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A Spatial Econometric Analysis of Air Pollutant Concentrations and Economic Growth on Public Health: Empirical Evidence from Central Asian Countries

Bolor-Erdene Turmunkh

PhD student, School of Economics and Trade, Hunan University, Changsha city, Hunan Province, China

ABSTRACT: Air pollution of the countries of Central Asia has affected not only the health of the population since 1990 but also influenced the environment. This study has been made empirically analyzes the spatial autocorrelation analysis that is based on the 1991 to 2017 database of Central Asian countries on the socio-economic factors influencing the concentration of Sulfur Dioxide (SO_2), Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Ozone (O_3), and Particulate Matter ($PM_{2.5}$) in the air. Besides, this study validated Global Moran's I statistics to determine spatial positive autocorrelations. The results show that there is a strong correlation between air pollution concentrations and Gross Domestic Product (GDP) per capita. The achievement identified that the concentrations of SO_2, CO, NO_2, O_3, and $PM_{2.5}$ have a spatial aggregation and distribution effect, which is significantly influenced by the spatial characteristics and the Central Asian Regional Economic Unions. It also determined that an energy policy of a country can be affected the emissions of air pollutants from neighboring countries due to policy effects. Therefore, there is a need for regional coordination of environmental policies and the transfer of pollution-intensive industries, to keep air pollution in countries of Central Asia at a normal level. In addition to the empirical results of this study, the following two conclusions can be identified. First, it identified the need for a unified policy to reduce air pollution to reduce emissions from air pollution sources. Second, there is a need for a renewable energy policy for the development and promotion of renewable energy.

KEYWORDS: Air pollution; Central Asia; Spatial Econometric; Public health; Respiratory disease; Environmental Economics

1. INTRODUCTION

Outdated heavy and light industry inefficiencies, air polluted technologies, and poor environmental management are exacerbating the region's environment. Air pollution is extremely harmful not only to human health but also to any living organism and the environment in which we live. Inhalation of air pollutants, especially fine particles, can cause significant damage to the heart and blood vessels, making the body vulnerable, and causing severe forms of any disease. As air pollution becomes more serious, Central Asian governments need to address it. Excessive dependence on the unbalanced energy structure of Central Asia and the use of highly polluting fossil fuels are exacerbating the damage to the country's environment, especially the atmosphere. Although carbon emissions have declined significantly since 1990, Central Asian countries still account for about 15 percent of global greenhouse gas emissions due to the transition economy. As soon as beginning the winter, some of the Central Asian cities are shrouded in smoke. The air is very toxic and people need to use respiratory masks and air purifiers. In Kazakhstan, the concentration of toxic particles in the air is 2.5 times higher than the annual norm. The capital of Kyrgyzstan, Bishkek, is one of the most polluted cities in the world. The most dangerous days of 2019 in Tajikistan are summer and autumn when dust storms cover the city. Air pollution levels are below acceptable levels in Ashgabat (Turkmenistan), and Tashkent (Uzbekistan) also has high levels of air pollution. Central Asian governments are hoping to reform public transport systems, including diesel, to reduce air pollution in major cities. Diesel emits a large number of nitrogen oxides, an air pollutant that increases the spread of respiratory diseases. As a short-term goal, governments can turn from coal to natural gas in the winter. Reforestation programs can significantly reduce urban air pollution through public transport reforms, including the electrification of buses and trucks. Another way to reduce air pollution in the region is to introduce updated pipe end technology that filters and reduces air pollutants emitted from factories and plants. Given the capacity of regional wind, solar, and hydropower plants, these clean energy sources offer Central Asian countries a ready-made way to meet the city's energy needs without harming the health of their citizens.

The relationship of the study has been determined between social and economic development has influenced in the environmental pollution in the field of environmental economics has long attracted the attention of researchers. As spatial measurements grew, many experts and scientists gradually began to use spatial measurement methods to study the effects of external spatial conditions, especially spatial spills (Sun et al., 2015; Lin and Chen,2019). Most empirical studies on this topic have shown a complex relationship between environmental pollution and the level of socio-economic development (Zhang et al., 2019; Feng et al., 2020). Due to the complexity and regional nature of air pollutants, urban agglomeration pollution has become more severe than in cities and more difficult to control (Wang et al., 2017). Air pollution control measures are urgently needed, especially in densely populated cities. Due to the imbalances in economic development and the industrial structure, the regulatory forces in Central Asia vary. Moreover, local air quality is affected by air pollution from other cities (Chen et al., 2017; Lu et al., 2019). $PM_{2.5}$, a major component of air pollution, is small enough to enter the lungs and bloodstream; in addition, they are stored in the air for a long time and spread easily, which can be dangerous to human health and life (Callen et al., 2014). According to a recent study in China, poor air quality reduces life expectancy by almost 25 months (Zeng et al., 2019). Most of the current research focuses on airborne particles such as SO_2, CO, CO_2, NO_x, $PM_{2.5}$, and PM_{10} (Roca et al., 2001).

However, research on the relationship between SO_2, CO, NO_2, O_3, $PM_{2.5}$, and socio-economic development using digital empirical tools is still rare. As Central Asian countries face high levels of air pollution, such empirical analysis is essential, as they can shed some light on the causes of air pollution, and the results of the calculations are very important for policymakers to formulate correctly. Therefore, Central Asian countries need to develop a unified policy to reduce air pollution, monitor it, and monitor each other. To address this issue, the study used appropriate spatial econometric methods to monitor the spatial correlation of air pollution. As a result, the empirical study of this paper is one of the main contributions of this study as it fills the academic gap in this field. The study used only the values of air pollutants in Central Asian cities between 1991 and 2017, as well as social, economic, and health data, due to the availability of data. to draw the attention of researchers. In addition, the identification of air pollution emitters will guide the development of policies to combat climate change and human activities in Central Asia. For example, the region still includes Turkmenistan, Uzbekistan, and Kazakhstan, the world's most CO emissions consuming countries, and has a wide range of environmental improvements. The article is divided into six sections. Following this introduction in Section 1, there is a review of related literature in Section 2. Section 3 discusses the methodology and data. Section 4 examines the data analysis. Section 5 is the discussion of the findings, while Section 6 concludes with some recommendations and suggestions for future research.

2. LITERATURE REVIEW

The environmental advocates and local populations have long called for greater action to mitigate extensive air pollution in the region's urban areas in Central Asia. Almaty and Bishkek, two of the largest cities in Central Asia, are located in plains surrounded by mountains and as a result, are often covered in thick layers of smog for much of the winter season. Across Central Asia, coal-fired power stations from the Soviet period continue to operate, contributing to heavy pollution and low air quality. The use of outdated stoves and old, high emissions automobiles exacerbates the already poor situation. Central Asian governments should heed the warnings of advisors and activists in clamping down on activities that yield large outputs of air pollution to protect their populations from its harmful effects. The empirical literature on the relationship between economic development and environmental quality has increased rapidly since the early 1990s. This study contributes to the growing literature that examines the interaction of city structure and environmental pollution. On the theoretical side, Borck and Schrauth (2021) analyze the channels through which population size affects pollution. They find that the concentration increases with density for NO_2 with an elasticity of 0.25 and particulate matter with an elasticity of 0.08. The O_3 concentration decreases with density with an elasticity of −0.14.

Anselin (1988) stressed the necessity of applying the specialized techniques of spatial econometrics in environmental mental and resource economics. There have been some empirical studies on the influential factors of environmental pollution employing the spatial econometric approach that addresses the spatial autocorrelation problem (Chen et al., 2020; Hao and Liu 2016; Liu et al., 2017; Ma et al., 2016; Wang et al., 2018; Zeng et al., 2019; and Zhou et al., 2019). For instance, Zeng et al., (2019) employ a spatial econometric method to empirically test the effects of these two types of energy policies on China's emissions of major air pollutants, namely PM_{10}, $PM_{2.5}$, and SO_2, using panel data from 27 provinces and four direct-controlled municipalities over the period from 2003 to 2016. The results offer evidence that provincial emission reduction policies have positive impacts on the reduction of PM_{10}, whereas provincial renewable energy policies have positive impacts on the reduction of SO_2 and $PM_{2.5}$. The results also show that energy policies in one province can influence emissions of pollutants in neighboring provinces due to policy spillover effects.

In most of the regional panel analyses that examined the environment-economic growth, their results indicate that economic development and environmental quality contributes to air pollution emissions (Fan et al., 2020; Hassan and Nosheen 2019; Jaung, et al., 2020; Liu and Yu 2020; Santri et al., 2021; Xian et al., 2020; Xie et al., 2021; Yang et al., 2020; and Zhao et al., 2021). For example, Liu and Yu (2020) results show that there is a significant and negative effect of air pollution on migrants' interest in settling down. Specifically, this negative effect of air pollution is greater for old, less-educated, within-city migrants and rural migrants - who comprise a large proportion of the Chinese urban labor force. They conclude that air pollution undermines investment in human capital and may become an obstacle to the sustainable development of cities; thus, we underline the potential benefits of more stringent environmental regulation.

Many studies have been conducted on the relationship between energy consumption, air pollutant emissions, and economic growth for different individual countries (Kusuma et al., 2019; Nguyen and Pham 2021; Romero, et al., 2020; Shi et al., 2020; and Valencia et al., 2020). Several of these panel studies inform this article's approach. For Ecuador, Valencia et al., (2020) results show that the Urban Background Model successfully predicts concentrations of CO, NO_2, NO_x, O_3, and $PM_{2.5}$ while the predicted SO_2 concentrations are unsatisfactory. $PM_{2.5}$ modeling meets the criteria of acceptance, but their results depend largely on the regional levels, so the quality of this information is extremely relevant. The Urban Background Model was applied for the years 2008 and 2010 using meteorological data retrieved from the modeling sites with emissions and calibration factors derived for the year 2009, showing a performance similar to that of 2009. The findings confirm the applicability of the Urban Background Model to predict air pollution at the urban background level in Quito. Satisfactory results are obtained by applying meteorological data derived from any of the available monitoring stations. The unsatisfactory results for SO_2 suggest that emission data should be reviewed and that this cannot be obtained simply by scaling.

Few studies have established that air pollution is a risk factor for public health (Manisalidis et al., 2020; Pandey et al., 2021; Schraufnagel et al., 2019; Wang et al., 2021; Zhong et al., 2019; and Taghizadeh-Hesary et al., 2020). For example, Zhong et al., (2019) calculated the daily concentrations of major air pollutants (including PM_{10}, $PM_{2.5}$, SO_2, O_3, NO_2, and CO) and the daily air quality index values, and three meteorological factors: daily mean wind level, daily mean air temperature, and daily mean relative humidity. Through the analysis, we produced the relative risks of the six main air pollutants for respiratory, and cardio- and cerebrovascular diseases. The results showed that O_3 and NO_2 have the highest health impact, followed by PM_{10} and $PM_{2.5}$. The effects of any pollutant on cardiovascular diseases were consistently higher than on respiratory diseases.

Some countries have already unveiled proposals to mitigate the harmful effects of high-pollutant activities in Central Asia. For example, environmental investments in Kazakhstan increased by 24 percent from January to August this year, reaching $216 million. To the best of our knowledge, there has not been a time-series study investigating the causal relationship between energy consumption, air pollution emissions, and economic growth in Central Asia. As a resource-rich country, Kazakhstan has been characterized by a considerable achievement in economic growth and it has been passed through different development stages. The government also hopes to reform the public transport system to reduce urban air pollution, including a ban on diesel fuel due to high emissions of nitrogen oxides, a group of air pollutants that increase the prevalence of respiratory diseases. The burning of coal to heat high-rise buildings and the use of outdated automobiles contribute significantly to Central Asia's polluted skies. Harmful particles suspended in the atmosphere have contributed to the increased prevalence of respiratory conditions and are destructive to the environment.

3. METHODOLOGY AND DATA

3.1. Source of Data and Model

The present article follows from this literature on air pollution. It seeks to extend knowledge on this topic and underline the roles of economic growth and public health in reducing emissions of hazardous air pollutants, using a broad range of the latest data. The space distribution of fog and haze is closely related to the position of the air-polluting source. This paper is focused on economic activities. The key contribution of the present research to the existing literature will be to shed light on and quantify the impact of energy consumption, economic growth, and public health on emissions of hazardous air pollutants in Central Asia. To study examine the relationship between emissions of hazardous air pollutants, and economic growth, panel data for Central Asian Countries was used, covering 27 years. This study collected data from official sources, including the World Development Indicators (WDI), Institute for Health Metrics and Evaluation (IHME), World Health Organization Global Health Expenditure (WHO) database, and Climate Analysis Indicators Tool (CAIT) database. The author used the average SO_2, CO, NO_2, O_3, and $PM_{2.5}$ levels at the Central

Asian countries level from 1991 to 2017, as reported in the official database, to measure the dependent variables of air pollution. Air pollution data from five countries were collected concerning Sulfur Dioxide (*lnSO₂*), Carbon Monoxide (*lnCO*), Nitrogen Dioxide (*lnNO₂*), Ozone (*lnO₃*), and Particulate Matter (*lnPM2.5*) yearly. The study uses Asthma Prevalence (*lnAST*), Chronic Respiratory Diseases Death (*lnCDR*), Deaths from Air Pollution (*lnDAP*), Forest Area (*lnFOA*), Gross Domestic Product (*lnGDP*) per capita, Deaths from Household Air Pollution (*lnHAP*), Private Expenditures on Health (*lnHEX*), and Population (*lnPOP*) as independent variables. For the estimates of the coefficient of the variables, the following empirical model is formulated. Stata 17.0 econometrics software was used for the analysis.

3.2. Unit Root tests

This section shows graphically the overall statistics of quantitative data in the survey. The different axes show the different units of measure of the variables, and the graphs for each are converted to natural logarithmic values. The simplest study of data properties begins with a study of relative averages and variances of the data. The descriptive statistics and correlation matrix in Table 1 show the logarithmic variable data. Table 2 presents the overall mean values and units of measure for the 28 years of the survey between 1990 and 2017. Also, in this study, the Bayesian information criterion (BIC) or Schwarz criterion performed relatively well, so the Author used the Akaike information criterion (AIC) to determine the optimal number of latencies for the conditional ECM. Table 3 also shows the Akaike information criterion (MAIC), Bayesian information criterion (MBIC), sequential modified CD test, coefficient of determination (CD) test (each test at 5% level), J - Hansen's J statistic, J p-value - Hansen's J statistics p-value (Hansen, 1982), and the Quinn information criterion (MQIC) introduced by Andrews and Lu (2001) the test was conducted for first- to third-order Panel Vector Autoregression (PVAR) using the first four lags of the regressors as instruments.

3.3. Spatial econometric Model and Weight matrix

The purpose of this section is to examine the relationship between emissions of hazardous air pollutants, and economic growth in Central Asia between 1991 to 2017. The application of spatial econometric techniques is necessary for economic and environmental. For a brief introduction to spatial econometrics, one could refer to Anselin (2001) and Dubin (1998) provided classic reviews of early literature. The Global Moran's I was first proposed by Moran (1948) to test the spatial autocorrelation of economic variables based on the phenomenon of spatial random distribution. This study represents the spatial correlation of the air pollutant emissions, which could be calculated using the formula is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \qquad (1)$$

where, $S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$ is the sample variance and $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ is the sample mean. n is the number of spatial units, x_i and x_j are referred to as the different observations of spatial units i and j, respectively, and W_{ij} is the spatial weight matrix generated based on the distance weight. The specification of a spatial weighting matrix W plays an important role in determining the appropriate form of the spatial model, which summarizes spatial relations between n spatial units. Referring to existing research (Zeng et al., 2021), this study defined the spatial weight matrix W_{ij} as whether two cities are neighboring, specifically, their spatial distance was defined as 1 when country i and country j have a common administrative jurisdictional boundary.

$$W_{ij} = \begin{cases} 1, \text{country } i \cap \text{country } j \neq 0 \\ 0, \text{country } i \cap \text{country } j = 0 \end{cases} \qquad (2)$$

When a country i did not share a common administrative jurisdictional boundary with a country j, the spatial distance of them was defined as 0. Matrix definition as Equation (2).

3.4. Spatial Autoregression Models

Spatial econometric models assume that the dependent variable of each region depends both on the data for each location and the neighboring observations. Three popular spatial regression models are the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM) (Anselin, 2013). The SAR incorporates substantive spatial effects due to significant linkages between neighboring regions, while the SEM aims to correct spatial errors. The SAR model assumes that the dependent variable is spatially autocorrelated. This model considers air pollutants to be autocorrelated across regions, which is explained not only by the associated attributes but also partially by traits of the neighbors of the countries or provinces. The expression for the SAR model was defined as follows:

$$y = pW_y + x\beta + \varepsilon, \quad \varepsilon \sim N(0, \delta^2 I_n) \qquad (3)$$

where, y is the column vector of air pollution, p is the spatial autoregression parameter, W is the dimensional row vector of constants, x denotes independent variables, β reflects the influence of the independent variables, and ε is an error term. The spatial dependence can be demonstrated through the error term as well, and such a model is called SEM, which is listed as follows:

$$y = x\beta + \varepsilon, \quad \varepsilon = \lambda W_\varepsilon + \mu \quad \mu \sim N(0, \delta^2 I_n) \qquad (4)$$

where, y is the dependent variables, containing five types of air pollutants, x represents explanatory variables, λ represents the spatial coefficient of the error term, W_ε represents the spatial error term, μ represents stochastic error, and ε is an error term. The parameter β describes the cause-effect of explanatory variables on the dependent variables y. The SDM, which has recently become more widely used in applied research, includes both a spatially lagged dependent variable and spatially lagged explanatory variables. Thus, the usual spatial specifications of the SEM and SLM are particular cases of the SDM. The SDM provides consistent estimates for the majority of spatially correlated data-generating processes. The general form of SDM is:

$$y = pW_y + x\beta + Wx_j + \varepsilon, \quad \varepsilon \sim N(0, \delta^2 I_n) \qquad (5)$$

Furthermore, in the spatial econometric model, independent variables usually exert indirect effects on the dependent variable of the surrounding non-local area. Generally, the total effect of each variable on eco-efficiency includes direct and indirect effects. The direct effect is the impact of changes in various factors on the Central Asian eco-efficiency via over-agglomeration. Direct effects encompass changes in local independent variables that impact local eco-efficiency as well as local independent variables impacting adjacent cities which are fed back to the local eco-efficiency.

3.5. Diagnostic Analysis

Diagnostic, stability, and Wald tests are conducted to assess serial correlation, functional form, and heteroscedasticity associated with the model. Tables 6 and Table 7 presents the residual Diagnostic test Panel Group-wise Heteroscedasticity test, Autocorrelation, and the Feasible generalized least square (FGLS) test are applied. Ignoring the correlation between the variables may have serious consequences on the estimated parameters. To test the long run relationship between the underlying variables, the author applies the Wald test. Rejecting the null hypothesis means the presence of a long run relationship, while its acceptance denotes the absence of a long run relationship.

4. RESULT

4.1. Unit Root tests Result

The descriptive statistics of the variables are provided in Table 1, respectively. A look at the descriptive analysis shows that the investigated variables display some insignificant variances in the statistics. For dependent variables, the average and standard deviation values of *lnSO₂* emissions are 2.897 and 1.291 respectively. The average and standard deviation values of *lnCO* stand at 1.156 and 1.266 respectively. *lnNO₂*, *lnO₃*, and *lnPM2.5* use have mean values of 1.321, 1.444, and 4.064 respectively, while the respective standard deviations are 0.903, 0.548, and 0.296 respectively. The large standard deviations of the variables are indications of large variations of the values around their averages, hence, large disparities. To test the distribution properties of these variables, the study uses Jarque-Bera, Skewness, and Kurtosis as indicators. In a normal distribution Kurtosis is 3, and skewness is 0. In what follows, more properties of these variables are presented.

Table 1: Descriptive statistics of variables.

	Mean	Std. Dev.	Min	Max	Variance	Skewness	Kurtosis	Jarque-Bera
$lnSO_2$	2.897	1.291	1.047	4.810	1.668	-0.149	1.437	0.001
$lnCO$	1.156	1.266	-1.229	2.769	1.603	-0.473	1.854	0.002
$lnNO_2$	1.321	0.903	-0.051	2.904	0.816	0.176	1.487	0.001
lnO_3	1.444	0.548	0.390	2.659	0.300	0.265	2.975	0.454
$lnPM_{2.5}$	4.064	0.296	3.560	4.678	0.087	0.490	2.141	0.009
$lnAST$	1.251	0.128	1.062	1.535	0.016	0.433	1.995	0.007
$lnCDR$	3.756	0.489	2.621	4.723	0.239	-0.391	3.060	0.177

lnDAP	8.733	0.734	7.680	9.897	0.538	0.270	1.714	0.004
lnFOA	1.441	0.741	0.132	2.173	0.548	-0.761	2.082	0.014
lnGDP	23.475	1.318	21.487	26.002	1.736	0.260	1.837	0.010
lnHAP	7.246	1.844	2.753	9.023	3.402	-1.319	3.211	0.003
lnHEX	3.997	1.293	0.693	6.132	1.671	-0.434	2.714	0.095
lnPOP	16.042	0.685	15.148	17.293	0.470	0.451	1.607	0.043

Notes: All variables are expressed in their logarithms, Std. Dev.=standard deviation, Min=minimum, and Max=maximum. Data source: Compiled by the author based on WDI, IHME, GHE, and CAIT database (1991-2017).

The correlation coefficient between *lnSO₂* emissions and *lnCDR* is 0.799, implying that the relationship between $lnSO_2$ emissions and *lnCDR* is 79.9% in a positive direction. The relationship between $lnSO_2$ emissions and *lnPOP* is approximately 64.8%. The relationship between *lnCO* emissions and *lnAST* is approximately strongly by 86.8%, while the relationship between *lnCO* emissions and *lnCDR* and *lnFOA* are 91.3% and 75.7%. The relationship between $lnNO_2$ emissions and *lnAST* and *lnCDR* is approximately 70.2% and 80.8%. The relationship between lnO_3 emissions and *lnDAP* is approximately 67.3%. The relationship between $lnPM_{2.5}$ emissions and *lnHAP* and *lnPOP* are approximately strongly by 96.7% and 61.9%. The correlation matrix of all variables is shown in Table 2.

Table 2: Correlation matrix of variables.

	$lnSO_2$	*lnCO*	$lnNO_2$	lnO_3	$lnPM_{2.5}$	*lnAST*	*lnCDR*	*lnDAP*	*lnFOA*	*lnGDP*	*lnHAP*	*lnHEX*	*lnPOP*
$lnSO_2$	1.000												
lnCO	0.719	1.000											
$lnNO_2$	0.800	0.897	1.000										
lnO_3	0.269	0.117	0.479	1.000									
$lnPM_{2.5}$	0.322	0.344	0.516	0.466	1.000								
lnAST	0.321	0.868	0.702	0.031	0.260	1.000							
lnCDR	0.799	0.913	0.808	0.013	0.446	0.717	1.000						
lnDAP	0.082	0.272	0.082	0.673	0.164	0.298	0.418	1.000					
lnFOA	0.164	0.757	0.561	0.074	0.028	0.948	0.542	0.331	1.000				
lnGDP	0.318	0.299	0.034	0.511	0.420	0.638	0.100	0.480	0.793	1.000			
lnHAP	0.302	0.220	0.421	0.454	0.967	0.105	0.354	0.292	0.149	0.552	1.000		
lnHEX	0.170	0.343	0.451	0.324	0.064	0.360	0.049	0.563	0.368	0.174	0.065	1.000	
lnPOP	0.648	0.439	0.513	0.212	0.619	0.171	0.654	0.021	0.115	0.482	0.683	0.112	1.000

Notes: All variables are expressed in their logarithms. Data source: Compiled by the author based on WDI, IHME, GHE, and CAIT database (1991-2017).

After analyzing the descriptive statistics and correlation matrix, it is one of the challenging tasks to utilize the PVAR to find out a selection of the optimal lag length. It requires precision, as the addition of lags to time series models has a direct impact on the estimation process, and four lags have been suggested by the SBIC method (Table 3). The likelihood ratio, sequentially modified coefficient of determination (CD) test, the J test (Hansen 1982), which is a statistical test used for testing over-identifying restrictions following the J p-value, the MBIC, MAIC, MQIC selected lag 4 as shown at the 0.05 significance level. This is sufficiently long for a panel data study to capture the dynamic relationship so that the MAIC statistic could then be used to choose the estimation of a first-order PVAR.

Table 3: Lag length selection order criteria

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.9999993	49.71279	0.004911	-77.20018	-4.287207	-33.8611
2	0.9999935	2.5351	0.9999997	-96.17499	-39.4649	-62.46682
3	0.9999929	1.661402	0.9997748	-54.74436	-22.3386	-35.48255
4	0.9999843	1.384361	0.9979172	-40.91996	-16.61564	-26.4736

Notes: This procedure gives us the CD test (each test at 5% level). All variables are expressed in their first difference of logarithm. Data source: Compiled by the author based on WDI, IHME, GHE, and CAIT database (1991-2017).

4.2. Spatial Correlation Result of Air Pollution in Central Asia

Air pollution in Central Asia is affected by local production, household activities, and regional air pollution. In terms of economic development in Central Asia, there is a big difference between capital cities and satellite cities. A set of Global Moran's I statistic tests were conducted to analyze the spatial autocorrelation of the dependent variables. The Global Moran's I statistics is considered to be an important indicator to measure spatial correlation, which can describe the spatial distribution of autocorrelation variables clearly (Wang et al., 2018). Table 4 shows Moran's I value in concentrations of air pollutants $lnSO_2$, $lnCO$, $lnNO_2$, lnO_3, and $lnPM_{2.5}$ in Central Asian countries between 1991 to 2017. Since Moran's I value is less than 0, it can be concluded that Central Asia's $lnCO$ emissions are negative. This means that $lnCO$ emitting areas are surrounded by high-emission regions and lower $lnCO$ emissions are surrounded by low emission states. In addition, Moran's I value fluctuates between 0.073 and 1.297 when viewed from 1994 to 2011. For air pollutants $lnSO_2$ and $lnPM_{2.5}$, the levels are high but tend to decrease slightly, and Moran's I value is positive, with all statistically stable levels averaging 0.42 and 0.47, respectively. For $lnNO_2$ and lnO_3, Moran's I value is greater than 0.3, and all values are at 1%. Areas around contaminated countries and cities are often heavily polluted. Some cities in Central Asia, especially those with abundant resources, lag far behind the capital cities in terms of the worst eco-efficiency and economic development in the region. Failure to cooperate with developed cities worsens their air pollution. Appropriate controls are needed at all regional levels to reduce urban air pollution.

Table 4: Global Moran's I statistics for SO_2, CO, NO_2, O_3, and $PM_{2.5}$ emissions in Central Asia.

	$lnSO_2$	$lnCO$	$lnNO_2$	lnO_3	$lnPM_{2.5}$
1991	1.150***(0.250)	-0.558***(1.423)	-1.347***(1.822)	-0.599***(1.451)	1.398***(0.162)
1992	1.163***(0.245)	-0.045***(1.036)	-1.630***(1.897)	0.231***(0.817)	1.571***(0.116)
1993	1.092***(0.275)	-0.117***(1.093)	-0.843***(1.601)	-0.094***(1.075)	1.560***(0.119)
1994	1.260***(0.208)	0.197***(0.844)	-1.472***(1.859)	-0.055***(1.044)	1.508***(0.131)
1995	1.389***(0.165)	0.820***(0.412)	-1.214***(1.775)	-0.027***(1.022)	1.464***(0.143)
1996	1.481***(0.139)	0.850***(0.395)	0.846***(0.397)	-0.323***(1.253)	1.440***(0.150)
1997	1.477***(0.140)	0.967***(0.334)	0.901***(0.368)	1.407***(0.159)	1.553***(0.120)
1998	1.471***(0.141)	0.939***(0.348)	1.495***(0.135)	-0.381***(1.297)	1.590***(0.112)
1999	1.468***(0.142)	1.233***(0.217)	0.553***(0.581)	-0.416***(1.323)	1.566***(0.117)
2000	1.473***(0.141)	1.148***(0.251)	0.630***(0.529)	-0.034***(1.027)	1.566***(0.117)
2001	1.467***(0.142)	1.297***(0.195)	1.297***(0.195)	0.184***(0.854)	1.570***(0.116)
2002	1.458***(0.145)	0.957***(0.339)	0.786***(0.432)	0.389***(0.697)	1.578***(0.115)
2003	1.447***(0.148)	0.997***(0.319)	0.190***(0.849)	0.522***(0.602)	1.576***(0.115)
2004	1.476***(0.140)	1.017***(0.309)	0.845***(0.398)	0.557***(0.577)	1.581***(0.114)
2005	1.460***(0.144)	0.926***(0.355)	1.023***(0.306)	0.395***(0.693)	1.577***(0.115)
2006	1.483***(0.138)	0.914***(0.361)	1.049***(0.294)	0.434***(0.664)	1.572***(0.116)
2007	1.491***(0.136)	0.861***(0.389)	1.425***(0.154)	0.535***(0.592)	1.570***(0.116)
2008	1.497***(0.135)	0.507***(0.612)	1.390***(0.165)	0.628***(0.530)	1.556***(0.120)
2009	1.518***(0.129)	0.349***(0.727)	1.557***(0.119)	0.837***(0.402)	1.539***(0.124)
2010	1.500***(0.134)	0.286***(0.775)	1.236***(0.217)	0.972***(0.331)	1.493***(0.135)
2011	1.479***(0.139)	0.073***(0.942)	1.020***(0.308)	1.016***(0.309)	1.400***(0.162)
2012	1.458***(0.145)	-0.170***(1.135)	0.807***(0.420)	1.056***(0.291)	1.391***(0.164)
2013	1.475***(0.140)	-0.258***(1.204)	1.082***(0.279)	1.000***(0.317)	1.357***(0.175)
2014	1.467***(0.142)	-0.393***(1.305)	1.150***(0.250)	0.950***(0.342)	1.297***(0.195)
2015	1.457***(0.145)	-0.473***(1.364)	0.662***(0.508)	0.962***(0.336)	1.251***(0.211)
2016	1.455***(0.146)	-0.709***(1.521)	0.314***(0.754)	0.937***(0.349)	1.211***(0.226)
2017	1.449***(0.147)	-0.695***(1.513)	0.623***(0.533)	0.920***(0.358)	1.133***(0.257)

Notes: All variables are expressed in their logarithms. *** indicate significant of the variables at 10% significance level. Data source: Compiled by the author based on WDI, IHME, GHE, and CAIT database (1991-2017).

4.3. Air pollutants in Central Asia

Air pollution affects all components of the environment, including groundwater, soil, and air. In Central Asia, environmentalists and local communities need to do more to reduce air pollution in the region's urban areas. Nur-Sultan

(Kazakhstan) and Bishkek (Kyrgyzstan), the largest cities in Central Asia, are located on a flat plateau surrounded by mountains and are covered in very thick smoke for most of the winter. Governments in Central Asia need to develop large-scale air pollution control plans to protect their people from the dangers of air pollution. The WHO has identified six major air pollutants: particulate matter, ground-level ozone, carbon monoxide, sulfur dioxide, nitrogen oxides, and lead. Due to the weather, air pollution from neighboring countries is transmitted through the wind, which harms air pollution. This further requires Central Asian countries to plant large quantities of trees (Figure 1). Of these, air pollution in the Central Asian countries studied in this study is illustrated.

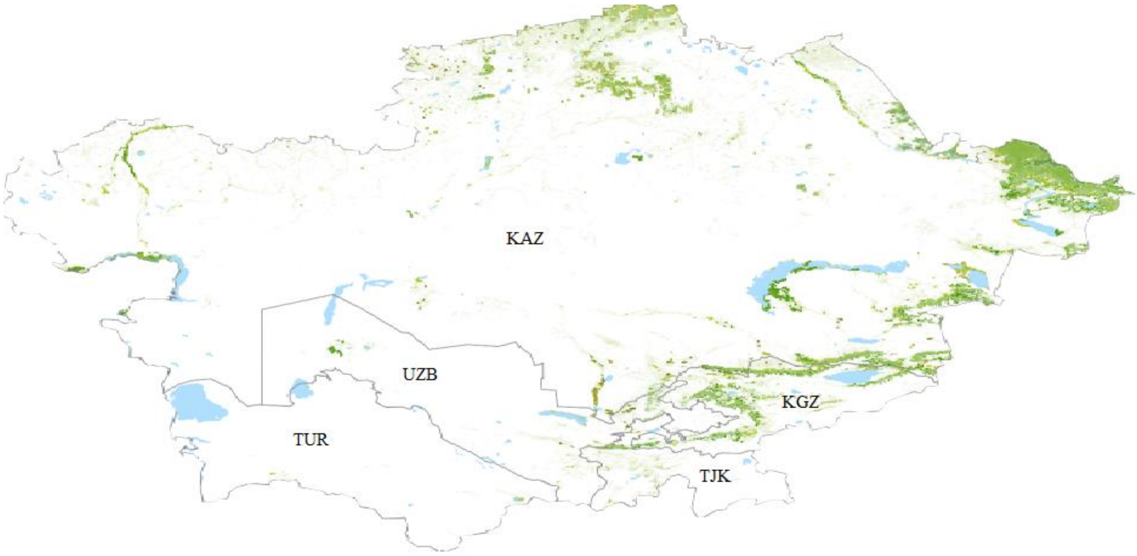

Figure 1: Forest cover by country in Central Asia.
Source: www.globalforestwatch.org

Sulfur Dioxide (SO_2) emission in Central Asia: SO_2 emissions are colorless and result from the combustion of sulfur-containing fuels such as coal and oil, vehicle emissions, maritime transport, electrical appliances, industrial facilities, volcanoes, and metal processing. SO_2 emissions adversely affect human, animal, and plant life. People with lung disease, the elderly and children, have a higher risk of injury. Major health problems associated with SO_2 emissions in industrialized areas include respiratory irritation, bronchitis, mucus secretion, and bronchospasm. In addition, redness of the skin, damage to the eyes and mucous membranes, and cardiovascular disease are common. Among Central Asian countries, Kazakhstan emits the highest SO_2 emissions (Figure 2). Tajikistan and Kyrgyzstan emit slightly less SO_2 than the other three countries. In Central Asia, SO_2 emissions are largely different from fossil fuel consumption, manufacturing activities, and transportation. In Central Asia, however, SO_2 emissions from vehicles are a major cause of air pollution in Central Asian cities. For example, Bishkek (Kyrgyzstan) has 420,000 registered cars, while the city has a maximum of 50,000 cars. Currently, there are 450,000 registered cars in Tashkent (Uzbekistan) and 472,000 in Almaty (Kazakhstan).

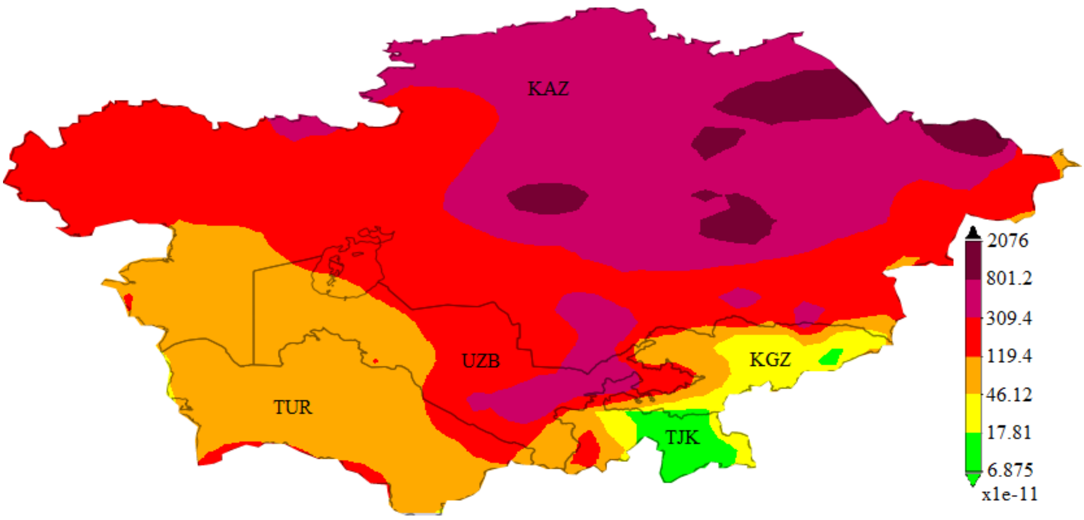

Figure 2: Spatial distribution for Sulfur Dioxide (SO_2) emission concentrations in Central Asia.
Source: https://giovanni.gsfc.nasa.gov/giovanni/

Carbon Monoxide (CO) emission in Central Asia: CO emissions are odorless, colorless gases that are usually released as a result of incomplete combustion of fuels, forest fires, and industrial operations. CO emissions affect greenhouse gases, which are closely related to global warming and climate. This can lead to an increase in soil and water temperatures, which can lead to extreme weather conditions and storms. CO emissions include inhalation of carbon monoxide from fossil fuels during incomplete combustion. Symptoms of poisoning include headache, dizziness, weakness, nausea, vomiting, and eventually loss of consciousness. This further increases the risk of cardiovascular disease. Air quality measurements show that CO emissions have reached alarming levels throughout Central Asia (Figure 3). Turkmenistan and Kyrgyzstan have slightly lower CO emissions than the other three countries. Coal-fired power plants in the former Soviet Union continue to operate throughout Central Asia, causing pollution and poor air quality. In addition, the use of outdated stoves and high-emission vehicles by households is already exacerbating the situation. Burning coal and using old cars to heat tall buildings contribute significantly to air pollution in Central Asia.

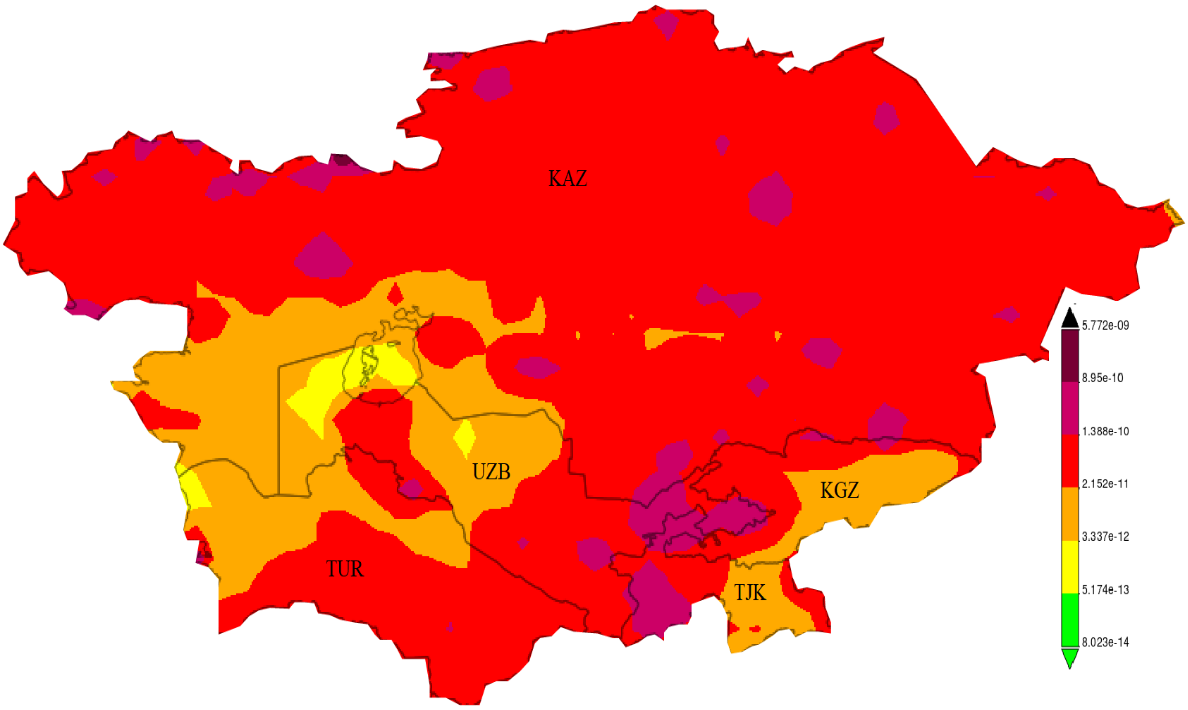

Figure 3: Spatial distribution for Carbon Monoxide (CO) emissions concentrations in Central Asia.
Source: https://giovanni.gsfc.nasa.gov/giovanni/

Nitrogen Dioxide (NO_2) emission in Central Asia: NO_2 emission is colorless, slightly unpleasant-smelling gas that, when highly concentrated in the atmosphere, turns brownish-yellow or reddish-brown and reacts actively. Nitrogen oxide (NO) released from air pollution sources is formed when it combines with oxygen in the air. The resulting nitrogen dioxide forms strong oxidizers, such as volatile organic compounds in the air. Occurs when any fuel burns at high temperatures and is emitted from sources of air pollution, such as internal combustion of vehicles, electric heaters, power plants, chemical plants, and incinerators. It penetrates deep into the lungs and irritates the respiratory system due to its high content in respiratory diseases, coughing, coughing, shortness of breath, bronchospasm, and even pulmonary edema. High levels of nitrogen dioxide can cause chronic lung disease. Nitrogen dioxide has been shown to reduce crop and plant growth efficiency, which is detrimental to crops and vegetation. Measurements show that Tashkent, the capital of Uzbekistan, emits NO_2. Elsewhere in Central Asia, NO_2 emissions are modest (Figure 4).

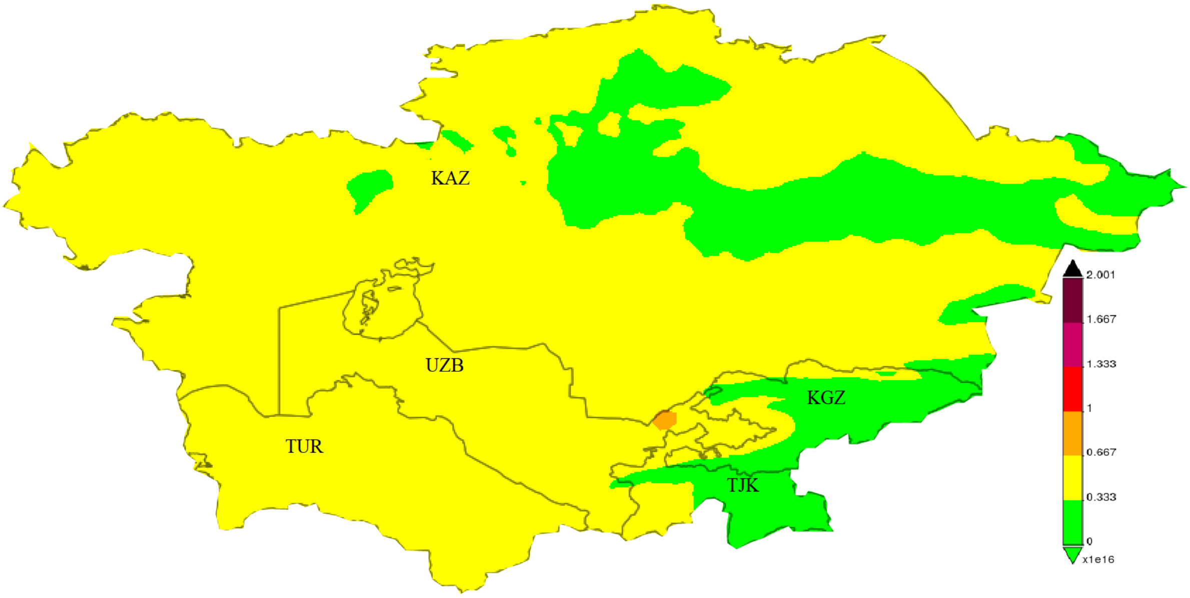

Figure 4: Spatial distribution for Nitrogen Dioxide (NO_2) emissions concentrations in Central Asia.
Source: https://giovanni.gsfc.nasa.gov/giovanni/

Ozone (O_3) emissions in Central Asia: O_3 emissions are an odorless, colorless gas composed of oxygen under a high voltage electric charge. Located in the upper atmosphere, O_3 is biologically important to protect humans and animals from the harmful effects of the sun's ultraviolet rays. In contrast, ground-level O_3 is harmful to human health and pollutes the environment. Pollutants from sources such as cars, power plants, and boilers in the lower atmosphere, or near the surface, react with hot, sunny days to form secondary pollutants, ozone. Pollutants released directly into the air from air pollution sources produce ozone due to the reaction of the sun's ultraviolet rays, and ozone pollution increases during the hot summer days. O_3 emissions are particularly high in the Nur-Sultan area of Kazakhstan's capital (Figure 5).

Figure 5: Spatial distribution for Ozone (O_3) emissions concentrations in Central Asia.
Source: https://giovanni.gsfc.nasa.gov/giovanni/

Particulate Matter ($PM_{2.5}$) emissions in Central Asia: PM emissions include fossil fuel combustion, industrial facilities, maritime transport, road dust, wildfires, biomass incineration, waste incineration, and fine dust in the air. PM emissions include very fine particles with a diameter of 10 micrometers or less, generally 2.5 micrometers in diameter, called PM_{10}. PM emissions contain small liquid or solid droplets that can be inhaled and adversely affected. After inhalation, PM_{10} can be entered the lungs and even reach the bloodstream. $PM_{2.5}$ poses a greater health risk. Decreased respiratory and immune systems can lead to long-term chronic consequences. People with asthma, pneumonia, diabetes, respiratory and cardiovascular diseases are especially susceptible to PM. Kazakhstan, Uzbekistan, and Turkmenistan had the highest $PM_{2.5}$ concentrations in winter, largely due to fossil fuel use and biomass combustion (Figure 6). In general, Kyrgyzstan and Tajikistan have the lowest $PM_{2.5}$ concentrations in Central Asia.

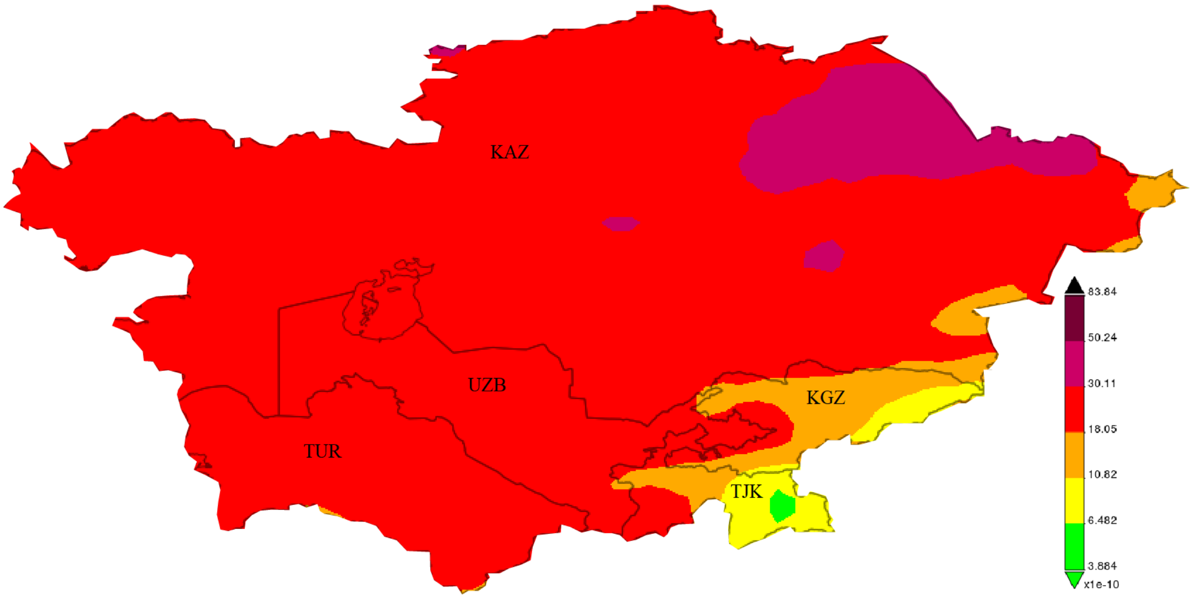

Figure 6: Spatial distribution for Particulate Matter ($PM_{2.5}$) emissions concentrations in Central Asia.
Source: https://giovanni.gsfc.nasa.gov/giovanni/

4.4. Direct effects, Indirect effects, and Total effects Results of Air Pollution in Central Asia

Table 5 shows the decomposition estimates of the direct, indirect, and total effects. The results of this table show the direct, indirect, and total effects of air pollution on the population of Central Asia. The growth of population and agglomeration appear to be important factors in determining local air quality. The indirect effects of urbanization and population are also important, indicating that population-related factors contribute to air pollution in neighboring cities. Direct effects show that a 1% increase in *lnGDP* in Central Asia will increase air pollutant *lnCO* by 0.557%. A 1% reduction in *lnHAP* could lead to a 0.624% reduction. This is due to households reducing their consumption of solid fuels. Also, a 1 percent decrease in *lnFOA* increases an 0.300 percent increase in lnO_3. At the same time, a 1 percent increase in Central Asia's population could lead to an increase in air pollutants such as *lnCO*, lnO_3, and $lnPM_{2.5}$ by 1.969%, 0.291%, and 0.874%, respectively. Indirect effects show that a 1 percent increase in total *lnFOA* in Central Asia could reduce lnO_3 by 0.008%. An increase of 1% in *lnGDP* will increase the amount of air pollutant *lnCO* by 0.505%. A 1% reduction in *lnHAP* could result in a 0.177% reduction. However, a 1 percent increase in the total population of Central Asia increases the levels of air pollutants such as *lnCO*, lnO_3, and $lnPM_{2.5}$ by 0.721%, 0.01%, and 0.46%, respectively. Both of the Direct effects and Indirect effects show that a 1 percent reduction in *lnFOA* can reduce lnO_3 by 0.292%. An increase of 1% in *lnGDP* will increase the amount of air pollutant *lnCO* by 1.062%. A 1% reduction in *lnHAP* could result in a 0.802% reduction. However, a 1 percent increase in the total population of Central Asia increases the levels of air pollutants such as *lnCO*, lnO_3, and $lnPM_{2.5}$ by 1.248%, 0.301%, and 0.414%, respectively. Central Asia's emissions are related to the use of natural resources.

Table 5: Direct effects, indirect effects, and total effects.

	$lnSO_2$	*lnCO*	$lnNO_2$	lnO_3	$lnPM_{2.5}$
Direct effects					
lnAST	0.808(0.496)	-0.310(0.667)	1.479*(0.605)	-0.282*(0.136)	-0.331(0.334)
lnCDR	0.422(1.135)	-0.005(0.000)	-0.983(1.378)	1.075***(0.039)	0.823(0.755)
lnDAP	1.010***(0.275)	-0.214(0.000)	0.224(0.000)	-0.081(0.289)	0.841**(0.314)
lnFOA	0.050(0.339)	0.099(0.133)	-0.433(0.409)	0.300***(0.024)	0.281(0.218)
lnGDP	-0.040(0.181)	0.557*(0.238)	0.322(0.256)	0.151**(0.053)	0.060(0.152)
lnHAP	-0.624***(0.141)	0.166(0.248)	0.026(0.134)	0.112(0.096)	-0.097(0.175)

lnHEX	-0.023(0.049)	0.006(0.069)	0.025(0.046)	0.024(0.019)	0.096***(0.020)
lnPOP	0.947(0.442)	-1.969***(0.502)	-0.214(0.531)	-0.291*(0.116)	-0.874**(0.267)
Indirect effects					
lnAST	0.825(0.462)	2.321(0.670)	0.077*(0.555)	-0.012*(0.116)	0.173(0.302)
lnCDR	0.053(1.127)	0.805(0.149)	1.096(1.377)	-0.012***(0.039)	-0.793(0.754)
lnDAP	0.571***(0.269)	1.320(0.342)	0.573(0.156)	-0.205(0.282)	0.287**(0.276)
lnFOA	-0.064(0.328)	-0.038(0.139)	0.278(0.401)	-0.008***(0.019)	-0.214(0.213)
lnGDP	0.239(0.171)	0.505*(0.232)	0.023(0.252)	0.037**(0.051)	-0.235(0.145)
lnHAP	-0.177***(0.136)	-0.638(0.246)	-0.198(0.131)	0.070(0.095)	-0.192(0.174)
lnHEX	0.028(0.048)	0.009(0.083)	0.034(0.047)	-0.010(0.017)	-0.013***(0.017)
lnPOP	-0.209(0.465)	0.721***(0.561)	0.203(0.546)	-0.010*(0.119)	0.460**(0.295)
Total effects					
lnAST	1.633(0.297)	2.010(0.532)	1.556*(0.250)	-0.295*(0.080)	-0.158(0.176)
lnCDR	0.475(0.081)	0.800(0.149)	0.113(0.069)	1.063***(0.022)	0.030(0.048)
lnDAP	1.581***(0.189)	1.106(0.342)	0.797(0.156)	-0.285(0.051)	1.129**(0.115)
lnFOA	-0.013(0.080)	0.061(0.142)	-0.155(0.067)	0.292***(0.021)	0.067(0.047)
lnGDP	0.199(0.063)	-1.062*(0.113)	0.345(0.053)	0.188**(0.017)	-0.175(0.037)
lnHAP	-0.802***(0.042)	-0.472(0.077)	-0.172(0.036)	0.182(0.011)	-0.288(0.025)
lnHEX	0.005(0.040)	0.015(0.071)	0.059(0.033)	0.014(0.011)	0.083***(0.024)
lnPOP	0.738(0.227)	-1.248***(0.424)	-0.010(0.193)	-0.301*(0.062)	-0.414**(0.138)

Notes: All variables are expressed in their logarithms. *, ** and *** indicate significant of the variables at 1, 5 and 10% significance level. Data source: Compiled by the author based on WDI, IHME, GHE, and CAIT database (1991-2017).

4.5. Diagnostic Analysis Result

Table 6 presents the diagnostic tests for the Panel Group-wise Heteroscedasticity test and Autocorrelation. A maximum of two lags were initially considered and both lag selection criteria and lag exclusion tests statistics proposed that indeed a lag of order two was optimal. The Wald test also shows the model is correctly specified. Here, the Wald test is 127764.14 with a p-value being 0.0000 which is less than 5% is no Autocorrelation, so the model has Group-wise heteroscedasticity in model.

Table 6: Panel Group-wise Heteroscedasticity test and Autocorrelation.

Ho: panel Homoscedasticity			
Ha: panel Group-wise heteroscedasticity			
Lagrangian multiplier LM test=	1.667584	Prob > chi2	0.0000
Likelihood Ratio LR test =	132.0403	Prob > chi2	0.0000
Wald test =	27764.14	Prob > chi2	0.0000
Diagnostic test for serial correlation and Autocorrelation:			
Wooldridge test for autocorrelation in panel data		F (1,4) =	8.743
Ho: no first-order autocorrelation		Prob > F =	0.0417

Notes: All variables are expressed in their logarithms. Null hypothesis: There is no auto-correlation and serial correlation in error terms; Alternative: There is auto-correlation and serial correlation in error terms. Data source: Compiled by the author based on WDI, IHME, GHE, and CAIT database (1991-2017).

The author uses FGLS in such a case then this model is not suffering from heteroscedasticity which means homoscedasticity and second this model is not suffering from Autocorrelation means there is no serial correlation in the model, so this is an appropriate model in the data set (Table 7). Thus, $lnSO_2$, $lnNO_2$, $lnPM_{2.5}$, *lnAST*, *lnCDR*, *lnDAP*, *lnFOA*, and *lnPOP* have a statistically significant and positive effect on the air whereas *lnCO*, lnO_3, *lnGDP*, *lnHAP*, and *lnHEX* have statistically insignificant and negative effects on Air Pollutant in Central Asian countries.

Table 7: Feasible generalized least square (FGLS) regression

Coefficients: Generalized least squares			Log likelihood	=118.2964
Panels:	Homoskedastic		Wald test	=21883.36
Correlation:	no autocorrelation		Prob > chi2	=0.0000
Variables	Coefficient	Standard error	z	p>|z|
lnSO₂ → $lnSO_2$	1.353***	0.1190419	11.36	0.000
$lnCO$	0.361***	0.0318012	-0.53	0.000
$lnNO_2$	0.367***	0.0644218	5.69	0.000
lnO_3	-0.635**	0.232399	-2.73	0.006
$lnPM_{2.5}$	0.201	0.1118382	1.80	0.072
lnAST	0.213	0.2126281	1.00	0.317
lnCDR	0.790**	0.2556852	3.09	0.002
lnDAP	0.542***	0.1571857	3.45	0.001
lnFOA	0.196*	0.0881313	2.22	0.026
lnGDP	-0.148*	0.0585452	-2.53	0.011
lnHAP	-0.387***	0.0477181	-8.10	0.000
lnHEX	-0.0240	0.0250519	-0.96	0.337
lnPOP	0.992***	0.1640889	6.04	0.000
Constant	-15.69***	1.563617	-10.03	0.000

Notes: All variables are expressed in their logarithms. *, ** and *** indicate significant of the variables at 1, 5 and 10% significance level. Data source: Compiled by the author based on WDI, IHME, GHE, and CAIT database (1991-2017).

5. DISCUSSION

Air pollution is a major social and environmental threat not only in Central Asia but around the world. The complex geography and strong winds on land affect the air quality in Central Asia and pose a serious threat to the health of the entire population. In major Central Asian cities, the air is polluted during the winter, and residents use raw coal to heat their homes without chimney filters. During the winter, the atmospheric circulation decreases, and toxic particles accumulate, creating urban fumes. Therefore, there is a need to develop technologies to reduce air pollution from sources and replace all plants and coal-fired power plants with new ones. Dust storms pose a major threat to the population of Dushanbe (Tajikistan). The frequency of dust storms in Tajikistan has increased at least 10 times in the last 30 years. The main reason for the increase in dust storms is desertification. In the early 1990s, people destroyed 70 percent of the country's forests or 700,000 hectares. Only trees that block the wind filter the air from the dust (Figure 1). Due to this, wind particles are increasing in other Central Asian countries. Interactions in neighboring regions that pollute the air indicate the need to expand cooperation between local governments in the prevention and control of air pollution. This type of cooperation requires the adoption of common legislation and related measures to monitor, monitor, evaluate and implement policies aimed at preventing and controlling air pollution at the Central Asian level. Due to anthropogenic factors, the rapid urbanization of Central Asian countries is a major cause of air pollution, and the concentration of urban population has a significant impact on air quality. It is necessary to limit the scope of high-density cities in order to develop small and medium-sized cities with low density. Industrial emissions are also an important source of flue gas pollution, so there are benefits to expanding the industrial structure, reducing Central Asia's dependence on coal, renewing it with wind and solar energy, and increasing clean energy sources. Air pollution has many negative effects on our health. Young children are especially vulnerable to respiratory diseases caused by air pollution. To protect their own health from air pollution, citizens should wear special breathing masks with a protection rating of N95 or higher on the street. Medical masks cannot filter $PM_{2.5}$ particles. Households also need to use air purifiers with good quality filters that can effectively filter out even the finest calculations. This compliance will reduce the effects of harmful particles on the human body. Smart green planning is needed to combat the negative health effects of air pollution and pollution. This work needs to be developed and implemented by the countries of the region, not just the five countries of Central Asia. To address the issue effectively, it should be used in conjunction with development experience and research from other sustainable regions.

6. CONCLUSION AND RECOMMENDATIONS

Air is one of the most important environmental elements for human existence, so air pollution is a global concern. This study examines the impact of Sulfur Dioxide (SO_2), Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Ozone (O_3), and Particulate Matter ($PM_{2.5}$) emission concentrations on air pollution in Central Asia, as well as the economic, social, and health effects of air pollution. The purpose of this study is to draw the attention of researchers to the macro perspective of the causes of severe air pollution in Central Asian cities today. The study is to use for the measurements of air pollutants in Central Asian cities between 1991 to 2017, as well as socio-economic and health data, based solely on the availability of data. In consideration of the spatial flow and spatial autocorrelation of Central Asian air pollution, the author estimated the spatial lag and spatial spillover effects through spatial Autoregression Models. Global Moran's I statistical tests and spatial autocorrelation models are able to represent the results of existing industries, so other spatial correlation indices have been studied. The results of Moran's I values and spatial Autoregression Models show a positive spatial correlation of air pollution concentrations in Central Asian cities. In addition, the estimates show that Central Asia's energy sector, Gross Domestic Product, and population growth have a significant negative impact on air pollution. In countries with high SO_2 emissions, governments need to focus on developing renewable energy policies. This is because SO_2 is twice as harmful to the human body as $PM_{2.5}$. Therefore, in order to reduce SO_2 emissions, Central Asian governments need to adopt new policies on renewable energy using wind and solar. Experience from other countries in combating and reducing air pollution suggests that it may take some time to improve air quality in Central Asia. Concentrations of urban air pollution are expected to remain relatively high in the near future as mining, especially coal, produces energy in the Central Asian economy. In addition, in order to improve air quality and reduce pollution, the first step is to reduce the amount of particulate matter in the area. To effectively reduce air pollution concentrations, Central Asia must accelerate economic restructuring and reduce dependence on mining, especially heavy industry. For example, improving the energy structure by forcibly shutting down old coal-fired boilers and heavily polluting plants, reducing coal consumption, and increasing the use of clean energy, such as natural gas and renewable energy, is an effective measure to reduce air pollution. Interregional cooperation is needed to address air pollution in Central Asia. Every city and local government in Central Asia needs to actively communicate, strengthen cooperation and develop common standards. The process of developing an air pollution reduction plan should take into account the differences and characteristics of the region. This study has made a significant contribution to the calculation of spatial autocorrelation, which contributes to the reduction of key emissions of air pollutants, such as the introduction of air pollution reduction policies and renewable energy policies in Central Asia. In the future, renewable energy policies will greatly help reduce air pollution in Central Asia. Further research is needed to more accurately define the appropriate level of policy for each Central Asian country, and additional research is needed to examine the impact of factors on a monthly or daily basis, using different spatial measures.

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