_2, NO_x, and $PM_{2.5}$, as dependent variables for nine South Asian countries. In another study, Rupasingha et al. (2004) incorporate socioeconomic variables with income into spatial models and investigate their impact on air, water, and soil toxic pollutants for 3029 U.S. districts. In both studies (Fong et al., 2020; Rupasingha et al., 2004), the EKC hypothesis is confirmed. Studies by Espoir and Sunge (2021) on 48 African countries, You and Lv (2018) on 83 countries, Mahmood (2022) on 6 GCC countries, and Mahmood (2023) on 18 Latin American countries all provide evidence of an inverted U-shaped relationship, consistent with the EKC hypothesis. In addition to studies on air pollution, there are also studies using more general indicators of environmental pollution, such as the ecological footprint. For example, Bucak et al. (2024) examine pollution spillovers in 26 EU countries from 1995 to 2020 and find empirical support for the validity of the EKC hypothesis. They also identify positive and significant ecological footprint spillovers between EU countries.

Regarding air pollution, China is the most intensively studied country in spatial studies at the regional, provincial, and district levels. Liu et al. (2017) analyze dust deposition in 272 Chinese cities and confirm the EKC hypothesis. Other studies confirming the EKC hypothesis include Hao and Liu (2016), Ma et al. (2016), Ding et al. (2019), and Gan et al. (2021), which specifically focus on PM2.5 as an environmental indicator, while Liu et al. (2019) analyze CO2 emissions. Despite the different pollutants studied, all these papers support the EKC hypothesis by showing that environmental degradation initially worsens with economic growth but improves once a certain income level is reached.

In another study at the county level, Li et al. (2014) examine the SO2 and COD data of 2329 Chinese counties and find high correlations between air pollution and economic variables, namely per capita income, population density, and industrial structure. At the regional level, Zhang et al. (2019) examine the levels of NOx, PM2.5, PM10, SO2, and VOC in 31 Chinese regions. The results show that NOx, PM10, VOC, and PM2.5 are consistent with the EKC hypothesis, while SO2 is not. Zhao et al. (2021), Zhou et al. (2017), and Kang et al. (2016) advanced the understanding of the Environmental Kuznets Curve (EKC) by identifying an inverted N-shaped relationship between economic growth and environmental degradation in Chinese provinces. Zhao et al. (2021) also highlighted the importance of spatial spillovers, where emissions from neighboring regions affect local environmental outcomes. Conversely, Huang (2018) and Wang and He (2019) find an N-shaped relationship between economic growth and environmental degradation.

There are spatial studies that consider meteorological data such as rainfall, temperature, humidity, and wind speed in addition to economic indicators. In one of these studies conducted for China, Wu et al. (2021) find that temperature and air pressure have an impact on $PM_{2.5}$ along with population density and traffic density. Their findings also indicate that secondary industry and GDP per capita have a significant impact on urban clustering in the initial stage, which decreases over time.

Electricity consumption is also considered as an explanatory variable in spatial models. Cheng et al. (2017) use a dynamic spatial panel data model for 285 Chinese cities between 2001 and 2012 to investigate the factors that may affect air pollution. While their results confirm the EKC hypothesis, population density, secondary industry, traffic density, central heating, and energy intensity are found to have an increasing impact on air pollution, represented by $PM_{2.5}$. In another study conducted by Xie et al. (2016), the results of the spatial Durbin model for 285 Chinese cities during the period 2003-2013 support the EKC hypothesis. Their results indicate that transportation infrastructure, population, per capita income, technological advancement, and energy intensity have a positive impact on SO_2 emissions. Burnett et al. (2013), examine energy emissions at the city level in the United States between 1970-2009. The study considers electricity prices, coal prices, natural gas prices, heating and cooling demand, and income as the environmental impact parameters. According to the fixed-effects SAR model, a 10% increase in electricity prices leads to an approximate 2% reduction in emissions. Similar results were obtained for the SDM model as well.

Numerous cross-sectional studies have examined the relationship between air pollution and income in Türkiye. However, panel data and spatial model studies are relatively limited. Akbostanci et al. (2009) examine the relationship between SO_2 and PM_{10} levels and per capita GDP using panel data for 58 provinces for 1992-2001. They find a U-shaped relationship between per capita GDP and air pollution, which does not support the EKC hypothesis. In a spatial study for a similar period, Çatık et al. (2016) find an inverted U-shaped relationship between per capita income and air pollution, represented by SO_2 and PM_{10}. The findings of Çatık et al. (2016), which confirm the EKC hypothesis, differ from the findings of other spatial studies conducted for Türkiye (Tuzcu and Usupbeyli, 2018; Yildirim et al., 2021; Karahasan and Pınar, 2022). However, it should be noted that Çatık et al. (2016) also differs in terms of the period analyzed.

SO_2 and PM_{10} are the most common variables used in the spatial studies conducted for Türkiye. All studies use either one or both of these variables. Accessibility of the data is the main reason for this preference. A spatial model is used by Tuzcu and Usupbeyli (2018) by using annual data of SO_2, PM_{10}, per capita income, and population density for the period 2007-2013 for 81 provinces in Türkiye. They find that the level of pollution in one province increases the level of pollution in neighboring provinces, which refers to a spillover effect. Furthermore, they conclude that the EKC hypothesis is not supported for Türkiye. In another study Yildirim et al. (2021) use a dynamic spatial Durbin model to examine the role of social capital in environmental pollution. PM_{10} levels, GDP, central government expenditure on environmental protection, population density, share of the manufacturing industry, and consumer price index data are used for the period 2009-2017. Their results do not support the EKC hypothesis as well. Additionally, they find that, while industrial production has a negative impact on environmental pollution, GDP exhibits a mitigating effect.

To the best of our knowledge, a limited number of studies have analyzed the effects of electricity consumption on air pollution in Türkiye (Karahasan and Pınar, 2022) based on spatial econometric methods. They use aggregated NUTS II level data for their spatial estimation. However, none of the studies on Türkiye that use spatial models have examined the direct and indirect effects of macroeconomic variables. In this study, we aim to contribute to the literature by examining the direct and indirect effects and providing findings on marginal effects using provincial data.

3. METHODOLOGY

The basic model used in this study is a fixed-effects model without spatial interaction effects and has the following form:

$$D_{it} = \mu_i + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 P_{it} + \beta_4 E_{it} + \varepsilon_{it}, \tag{3.1}$$

where D_{it} represents pollutant (SO_2 or PM_{10}) for province i $(i = 1, \dots . N)$ at time $t (t = 1, \dots . T)$. μ_i represents the province fixed effects. The independent variables income, population density, and electricity consumption are represented by *GDP*, *P*, and *E*, respectively. The selection of the independent variables is mainly based on the literature presented in Section 2. We include the squared GDP term in the model to test for the EKC hypothesis. ε_{it} is the error term. All dependent and explanatory variables are presented as natural logarithm values.

The spatial autoregressive (SAR) model incorporates the spatial lag of the dependent variable to account for endogenous interaction effects. The spatial lag model can be defined as follows:

$$D_{it} = \rho \sum_{j=1}^{N} w_{ij} D_{jt} + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 P_{it} + \beta_4 E_{it} + \mu_i + \varepsilon_{it},$$
(3.2)

where w_{ij} is the *ij*th element of the *NxN* spatial weight matrix W and ρ is the spatial autocorrelation coefficient.

An alternative is the spatial error model (SEM) represented by

$$D_{it} = \mu_i + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 P_{it} + \beta_4 E_{it} + u_{it}, \tag{3.3}$$

where $u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{it} + \varepsilon_{it}$.

Utilizing the residuals of the fixed effects model (3.1), the Lagrange multiplier (LM) tests (Anselin 1988) and robust LM tests (Anselin et al. 1996) were used to determine the existence of spatial effects in the model.

LeSage and Pace (2009) recommend also considering the more general spatial Durbin model (SDM) which can be expressed as:

$$\begin{aligned} D_{it} = {} & \rho \sum_{j=1}^{N} w_{ij} D_{jt} + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 P_{it} + \beta_4 E_{it} + \theta_1 \sum_{j=1}^{N} w_{ij} GDP_{it} + \\ & + \theta_2 \sum_{j=1}^{N} w_{ij} GDP_{it}^2 + \theta_3 \sum_{j=1}^{N} w_{ij} P_{it} + \theta_4 \sum_{j=1}^{N} w_{ij} E_{it} + \mu_i + \varepsilon_{it}. \end{aligned} \tag{3.4}$$

The hypothesis $H_0: \theta = 0$ can be used to test whether the spatial Durbin could be reduced to the spatial lag model or the hypothesis $H_0: \theta + \rho\beta = 0$ can be used to test whether it can be reduced to the spatial error model. Likelihood ratio (LR) tests were developed for this purpose.

As described by LeSage and Pace (2009) in the SDM, the marginal effect of the explanatory variable is not represented by β coefficients. The average effect of a change in one of the explanatory variables in a province on the pollution in that province is called the direct effect. On the other hand, the average effect of a change in one of the explanatory variables in a province on the pollution in all other provinces is called the indirect effect.

We can reformulate equation 3.4 to show the marginal impact of explanatory variables on pollution as

$$D_t = (I_N - \rho W)^{-1} \mathrm{X}_t \beta + (I_N - \rho W)^{-1} W \mathrm{X}_t \theta + (I_N - \rho W)^{-1} \mu\iota_N + (I_N - \rho W)^{-1} \varepsilon_t , \quad (3.5)$$

where X_t represents the matrix of explanatory variables and I_N is identity matrix of dimension N,

$$D_t = \sum_{r=1}^{k} S_r(\mathrm{W}) x_{rt} + \mathrm{V}(\mathrm{W}) \mu\iota_N + \mathrm{V}(\mathrm{W}) \varepsilon_t, \quad (3.6)$$

where $S_r(W) = V(W)(I_N \beta_r + W \beta \theta_r)$ and $V(W) = (I_N - \rho W)^{-1}$.

The diagonal average of the S_r matrix provides the direct effects. The difference between the direct effects and the β_r estimator represents the feedback effect (Huyugüzel Kışla et al., 2022; Seldadyo et al., 2010) Spatial spillovers create a feedback effect, where the impacts pass through neighboring provinces and then circle back to affect the original spatial unit. Indirect effects are obtained by averaging row sums (or column sums), excluding the diagonal terms of the S_r matrix (see, LeSage and Pace, 2009 for details).

We constructed each entry of the weight matrix W by using inverse distances between provinces so that the nearest neighbors have larger weights as follows:

$$w_{ij} = \frac{1}{d_{ij}} , \quad (3.7)$$

where d_{ij} represents the Euclidean distance between provinces i and j. We also used two different weight matrices by using the inverse distance of the 5 and 10 nearest neighbors of each province in the sample. In 5 nearest neighbors weight matrix w_{ij} takes its original value, obtained from the inverse Euclidean distance, if province j is among the 5 nearest neighbors of province i in the sample. Otherwise, w_{ij} is equal to 0. Similarly, we construct 10 nearest neighbors matrix by using the inverse distance of the 10 nearest neighbors of each province.

4. DATA

Annual panel data from 81 provinces in Türkiye are used for the period 2008-2021. The time period is determined according to the availability of data.

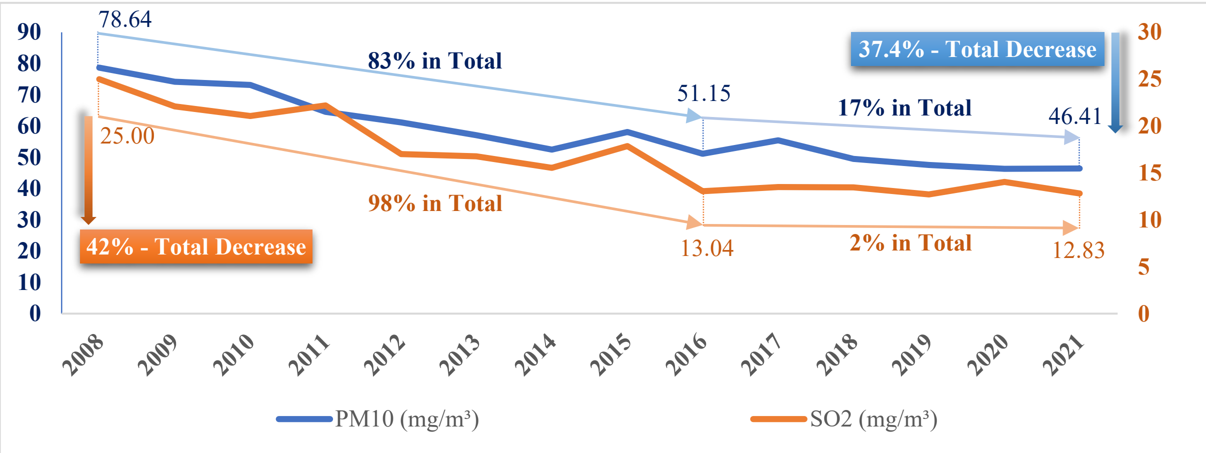
SO_2 is defined by the Ministry of Environment and Urbanization as a pollutant that primarily originates from the burning of high-sulfur-content fuels, coal, and lignite. This is mainly associated with emissions from heating, industrial processes, and traffic. The unit of measurement for SO_2 data used in this study is micrograms per cubic meter (µg/m³).

PM_{10} represents suspended particles in the air with aerodynamic diameters smaller than 10 µm, as defined by the Ministry of Environment, Urbanization and Climate Change. Its primary sources are energy facilities, factories, construction activities, fires, and windblown dust. The unit of measurement for the PM_{10} data is micrograms per cubic meter (µg/m³) the same as SO_2 data.

Annual average air pollution indicator data for SO_2 and PM_{10} are obtained from the European Environment Agency/European Air Quality Portal and the Ministry of Environment, Urbanization and Climate Change/National Air Pollution Monitoring Portal. Although SO_2 and PM_{10} data are measured at 359 individual stations for all 81 provinces, some stations cover only the first or last years. Therefore, stations covering a significant part of the examined period are selected to avoid inconsistencies in the data structure. Accordingly, SO_2 data are obtained from 141 stations and PM_{10} data from 126 stations. In the model, the arithmetic averages of the selected stations are considered on a provincial basis.

Figure 4.1 shows the average measurements of SO_2 and PM_{10} in Türkiye as indicators of air pollution between 2008 and 2021. While PM_{10} levels show a remarkable decrease of 37.4% over the period, SO_2 levels show better progress with a decrease of 42%. However, there is a noticeable slowdown over time.

Figure 4.1 Average SO_2 and PM_{10} Levels of Türkiye During 2008-2021



Income is represented by real GDP, calculated at constant 2009 prices, and obtained from the database of the Turkish Statistical Institute (TURKSTAT). The other explanatory variable, population density, is calculated by dividing the population of the provinces obtained from TURKSTAT by the area of the provinces obtained from the Ministry of National Defence/General Directorate of Mapping. Finally, electricity consumption data for the provinces are obtained from TURKSTAT in megawatt hours.

The descriptive statistics of the data are presented in Table 4.1. Although the standard deviations of GDP and electricity consumption are higher, their relative standard deviations are lower than those of SO_2 and PM_{10} and population density. The distribution of all variables, except PM_{10}, is skewed to the left, and the skewness coefficients are within or very close to the limits of +/- 1, indicating that the data do not deviate significantly from a normal distribution. While the electricity consumption data have negative kurtosis, the rest have positive kurtosis.

The spatial appearance and interactions of the data used in this study are examined. The base map of Türkiye is obtained from The Humanitarian Data Exchange and the data are combined with the base map using QGIS software. The spatial data are displayed on maps based on the mean values of the variables for 2008-2021, and Moran's I tests are conducted for 2008, 2012, 2017, and 2021 using the GeoDa software. Moran's I statistic is a measure of spatial autocorrelation and tests the null hypothesis of spatial randomness.

	SO_2	PM_{10}	GDP	Elec. Cons.	Pop. Dens.
Mean	2.512	3.984	22.71	13.976	4.25
Median	2.434	3.998	22.51	13.858	4.096
Max.	5.156	5.42	27.172	17.542	7.973
Min.	0.299	0.04	20.24	10.982	2.314
Stand. Dev.	0.733	0.424	1.107	1.25	0.847
Rel. Stand. Dev.	29.180	10.643	4.875	8.944	19.929
Skewness	0.608	-1.09	0.948	0.233	1.092
Kurtosis	0.924	6.819	1.639	-0.124	2.928
Observation	1134	1134	1134	1134	1134

Table 4.1 Descriptive Statistics

Figures 4.2 and 4.3 visualize the spatial distribution of mean SO_2 and PM_{10} levels, clearly displaying distinct clusters at different levels on the maps. The Moran's I statistics in Table 4.2 support spatial autocorrelation for the examined four years, except for the SO_2 values in 2017. In addition, the Moran's I statistics for PM_{10} are all significant throughout the entire period.

Figure 4.2 Average SO_2 Levels by Province Between 2008-2021

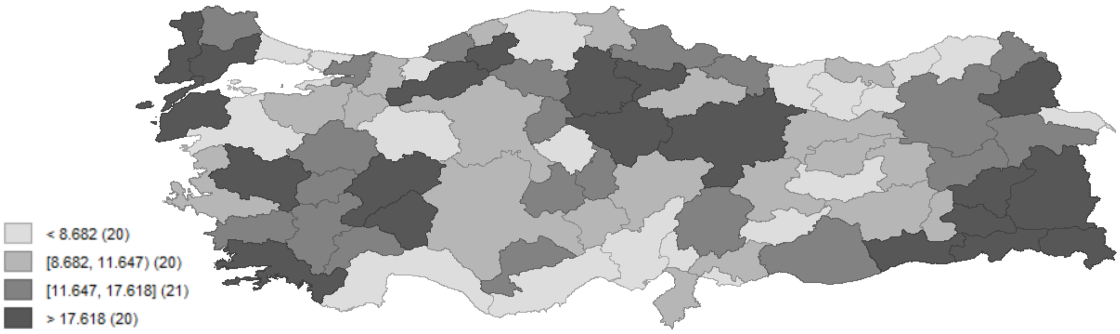


Figure 4.3 Average PM_{10} Levels by Province Between 2008-2021

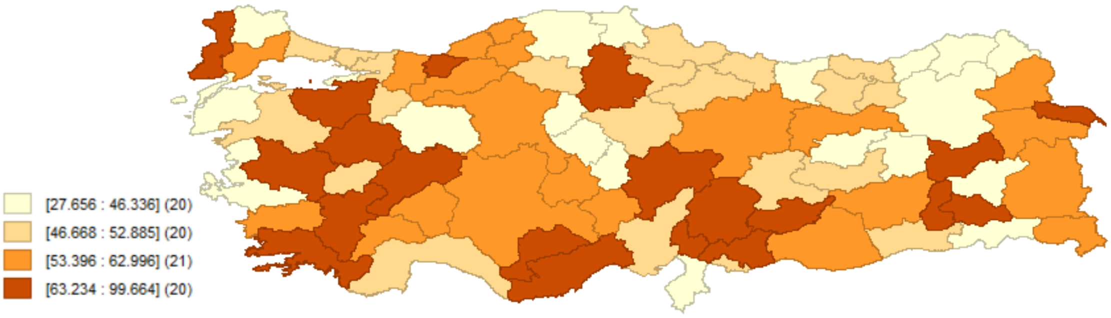
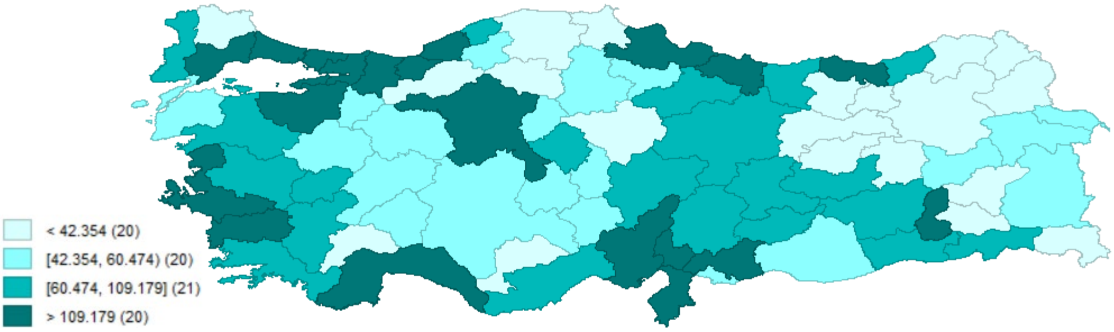


Figure 4.4 also shows clusters for population density. Moran's I statistics in Table 4.2 indicate significant spatial autocorrelation for population density for all four years.

Figure 4.4 Average Population Density by Province Between 2008-2021



Figures 4.5 and 4.6 show regional disparities between the eastern and western parts of Türkiye. While clusters at lower GDP and electricity consumption levels are observed in the eastern provinces, the more industrialized western provinces form clusters at higher GDP and electricity consumption levels. The Moran's I statistics of GDP in Table 4.2 are statistically significant for the years 2017 and 2021. Moran's I statistics for the electricity data are statistically significant for all four years examined and show an increasing trend, suggesting increasing spatial autocorrelation.

Figure 4.5 Average GDP by Province Between 2008-2021

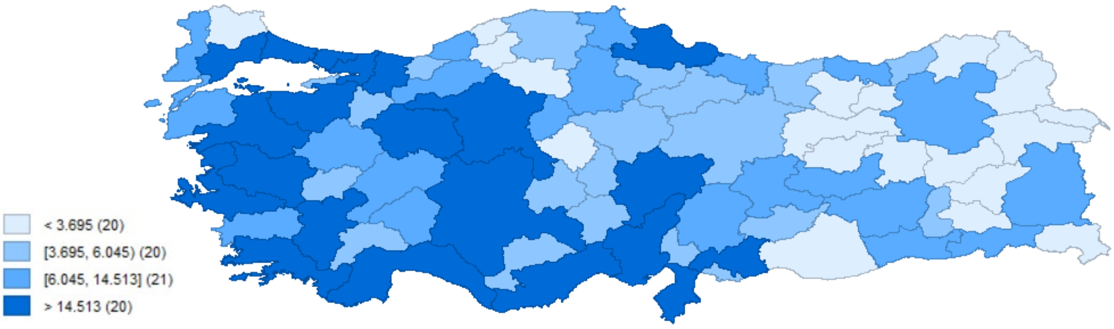
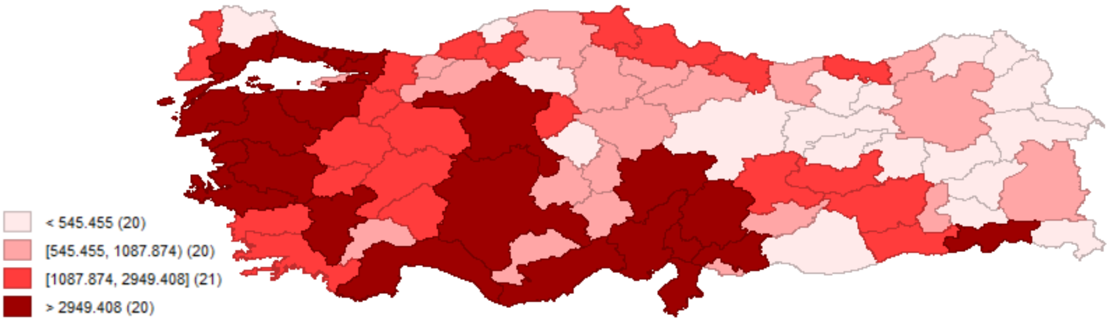


Figure 4.6 Average Electricity Consumption by Province Between 2008-2021



	SO_2	PM_{10}	GDP	Pop. Dens.	Elec. Cons.
2008	0.144**	0.129***	0.037	0.093***	0.152**
	[0.0199]	[0.00145]	[0.10168]	[0.00477]	[0.016]
2012	0.394***	0.162**	0.034	0.094***	0.169**
	[0.00036]	[0.01041]	[0.10489]	[0.00447]	[0.01009]
2017	0.036	0.103*	0.04*	0.106***	0.184***
	[0.21574]	[0.0567]	[0.09014]	[0.00318]	[0.00678]
2021	0.209***	0.087*	0.045*	0.112***	0.181***
	[0.00127]	[0.0838]	[0.08155]	[0.00243]	[0.00779]

Table 4.2 Moran's I Statistics
***, **, * symbols represent significance at the 1%, 5%, and 10% levels respectively
p-values are presented in parentheses.

5. MODEL AND EMPIRICAL RESULTS

The SO_2 and PM_{10} variables are employed as dependent variables in separate models and spatial weight matrices are constructed based on inverse distances between provinces.[1] MATLAB codes form Elhorst (2014) are used for the analysis. The maximum likelihood method is used to obtain consistent parameter estimates. Table 5.1 shows the estimation results of the SO_2 models. Likelihood Ratio tests (LR Test) and Lagrange multiplier (LM) tests are carried out to determine the best fit among fixed effects, SAR, SEM, and SDM.

The Lagrange multiplier test (Anselin, 1988) and the robust Lagrange multiplier test (Anselin et al., 1996) are based on the residuals of the fixed effects model and are recommended for the selection process between fixed effects and spatial models i.e. SAR and SEM. As a result of the classical and robust LM tests, both the null hypotheses of no spatially lagged dependent variable and no spatially autocorrelated error term are rejected in favor of spatial models. In addition, the Hausman test is performed to determine whether the fixed effects or random effects models are more appropriate, and the null hypothesis is rejected in favor of the fixed effects model.

LM tests indicate strong spatial interactions. In addition, the spatial autocorrelation coefficient ρ and spatial error correlation coefficient λ are statistically significant, indicating the existence of spatial effects. The fixed effects model estimates could be biased due to the existence of spatial effects in the data. Nevertheless, the LM tests have not put forward SAR or SEM models over the other. Consequently, we consider a more general model i.e. SDM, as recommended by LeSage and Pace (2009), and perform likelihood ratio tests to compare the SAR and SEM models with SDM. According to the results of the LR tests, the null hypothesis of $LR_{\theta=0}$ and $LR_{\theta+\rho\beta=0}$ are rejected in favor of SDM, which means that the model cannot be reduced to SAR or SEM models. Thus, SDM is selected as the best model to describe the data.

Since the model specification tests show the spatial Durbin model as the appropriate model, the coefficients of the fixed effects model could be biased due to the omitted variable problem. According to the estimation results of SDM (column 4a in Table 5.1), the coefficients of GDP and GDP^2, as representative of income, population density, and electricity consumption, are statistically significant and have the same signs as the coefficient of the fixed effects model. While GDP has a decreasing effect on the level of SO_2 with a negative coefficient, GDP^2 has a positive coefficient. These coefficients imply a non-linear U-

[1] We also use two alternative weight matrices and present our results below. The inverse distance weight matrix provides the highest log-likelihood value for the SO_2 model among them.

shaped relationship between SO_2 and income, which does not support the EKC hypothesis, has been similarly identified for Türkiye in studies conducted by Yildirim et al. (2021), Tuzcu and Usupbeyli (2018), Akbostanci et al. (2009), Karahasan and Pınar (2022).

As mentioned above, the coefficients of population density and electricity consumption variables are statistically significant. Population density has a decreasing effect on air pollution, as indicated by the negative sign of the coefficient, whereas electricity consumption has an increasing effect, as indicated by the positive sign of the coefficient. Karahasan and Pınar (2022) find no statistically significant results for population density and electricity consumption using NUTS 2 level data, whereas Yildirim et al (2021) find a decreasing effect of population density on air pollution. The signs of the coefficients of all spatially lagged independent variables (column 4b) are the same as those of the coefficients of the independent variables (column 4a). The coefficients of the lagged values of GDP and GDP^2 are found to be significant (column 4b in Table 5.1).

Variables	**Fixed Effects (1)**	**SAR (2)**	**SEM (3)**	**SDM (X) (4a)**	**SDM (W*X) (4b)**
GDP	-4.416*** (-2.888)	-3.76** (-2.414)	-3.484** (-2.162)	-2.794* (-1.701)	-15.462** (-2.161)
GDP^2	0.077** (2.304)	0.07** (2.047)	0.061* (1.719)	0.067* (1.85)	0.323** (2.058)
Pop. Density	-1.246** (-2.564)	-1.258** (-2.543)	-1.177** (-2.287)	-1.53*** (-2.879)	-2.99 (-1.349)
Electricity	0.466*** (3.580)	0.484*** (3.655)	0.469*** (3.442)	0.566*** (4.081)	0.323 (0.491)
σ^2	0.2325	0.241	0.2429	0.2383	
Log-likelihood	-779.8327	-766.4872	-770.5424	-757.9339	
R^2	0.0847	0.5827	0.565	0.588	
ρ or λ		ρ: 0.52***	λ: 0.49***	ρ: 0.40***	

Fixed/SAR		**SAR/SDM**	
$LM_{\rho=0}$	49.7795***	$LR_{\theta=0}$	17.1066***
$LM^r_{\rho=0}$	26.0736***		
Fixed/SEM		**SEM/SDM**	
$LM_{\lambda=0}$	32.8583***	$LR_{\theta+\rho\beta=0}$	25.2170***
$LM^r_{\lambda=0}$	9.1524***		
Hausman Test	67.442***		

Table 5.1 Estimation Results of SO_2 Models (Inverse Distance Matrix)
***, **, * symbols represent significance at the 1%, 5%, and 10% levels respectively
t-statistics are presented in parentheses.

We also conduct model estimations by replacing the dependent variable SO_2 with PM_{10} and following the same model selection procedure explained above. Table 5.2. presents the estimation results of the PM_{10} models. As can be seen from the table, the LM and LR test results imply that the SDM is the best model to describe the data. The statistically significant spatial autocorrelation coefficient ρ and spatial error correlation coefficient λ further support the existence of spatial effects. The null hypothesis in the Hausman test is accepted in favor of random effects models. Despite this, Elhorst (2014, p56), suggests proceeding with fixed-effects models instead of random effects when space-time data consist of adjacent spatial units. Since the spatial units in our data consist of all the provinces in Türkiye, we decide to proceed with fixed effects models.

According to the SDM estimation results, the coefficients of all explanatory variables except population density are statistically significant. Similar to our previous model, income shows a U-shaped relationship with air pollution. Electricity consumption has an increasing effect on air pollution, with a positive coefficient sign, as expected. It is interesting to note that the coefficient of electricity is insignificant in the fixed effects model. All coefficients are significant for the spatially lagged independent variables and have the same signs as the explanatory variables (column 4b).

Variables	**Fixed Effects (1)**	**SAR (2)**	**SEM (3)**	**SDM (X) (4a)**	**SDM (W*X) (4b)**
GDP	-3.661*** (-3.809)	-3.186*** (-3.251)	-3.226*** (-3.182)	-2.944*** (-2.842)	-9.191** (-2.016)
GDP^2	0.062*** (2.935)	0.059*** (2.761)	0.054** (2.431)	0.06*** (2.647)	0.191* (1.909)
Pop. Density	-0.272 (-0.892)	-0.317 (-1.017)	-0.151 (-0.465)	-0.271 (-0.809)	-3.257** (-2.314)
Electricity	0.122 (1.496)	0.14* (1.677)	0.102 (1.191)	0.152* (1.731)	0.659*** (1.581)
σ^2	0.0918	0.0953	0.0966	0.0948	
Log-likelihood	-253.2626	-240.2493	-246.7045	-234.6377	
R^2	0.220	0.507	0.489	0.510	
ρ or λ		ρ: 0.50***	λ: 0.45***	ρ: 0.36***	

Fixed/SAR		**SAR/SDM**	
$LM_{\rho=0}$	40.1551***	$LR_{\theta=0}$	11.2231**
$LM^r_{\rho=0}$	20.3494***		
Fixed/SEM		**SEM/SDM**	
$LM_{\lambda=0}$	21.8035***	$LR_{\theta+\rho\beta=0}$	24.1335***
$LM^r_{\lambda=0}$	1.9978		
Hausman Test	14.346		

Table 5.2 Estimation Results of PM_{10} Models (Inverse Distance Matrix)

***, **, * symbols represent significance at the 1%, 5%, and 10% levels respectively t-statistics are presented in parentheses.

Although the coefficient estimates of the fixed effects (column 1 in Tables 5.1 and 5.2) give us the marginal effects of the explanatory variables, the coefficient estimates of the spatial Durbin model (column 4a in Tables 5.1 and 5.2) do not provide the marginal effects of the explanatory variables. For this purpose, we calculate the direct and indirect effects of the independent variables, as explained in Section 3. The direct and indirect effects of the explanatory variables on air pollution, represented by SO_2 and PM_{10}, are given in Table 5.3[2].

For the model with SO_2, the coefficients of the estimated direct and indirect effects are all significant, except for the indirect effect of electricity on SO_2. The magnitude of the indirect effects is much higher than that of the direct effect estimates. The direct effect coefficients of GDP and GDP^2 are negative and positive respectively, which does not support the EKC hypothesis and shows a U-shaped curve. Regarding the indirect effects, the coefficient of GDP is also negative, while the squared term is positive and all are significant. Similarly, the results of Yildirim et al. (2021), Tuzcu and Usupbeyli (2018), Akbostanci et al. (2009) and Karahasan Pınar (2022) do not support the EKC hypothesis for Türkiye.

Estimates of the direct and indirect effects of population density are negative. To express numerically, a 1% increase in population density in a province leads to a 1.6% decrease in SO_2 levels within that province, which is a 1.2% decrease in the fixed effects model (column 1 in Table 5.1). Furthermore, a 1% decrease in population density in a province leads to a 5.9% decrease in SO_2 levels in neighboring provinces due to spillover effects. Although it is reasonable to expect potential negative effects of population density on air pollution, Yildirim et al. (2021) explain this issue within the framework of the crowd and the civilization effect. In this context, a higher population density may indicate higher levels of urbanization, followed by higher levels of environmental awareness and policy, leading to a civilization effect for cities.

Lastly, the direct effect coefficient estimates of electricity consumption are statistically significant and have positive signs, as expected. Specifically, a 1% increase in electricity consumption in a province increases its SO_2 level by 0.57%. The marginal effect of electricity is much higher than the fixed effect model (0.47 in Table 5.1).

When we performed the same calculations for PM_{10}, we obtained the same coefficient signs as for SO_2. The coefficients of the direct and indirect effect estimates are all significant, except for the direct effect of population density on PM_{10}. It is interesting to note that the direct effect estimate of electricity is positive and significant (0.16), while the marginal effect is insignificant in the fixed effects model (column 1 in Table 5.2). Furthermore, the indirect effect is 1.106. In other words, a 1% increase in electricity consumption in a province leads to a 0.16% increase in PM_{10} levels within that province and a 1.1% increase in PM_{10} levels in neighboring provinces due to spillover effects. The total impact is up to 1.27%. In addition, the magnitudes of the indirect effects are higher than those of the direct effects, as is the case for SO_2.

[2] Please note that the spatial Durbin model includes the lag of the dependent variable, leading to a feedback effect wherein impacts in provinces pass through neighbors and affect themselves. This endogenous interaction is the reason why the direct effect coefficients of the explanatory variables in Table 5.3 differ slightly from the coefficient estimates reported in column 4a of Tables 5.1 and 5.2.

To show the robustness of our analysis, we perform the same estimations with two alternative weight matrices. Following Seldadyo et.al. (2010), we first construct a 5 nearest neighbors matrix by using the inverse distance of the 5 nearest neighbors of each province in the sample and zero otherwise. Similarly, we construct a 10 nearest neighbors matrix using the inverse distance of the 10 nearest neighbors of each province. Table 5.4 presents our results. As can be followed from the table, the coefficients of the direct effect estimates are similar to our direct effect estimates in Table 5.3. A 1% increase in electricity consumption in a province leads to an approximately 0.5% increase in SO_2 and a 0.19%-0.20% increase in PM_{10} levels in that province. It is noteworthy that the indirect effect estimates are positive and significant for the SO_2 model (0.47) with the 5 nearest neighbors matrix, while for the other models, the indirect effects of electricity are positive but insignificant.

	SO_2			**PM_{10}**		
Variables	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
GDP	-3.018*	-28.074**	-31.091***	-3.042***	-16.092**	-19.134***
	(-1.811)	(-2.406)	(-2.694)	(-2.939)	(-2.274)	(-2.731)
GDP^2	0.072*	0.593**	0.665**	0.062***	0.333**	0.396**
	(1.964)	(2.303)	(2.606)	(2.718)	(2.147)	(2.569)
Pop. Density	-1.588***	-5.912*	-7.5**	-0.317	-5.233**	-5.55**
	(-3.019)	(-1.67)	(-2.147)	(-0.945)	(-2.389)	(-2.549)
Electricity	0.573***	0.877	1.45	0.163*	1.106*	1.27*
	(4.279)	(0.826)	(1.376)	(1.889)	(1.668)	(1.93)

Table 5.3 Spatial Durbin Model Direct and Indirect Effects (Inverse Distance Matrix)
***, **, * symbols represent significance at the 1%, 5%, and 10% levels respectively
t-statistics are presented in parentheses.

Variables	5 Nearest Neighbors Matrix						10 Nearest Neighbors Matrix					
	SO_2			PM_{10}			SO_2			PM_{10}		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
GDP	-2.847*	-12.613***	-15.46***	-3.514***	-4.576**	-8.09***	-2.844*	-12.247***	-15.091***	-3.155***	-7.235***	-10.39***
	(-1.769)	(-3.979)	(-4.532)	(-3.488)	(-2.313)	(-3.739)	(-1.732)	(-3.116)	(-3.723)	(-3.06)	(-2.824)	(-3.847)
GDP^2	0.061*	0.254***	0.316***	0.076***	0.084*	0.16***	0.064*	0.247***	0.311***	0.067***	0.149**	0.215***
	(1.717)	(3.628)	(4.152)	(3.421)	(1.929)	(3.343)	(1.795)	(2.842)	(3.446)	(2.922)	(2.602)	(3.555)
Pop. Density	-1.516***	-1.59	-3.106***	-0.29	-1.249*	-1.539**	-1.399***	-2.464*	-3.864***	-0.308	-2.01**	-2.318***
	(-2.755)	(-1.484)	(-2.942)	(-0.857)	(-1.891)	(-2.288)	(-2.677)	(-1.837)	(-2.889)	(-0.934)	(-2.394)	(-2.731)
Electricity	0.495***	0.474*	0.968***	0.199**	0.096	0.294	0.509***	0,406	0.916**	0.187**	0.032	0.22
	(3.722)	(1.667)	(3.208)	(2.161)	(0.503)	(1.455)	(3.713)	(0,99)	(2.233)	(2.171)	(0.131)	(0.859)

Table 5.4 Spatial Durbin Model Direct and Indirect Effects (5 Nearest Neighbors Matrix, Left & 10 Nearest Neighbors Matrix, Right)
***, **, * symbols represent significance at the 1%, 5%, and 10% levels respectively
t-statistics are presented in parentheses.

6. CONCLUSION

This study investigates the impact of electricity consumption on air pollution in Türkiye at the provincial level by using spatial panel data models. Two pollution indicators, SO_2 and PM_{10}, are used in the analysis. GDP, population density, and electricity consumption are considered as explanatory variables. We estimate spatial effects using the SDM. In addition, we extend previous studies on Türkiye by looking at direct and indirect effects, thus providing insights into marginal effects.

Our results show that an increase in income has a decreasing effect on SO_2 and PM_{10} levels both in terms of the direct and indirect effects. After a certain point, this effect is reversed, resulting in a U-shaped relationship. This result, which contradicts with the EKC hypothesis, is consistent with other studies conducted in Türkiye for similar periods. The estimated direct and indirect effects of the population density are negative, mainly explained by the civilization effect. On the other hand, electricity consumption has a significant positive direct effect on air pollution. Furthermore, as observed with PM_{10}, the positive impact of electricity consumption on air pollution extends to neighboring provinces due to the spillover effects.

Over the period considered, air pollution variables show a decreasing trend, while GDP, population density and electricity consumption show an increasing trend. The expansion of the use of natural gas, the improvement of fuel quality and the development of filtering technologies can be considered as the main drivers of the decrease in air pollution during a period of increasing income. However, the empirical results show that these effects can reverse with further growth, indicating the importance of sustainable growth.

According to our spatial analysis, SO_2 and PM_{10} clusters are observed in various regions of the country. In addition, clusters of higher levels of GDP, population density, and electricity consumption are observed in the western regions and lower levels in the eastern regions. These clusters in the control variables indicate that more developed and industrialized provinces, especially in the western part of Türkiye, may be more prone to pollution due to higher production and electricity consumption.

The presence of spatial effects calls for a holistic approach to air pollution policies, ensuring that spillover impacts are addressed for more comprehensive and effective solutions. Efforts to increase the share of clean energy in electricity generation are crucial given the impact of electricity consumption on air pollution as investments in renewable energy in certain regions can have positive impacts on air quality in neighboring areas as well. In this context, it is essential to increase incentives for the renewable energy industry. The provision of affordable loans to support renewable energy investments and the acceleration of the pre-licensing process for renewable energy plants will be supportive contributions. In addition, the EU Carbon Border Adjustment Mechanism will be fully implemented by 2026. Accordingly, preparations for legislative harmonization have already started under the Ministry of the Environment, Urbanization and Climate Change in Türkiye. A notable expected outcome of these preparations is the establishment of a mandatory carbon market, similar to the EU Emissions Trading System. The observed spatial interaction between air pollution and electricity consumption indicates the need to consider the spatial effects in the formation of a mandatory carbon market. Within this framework, regulations should be put in place to ensure that carbon prices are higher in areas with high levels of pollution clusters.

This study has a number of limitations. Firstly, it focuses on two pollutants, SO_2 and PM_{10}. As more data become available, future research could include other pollutants, such as NO_x, VOC, CO_2, to expand the scope. Secondly, while this analysis uses economic and social indicators as control variables, additional factors like meteorological data could be considered in further studies to provide a more comprehensive understanding. Finally, the impact of electricity consumption on air pollution in highly polluted provinces could be explored at the district level to further investigate the spatial effects and identify targeted solutions.

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