7. WHAT MAKES THE LEVEL OF PARTICULATE MATTER EMISSIONS WORSE IN KOREA?[1]

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Abstract

This study empirically examines the effects of economic activities on air pollution, especially particulate matter 2.5 (PM2.5) and particulate matter 10 (PM10). Using monthly regional panel data, we explain which socioeconomic activities worsen air pollution levels. Our results show that some economic activities, such as manufacturing of chemical products and chemicals, and diesel consumption increase both PM10 and PM2.5 emission levels. As diesel consumption increases, PM10 emission level increases according to the GLS (generalized least squares) estimations. In addition, as the manufacturing of coke, briquettes, and petroleum products increases, the PM2.5 emission level increases. As the manufacturing of chemical products and chemicals increases, both PM10 and PM2.5 emission levels increase in neighboring regions using SDM(b). Diesel consumption has also a positive effect on the increase in the PM2.5 emission level in neighboring regions using SDM(a). As the number of precipitation days increases, both PM10 and PM2.5 emission levels decrease according to the GLS estimates, SDM(b). We forecast that both PM10 and PM2.5 levels will continue to rise if people continue to engage in certain socioeconomic activities, such as chemicals, coke, briquettes, petroleum products manufacturing, and diesel consumption. However, serious levels of pollution may not necessarily arise in the future, as using new and renewable energy lowers the levels of both PM10 and PM2.5 according to the SDM(a) and (b). These findings help to explain future air quality level forecasts using monthly regional data with spatial dependence.

Keywords: air pollution forecasting; emerging economy; particulate matter emission; spatial dependence; sustainable development

JEL Classification: Q53, Q54, Q58

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1. Introduction

No creature can live without air. As the word “airpocalypse” indicates, air pollution has become one of the biggest environmental issues that people can experience, and it threatens human health.[4] It is calculated that exposure to air pollution causes millions of deaths and loss of healthy life annually. With the increasing demand for clean air in many regions, the World Health Organization (WHO) established air quality guidelines in 2006, titled *Air Quality Guidelines: Global Update 2005*. This publication provides health-based air quality guidelines for particulate matter and other major health-damaging air pollutants (WHO, 2006). The WHO updated these global air quality guidelines in 2021 and warned that particulate matter exposure can adversely affect human health (WHO, 2021).

This study examines the socioeconomic activities that worsen air pollution levels, especially particulate matter 2.5 (PM2.5) and particulate matter 10 (PM10) emissions, in the Republic of Korea (hereafter, Korea). This study focuses on air pollution generation among various environmental issues for two reasons. First, the WHO’s air quality guidelines, which were first enacted in 2005, were updated recently in 2021. *Air Quality Guidelines: Global Update 2005* has significantly impacted worldwide abatement policies. Thus, most countries are expected to upgrade their air pollution-related policies according to updated guidelines. To support policymakers in their decision-making and to predict their policy effects, the results of this study provide an empirical analysis of the effects of economic activities on air pollution to allow future system improvements. Second, air pollution is not only unpleasant to look at but is also a key factor in human health and life satisfaction. It is also related to the phenomenon of increasing demand for clean air worldwide.

In this study, we focus on air pollution in Korea, not in other regions, for two reasons. First, despite rapid economic development, air pollution levels in the Asian countries remain high. According to WHO, the annual population-weighted PM2.5 concentrations in South-East Asia were highest in 2019 (WHO, 2021). In particular, the mean population exposure to fine particulates (*i.e.*, PM2.5) in Korea was the highest among the Organisation for Economic Cooperation and Development (OECD) countries and reached about 27.4 micrograms per cubic meter in 2019 (OECD, 2022). Second, air pollution significantly affects human health more than any other pollutant (WHO, 2021), and exposure to PM2.5 can trigger severe diseases. It should be noticed that it affects regional economies in the end (Schweitzer and Zhou, 2010). In Korea, the annual mortality attributed to exposure to PM2.5 is 427 per million inhabitants (OECD, 2022). Premature deaths due to PM2.5 exposure have generally decreased across the OECD, and reached an average of 275 per million inhabitants in 2019. According to OECD (2022), exposure to PM2.5 causes more than 500 premature deaths per million people annually in some countries, such as the Czech Republic, Greece, Slovak Republic, and Hungary. The premature deaths because of PM2.5 exposure incur a

4 The word “airpocalypse” was first used in 2013 by major newspapers, such as The Financial Times and The Guardian. It is a portmanteau word for “air” and “apocalypse” and was used to describe severe air pollution in China. At that time, the airborne toxic smog level in Beijing was nearly 30 times above the World Health Organization’s recommended limit. The source of newspapers: Jamil Anderlini. “‘Airpocalypse’ drives expats out of Beijing.” The Financial Times, 1 Apr 2013, accessed 29 March 2022. https://www.ft.com/content/46d11e30-99e9-11e2-83ca-00144feabdc0; Jonathan Kaiman. “Chinese struggle through 'airpocalypse' smog.” The Guardian, 16 Feb 2013, accessed 29 March 2022. https://www.theguardian.com/world/2013/feb/16/chinese-struggle-through-airpocalypse-smog.

significant amount of social welfare costs, which is equivalent to 2.4% of the gross domestic product (GDP) (OECD, 2022). The premature death issue in other countries is even worse. The welfare costs of premature deaths attributed to PM2.5 pollution are equivalent to 5.8% of GDP worldwide, according to OECD (2022). Thus, it is necessary to examine domestic factors affecting air pollution.

In this study, air pollution refers to the level of particulate matter. Particulate matter is a mixture of solid and liquid particles in the air and it is classified by particle size as PM10 (*i.e.*, particles with an aerodynamic diameter less than or equal to 10μm) and PM2.5 (*i.e.*, particles with an aerodynamic diameter less than or equal to 2.5μm) (WHO, 2021). It is too small to settle onto the Earth's surface by gravity (Thai, Bernatik, and Kučera, 2021). This study empirically examines the effects of economic activities on air pollution, especially particulate matter (*i.e.*, PM2.5 and PM10) in Korea. Using monthly regional data, it explains the worsening air pollution emission levels.

The remainder of this paper is organized as follows. In Section 2, we review the existing literature on the causes of air pollution and spatial analysis in environmental economics. Section 3 explains the study's empirical methodology and data. Section 4 presents the empirical results. The last section summarizes the test results and concludes.

2. Related Literature

The non-stationarity of macro variables used in the panel model becomes one of the important issues in analysis. Therefore, the unit roots test in heterogeneous panels has been debated for the past decade (Pesaran, 2007). Maddala and Wu (1999) compare the Levin-Lin tests, the Im-Pesaran-Shin (IPS) test, and the Fisher test. Moon and Perron (2004) explain unit root test statistics for large n and T panels in which cross-sections are correlated. The heterogeneous panel is also one of the main issues in panel analysis. Since panel data has been widely used for various empirical analyses recently, several empirical studies have tried to develop a methodology that is more suitable for each characteristic of panel data. Pesaran and Smith (1995) present theoretical and empirical work on the inconsistency of the pooled estimators in dynamic heterogeneous panel models. Im, Pesaran, and Shin (2003) provide unit root tests for dynamic heterogeneous panels. Phillips and Sul (2003) explain the coefficient homogeneity test under cross-section dependence. They also explain the sample bias problem in dynamic panel regressions. The new methodology named PANIC is introduced by Bai and Ng (2004). The PANIC means panel analysis of nonstationarity in idiosyncratic and common components. Andrews (2005) deals with regression models for cross-section data under cross-section dependence due to macroeconomic shocks. The new regression test of convergence is developed by Phillips and Sul (2007) and they explain it with some economic examples.

Some studies showed that air pollution affects socioeconomic factors. Cho, Lee, and Kim (2013) investigate the relationship between air pollution and low birth weight in Korea. They show that the probability of low birth weight is expected to increase because of the mother's exposure to ozone during the first trimester and carbon monoxide or sulfur dioxide during the third trimester. Rupasingha, Goetz, Debertin, and Pagoulatos (2004) describe the relationship between personal income and pollution in the US using spatial econometric analysis. Ersin and Bildirici (2019) examine the connection among carbon dioxide emissions, gas prices, and levels of economic prosperity using data from the US and the UK from 1861 to 2012 and 1871 to 2012. They explain that economic growth rates have asymmetric impacts on emissions during both expansion and recession periods in both countries.

However, research on the socioeconomic activities that cause air pollution is lacking.[5] Thus, this study aims to analyze the effects of economic activities on air pollution.

In addition, recent studies highlight the seriousness of air pollution in Korea and analyze Korean cases. Yi and Sung (forthcoming) investigate the effects of aged coal-fired generators on PM2.5 using the difference-in-differences method. They show that Korea's shutting down policy of old coal-fired power plants reduces daily PM2.5. These results differ from those of previous studies in that they control for the effects of wind and overseas pollutants. Chung, Kim, and Kim (2019) examine the relationship between particulate matter and pedestrian street volumes in Korea. They find that the PM10 concentration reduces street pedestrian volumes. These findings prove that deteriorating air quality impacts both people's health and the local economy. Kang, Suh, and Yu (2019) examine the relationship between air pollution and retail sales using monthly regional panel data from Korea. They show that the monthly retail sales fall by 0.1% generally as the number of additional days of exposure to the PM10 level above 80 μg/㎥increased.

Several studies highlight the importance of incorporating geographic information and spatial analysis into environmental research. Elhorst (2003) introduces the importance of panel data with spatial error autocorrelation or a spatially lagged dependent variable through the analysis of four spatial panel data models: the fixed effects model, the random effects model, the fixed coefficients model, and the random coefficients model. Anselin (2001) describes how spatial econometric methods can be used in environmental and resource economics and why these methods should be used. First, environmental issues are often identified from physical measurements that result from spatial sampling. Second, most environmental and resource economics research uses a combination of data from different sources. These integrated data from various sources tend to be spatially dependent. Thus, spatial analysis is necessary to conduct applied research in environmental economics (Anselin, 1988). Social sciences, including environmental economics, are often characterized by high spatial dependence. Thus, inaccurate results tend to be derived if spatial dependence is not considered. Spatial dependence exists when one observation in a sample of cross-sectional observations depends on other cross-sectional observations (Rupasingha, Goetz, Debertin, and Pagoulatos, 2004). Some ecological problems, such as pollution, water quality, biodiversity, and global climate change, are based on spatial processes, implying that spatial relationships must be acknowledged in the related econometric models (Bockstael, 1996). Goodchild, Anselin, Appelbaum, and Harthorn (2000) suggest that the importance of the spatial approach in social science literature is growing. They explain that environmental and climate change issues necessarily drive human effects, such as migration, urbanization, industrialization, and differences in population growth by region. To consider the relationship between socioeconomic and physical changes, it is necessary to conduct spatial analyses.

3. Methods

This study empirically examines the effects of economic activities on air pollution, especially particulate matter (*i.e.*, PM2.5, PM10). We use monthly regional data from Korea spanning from January 2016 to April 2021. The sample area includes 16 Korean cities. Conducting the analysis on a monthly rather than an annual basis (*i.e.*, the analysis based on a higher

[5] *In some different aspects, studies in the field of financial economics analyze the various aspects of emission allowance markets (Hanif, Hernandez, Mensi, Kang, Uddin, and Yoon, 2021; Kim, Ahn, and Ryu, 2014; Kim, Park, and Ryu, 2017).*

frequency dataset) is important because air pollution emissions have large regional and seasonal impacts. The econometric model to test the effects of economic activities on air pollution is as follows:

$$P_{it} = \alpha + \beta_1 X_{it} + u_i + e_{it} \quad . \tag{1}$$

Here, P_{it}, the dependent variable, represents air pollution emissions in region *i* in month *t*. X_{it} is a vector of independent variables. The independent variables include socioeconomic activities known to cause air pollution in Korea, such as chemical product manufacturing, petroleum product manufacturing, diesel consumption, and the coal electricity trading volume. We also consider alternative energy, such as new and renewable energy (NRN) trading volumes, to reflect efforts to reduce air pollution. Regional weather factors, such as the number of precipitation days, are included as independent variables (Shim, Kim, Kim, and Ryu, 2015; Shim, Kim, and Ryu, 2017). u_i represents household fixed effects, and e_{it} is the error term.

The spatial panel model is used to consider spatial autocorrelation. It is confirmed that there is a spatial autocorrelation and time dependence in the dependent variable, and it is assumed that the dependent variable is also affected by independent variables in their neighboring areas. The panel Spatial Durbin model (SDM) is as follows:

$$P_{it} = \rho W_{ij} P_{jt} + \beta_1 X_{it} + \theta X_{jt} W_{ij} + u_i + e_{it}. \tag{2}$$

Here, the new parameters, θ and ρ, are the spatial autocorrelation coefficients. $\rho W_{ij} P_{jt}$ is the spatial dependence in the dependent variable. $\theta X_{jt} W_{ij}$, the spatial weighted effects of the independent variable in region *j* in month *t*. W_{ij}, the spatial weighted matrix.

Table 1 lists the variables used in the model. We use major public data to analyze the relationship between economic activities and air pollution levels. Air pollution index data are collected from AirKorea. In addition, data on economic activity are collected from the Korean Statistical Information Service and the Korea Meteorological Administration. To measure air pollution (*i.e*., the dependent variable), this study uses PM10 and PM2.5 data from AirKorea. Since December 2005, AirKorea has provided the most reliable air quality data to the public. The PM10 index refers to fine dust with a diameter less than 10/1000mm, and the PM2.5 index refers to fine dust with a diameter less than 2.5/1000mm. Data on both PM10 and PM2.5 emissions are released by the Korean Ministry of Environment on the AirKorea website. The variable of Chemicals is the manufacturing production index for chemical goods and chemicals, excluding pharmaceuticals. Petroleum is the manufacturing production index for coke, briquettes, and petroleum products. Diesel refers to the amount of diesel consumed by product and region. Coal refers to the electricity trading volume of bituminous and anthracite coal. The electricity trading volume of new and renewable energy is represented as NRN. In Korea, the term “new and renewable energy” means the sum of the words “new energy” and “renewable energy”. The term “new energy” refers to any energy that is converted from existing fossil fuels. The term “renewable energy” refers to any energy that is converted from renewable energy, including sunlight, water, geothermal energy, precipitation, biological organisms, etc. This definition comes from Article 2 of *the Act on the Promotion of the Development, Use and Diffusion of New and Renewable Energy (Act No. 17533)*.[6] It refers to eleven fields, including solar energy, bioenergy, wind energy, hydropower, fuel cells, coal liquefaction and gasification, heavy residual oil gasification,

[6] *Source: Korean Law Information Center (https://www.law.go.kr/LSW/eng/engMain.do).*

marine energy, waste, geothermal energy, and hydrogen. Rain is the number of precipitation days with daily precipitation of 0.1 mm or more in each region. The number of precipitation days is considered a variable, not the amount of precipitation. The reason is not how much rain has fallen, but because it is important to wash away particulate matter in the atmosphere due to rain.

Table 1. Variables of the Model

	Definition
PM10	Particulate matter 10 index (µg/m³)
PM2.5	Particulate matter 2.5 index (µg/m³)
Chemicals	Manufacturing production index of chemical goods and chemicals, excluding pharmaceuticals (2015=100)
Petroleum	Manufacturing production index of coke, briquettes, and petroleum products (2015=100)
Diesel	Diesel consumption by product and region (thousand barrels)
Coal	Electricity trading volume: bituminous and anthracite coal (MW)
NRN	Electricity trading volume: new and renewable energy total (MW)
Rain	Number of days with daily precipitation of 0.1mm or more by region (days)

Note: The first column shows the variables of the model. The second column (Definition) shows the definitions of each variable. Definition sources: AirKorea. Korean Statistical Information Service, and Korea Meteorological Administration.

Table 2 presents summary statistics for the variables used in this model.

Table 2. Descriptive Statistics

	Mean	Std. Dev.	Minimum	Maximum
PM10	40.62	11.97	15	79
PM2.5	22.68	7.05	9	47
Chemicals	111.74	44.34	0	433.2
Petroleum	74.15	54.53	0	266.2
Diesel	866.12	731.89	163	4,153
Coal	1,099.46	2,189.09	0	10,461.32
NRN	119.92	145.88	0.59	775.9
Rain	8.49	3.73	0	22.4

Note: The first column shows the variables of the model. The second column (Mean) shows the average of each variable, and the third column (Std. Dev.) shows the standard deviation of each variable. The fourth (Minimum) and fifth (Maximum) columns present the minimum and maximum values of each variable, respectively.

The mean values of PM10 and PM2.5 are 40.62 µg/m³ and 22.68 µg/m³, respectively. Fine dust has large seasonal and daily variations, meaning that the average over the entire period should be discussed carefully. However, the mean value of PM2.5 is above Korea's national ambient air quality standard (AAQS). Air quality standards are generally set by considering not only the WHO's limitations but also each country's local circumstances, such as its current pollution level, its social and economic development stages, political decisions, and technological aspects. The AAQS is based on the WHO's interim target as of 2005 and is 15 µg/m³ or less (yearly) and 35 µg/m³ or less (24-hour period) for PM2.5. The AAQS for PM10 is 50 µg/m³ or less (yearly) and 100 µg/m³ or less (24-hour period). The mean manufacturing production index (2015=100) of chemical goods and chemicals, excluding pharmaceuticals, is 111.74 per month. The mean manufacturing production index

(2015=100) of coke, briquettes, and petroleum products is 74.15 per month. The mean consumption of diesel by product and region is 866.12 thousand barrels per month. The mean trading volume of electricity coal power, defined as the sum of the bituminous and anthracite coal power trading volumes, is 1,099.46 MW per month. The mean new and renewable energy trading volume is 119.92 MW per month. The mean number of precipitation days is approximately eight per month.

4. Results

The dataset analyzed in our study contains observations on geographical areas. In this case, when the dependent variable is spatial data, it is appropriate to use the spatial analysis model as in several previous studies on environmental research (Anselin, 1988, 2001; Bockstael, 1996). Therefore, first, we use the traditional panel regression analysis. Second, the statistically significant spatial dependency or heterogeneity is confirmed through Pesaran's CD test. After that, we use the spatial econometric model in consideration of spatial correlation in order to expand the analysis.

Table 3 presents the results of the analysis to determine the effects of the factors on the levels of air pollution emissions, especially PM10 and PM2.5 emissions. First, we use the pooled ordinary least squares (OLS) model. According to the result of the Breusch-Pagan Lagrangian Multiplier (LM) test, the null hypothesis is rejected at the 1% significance level because the *p*-value is lower than 0.01 (PM10: LM test = 45.68, *p*-value = 0.000, PM2.5: LM test = 212.27, *p*-value = 0.000). Therefore, the panel model is the appropriate method, rather than using the pooled OLS. In addition, when there is no correlation between the error terms at all time t, and the variance of the error terms is all the same, the pooled OLS estimator becomes the best linear unbiased estimator (BLUE). According to the result of the likelihood ratio (LR) test, the null hypothesis is rejected at the 1% significance level because the *p*-value is lower than 0.01 (PM10: LR test = 32.75, *p*-value = 0.005, PM2.5: LR test = 73.47, *p*-value = 0.000). Therefore, there is heteroskedasticity in this panel data. We test whether PM10 and PM2.5 emissions contain a unit root for the panels using the IPS unit-root test. According to the unit-root test, the *p*-value corresponding to Z-t-tilde-bar is essentially zero, so we strongly reject the null hypothesis that all series contain unit roots. The panel data needs to identify the autocorrelation issue. If there is autocorrelation in the panel dataset, a bias occurs in the standard error, and the efficiency of the estimate decreases. The Wooldridge test is used to test the autocorrelation of panel data. According to the Wooldridge test for autocorrelation in panel data, the *p*-value is lower than 0.01 (PM10: Wooldridge F-test = 88.22, *p*-value = 0.000, PM2.5: Wooldridge F-test = 72.94, *p*-value = 0.000) and there is a first-order autocorrelation in panel data. If there are both heteroskedasticity and autocorrelation in panel data, the panel generalized least squares (GLS) should be used to obtain an efficient estimator. The second and third columns of Table 3 show the results of estimating pooled OLS and panel GLS models for PM10. The pooled OLS method shows that the manufacturing production index of chemical goods and chemicals, the amount of diesel consumed by product and region, and the electricity trading volume of bituminous and anthracite coal have statistically positive effects on PM10 emissions. Thus, PM10 emissions increase as these three variables increase. Both the electricity trading volume of new and renewable energy sources and the number of precipitation days by region have statistically significant effects on PM10 emissions. As the volume of new and renewable energy increases, PM10 emission level decreases. As the number of precipitation days increases, the PM10 emission level decreases, as well. However, the pooled OLS method has considerable limitations because this study analyzes panel data. The results of estimating the GLS model show that the manufacturing production index of chemical goods and chemicals has a statistically positive effect on PM10 emissions. Diesel consumption by product and region also has a statistically positive effect on PM10 emissions. That is, as both the manufacturing production index of chemical goods and diesel consumption increase, PM10 emissions increase. Additionally, the number of precipitation days per region is negatively associated with PM10 emissions. The electricity trading volume of new and renewable energy sources has a negative effect on PM10 emissions, but it is not statistically significant. In addition, neither the manufacturing production index of coke, briquettes, and petroleum products nor the electricity trading volume of bituminous and anthracite coal have statistically significant effects on PM10 emissions.

Table 3. Estimation results using panel data

	Pooled OLS (PM10)	GLS (PM10)	Pooled OLS (PM2.5)	GLS (PM2.5)
Chemicals	0.0278*** (0.0077)	0.0305** (0.0103)	0.0182*** (0.0046)	0.0150* (0.0060)
Petroleum	-0.0054 (0.0074)	0.0140 (0.0094)	0.0080* (0.0044)	0.0162** (0.0056)
Diesel	0.0024*** (0.0005)	0.0021* (0.0009)	0.0010*** (0.0003)	0.0012* (0.0006)
Coal	0.0007*** (0.0002)	0.0001 (0.0003)	0.0002 (0.0001)	-0.0000 (0.0002)
NRN	-0.0108*** (0.0031)	-0.0041 (0.0046)	-0.0052*** (0.0019)	-0.0033 (0.0027)
Rain	-1.3520*** (0.0929)	-0.8640*** (0.0746)	-0.6902*** (0.0558)	-0.4234*** (0.0420)
Constant	47.8238*** (1.3310)	41.7885*** (1.6328)	25.5345*** (0.7992)	22.3266*** (0.9352)
Observations	1,024	1,024	1,024	1,024

*Note: The first column shows the variables of the model. The second column shows the results of estimating the pooled OLS model for PM10. The third column shows the results of estimating the GLS model for PM10. The fourth column shows the results of estimating the pooled OLS model for PM2.5. The fifth column shows the results of estimating the GLS model for PM2.5. Standard errors are shown in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: AirKorea. Korean Statistical Information Service, and Korea Meteorological Administration, January 2016 to April 2021.*

The fourth and fifth columns of Table 3 present the results of estimating pooled OLS and GLS models for PM2.5, respectively. The pooled OLS results show that PM2.5 emissions increase clearly as the manufacturing production index of the chemical goods and chemicals, and the diesel consumption amount increase. PM2.5 emissions increase as the coke, briquette, and petroleum product manufacturing index increases with the pooled OLS model, as well. These three variables have statistically positive effects on PM2.5 with the pooled OLS model. The GLS analysis results of PM2.5 are slightly different from the pooled OLS results of PM2.5. The results of the GLS analysis show that PM2.5 emissions increase as the manufacturing production index of the chemical goods and chemicals increases. The diesel consumption and the manufacturing production index of coke, briquettes, and petroleum products have a statistically positive effect on PM2.5 emissions with the GLS model, as well. In summary, according to the GLS analysis results, the manufacturing production index of petroleum products affects not PM10 but PM2.5 emissions. The electricity trading volume of bituminous and anthracite coal does not statistically significantly affect both PM10 and PM2.5 emissions with the GLS model. The electricity trading volume of new and renewable energy sources has a negative effect on PM2.5 emissions, but it is not statistically significant. It contrasts with the fact that the electricity trading volume of new and renewable energy sources has a statistically significant effect on both PM10 and PM2.5 emissions according to the pooled OLS analysis results. The number of precipitation days has statistical effects on PM2.5 and these results are similar to that of PM10. As the number of precipitation days increases, PM2.5 emissions decrease.

Next, we expand our analysis by applying spatial econometrics. Although the panel GLS model describes the air pollution panel data, it ignores the spatial dependence among the units. Compared to the traditional regression analysis, the spatial panel model controls the spatial dependences. The spatial panel model explains the time series observations of spatial units more effectively. Air pollution is differentiated from other pollution in that it is transboundary pollution. That is, it is important to consider spatial relationships because air pollution is regionally dependent. Therefore, we analyze the data using a spatial panel model to reduce the error of estimation and increase accuracy through consideration of both time and spatial dependencies. Moran (1948) and Geary (1954) explain that there is a question of whether some phenomenon in an area (*e.g.*, country, states, etc.) occurs statistically independent of the neighboring areas, and it is essential to consider the geographical distribution. Moran's I is generally used to verify that spatial correlation exists. However, it is not an appropriate test for the panel data, so we use Pesaran's CD test (Pesaran, Ullah, and Yamagata, 2008; Pesaran, 2015). According to the result of the Pesaran's test of cross-sectional independence, the null hypothesis is rejected at the 1% significance level because the *p*-value is lower than 0.01 (PM10: Pesaran's test = 72.22, *p*-value = 0.000, PM2.5: Pesaran's test = 65.80, *p*-value = 0.000). Therefore, there is a cross-regional correlation in this panel data. In addition, we check cross-sectional independence using additional test such as Frees' test (PM10: Frees' test = 10.156, *p*-value = 0.0000, PM2.5: Frees' test = 9.01, *p*-value = 0.000). and Friedman's test (PM10: Friedman's test = 820.04, *p*-value = 0.000, PM2.5: Friedman's test = 775.90, *p*-value = 0.000). Both test results also show that there is a cross-regional correlation.

Through several tests, it is confirmed that the data set used in our study is spatial data with spatial autocorrelation. That is, the more spatially adjacent it is, the more similar the characteristics are and the higher the correlation is. Therefore, it is important to define the spatial neighborhood to estimate the spatial econometrics model, and the spatial proximity among regions is indicated by the spatial weighted matrix. There are two ways to define the spatial weighted matrix: spatial contiguity and spatial distance. First, we measure the spatial contiguity in the Queen method to define the spatial weighted matrix (W_a). The Queen method defines that the two regions are spatially adjacent to each other when the boundaries (sides or edges) of the two regions are shared. In this case, the weight in the spatial weighted matrix is 1. Otherwise, the weight in the matrix is 0. Equation (3) shows the spatial weighted matrix (W_a) using the Queen method. It is a 16 by 16 matrix and it contains one island which is called Jeju-do. There are three regions with the largest number of links: Chungcheongbuk-do, Gyeongsangbuk-do, and Gyeongsangnam-do.

$$W_a = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (3)$$

Second, we define the spatial weighted matrix (W_b) based on geographical distances among regions. Calculate the geographical distance between the centre of one region and the centre of another region, and construct a matrix using this calculated value instead of 0 and 1. In this case, it is possible to distinguish the difference in the degree of proximity, rather than being adjacent (0 and 1) between regions.

We estimate the panel SDM with spatial fixed effect to analyze the effects of economic activities on air pollution and the results are shown in Table 4. The panel SDM(a) and (b) show the estimation results using the spatial weighted matrix (W_a) and spatial weighted matrix (W_b), respectively. The spatial weighted matrix (W_a) is defined as the spatial contiguity in the Queen method and spatial weighted matrix (W_b) is defined based on geographical distances (km; kilometre).

Table 4. Spatial Durbin Model Results

	SDM (a) (PM10)	*SDM (b) (PM10)*	*SDM (a) (PM2.5)*	*SDM (b) (PM2.5)*
Chemicals	0.0026 (0.0043)	-0.0091** (0.0045)	-0.0020 (0.0029)	-0.0049 (0.0032)
Petroleum	0.0109*** (0.0039)	0.0168*** (0.0043)	0.0077*** (0.0026)	0.0155*** (0.0031)
Diesel	-0.0007 (0.0014)	-0.0004 (0.0016)	-0.0017* (0.0009)	-0.0021* (0.0011)
Coal	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0003 (0.0002)	-0.0004 (0.0002)
NRN	-0.0137*** (0.0025)	-0.0119*** (0.0026)	-0.0100*** (0.0017)	-0.0097*** (0.0019)
Rain	-0.2873*** (0.0893)	-0.4797*** (0.0641)	-0.0347 (0.0601)	-0.2082*** (0.0463)
W*Chemicals	-0.0119 (0.0084)	0.0711*** (0.0144)	-0.0026 (0.0057)	0.0401*** (0.0103)
W*Petroleum	-0.0113* (0.0060)	-0.0227*** (0.0084)	-0.0064 (0.0040)	-0.0144** (0.0061)
W*Diesel	0.0013	0.0007	0.0021**	0.0021

	SDM (a) (PM10)	SDM (b) (PM10)	SDM (a) (PM2.5)	SDM (b) (PM2.5)
	(0.0015)	(0.0025)	(0.0010)	(0.0018)
W*Coal	-0.0006 (0.0005)	-0.0001 (0.0011)	0.0005* (0.0003)	0.0011 (0.0008)
W*NRN	0.0130*** (0.0036)	0.0033 (0.0081)	0.0027 (0.0024)	-0.0007 (0.0059)
W*Rain	0.0572 (0.0984)	0.2376*** (0.0823)	-0.1178* (0.0661)	0.0470 (0.0595)
Spatial rho (ρ)	0.8578*** (0.0107)	0.8725*** (0.0116)	0.8126*** (0.0128)	0.8344*** (0.0152)
Log-likelihood	-3060.2607	-3026.7907	-2627.2338	-2678.5076
R-sq	0.2308	0.3622	0.2415	0.3599
Hausman test	212.60***	140.54***	104.21***	380.11***
Observations	1,024	1,024	1,024	1,024

*Note: The first column shows the variables of the model. The second column shows the results of estimating the SDM(a) with a spatial weighted matrix (W_a) and the third column shows the results of estimating the SDM(b) with a spatial weighted matrix (W_b) for PM10. The fourth column shows the results of estimating the SDM(a) with a spatial weighted matrix (W_a) and the fifth column shows the results of estimating the SDM(b) with a spatial weighted matrix (W_b) for PM2.5. The spatial weighted matrix (W_a) is defined based on spatial contiguity using the Queen method. The spatial weighted matrix (W_b) is defined based on geographical distances among regions. The first line describes each model. The second to sixth lines shows the direct effect of changes in dependent variables due to changes in each variable. Line seven to twelve shows the indirect effects considering spatial dependency. The thirteenth line shows the spatial dependence of each model. Standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: AirKorea, Korean Statistical Information Service, and Korea Meteorological Administration, January 2016 to April 2021.*

The SDM results show the spatial rho (ρ) of the SDM analysis for PM10 and PM2.5. The spatial rho (ρ) values for PM10 and PM2.5 in SDM(a) are 0.8578 and 0.8126, respectively. The spatial rho (ρ) values for PM10 and PM2.5 in SDM(b) are 0.8725 and 0.8344, respectively. All four rho (ρ) values are statistically significant, which means that the dependent variables, PM10 and PM2.5, have inter-regional effects. According to the spatial rho (ρ) values in Table 4, the analysis using the spatial weighted matrix (W_b) based on geographical distances more clearly shows the spatial effects than the spatial weighted matrix (W_a).

Table 4 shows that the manufacturing production index of petroleum products has a statistically positive effect on PM10 and PM2.5 directly. In direct effects, both PM10 and PM2.5 emission levels decrease as new and renewable energy volumes increase. In main effects, as the number of precipitation days increases, PM10 emission decreases. However, the PM2.5 emission level decreases as the number of precipitation days increase only in SDM(b). The number of precipitation days has a negative effect on PM2.5 emission level in SDM(a) but it is not statistically significant. Comparing Tables 3 and 4, it is confirmed the negative relationship between new and renewable energy volumes and air pollution emissions in both pooled OLS and SDM. However, the pooled OLS estimates are slightly underestimated as compared to SDM. That is, the new and renewable energy effects on air pollution are greater with spatial dependence. The GLS estimates are also slightly underestimated as compared to SDM but not statistically significant. The weather conditions, especially the number of precipitation days, on the other hand, are slightly overestimated by the GLS model. That is, the effect of precipitation days on air pollution is smaller with spatial dependence. Next, the indirect effects, that is the effect of a change in a specific variable on the dependent variable in an adjacent region, are derived by the SDM estimation. The manufacturing production index of the chemical goods and chemicals in one region increases the PM10 and PM2.5 emission levels in neighboring regions and it is statistically significant in the SDM(b). The diesel consumption and the trading volume of electricity coal power have statistically positive effects on the PM2.5 emission level in neighboring regions in the SDM(a). As the precipitation days increase, the PM2.5 emission level decreases in neighboring regions in the SDM(a). However, as the new and renewable energy volumes increase, the PM10 emission level increases in neighboring regions in the SDM(a). As the precipitation days increase, the PM10 emission level increases in neighboring regions in the SDM(b).

We estimate the panel Spatial autoregressive (SAR) model with spatial fixed effect to analyze the effects of economic activities on air pollution and the results are shown in Table 5. It shows that the manufacturing production index for coke, briquettes, and petroleum products increases both PM10 and PM2.5 emission levels using SAR(b).

Table 5. Spatial Autoregressive Model Results

	SAR (a) (PM10)	SAR (b) (PM10)	SAR (a) (PM2.5)	SAR (b) (PM2.5)
Chemicals	0.0040 (0.0043)	-0.0112** (0.0046)	-0.0017 (0.0029)	-0.0058* (0.0033)
Petroleum	0.0058 (0.0036)	0.0111*** (0.0038)	0.0065*** (0.0024)	0.0131*** (0.0027)
Diesel	-0.0001 (0.0012)	0.0006 (0.0013)	-0.0005 (0.0008)	-0.0008 (0.0009)
Coal	-0.0001 (0.0003)	-0.0002 (0.0003)	-0.0003 (0.0002)	-0.0003 (0.0002)
NRN	-0.0137*** (0.0025)	-0.0112*** (0.0026)	-0.0097*** (0.0016)	-0.0094*** (0.0019)
Rain	-0.2233*** (0.0393)	-0.3102*** (0.0408)	-0.1142*** (0.0260)	-0.1577*** (0.0290)
Spatial rho (ρ)	0.8518*** (0.0108)	0.8752*** (0.0108)	0.8129*** (0.0126)	0.8412*** (0.0137)
Log-likelihood	-3072.0004	-3047.9729	-2634.1816	-2691.3393
R-sq	0.2225	0.2218	0.2042	0.2377
Hausman test	37.04***	18.82***	72.56***	16.83**
Observations	1,024	1,024	1,024	1,024

*Note: The first column shows the variables of the model. The second and fourth columns show the results of estimating the SAR(a) with a spatial weighted matrix (W_a) for PM10 and PM2.5, respectively. The third and fifth columns show the results of estimating the SAR(b) with a spatial weighted matrix (W_b) for PM10 and PM2.5, respectively. The spatial weighted matrix (W_a) is defined based on spatial contiguity using the Queen method. The spatial weighted matrix (W_b) is defined based on geographical distances among regions (km; kilometer). Standard errors are shown in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: AirKorea, Korean Statistical Information Service, and Korea Meteorological Administration, January 2016 to April 2021.*

In addition, as the number of precipitation days, and electricity trading volume of new and renewable energy increase, both PM10 and PM2.5 emission levels decrease in neighboring regions using both SDM(a) and (b). The spatial rho values for PM10 and PM2.5 in SAR are statistically significant, which means that the dependent variables, PM10 and PM2.5, have inter-regional effects. According to the SAR results, both PM10 and PM2.5 emission levels decrease as new and renewable energy volumes increase. As the number of precipitation days increases, both PM10 and PM2.5 emission levels decrease in the SAR model. These results are similar to those of SDM.

To select the model, we perform the LR test and the Wald test. According to the result of the LR test, the null hypothesis is rejected at the 1% significance level because the *p*-value is lower than 0.01 (PM10: LR test = 23.48, *p*-value = 0.000, PM2.5: LR test = 13.90, *p*-value = 0.001). Therefore, the SDM is a statistically significant improvement in model fit. In addition, the SDM is a statistically significant improvement in model fit even according to a Wald test (PM10: Wald test = 23.91, *p*-value = 0.001, PM2.5: Wald test = 13.98, *p*-value = 0.030).

5. Conclusion

Environmental issues create inequity. Air pollution is caused by people who actively participate in economic activities, whereas socially disadvantaged people bear more of its costs. For example, purchasing a household air pollution filter or air purifier is costly, and some people must live or work in polluted environments without proper air pollution filters. For this reason, it is important to accurately identify the causes of air pollution and develop effective countermeasures. Nowadays, the emerging countries are constantly generating air pollution, as the developed countries in the past. Emerging countries have just begun to take an interest in the environmental issues. However, it is important to study air pollution in Korea, where particulate matter emissions are serious.

Findings from this study confirm that some economic activities affect air pollution. First, some economic activities, such as manufacturing of chemical products and chemicals, and diesel consumption increase both PM10 and PM2.5 emission levels according to the GLS estimates. The manufacturing index of coke, briquette, and petroleum product only affects the increase in PM2.5 emission level according to the GLS estimates. Second, both PM10 and PM2.5 emission levels in neighboring regions increase as the manufacturing of chemical products and chemicals increases using SDM(b). Diesel consumption also has a positive effect on PM10 and PM2.5 emission levels in neighboring regions but it has a statistically significant effect on only PM2.5 using SDM(a). Third, as the number of precipitation days increases, both PM10 and PM2.5 emission levels decrease according to the GLS, SDM(a), and (b) estimates. However, the number of precipitation days does not have a statistically significant effect on PM2.5 in the SDM(a). Finally, we forecast that both PM10 and PM2.5 levels will continue to increase unless an alternative to chemicals, diesel, and petroleum products can be identified. However, according to SDM(a) and (b), serious levels of pollution may not necessarily arise in the future, as using new and renewable energy lowers the levels of both PM10 and PM2.5. The Korean government announced a basic plan for renewable energy to respond to the climate crisis and aimed to achieve 10.3% renewable energy in 2025 and 14.3% renewable energy in 2030 (Korea Energy Agency, 2020). According to the Seoul metropolitan government, they are installing a ‘total energy station (TES)’ to charge electric vehicles and fuel cell vehicles using photovoltaics, and the municipal government is increasing financial investments for TES. Through these efforts, the government aims to reduce fossil fuels and increase the supply of new and renewable energy instead as part of the 'Seoul Vision 2030' which is one of the climate action plans. The plan is to increase the fraction of renewable energy supply from 4.3% (0.8GW) by 2021 to 21% (2.4GW) by 2030.[7] Thus, air pollution may decline in the future because the use of new and renewable energy is increasing in both developed countries in Europe and emerging countries in Asia.

A sound environment is not just an additional pleasure, but a goal that must be achieved to promote one's social welfare. Environmental damage imposes high social costs on both developed and developing countries through health spending. Thus, from a long-term perspective, an environmental impact assessment should be considered in establishing national policies. It begins with an understanding of the current status of countries suffering from serious air pollution. Thus, these findings may help to check whether atmosphere environmental regulations are properly designed to reduce air pollutants. In addition, these findings contribute to predicting the future levels of air pollutants.

Reference

Andrews, D.W.K., 2005. Cross-section regression with common shocks. *Econometrica*, 73(5), pp.1551-1585. https://doi.org/10.1111/j.1468-0262.2005.00629.x

Anselin, L., 1988. Spatial econometrics: Methods and models. *Boston: Kluwer Academic*. https://doi.org/10.1007/978-94-015-7799-1

Anselin, L., 2001. Spatial effects in econometric practice in environmental and resource economics. *American Journal of Agricultural Economics*, 83(3), pp.705-710. https://doi.org/10.1111/0002-9092.00194

Bai, J. and Ng, S., 2004. A panic attack on unit roots and cointegration. *Econometrica*, 72(4), pp.1127-1177. https://doi.org/10.1111/j.1468-0262.2004.00528.x

Bockstael, N.E., 1996. Modeling economics and ecology: the importance of a spatial perspective. *American Journal of Agricultural Economics*, 78(5), pp.1168-1180. https://doi.org/10.2307/1243487

Cho, S., Lee, C.K. and Kim, B., 2013. The impacts of air pollution on low birth weight. *Applied Economics Letters*, 20(3), pp.208-212. https://doi.org/10.1080/13504851.2012.689100

Chung, J., Kim, S.N. and Kim, H., 2019. The Impact of PM10 Levels on Pedestrian Volume: Findings from Streets in Seoul, South Korea. *International Journal of Environmental Research and Public Health*, 16(23), pp.4833. https://doi.org/10.3390/ijerph16234833

Elhorst, J.P., 2003. Specification and Estimation of Spatial Panel Data Models. *International Regional Science Review*, 26(3), pp.244–268. https://doi.org/10.1177/0160017603253791

Ersin, Ö. and Bildirici, M., 2019. Asymmetry in the Environmental Pollution, Economic Development and Petrol Price Relationship: MRS-VAR and Nonlinear Causality Analyses. *Romanian Journal of Economic Forecasting*, 22(3), pp.25-50.

Geary, R.C., 1954. The contiguity ratio and statistical mapping. *Incorporated Statistician*, 5(3), pp.115-146. https://doi.org/10.2307/2986645

Goodchild, M.F., Anselin, L., Appelbaum, R.P. and Harthorn, B.H., 2000. Toward spatially integrated social science. *International Regional Science Review*, 23(2), pp.139-159. https://doi.org/10.1177/016001760002300201

[7] *See the news of "Total Energy Stations for EV & FCV Charging with Photovoltaic Cell and Fuel Cell Systems" of Seoul Metropolitan Government (https://english.seoul.go.kr/total-energy-stations-for-ev-fcv-charging-with-photovoltaic-cell-and-fuel-cell-systems).*

Hanif, W., Hernandez, J.A., Mensi, W., Kang, S.H., Uddin, G.S., Yoon, S.M. 2021. Nonlinear dependence and connectedness between clean/renewable energy sector equity and European emission allowance prices. *Energy Economics*, 101, 105409. https://doi.org/10.1016/j.eneco.2021.105409

Im, K.., Pesaran, M.H. and Shin, Y., 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1), pp.53-74. https://doi.org/10.1016/S0304-4076(03)00092-7

Kang, H., Suh, H. and Yu, J., 2019. Does air pollution affect consumption behavior? Evidence from Korean retail sales. *Asian Economic Journal*, 33(3), pp.235-251. https://doi.org/10.1111/asej.12185

Kim, E., Ahn, Y., Ryu, D. 2014. Application of the carbon emission pricing model in the Korean market. *Energy and Environment*, 25(1), 63-78. https://doi.org/10.1260/0958-305X.25.1.63

Kim, J., Park, Y.J. and Ryu, D. 2017. Stochastic volatility of the futures prices of emission allowances: A Bayesian approach. *Physica A: Statistical Mechanics and its Applications*, 465, 714-724. https://doi.org/10.1016/j.physa.2016.08.036

Korea Energy Agency, and Ministry of Trade, Industry and Energy, 2020. New and renewable energy white paper 2020. pp.102-103. *Sejong: Ministry of Trade, Industry and Energy*. http://lod.nl.go.kr/resource/KMO202169495

Maddala, G.S. and Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics,* 61(S1), pp.631-652. https://doi.org/10.1111/1468-0084.0610s1631

Moon, H.R. and Perron, B., 2004. Testing for a unit root in panels with dynamic factors. *Journal of Econometrics*, 122(1), pp.81-126. https://doi.org/10.1016/j.jeconom.2003.10.020

Moran, P.A.P, 1948. The interpretation of statistical maps. *Journal of the Royal Statistical Society. Series B (Methodological)*, 10(2), pp.243-251. https://doi.org/10.1111/j.2517-6161.1948.tb00012.x

OECD, 2022. Environment at a Glance Indicators. *Paris: OECD Publishing.* https://doi.org/10.1787/ac4b8b89-en.

Pesaran, M.H. and Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), pp.79-113. https://doi.org/10.1016/0304-4076(94)01644-F

Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics,* 22(2), pp.265-312. https://doi.org/10.1002/jae.951

Pesaran, M.H., Ullah, A. and Yamagata, T., 2008. A bias-adjusted LM test of error cross-section independence. *Econometrics Journal*, 11(1), pp.105-127. https://doi.org/10.1111/j.1368-423X.2007.00227.x

Pesaran, M.H., 2015. Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, 34(6-10), pp.1089-1117. https://doi.org/10.1080/07474938.2014.956623

Phillips, P.C.B. and Sul, D., 2003. Dynamic panel estimation and homogeneity testing under cross section dependence. *Econometrics Journal*, 6(1), pp.217-259. https://doi.org/10.1111/1368-423X.00108

Phillips, P.C.B. and Sul, D., 2007. Transition modeling and econometric convergence tests. *Econometrica*, 75(6), pp.1771-1855. https://doi.org/10.1111/j.1468-0262.2007.00811.x

Rupasingha, A., Goetz, S.J., Debertin, D.L. and Pagoulatos, A., 2004. The environmental Kuznets curve for US counties: A spatial econometric analysis with extensions. *Papers in Regional Science*, 83(2), pp.407-424. https://doi.org/10.1111/j.1435-5597.2004.tb01915.x

Schweitzer, L. and Zhou, J., 2010. Neighborhood air quality, respiratory health, and vulnerable populations in compact and sprawled regions. *Journal of the American Planning Association*, 76(3), pp.363-371. https://doi.org/10.1080/01944363.2010.486623

Shim, H., Kim, H., Kim, J.Y. and Ryu, D. 2015. Weather and stock market volatility: The case of a leading emerging market. *Applied Economics Letters*, 22(12), 987-992. https://doi.org/10.1080/13504851.2014.993129

Shim, H., Kim, M.H. and Ryu, D. 2017. Effects of intraday weather changes on asset returns and volatilities. *Proceedings of Rijeka Faculty of Economics: Journal of Economics and Business*, 35(2), 301-330. https://doi.org/10.18045/zbefri.2017.2.301

Thai, T., Bernatik, A. and Kučera, P., 2021. Air Pollution Associated with Total Suspended Particulate and Particulate Matter in Cement Grinding Plant in Vietnam. *Atmosphere*, 12(12), pp.1707. https://doi.org/10.3390/atmos12121707

World Health Organization, 2006. Air quality guidelines: global update 2005. Particulate matter, ozone, nitrogen dioxide and sulfur dioxide. *Copenhagen: WHO Regional Office for Europe*. https://apps.who.int/iris/handle/10665/107823

World Health Organization, 2021. WHO global air quality guidelines: particulate matter (PM2. 5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. *WHO European Centre for Environment and Health*. https://apps.who.int/iris/handle/10665/345329

Yi, D. and Sung, J.H., Forthcoming. An environmentally related policy impact analysis considering wind effect: evidence from suspending old coal-fired generators in South Korea. *Applied Economics Letters*. https://doi.org/10.1080/13504851.2021.2005765