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Spatial Panel Analysis of Ambient Air Pollution in Korea*

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This study investigates the underlying drivers behind air quality pollution in Korea by using spatial panel analysis. Specifically, we consider the local and transboundary effects of economic, climatic, and geographical factors leading to the heightened presence of fine particulate matter (PM2.5). Furthermore, our study expands its scope beyond national boundaries to include an evaluation of external sources that contribute to elevated pollution levels within Korea. Consequently, this research adopts a multilevel approach to assess the within and outer factors of air pollution in Korea. Our analysis is based on a spatial panel dataset spanning all districts of Korea by incorporating satellite-based air pollution, meteorological, and geographic information for 2010–2016. Empirical results indicate that air pollution degrades the air quality in other cities and the overall national ambient pollution as well. Moreover, empirical results from the general nesting spatial (GNS) specification of spatial interaction suggest that the impacts of economic and climatic factors on air pollution are substantial. In addition, our analysis incorporates cross-country spatial effects of air pollution, which reveals a significant transboundary spillover effect. Furthermore, a deeper analysis of spatial heterogeneity underscores intriguing disparities in the impact estimates. Changes in domestic and foreign factors in the northwest region are linked to a more pronounced diffusion of pollution to multiple cities in contrast to the impacts originating from the southeast.

JEL Classification: C33, Q53, R11
Keywords: Air Pollution, GNS Model, PM2.5, Spatial Heterogeneity, Spillover Effects

I. Introduction

The global consensus within the international community underscores the

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substantial impact of atmospheric pollution on human health and global economic advancement. Accordingly, the Organization for Economic Co-operation and Development (OECD) launched the Green Growth Strategy in 2011. In adhering to the Green Growth initiative, the OECD has been providing possible policy frameworks to address environmental problems deemed as most threatening to the human population and promote member countries' progress toward economic development while ensuring the preservation of the environment. In particular, the OECD and many others have clearly acknowledged that air pollution is one of the key areas to be of high risk to the human population and the ecosystem (Hanna and Oliva, 2015; Deryugina et al., 2019; Eom and Oh, 2019; Yim et al., 2021; Yim and Seo, 2023). Accordingly, the OECD provides indicators that measure the extent of population exposure to particulate matter (PM2.5) and policy designs to improve air quality.

The degradation of ambient air quality is still highly persistent in spite of increased efforts to resolve air pollution at a global and national level. The international pollution level measured by PM2.5 is much higher than the World Health Organization (WHO) standard (10 $\mu g/m^3$). Notably, atmospheric pollution remains a serious issue in Korea. Driven by a combination of intense emissions from human activities, global warming, deforestation, and external pollution sources, air quality in Korea has been consistently surpassing the WHO standard since as early as 1990, as indicated by OECD Statistics in 2020.

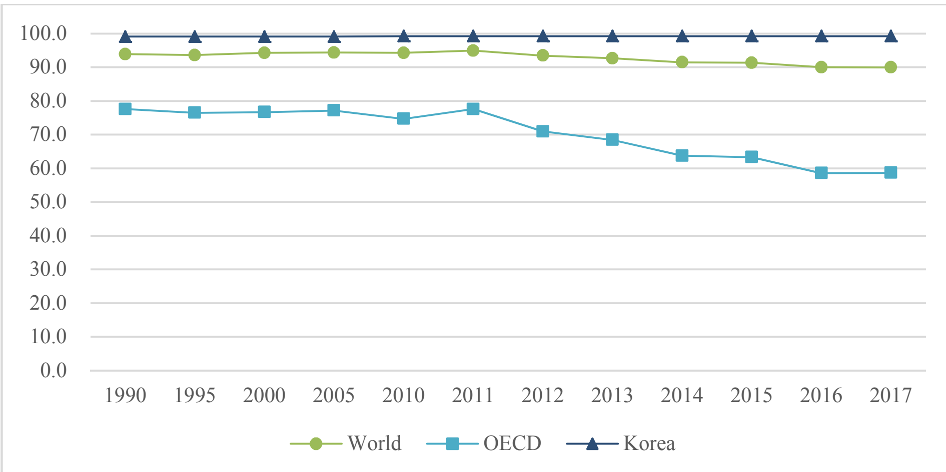
As illustrated in Figure 1, the trajectory of the population exposed to PM2.5 levels surpassing the WHO standard presents a concerning picture. Nearly 100 percent of the Korean population has remained consistently exposed to elevated levels of PM2.5. This number stands in stark contrast to those of other member nations of the OECD, where these figures have declined since 2011.

Amid growing concerns about environmental degradation, a substantial body of literature has extensively studied the factors driving air pollution dynamics (Grossman and Krueger, 1995). Earlier studies approached the subject by viewing different regions as discrete entities, which are isolated from pollution influences beyond their boundaries. However, a shift occurred as researchers highlighted the close connection between air pollution and spatial relationships (Henderson, 1977). Neglecting the geographical links arising from the diffusion of air pollution could potentially mislead the estimation of the relationship between air pollution and its contributing factors. Furthermore, the degree to which air pollution externalities contribute to observed pollution patterns must be explicitly assessed.

In response to these complexities, recent studies have made strides by incorporating interregional interactions into their analytical models, thus accounting for the potential alterations in pollution levels driven by spatial dynamics (Rupasingha et al., 2005; Maddison, 2007; Aklin, 2016; Marbuah and Amuakwa-Mensah, 2017). Our study builds upon this line of research by extending the exploration to employing spatial panel models (Anselin et al., 2008; Lesage and Pace, 2009; Elhorst, 2014; Kelejian and Piras, 2017). Through this approach, we endeavor to identify the intricate factors contributing to heightened pollution levels in Korea.

[Figure 1] Trends of Population Exposed to PM2.5 Higher than 10 $\mu g\ /\ m^3$

(Unit: %)



Note: Figure shows the percentage of population exposed to PM2.5. (Source: OECD Statistics).

National and local government decisions affect the extent to which air pollution is alleviated. For instance, the car-free weekdays policy has been implemented in metropolitan cities of Korea to decrease vehicle emissions during highly polluted seasons. Another attempt was experimenting with artificial rainmakers to wash out pollutants suspended in the atmosphere with water droplets. For such policies to be effective, the driving factors of regional air pollution must be confirmed. Understanding which factors most lead to high atmospheric pollution can assist policies aimed at restoring air quality and subsequently alleviate population exposure. Thus, the objective of this study is to assess the determinants of air pollution in Korea using the city-level regional data with a macroeconomic perspective.

However, assessing the leading factors of regional air pollution remains a challenge. The first complication pertains to accounting for the externalities of ambient pollution that arise from spatial connections between cities. Air pollutants that are generated from sources travel long distances depending on climate and geological conditions. In the case of Korea, pollution sources are concentrated in urban regions that are in the northwest of the peninsula. Meteorological conditions along with the urban landscape increases the suspension of air pollutants in the atmosphere. Through constant formation and suspension, the ambient level of air pollution rises, and once the wind blows from the northwest, it causes dispersions directed toward the south. Without accounting for such transboundary mechanisms of air pollution, estimations are potentially biased. More importantly, the impact of air pollution flowing in from other cities cannot be explicitly evaluated.

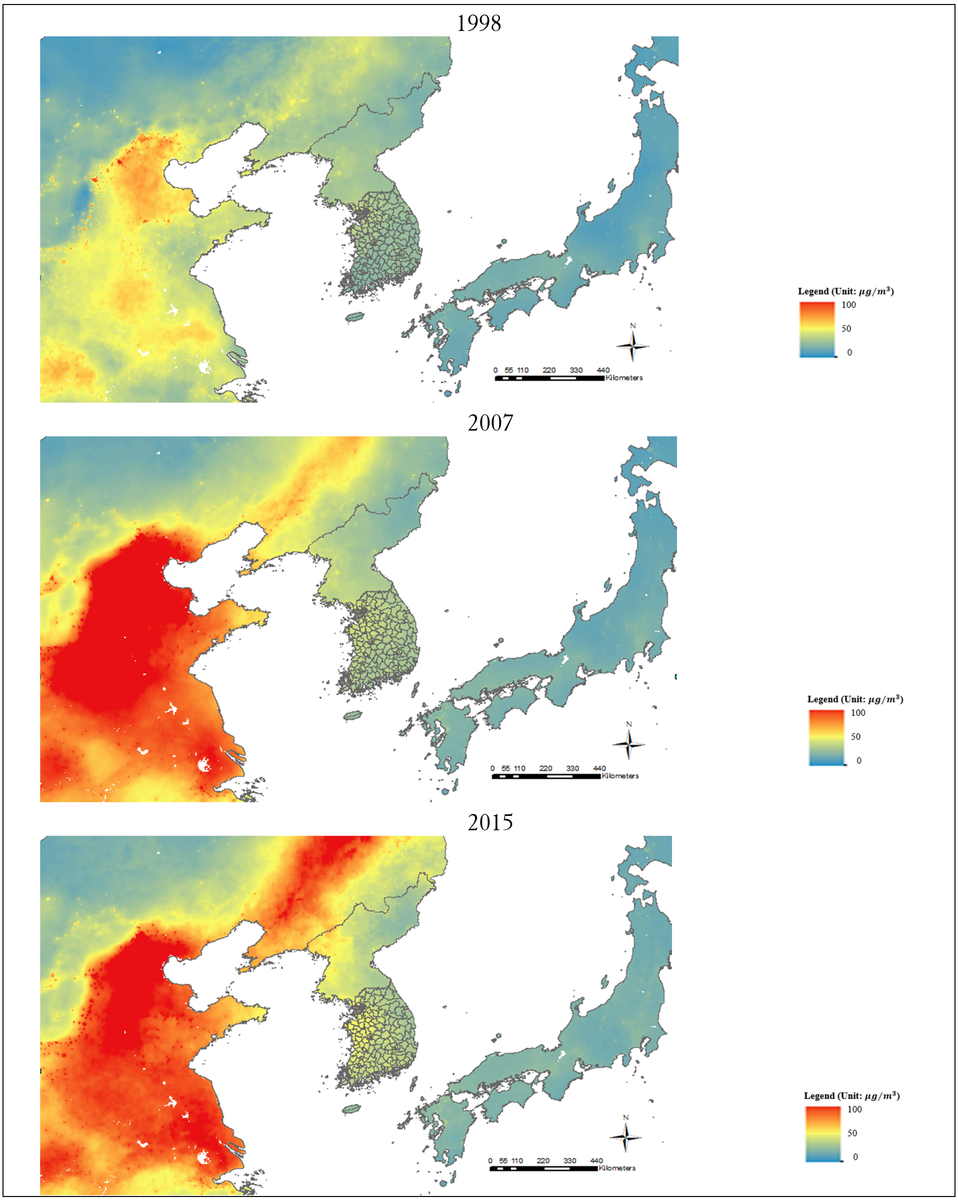
We conduct the first investigation of the cross-city and cross-country effects of driving factors on transboundary air pollution in Korea. We overcome the challenge discussed earlier by constructing a panel dataset covering 226 cities (all the cities except for three) of Korea for 2010–2016 by merging satellite-based information on domestic and foreign air pollution. PM2.5 is a major air pollutant known to have adverse health effects. However, most previous studies (Kang, 2019; Park et al., 2020) in the context of Korea estimate the determinants of PM10 rather than PM2.5. Ground-level measurements of PM2.5 in Korea have only been officially provided since 2015, making the data limited. Instead, we rely on satellite-based information of annual PM2.5 and construct an extensive panel dataset for a relatively long period starting from 2010. We merge this air pollution measurement with economic, weather, and geographic data for the 226 cities. With the use of this rich dataset, we were able to apply several specifications of the spatial panel model to find that high pollution levels in Korea are not only in close relation to domestic factors but with foreign factors as well.

Second, air pollutants emitted from the source site dissipate long distances supposedly having far-reaching impacts not only on cities within the national borders but also beyond those borders as well. Such international impacts of air pollution have appeared in some literature. You and Lv (2018) applied the spatial panel model to investigate the effects of economic development on carbon dioxide emissions in 83 countries. The study found that atmospheric pollution is increased by emissions from surrounding countries but is lowered by economic globalization. Another is the Korea-United States Air Quality (KORUS-AQ) field study, which employed ground and satellite observations to explain the factors of air quality in Korea. Along with the United States National Aeronautics and Space Administration (NASA), the National Institute of Environmental Research (NIER) provided model simulations of PM2.5. The simulation targeting Olympic Park in Seoul from May 10 to June 10 found domestic factors to be 52 percent, and foreign effects to be the rest. Park et al. (2020) assessed the direction and extent of the spillover effects between China and Korea using the time series data of PM10. As such, countries are spatially connected in terms of ambient air pollution, and Korea and nearby countries are no exception. This stylized fact calls for a comprehensive study that elicits not only domestic but also foreign factors leading to severe levels of atmospheric pollution in Korea.

Figure 2 shows the changes of PM2.5 from 1998 to 2015 in East Asian countries. While the map clearly shows an increase in atmospheric pollution in Korea, it also demonstrates the increase in pollution levels of nearby countries: China, Japan, and

North Korea. As revealed in previous scientific studies by KORUS-AQ, this map indicates the existence of foreign impacts in the ambient air pollution in Korea. This information calls for an empirical analysis for confirming the existence of such foreign effects with econometric models, an endeavor that would be of notable addition to the literature.

[Figure 2] Trends of PM2.5



Note: The map shows PM2.5 for each year as an annual average. Maps were created using GIS with data from van Donkelaar et al. (2018) retrieved from NASA Earthdata.

The third objective is to explore the spatial heterogeneity of domestic and foreign factors' effect on air pollution. We create spatial impulse response maps from the estimates of our main result to explore the heterogeneous impacts for domestic and foreign factors emanating from the northwest and southeast. We present a set of maps that display the diffusing impact to 226 cities from an initial increase of a factor from three northwest cities (Dangjin-si, Taean-gun, and Boryeong-si of Chungnam-do). We present another set of maps that show the diffusion of the impacts emanating from the southeast cities (Pohang-si, Changwon-si, and Ulsan-si). We find that for domestic and foreign factors, the impacts emanating from the northwest were more persistent in reaching other cities compared with impacts from the southeast. This difference was especially clear for the foreign factor.

Another contribution of this study is the empirical application of less restricted spatial models. Previous studies have applied spatial models that allow spatial interaction for the endogenous variable, exogenous variables, or at most both. However, in real-world situations, unobserved factors, such as unanticipated pollution policies or population migration, could also change the diffusion pattern of ambient air pollution. We apply the general nesting spatial (GNS) model, which allows for spatial interaction for all the terms, including the error term. We further provide implications by comparing our main results with those from more restricted spatial panel models: the spatial Durbin model (SDM) and the spatial Durbin error model (SDEM). We show that the GNS model outperforms other nested restricted models in identifying economic and weather factors' effect on air pollution.

Pioneering the spatial approach in air pollution research, Rupasingha et al. (2005) accounted for spatial dependence in the error term and examined the factors leading to an increase in toxic pollutants within the United States. They observed noteworthy spatial autocorrelation and enhanced estimates through their spatial model. Another endeavor that considered the relationship between cities within a country is Marbuah and Amuakwa-Mensah (2017), where PM10 and PM2.5 have been found to have positive transboundary impacts among low-income districts and negative impacts among high-income districts in Sweden.

Cross-country studies on the spatial impact of air pollution have also been conducted. Maddison (2007) explored the spatial effect of sulfur emissions among European countries using various spatial dependence specifications. The model considering the spatial dependence of emitted pollutants revealed a significantly positive spatial effect, thus indicating that increased air pollutants lead to an emission rise in neighboring countries. In addition, Aklin (2016) analyzed how trade contributes to carbon dioxide (CO2) emission transfer between nations by employing the spatial autoregressive (SAR) model. Their research identified significant CO2 diffusion between countries. Similarly, You and Lv (2018) employed a spatial panel model to examine the influence of economic interconnectedness on carbon dioxide emissions across different countries.

In the context of Korea, Lee et al. (2017) identified the determinant factors for PM2.5 of Seoul by using the spatial model with wind speed and direction. They linked changes in PM2.5 to wind speed and precipitation. Kang (2019) found significant spatial interactions between 16 districts for PM10 within Korea. Park et al. (2020) found significant cross-border PM10 pollution effects among Beijing, Shanghai, and Seoul. As such, the three topics—PM2.5, spatial models, and foreign externalities—have so far only been separately addressed. We will extend the realms of this research by dealing with the three important topics all at once.

This work distinguishes itself from the current line of studies mainly in two aspects. First, it is the pioneer in conducting a multilevel analysis to uncover air pollution factors. Unlike existing research that focuses on spatial relationships either within a country or across countries, our study uniquely reveals empirical outcomes connecting cities in Korea to foreign locations. We establish these multilevel links by moderately adjusting the spatial weight matrix of the conventional spatial panel model. Second, we enhance our analysis by incorporating air pollution data at a granular level using satellite-based georeferenced image datasets. By amalgamating this information with the regional climate and geographical attributes of spatial entities in our sample, we construct a comprehensive panel dataset encompassing nearly all Korean cities. This dataset empowers us to apply a spatially explicit model, thereby enabling us to unearth the cross-border repercussions of economic, climatic, and geological determinants that contribute to heightened atmospheric pollution. Furthermore, our research yields long-term insights into air pollution levels in foreign locations, thus confirming the presence of external factors impacting ambient pollution in Korea.

The paper is organized as follows. Section II elaborates on the spatial panel model employed in our research. Then, Section III provides details about the data. In Section IV, the main empirical results are presented, and Section V concludes.

II. Methodology

For our empirical analysis, our baseline model is the nonspatial panel specification with city-specific fixed effects as follows:

$$Y_{it} = X_{it}\beta + \mu_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the level of air pollution for city $i\,(i=1,2,\ldots,N)$ at year $t\,(t=1,2,\ldots,T)$, X_{it} includes the economic, climatic, and geographical factors related to air pollution, μ_i represents the city-specific fixed effect, ε_{it} is the purely stochastic error, and β captures the effect of each factor.

In the nonspatial panel model, however, the interregional spatial effects of ambient air pollution are not captured. Thus, we cannot identify the impact of domestic factors on transboundary air pollution in the nonspatial specification. For a spatial econometric analysis, the specification of spatial effects involves three types of interaction effects: the endogenous interaction effect, exogenous interaction effect, and interaction among the error terms (Elhorst, 2014). The endogenous interaction spatial effect is the effect of air pollution from other cities on city *i*'s air pollution. Exogenous interaction spatial effect is the effect of driving factors from other cities on *i*'s air pollution. The interaction effect of the error term is the spatial correlation among the error terms across different cities.

In our study, we apply the most general specification, the GNS model with all the three spatially interacted effects as in (2) (Elhorst, 2014; Lesage and Pace, 2009; Anselin et al., 2008).

$$Y_{it} = \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + \sum_{k=1}^{K} X_{itk} \beta_k + \sum_{k=1}^{K} \sum_{j=1}^{N} w_{ij} X_{jtk} \theta_k + \mu_i + u_{it}, \quad (2)$$
$$u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it},$$

where w_{ij} is the element of the spatial weight matrix, W_N, which is 1 if city *i* and *j* share borders or 0 otherwise, X_{jtk} is the economic, climatic, and geographic factor in city *j* where *K* is the total number of factors, ρ is the spatial effect of the endogenous interaction term, θ_k is the spatial effect of the exogenous interaction term, λ is the spatial effect of the interacted disturbance term, μ_i is the city fixed effect, and ε_{it} is the stochastic error. Following Anselin et al. (2008), the rows of the matrix are normalized, thus equalizing the impact from other cities on each city.

The GNS model can be rearranged and expressed for each t as (3).

$$Y_t = \rho W_N Y_t + X_t \beta + W_N X_t \theta + \mu + u_t, \quad (3)$$
$$u_t = \lambda W_N u_t + \varepsilon_t,$$

where Y_t is the $\mathrm{N} \times 1$ vector of air pollution at year t, W_N is the spatial weight matrix, X_t is the $\mathrm{N} \times K$ matrix of driving factors at year t, ε_t is the $\mathrm{N} \times 1$ vector of the error term, θ is the $K \times 1$ vector of the spatial interaction effect of covariates, and λ is the spatial effect of the error term.

Along with the GNS model, we estimate spatial panel models that are nested on the GNS model. For the SDM, we restrict the spatial interaction term $\lambda = 0$ by only allowing for spatial endogenous and exogenous interaction effects. The SDEM includes only the spatial interactions for the error term and exogenous variables with restriction $\rho = 0$ (Elhorst, 2014). The SAR model of Anselin et al. (2008) restricts the spatial error term $\lambda = 0$ and the spatial exogenous term $\theta = 0$. The nonspatial panel model (1) is a nested case with restriction $\lambda = 0$, $\theta = 0$, and $\rho = 0$.

To test whether applying the spatial panel model is valid for the spatial panel data in our study, we conduct specification tests, such as the likelihood ratio (LR) test. With the rejection of the restricted model at a statistically significant level, the explanation will improve when applying the spatial model. In addition, we apply the Akaike information criterion (AIC) and Bayesian information criterion (BIC) for model specification.

The GNS model has the potential problem of being weakly identified because it is overparametrized. However, in our analysis, the GNS model outperforms other restricted models because the spatial interaction terms significantly change the spatial effects, and the nested (restricted) models are rejected by the LR test (Elhorst, 2014).

Air pollution is supposedly increased by not only domestic but also foreign factors. Accordingly, we include factors from foreign sources that could lead to elevated atmospheric pollution. The extended GNS model with foreign air pollution is specified as (4).

$$\begin{aligned} Y_t &= \rho W_N Y_t + X_t\beta + W_N X_t\theta + Z_t\gamma + \mu + u_t, \\ u_t &= \lambda W_N u_t + \varepsilon_t, \end{aligned} \tag{4}$$

where Z_t is the distance-weighted foreign air pollution at time t, that is, $Z_t = \{m_{il} z_{lt}\}_{il}$. Here, z_{lt} denotes foreign air pollution in China, Japan, and North Korea, and m_{il} denotes the normalized inverse distance between city $i\,(i = 1,2,\ldots,N)$ and foreign site $l\,(l = 1,2,\ldots,L)$.

We are interested in the spatial effect parameters ρ, θ, and λ, the effect of each covariate on within-city air pollution β, and the foreign effects γ. These parameters are used to estimate the total marginal impact of each factor and the decomposition of the total marginal impact into indirect and direct impacts.

$$\begin{aligned} Y_t &= (I_N - \rho W_N)^{-1}[X_t\beta + W_N X_t\theta + Z_t\gamma + \mu + (I_N - \lambda W_N)^{-1}\varepsilon_t] \\ &= (I_N + \rho W_N + \rho^2 W_N^2 + \ldots)[X_t\beta + W_N X_t\theta + Z_t\gamma + \mu \\ &\quad + (I_N + \lambda W_N + \lambda^2 W_N^2 + \ldots)\varepsilon_t], \end{aligned} \tag{5}$$

where I_N is the identity matrix.

Taking the partial derivatives of (5) with respect to X_t and Z_t yields marginal impacts. Total marginal impacts can be decomposed into direct (local) and indirect (transboundary) impacts by using the decomposition of Lesage and Pace (2009) and Elhorst (2014). Direct impacts are the effects of the factor within the borders of the city on its own air pollution. Indirect impacts pertain to the impacts of factors from other cities, which is the average of the off-diagonal elements of the geometric series with the coefficients and the spatial effect.

[Table 1] Description of Variables

Variable			Description	Source
Air pollution		PM2.5	Annual mean PM2.5 ($\mu g / m^3$) of cities in Korea	NASA's Earth Observing System Data and Information System (EODIS), GIS
Domestic	Economic	Cars	Registered number of cars per person	Korea Statistical Information Services (KOSIS)
		Factory area	Area covered by factories / Total area (%)	KOSIS
		GRDP	GDP per capita of each district (Won, 2010 constant price)	KOSIS
		Coal power	Coal-fired power generated (TWh) × (1 / distance from city with power station in the Northwest) (Distance within 100 km)	Electric Power Statistics Information System (EPSIS), GIS
	Climatic	Temperature	Annual mean air temperature (Celsius)	NASA's EODIS, GIS
		Precipitation	Annual mean precipitation ($kg / m^2 /s$)	NASA's EODIS, GIS
		Wind speed	Annual mean wind speed (m/s)	NASA's EODIS, GIS
	Geographic	Tree cover	Area covered by tree canopy / Total area (%)	KOSIS
		City area	City area / Total area (%)	KOSIS
Foreign		PM2.5_1	Annual mean PM2.5 ($\mu g / m^3$) of all the cities of China	NASA's EODIS, GIS
		PM2.5_2	Annual mean PM2.5 ($\mu g / m^3$) of cities on the east-coast of China and same latitude as Korea	NASA's EODIS, GIS
		PM2.5_3	Annual mean PM2.5 ($\mu g / m^3$) of all the cities of Japan	NASA's EODIS, GIS
		PM2.5_4	Annual mean PM2.5 ($\mu g / m^3$) of all the cities of North Korea	NASA's EODIS, GIS

III. Data

Our dataset for spatial panel analysis encompasses 226 cities in Korea from 2010 to 2016. We retrieve satellite-based data on domestic and foreign air pollution (PM2.5) as well as air temperature, precipitation, and wind speed from NASA's Earth Observing System Data and Information System (EODIS). This dataset amalgamates information on air pollution, economic indicators, climatic variables, and geographic attributes. The specifics of the data and their origins are detailed in Table 1.

The selected sample period aligns with data availability. NASA's EODIS provides annual PM2.5 measurements from 1998 to 2016. Economic variables for all the domestic cities have been more recently gathered and reported starting from 2010.

3.1. Spatial Dependence of Air Pollution from Georeferenced Data

We obtain the satellite-based measurement of annual PM2.5 for domestic and foreign air pollution. NASA's database covers annual average PM2.5, which is produced from aerosol optical depth (AOD) measurements from Moderate Resolution Imaging Spectroradiometer (MODIS) and Multi-angle Imaging Spectroradiometer (MISR) satellites (van Donkelaar et al., 2018). Annual PM2.5 are reported as a georeferenced dataset covering all the countries at a spatial resolution of 0.01 degrees. We use GIS to retrieve annual PM2.5 for cities in Korea and foreign regions for 2010–2016 using GIS.

As Figure 3 shows, the increase in regional PM2.5 appears to have spread out from the northwest of Korea over the years. While domestic factors are concentrated in urban areas in the northwestern part of the peninsula, emissions from these sources appear to have diffused toward the south, thus possibly leading to higher levels of air pollution for the entire country.

In light of the spatial dynamics of air pollution and its transboundary property, we test for spatial dependence of PM2.5 between cities of Korea for 2010–2016 using Moran's I and Pesaran's CD statistic (Pesaran, 2004).

$$\text{Moran's I} = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right)\sum_{i=1}^{N}(y_i - \overline{y})^2},$$

$$\text{Pesaran's CD} = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij},$$

where T and N are the number of years and districts, respectively. Here, w_{ij} is the element of the spatial weight matrix, W_N, which is 1 if city i and j share borders or

0 otherwise, and $\hat{\rho}_{ij}$ is the estimated correlation coefficient of the residuals from the panel regression with fixed effects.

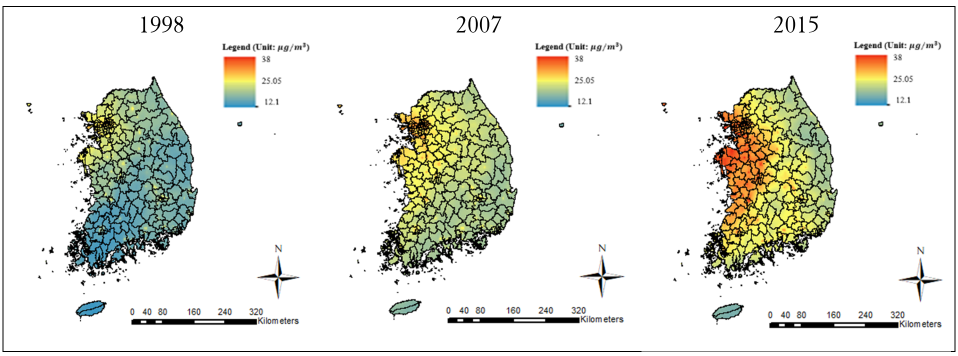
Table 2 reports the Moran's I and Pesaran's CD statistic. Moran's I statistic is close to 1 and significant across the years indicating that PM2.5 in neighboring cities are spatially correlated. In addition, Pesaran's CD statistic reveals significant spatial dependence for PM2.5 for domestic cities in the sample.

[Table 2] Moran's I and Pesaran's CD Statistics

	2010	2011	2012	2013	2014	2015	2016
Moran's I	0.917***	0.841***	0.915***	0.882***	0.924***	0.908***	0.904***
Pesaran's CD	384.436***						

Note: ***, **, and * denote significance at 1, 5, and 10 percent level, respectively.

[Figure 3] Trends in PM2.5 in Korea



Note: Maps show the PM2.5 as annual average and were created based on data from van Donkelaar et al. (2018) retrieved from NASA Earthdata.

3.2. Economic, Climatic, and Geographic Variables

For economic variables, we account for vehicle emissions with the number of registered cars because emissions from petroleum and diesel fueling cars are one of the major sources of PM2.5 emissions in Korea. The factory occupation rate is the percentage of area designated as industrial within each city. It is included as an indicator of emission from the manufacturing sector. We also include the gross regional domestic product (GRDP) as an indicator of the overall income of the city. Higher income can maintain low pollution levels with improved road pavement, environmentally favorable facilities, and public transportation. However, GRDP can also be a measurement of total production representing the density of manufacturing factories and population. The dataset on economic factors is retrieved from the Korea Statistical Information Systems (KOSIS).

To quantify the impact of the energy sector, we use emissions from the production of energy that is reported by the Electric Power Statistics Information

System (EPSIS). For cities where the power plants are built, the variable measures the total power generated by coal-fired power plants. As for cities located within a 100 km radius from cities with the power plants, we calculated the inverse distance-weighted sum of coal-fired power generated. Specifically, coal-fired power plants in the northwestern part of the peninsula[1] are considered because this region is where a major portion of total energy is produced.

Given that studies on air pollution have demonstrated its close association to meteorological conditions, we account for meteorological factors including precipitation, wind speed, and air temperature. Temperature measures the annual average air temperature, and precipitation measures the annual average precipitation rate. Given the wash-out effect of precipitation, air pollution is expected to decrease with increased precipitation. Wind speed is measured as the annual average rate possibly having two sided effects on air pollution. Stronger winds can redistribute internally produced air pollution to other cities, thus increasing the level of pollution in the neighbors. Alternatively, wind can transport externally emitted pollutants into the city, thus increasing local pollution. Data for meteorological factors are from NASA Global Land Data Assimilation System (GLDAS), which are provided at a temporal resolution of one month and spatial resolution of 0.25 degrees. For annual data, we average the monthly measurements across all the months for each city to obtain city-by-year measure.

For geographic factors, data on the percentage of area covered in tree canopy out of total area of the city are retrieved from KOSIS. Higher vegetation purifies the PM2.5 suspended in the atmosphere and can decrease within- and across-city pollution. City area consists of commercial and residential areas and is packed with high-level buildings and high population in limited land space. This variable is included because it is an indicator of the urbanization level in cities of Korea. Cities that are characterized by high urbanization are generally highly populated by vehicles and industrial facilities. High urbanization is also characterized by densely built skyscrapers in limited spaces in cities, which prevent wind from washing out the air pollutants suspended in the atmosphere. This characteristic can lead to high pollution levels.

For foreign sources, our initial attempt was to collect data on all relevant variables, such as air pollution, economic, meteorological, and geographic factors for each foreign country and apply the spatial panel model by including cities of Korea and foreign countries in our sample. However, we ran into difficulties attaining reliable sources for economic and geographic factors in foreign countries. Instead, the model includes the air pollution of foreign regions that are likely to be related to the

[1] The northwestern regions refer to Dangjin-si, Taean-gun, and Boryeong-si of Chungnam-do. Power plants are also located in Gangwon-do, Chunnam-do, and Gyeongnam-do. However, emissions from the far end of the northeast and southeast are more likely to be transported beyond the national borders because of the northwestern wind and highly elevated mountains in these regions.

formation of domestic atmospheric pollution.

The international cooperative field study by NASA and NIER traced air pollution in Korea back to its sources using geostationary satellite-based observations and back-trajectory analysis. According to their findings, high AOD in Korea traces back to pollution in east-central China but not northern China or Mongolia. To compare the impact of sources from China on transboundary air pollution, we use two measures. For the first measure, we average the annual PM2.5 across all the cities of China. The second measures the average of the annual PM2.5 level across the eastern coastal regions of China and on the same latitude as Korea. Moreover, air pollution in Korea traces back to regional contributions from North Korea, Japan, and the Yellow Sea. During the transport period that follows the stagnant period, AOD is transported from China to Korea and to Japan. To quantify the extent to which air pollution observed from these regions changes the dynamics of transboundary atmospheric pollution, we also include the annual measure of PM2.5 for Japan and North Korea. Each measure of foreign pollution is spatially lagged with the spatial weight matrix of the foreign region. For instance, spatial weights in the matrix of eastern China are measures of the inverse distance between the centroid of the merged polygon of eastern China and each of the 226 cities in Korea.

IV. Main Results

4.1. Driving Forces of Air Pollution

Table 3 reports the estimation results of the spatial and nonspatial panel model of the relationship between air pollution and domestic factors. Panel A shows results for the coefficients of the spatial interaction terms. Panel B shows the direct effects of the variables that are not spatially interacted. Columns 1–3 show the results estimated with the GNS model, SDM, and SDEM, respectively. Column 4 provides estimates stemming from the nonspatial panel model, which is devoid of any spatial effects. The interpretation of marginal impacts for each driving factor will be deferred for a later discussion given that the coefficients presented here lack direct interpretability as marginal effects. However, we must note the implications arising from changes in the estimates as we progressively integrate additional spatial interactions into the model.

Three notable points arise. First, the positive and significant spatial impact of air pollution holds true across all spatial panel models: GNS, SDM, and SDEM. As illustrated by Panel A of columns 1 and 2, the endogenous interaction effect, or the spatial effect of PM2.5, is positive and statistically significant. In column 1, a 1 percent increase in PM2.5 level is associated with a 0.549 percent increase in ambient pollution in other cities. In addition, the coefficient of spatial error dependence is also positive and significant. Furthermore, the exogenous interaction effects of registered cars and emission from coal-fired power plants are positive and statistically significant.

[Table 3] Spatial and Nonspatial Panel Models with Domestic Factors

		(1) GNS	(2) SDM	(3) SDEM	(4) None
Panel A. Spatial Interaction					
Air pollution	ρ (SAR)	0.549***	0.843***		
		(0.109)	(0.010)		
	λ (SEM)	0.618***		0.852***	
		(0.098)		(0.010)	
Economic	Cars	0.111***	−0.015	0.176***	
		(0.042)	(0.023)	(0.036)	
	Factory area	0.026*	0.022*	0.020	
		(0.015)	(0.013)	(0.016)	
	GRDP	−0.016	−0.029	−0.001	
		(0.027)	(0.022)	(0.027)	
	Coal power	1.624**	−0.425	2.901***	
		(0.843)	(0.382)	(0.879)	
Climatic	Precipitation	0.324***	0.465***	0.089*	
		(0.061)	(0.026)	(0.052)	
	Wind speed	0.214***	0.255***	0.103	
		(0.052)	(0.034)	(0.074)	
	Temperature	−0.717***	−1.030***	−0.106	
		(0.143)	(0.075)	(0.132)	
Geographic	Tree cover	0.009	0.001	0.009	
		(0.008)	(0.006)	(0.009)	
	City area	−0.008	−0.008*	−0.007	
		(0.005)	(0.005)	(0.005)	
Panel B. Direct Effects					
Economic	Cars	0.161***	0.115***	0.191***	0.315***
		(0.027)	(0.018)	(0.026)	(0.040)
	Factory area	0.008	0.001	0.008	0.054***
		(0.009)	(0.007)	(0.009)	(0.017)
	GRDP	0.009	0.015	0.014	−0.024
		(0.015)	(0.013)	(0.016)	(0.031)
	Coal power	1.689***	1.670***	1.891***	4.576***
		(0.265)	(0.259)	(0.259)	(0.460)
Climatic	Precipitation	−0.560***	−0.549***	−0.551***	−0.520***
		(0.023)	(0.023)	(0.022)	(0.023)
	Wind speed	−0.249***	−0.259***	−0.243***	−0.121***
		(0.029)	(0.028)	(0.028)	(0.035)
	Temperature	0.953***	1.083***	0.980***	0.526***
		(0.068)	(0.067)	(0.067)	(0.075)

Geographic	Tree cover	0.002	0.002	0.003	−0.001
		(0.003)	(0.003)	(0.003)	(0.006)
	City area	0.000	−0.001	−0.000	0.001
		(0.001)	(0.001)	(0.001)	(0.003)
Groups	226	Year	7	N	1,528

Note: Standard errors are in parentheses. ***, **, and * denote significance at 1, 5, and 10 percent, respectively.

Second, the driving forces of air pollution, such as registered cars and emission from coal-fired power plants, involve positive and significant coefficients. The estimation of the GNS model evidences spatial interaction effects in Panel A as well as the direct effects of registered cars and coal-fired power in Panel B. Comparing Panel A of columns 1 and 3 with that of column 2, the estimate of spatially interacted registered cars and emission from coal-fired power plants becomes positive and statistically significant as we allow unobserved factors to be spatially correlated. This outcome implies that we have some omitted factors, such as unanticipated environmental policy changes targeting economic activities, that are related to improved air quality. Consistent with the situation where cross-city air pollution changes in the same direction, the positive estimate of the error term implies that determinants of air pollution omitted from the model follow a positive spatial pattern (Elhorst, 2014).

The climatic factors, such as precipitation and wind speed, involve negative and significant coefficients. Meanwhile, the climatic factor of temperature entails positive and significant coefficients. Thus, the direct effects in Panel B show that precipitation and wind speed are related to lower pollution and temperature with higher pollution. The spatial interaction effects of meteorological factors are not better identified with the spatial interaction of the error terms but instead with the spatial term of the autoregressive process (Panel A). This outcome suggests that the diffusion of air pollution from and to other cities is closely related with meteorological conditions, specifically as shown by the intensification of the estimates in Panel A of columns 1 and 2. The geographic factors, such as tree cover and city area, do not show significance.

Third, as in Table 4, the LR test rejects each nested (restricted) model with respect to the GNS model. The AIC and the BIC of the GNS model indicate model relevancy compared with other spatial models and the nonspatial model. The reason above and these indicators validate the use of the GNS model in assessing the leading determinants of air pollution in Korea. Thus, we hereafter resort to the GNS model for presenting the main empirical results.

Next, we estimate the marginal impact for each of the domestic factors. Table 5 reports the total marginal impacts for each model. In Table 6, we decompose marginal impacts into indirect and direct impacts and calculate the percentage of the direct/indirect impact of each variable relative to its total impact. Panel A reports the indirect impacts and Panel B shows the direct impacts.

[Table 4] Model Specification

	Log-likelihood	LR test	AIC	BIC
(1) GNS	2,241.580		−4,441.159	−4,328.464
(2) SDM	2,223.509	36.142 [0.000]	−4,407.017	−4,299.688
(3) SDEM	2,221.487	40.186 [0.000]	−4,402.975	−4,295.646
(4) None	1,564.805	1,535.550 [0.000]	−3,109.609	−3,055.945

Note: The p-values are in square brackets.

Table 5 shows that a 1 percent increase in registered cars per person is associated with a 0.315–0.557 percent increase in overall air pollution. The positive relationship is more pronounced when including the spatial effects of observed air pollution and its unobserved error dependence, particularly the endogenous spatial interaction term. This correlation suggests that emissions from vehicles have strong positive impacts on air pollution in other cities, thereby having stronger transboundary impacts than local impacts (Table 6).

Table 5 reports that a 1 percent increase in emissions from coal-fired power plants in the northwestern region is associated with a 4.381–6.974 percent increase in air pollution. This relationship becomes stronger as we account for the spatial effects of air pollution across cities. Even though the spatial effect of coal-fired emissions is highest for the SDEM (Table 3), the total marginal impact is highest when we allow for the cross-city correlation of endogenous air pollution (Table 5). This outcome suggests that an increase in coal-fired emissions have implications for air pollution in faraway locations as emissions accumulate and diffuse through transboundary air pollution, the endogenous air pollution channel. As illustrated in Table 6 Panel A, the indirect impacts of the GNS model and the SDM are about 1.7-1.9 times that of the SDEM without the spatial autoregressive channel. In addition, we find that the indirect impacts are higher than the direct impacts for all the models. A 1 percent increase in emission from coal-fired power plant is associated with a 1.891–2.241 percent increase in air pollution for cities within 100 km of northwestern cities with power plants and a 2.490–4.640 percent increase in air pollution for other cities.

Estimates for factory area and GRDP show no significant correlation with within- and cross-city air pollution. GRDP can be an indicator of income and production of the city, and both effects are represented by the ambiguous direction of the coefficient. Furthermore, the relationship between air pollution and factory area and GRDP may be absorbed by the strong relationship between air pollution and emissions from registered cars and coal-fired power plants.

As for the climatic factors, Table 5 reports that a 1 percent increase in precipitation is related to 0.475–0.538 percent decrease in air pollution. The direct impacts are stronger than the indirect impacts as in Table 6. This result suggests that while precipitation is related to lower average air pollution observed throughout the year, this wash-out effect is limited to within-city pollution having almost no effect for pollution in other cities. Moreover, increase in wind speed is associated with lower within-city air pollution but higher cross-city pollution. Higher wind speed is likely to carry air pollutants to neighboring cities, thus leading to leading to decreased within-city pollution and increased pollution in other cities. Air temperature appears to be positively associated with air pollution, thereby suggesting that when coupled with global warming, air pollution may further increase in the long run.

[Table 5] Marginal Impacts of Domestic Factors

		(1) GNS	(2) SDM	(3) SDEM	(4) None
Total Impacts					
Economic	Cars	0.539***	0.557***	0.342***	0.315***
		(0.098)	(0.131)	(0.053)	(0.040)
	Factory area	0.065	0.123*	0.026	0.054***
		(0.042)	(0.075)	(0.020)	(0.017)
	GRDP	−0.013	−0.074	0.012	−0.024
		(0.071)	(0.122)	(0.036)	(0.031)
	Coal power	6.519***	6.974***	4.381***	4.576***
		(1.235)	(1.507)	(0.825)	(0.460)
Climatic	Precipitation	−0.527***	−0.538***	−0.475***	−0.520***
		(0.052)	(0.058)	(0.046)	(0.023)
	Wind speed	−0.102	−0.065	−0.154**	−0.121***
		(0.081)	(0.096)	(0.064)	(0.035)
	Temperature	0.584***	0.448**	0.888***	0.526***
		(0.177)	(0.208)	(0.132)	(0.075)
Geographic	Tree cover	0.022	0.014	0.011	−0.001
		(0.018)	(0.030)	(0.009)	(0.006)
	City area	−0.015	−0.048*	−0.006	0.001
		(0.012)	(0.029)	(0.005)	(0.003)

Note: Standard errors are in parentheses. ***, **, and * denote significance at 1, 5, and 10 percent.

Table 6 provides the decomposition of marginal effects to assess the extent to which transboundary (indirect) impacts are accountable for the total change in air pollution. The fraction of local (intracity) impacts out of the total marginal impacts is higher for economic and geographic driving factors but not for meteorological determinants. As such, the rise in air pollution is contributable in part to climate factors within the city. However, economic and geographic factors from neighboring cities appear to be more substantial in the formation of ambient atmospheric pollution.

[Table 6] Decomposition of the Marginal Impacts: Indirect and Direct Impacts

		(1) GNS		(2) SDM		(3) SDEM	
		Coeff.	%	Coeff.	%	Coeff.	%
Panel A. Indirect Transboundary Impacts							
Economic	Cars	0.335***	0.62	0.386***	0.69	0.151***	0.44
		(0.078)		(0.109)		(0.031)	
	Factory area	0.050	0.78	0.106*	0.87	0.017	0.68
		(0.032)		(0.063)		(0.014)	
	GRDP	−0.019	1.45	−0.078	1.05	−-0.001	−0.09
		(0.053)		(0.103)		(0.023)	
	Coal power	4.278***	0.66	4.640***	0.67	2.490***	0.57
		(1.062)		(1.324)		(0.754)	
Climatic	Precipitation	0.029	−0.05	0.009	−0.02	0.076**	−0.16
		(0.047)		(0.053)		(0.044)	
	Wind speed	0.130*	−1.28	0.170**	-2.62	0.088	−0.57
		(0.073)		(0.088)		(0.063)	
	Temperature	−0.326**	−0.56	-0.555***	−1.24	−0.091	−0.10
		(0.154)		(0.185)		(0.114)	
Geographic	Tree cover	0.017	0.79	0.011	0.76	0.008	0.70
		(0.014)		(0.025)		(0.008)	
	City area	−0.013	0.89	-0.041*	0.86	−0.006	1.00
		(0.010)		(0.025)		(0.004)	
Panel B. Direct Local Impacts							
Economic	Cars	0.204***	0.38	0.171***	0.31	0.191***	0.56
		(0.029)		(0.027)		(0.026)	
	Factory area	0.014	0.22	0.016	0.13	0.008	0.32
		(0.011)		(0.013)		(0.009)	
	GRDP	0.006	−0.45	0.004	−0.05	0.014	1.09
		(0.020)		(0.022)		(0.016)	
	Coal power	2.241***	0.34	2.334***	0.33	1.891***	0.43
		(0.297)		(0.303)		(0.259)	
Climatic	Precipitation	−0.556***	1.05	−0.548***	1.02	−0.551***	1.16
		(0.022)		(0.022)		(0.022)	
	Wind speed	−0.232***	2.28	−0.235***	3.62	−0.243***	1.57
		(0.028)		(0.027)		(0.028)	
	Temperature	0.910***	1.56	1.003***	2.24	0.980***	1.10
		(0.067)		(0.067)		(0.067)	
Geographic	Tree cover	0.004	0.21	0.003	0.24	0.003	0.30
		(0.004)		(0.005)		(0.003)	
	City area	−0.002	0.11	−0.006	0.14	−0.000	0.00
		(0.002)		(0.004)		(0.001)	

Note: Standard errors are in parentheses. ***, **, and * denote significance at 1, 5, and 10 percent, respectively.

4.2. Extended GNS Model with Foreign Air Pollution

We further extend the GNS model to incorporate the transboundary impacts of foreign air pollution. Table 7 shows the estimation of the extended GNS model with foreign air pollution as measured by the spatially lagged PM2.5 of each foreign region.

Columns 1–3 in Table 7 display the estimates of the GNS model, equation (4), for the spatial interactions of endogenous air pollution, error term, exogenous interaction, and foreign air pollution. Column 1 shows the estimates when $L = 3$, and columns 2–3 are estimates when $L = 1$.

Our analysis incorporates cross-country spatial effects of air pollution, which reveals significant transboundary spillover effect. The positive transboundary impacts appear robust to specifying foreign variables as pollution from all cities of China (Column 3), east coast cities of China (Column 2), and all the cities of Japan and North Korea along with east coast cities of China (Column 1). As we add the cross-border effects of foreign air pollution, a 1 percent increase in PM2.5 is associated with a 0.289–0.628 percent increase in air pollution from neighboring cities.

Air pollution blown from foreign countries is expected to increase the positive correlation of cross-city air pollution. In Panel A of Table 7, the spatial effect of the endogenous and error terms are significantly positive. Given that the exogenous spatial effect of pollution from foreign countries is negative as in Panel A, including more foreign air pollution strengthens the positive relationship of transboundary air pollution between domestic cities.

Table 7 shows that an increase in registered cars is related with more air pollution within and across cities. However, the spatial (0.121 and 0.235 in Panel A) and nonspatial (0.163 and 0.259 in Panel B) effects are substantially larger in columns 2 and 3 compared with when we include all foreign air pollution as in column 1 (0.065 in Panel A; 0.095 in Panel B). This outcome suggests that air pollution from foreign sources surrounding the Korean peninsula enhances the correlation between vehicle emissions and air pollution within individual cities and across different cities. This trend is also consistent for factory area, where the spatial and direct effect, although small, also decreases as we account for pollution from more foreign sources. This pattern is as expected because cities with a high number of registered cars and factory area are located near the northwestern and southeastern coasts of the peninsula, which also happen to be near foreign sources of air pollution. Other variables, such as weather and geographic factors, do not lend significant support to this implication of the main results.

As we include cross-border effects, the results indicate a notable decrease in the magnitude and significance of the exogenous spatial effect and the direct effect of coal-fired emissions. Relative to the estimates of the domestic GNS model in Table 3, isolating foreign sources from the energy sector suggests that these effects become mitigated. This trend is particularly evident in Chungnam cities with energy facilities because they are located downwind from foreign regions, especially China.

To facilitate a comparison between the marginal impact of emission from coal-fired power plant and foreign sources, we first highlight the difference in the spatial interaction and direct effect of these two. Columns 1–3 of Panel A in Table 7 show that an increase in emission from coal-fired power plants in cities that are within 100 km of Chungnam cities is associated with higher PM2.5 in neighboring cities.. However, the positive relationship between emissions from coal-fired power plants and air pollution for cities within 100 km of Chungnam cities is weaker as shown in Panel B. For instance, in column 2, the spatial interaction term of coal-fired power plants is 1.205, and the direct effect is 0.373. A different pattern appears for foreign sources. Foreign air pollution appears to be positively associated with within-city PM2.5 but negatively associated with cross-city PM2.5. The spatial interaction is estimated as −0.602–−0.280 (Panel A), and the direct effect is estimated as 0.243–1.536 (Panel B). Overall, these comparisons suggest that the increase in within-city PM2.5 is explained by foreign sources rather than emission from coal-fired power plants. After the first-order impact, a significantly positive diffusion from coal-fired power emissions occurs. The concern for this result is that the annual data deter us from disaggregating the effect for these two variables across months because foreign-induced pollution varies by season. Nevertheless, the result implies that emissions from coal-fired power plants appear to diffuse throughout the year while pollution from foreign sources do not. This trend will be discussed later as we explore the heterogeneous impacts on each city from an increase of domestic and foreign sources in the northwest and southeast cities.

Comparing domestic and extended GNS models, we find that adding foreign air pollution significantly improves the explanatory power of the GNS model. As more relevant foreign sources are added to the GNS model, there will be a larger increase in transboundary air pollution blown from other cities.

Furthermore, while the initial impact from foreign air pollution is associated with more severe air pollution, the diffusion of foreign-induced effect does not appear to be positively associated with domestic air pollution. This pattern is especially strong for PM2.5_3, or the air pollution from Japan. We return to this point when we discuss the decomposition of the marginal impact and the impulse response from foreign sources.

Next, we estimate the marginal impact of each variable on PM2.5. Table 8 presents the total marginal impact of economic and foreign factors, and Table 9 reports the decomposed indirect impact in Panel A and direct impact in Panel B. We also calculate the percentage of the direct/indirect impact of each factor relative to its total marginal impact.

Panel A of Table 9 shows that 64–79 percent accounts for cross-city effect of factory area and that rest is from within-city effect as in Panel B. This outcome is consistent with the estimate of the spatial interaction term of factory area in Table 7, where the spatial effect is about double the direct effect. However, the indirect transboundary impact of the factory area is more than twice the direct local impact, which is again attributable to the nationwide diffusion of factory emissions from the spatial autoregressive channel.

Notably, columns 1–3 in Table 8 present that the increase in emissions from coal-fired power plants in cities within 100 km is associated with higher air pollution overall. While this outcome is consistent with the trend, one caveat emerges: the positive relationship is largest for column 2. Given that east-coast China is geographically close to northwestern Chungnam cities, the impact from coal-fired power plants in this region may be overstated. The estimate decreased from 6.519 (Table 5) to 2.990 (Table 8) because the extended GNS model involves foreign air pollution in east-coast China that partly explains the overestimation of the coal-fired power plant emissions effect in Korea.

For foreign factors, column 1 of Table 8 shows that a 0.571 percent increase in overall air pollution is related to a 1 percent increase in pollution in east-coast China. This outcome is the sum of indirect transboundary impact (0.222 as in Table 9 Panel A) and direct local impact (0.349 as in Table 9 Panel B). For pollution from Japan, the total marginal impact shows that its contribution is a 0.214 percent increase in domestic pollution overall. However, in contrast to east-coast China, the indirect transboundary impact is negative (−0.300 as in Table 9 Panel A), and the direct local impact is positive (0.514 as in Table 9 Panel B). We can assume higher-order impacts will occur after the initial impact from China, which diffuses to other cities located downwind of northwestern Korea. Meanwhile, the initial spontaneous impact from Japan will not diffuse to other cities of Korea. This trend is further illustrated in the spatial impulse response examples in Section 4.3.

[Table 7] Extended GNS Model with Foreign Air Pollution

		(1) GNS F1	(2) GNS F2	(3) GNS F3
Panel A. Spatial Interaction				
Air pollution	ρ (SAR)	0.628***	0.541***	0.289***
		(0.109)	(0.091)	(0.078)
	λ (SEM)	0.425***	0.547***	0.688***
		(0.154)	(0.094)	(0.047)
Economic	Cars	0.065**	0.121***	0.235***
		(0.030)	(0.036)	(0.030)
	Factory area	0.015	0.024**	0.036***
		(0.010)	(0.012)	(0.012)
	GRDP	−0.004	−0.009	0.015
		(0.016)	(0.021)	(0.021)
	Coal power	0.352	1.205**	0.792
		(0.353)	(0.529)	(0.554)

Climatic	Precipitation	0.109***	0.176***	0.157***
		(0.029)	(0.045)	(0.033)
	Wind speed	−0.010	0.122***	0.137***
		(0.030)	(0.038)	(0.045)
	Temperature	−0.148**	−0.689***	−0.558***
		(0.071)	(0.086)	(0.125)
Geographic	Tree cover	−0.003	0.002	−0.003
		(0.005)	(0.006)	(0.006)
	City area	−0.007*	−0.007	−0.010**
		(0.004)	(0.004)	(0.004)
Foreign	PM2.5_1			-0.280*
				(0.150)
	PM2.5_2	−0.090	−0.602***	
		(0.088)	(0.118)	
	PM2.5_3	−0.498***		
		(0.058)		
	PM2.5_4	-0.084		
		(0.055)		
Panel B. Direct Effects				
Economic	Cars	0.095***	0.163***	0.259***
		(0.018)	(0.022)	(0.020)
	Factory area	0.004	0.012*	0.023***
		(0.005)	(0.007)	(0.007)
	GRDP	0.005	0.010	0.031***
		(0.009)	(0.012)	(0.012)
	Coal power	−0.097	0.373*	−0.246
		(0.176)	(0.219)	(0.020)
Climatic	Precipitation	−0.157***	−0.389***	−0.240***
		(0.019)	(0.020)	(0.021)
	Wind speed	0.010	−0.128***	−0.215***
		(0.022)	(0.024)	(0.022)
	Temperature	0.101*	0.618***	0.998***
		(0.058)	(0.060)	(0.051)
Geographic	Tree cover	−0.002	−0.003	−0.007***
		(0.002)	(0.002)	(0.002)
	City area	−0.000	0.001	0.000
		(0.001)	(0.001)	(0.001)
Foreign	PM2.5_1			1.536***
				(0.053)
	PM2.5_2	0.318***	1.144***	
		(0.054)	(0.047)	
	PM2.5_3	0.556***		
		(0.043)		
	PM2.5_4	0.243***		
		(0.027)		

Note: Standard errors are in parentheses. ***, **, and * denote significance at 1, 5, and 10 percent, respectively.

[Table 8] Marginal Impacts of Extended GNS Model with Foreign Air Pollution

		(1) GNS F1	(2) GNS F2	(3) GNS F3
Economic	Cars	0.380***	0.551***	0.632***
		(0.061)	(0.072)	(0.058)
	Factory area	0.045	0.068**	0.075***
		(0.028)	(0.031)	(0.021)
	GRDP	0.003	0.003	0.061*
		(0.048)	(0.054)	(0.037)
	Coal power	0.571	2.990***	0.624
		(0.746)	(0.886)	(0.700)
Climatic	Precipitation	−0.133***	−0.453***	−0.133***
		(0.041)	(0.037)	(0.034)
	Wind speed	0.002	−0.029	−0.125***
		(0.049)	(0.057)	(0.046)
	Temperature	−0.093	−0.043	0.674***
		(0.128)	(0.135)	(0.110)
Geographic	Tree cover	−0.012	−0.004	−0.014
		(0.012)	(0.013)	(0.009)
	City area	−0.016	−0.011	−0.012**
		(0.011)	(0.010)	(0.006)
Foreign	PM2.5_1			1.733***
				(0.082)
	PM2.5_2	0.571***	1.175***	
		(0.100)	(0.075)	
	PM2.5_3	0.214***		
		(0.083)		
	PM2.5_4	0.400***		
		(0.051)		

Note: Standard errors are in parentheses. ***, **, and * denote significance at 1, 5, and 10 percent, respectively.

[Table 9] Decomposition of the Marginal Impacts: Indirect and Direct Impacts

		(1) GNS F1		(2) GNS F2		(3) GNS F3	
		Coeff.	%	Coeff.	%	Coeff.	%
Panel A. Indirect Transboundary Impacts							
Economic	Cars	0.250***	0.66	0.344***	0.62	0.345***	0.55
		(0.050)		(0.057)		(0.045)	
	Factory area	0.035	0.79	0.050**	0.74	0.048***	0.64
		(0.022)		(0.024)		(0.015)	
	GRDP	−0.002	−0.62	−0.006	−1.86	0.027	0.45
		(0.037)		(0.040)		(0.026)	
	Coal power	0.587	1.03	2.320***	0.78	0.805	1.29
		(0.648)		(0.767)		(0.617)	

Climatic	Precipitation	0.021 (0.037)	−0.16	−0.057* (0.035)	0.13	0.098*** (0.033)	−0.74
	Wind speed	−0.007 (0.045)	−3.79	0.088* (0.052)	−3.07	0.083** (0.044)	−0.66
	Temperature	−0.171 (0.113)	1.83	−0.586*** (0.124)	13.68	−0.300*** (0.096)	−0.45
Geographic	Tree cover	−0.009 (0.010)	0.73	−0.000 (0.011)	0.11	−0.006 (0.007)	0.42
	City area	−0.014 (0.009)	0.87	−0.010 (0.008)	0.94	−0.011** (0.005)	0.94
Foreign	PM2.5_1					0.183** (0.083)	0.11
	PM2.5_2	0.222** (0.095)	0.39	0.027 (0.074)	0.02		
	PM2.5_3	−0.300*** (0.076)	−1.40				
	PM2.5_4	0.138*** (0.048)	0.35				
Panel B. Direct Local Impacts							
Economic	Cars	0.130*** (0.018)	0.34	0.207*** (0.022)	0.38	0.287*** (0.020)	0.45
	Factory area	0.009 (0.007)	0.21	0.018** (0.009)	0.26	0.027*** (0.007)	0.36
	GRDP	0.005 (0.013)	1.62	0.009 (0.016)	2.86	0.033** (0.013)	0.55
	Coal power	−0.015 (0.192)	−0.03	0.670*** (0.236)	0.22	−0.181 (0.216)	−0.29
Climatic	Precipitation	−0.154*** (0.018)	1.16	−0.396*** (0.019)	0.87	−0.231*** (0.020)	1.74
	Wind speed	0.009 (0.020)	4.79	−0.116*** (0.023)	4.07	−0.208*** (0.021)	1.66
	Temperature	0.078 (0.056)	−0.83	0.543*** (0.055)	−12.68	0.974*** (0.050)	1.45
Geographic	Tree cover	−0.003 (0.003)	0.27	−0.003 (0.003)	0.89	−0.008*** (0.003)	0.58
	City area	−0.002 (0.002)	0.13	−0.001 (0.002)	0.06	−0.001 (0.001)	0.06
Foreign	PM2.5_1					1.551*** (0.050)	0.89
	PM2.5_2	0.349*** (0.050)	0.61	1.148*** (0.043)	0.98		
	PM2.5_3	0.514*** (0.041)	2.40				
	PM2.5_4	0.262*** (0.025)	0.65				

Note: Standard errors are in parentheses. ***, **, and * denote significance at 1, 5, and 10 percent, respectively.

4.3. Spatial Heterogeneity

To explore the heterogenous impacts of factors emanating from the northwest and southeast, we create Figures 4 and 5 from the estimates in column 1 of Table 7. Our analysis on spatial heterogeneity shows that change in the domestic and foreign factors in the northwest results in a higher diffusion of pollution to more cities compared with the impacts from the southeast.

The overall patterns of the spatial impulse response in Figure 4 shows that the degree of spatial responses to other cities are similar for domestic and foreign factors for the northwest cities. Table 10 shows the summary statistics of the impacts for each of the 226 cities. For instance, a 1 percent increase in emission from coal-fired power plant in Dangjin-si is associated with an average 0.003 percentage increase in other cities' PM2.5. The largest decrease of city-level PM2.5 from the spatial impulse response of coal-fired power plant emissions (from Dangjin-si) is −0.0431 percent.

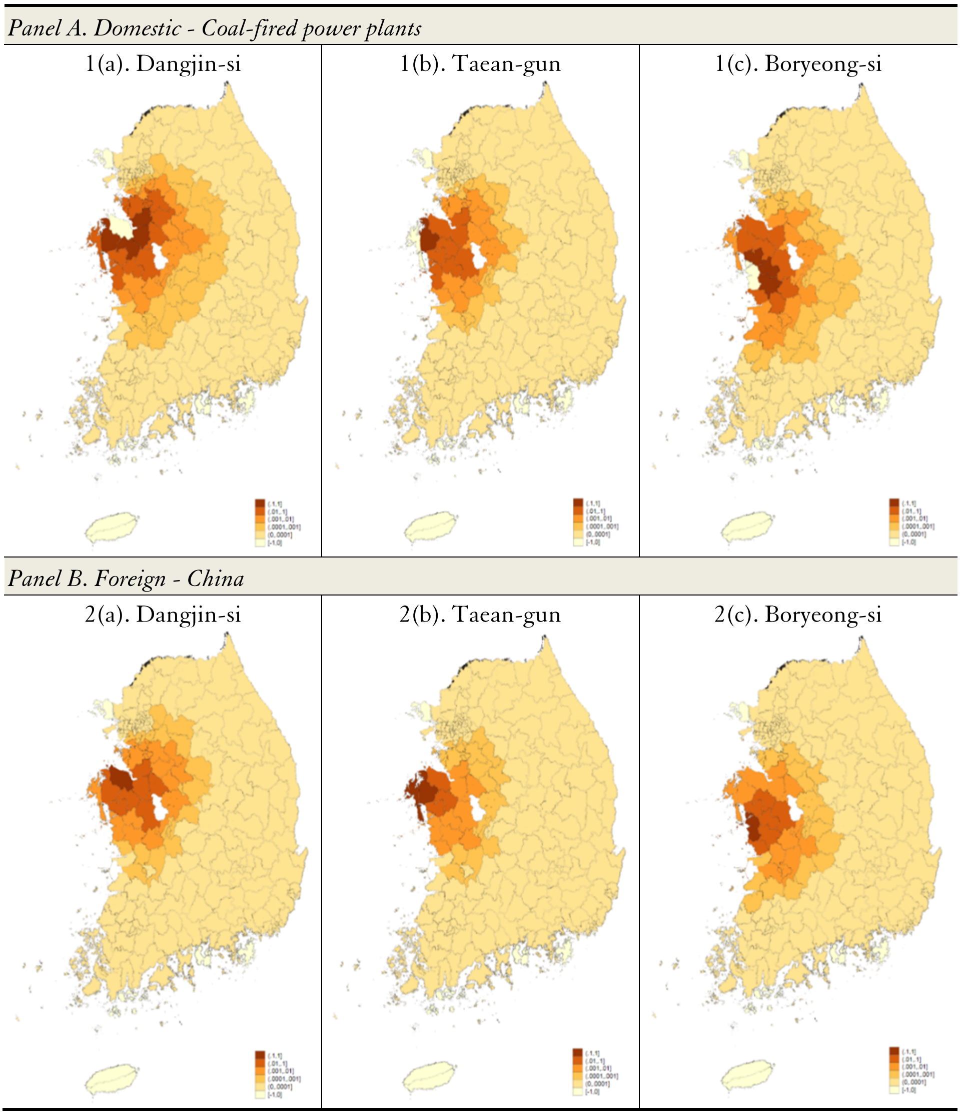
The mean of the impacts in Table 10 appears to be much smaller than the total marginal impact of each factor in Table 8 because these estimates are disaggregated impacts from a single city. The maximum impact is higher for pollution from China, but the mean is smaller compared with the domestic factor. This outcome suggests that the initial impact to each of the three northwest cities is higher for the foreign factor but has lower diffusion effect compared with the domestic factor.

Returning to the discussion of Figure 4, although similar, the range of the domestic impact appears to be more persistent than the foreign factor. This outcome is consistent with our discussion of the estimates in Table 7. Notably, the spatial effect of coal-fired power emissions is larger relative to the direct effect, and the estimate of the direct effect is smaller relative to the spatial effect of pollution from east-coast China.

Figure 5 displays the spatial impulse response from the southeast. We find that the pattern of diffusion of the impacts from a change in the southeast differs for the domestic and foreign factors. In Panel A, the change in air pollution from an increase in factory area in the southeast appears to persist throughout cities in either the south or east but not beyond those regions. However, for Panel B, no positive diffusion of the initial impact from a change of air pollution in Japan occurs. This outcome is reasonable when relating the regional heterogeneity of the impacts with the estimates in Table 7. The spatial interaction term of pollution from Japan is −0.498, and the direct effect coefficient is 0.556. For the factory area, the spatial interaction effect is estimated to be positive, which is illustrated by the spread of the impacts in Panel A of Figure 5.

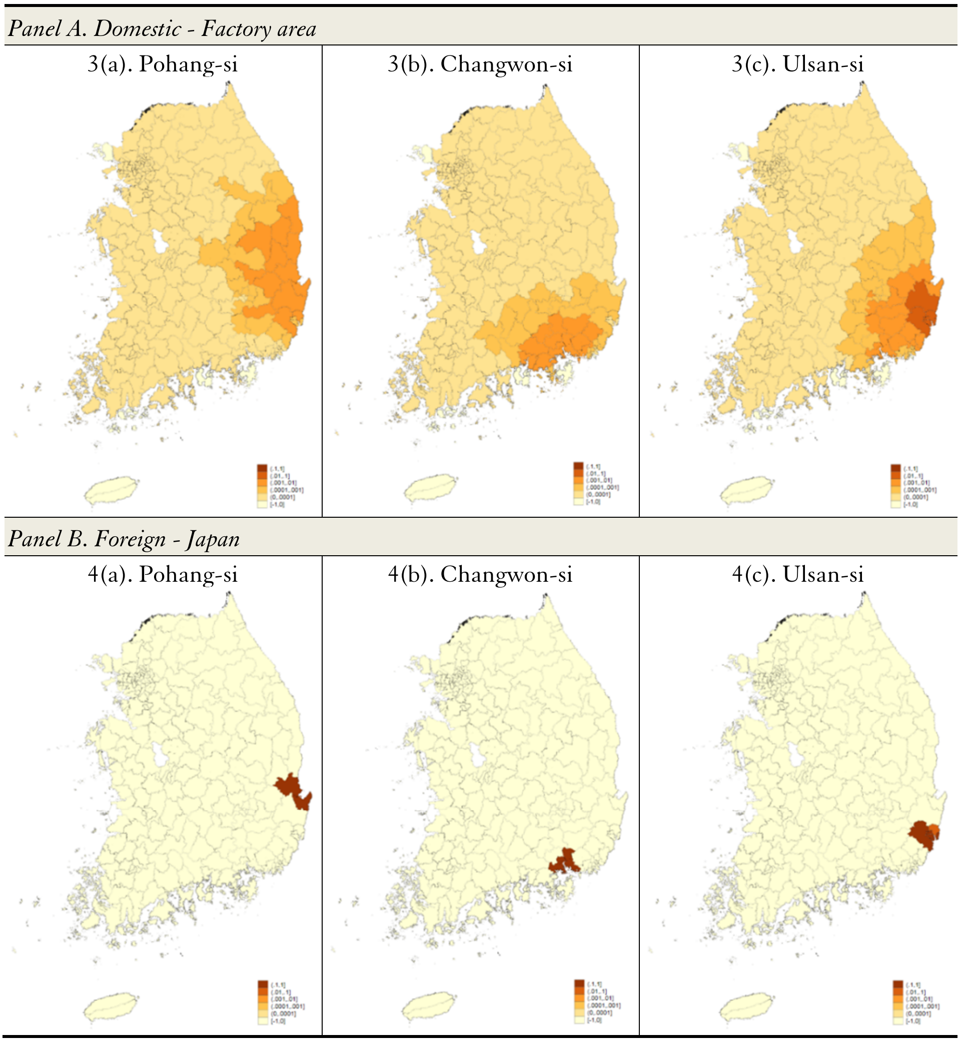
We find spatial heterogeneity in the extent to which the impact from a change in domestic and foreign factors diffuses to other cities, especially for impacts from the southeast. For the initial impact in the northwest cities, domestic and foreign factors were similarly persistent in reaching other cities. By contrast, for impacts emanating from cities in the southeast, the effects were more far reaching for the domestic factor compared with the foreign factor.

[Figure 4] Spatial Heterogeneity: Impulse Response in the Northwest



Note: Panel A displays the impact that diffuses from an initial increase in coal-fired power emissions in the northwest to each of the 226 cities in the sample. Panel B shows the spatial diffusion of air pollution from China after the initial impact on the northwestern cities. Cities with higher estimated impacts are filled with a darker color. Three cities in the northwest, namely, Dangjin-si, Taean-gun, and Boryeong-si, were selected because they are assumed to be the most affected by emissions from coal-fired power plants and China.

[Figure 5] Spatial Heterogeneity: Impulse Response in the Southeast



Note: Panel A displays the impact that diffuses from an initial increase in factory area in the southeast to each of the 226 cities in the sample. Panel B shows the spatial diffusion of air pollution from Japan after the initial impact on the southeastern cities. Cities with higher estimated impacts are filled with a darker color. Three cities in the southeast are Pohang-si, Changwon-si, and Ulsan-si. These cities were selected because of the high factory area and proximity to Japan.

[Table 10] Descriptive Statistics of Heterogeneous Impacts

			Figure	Mean	Std. Dev.	Min	Max
Panel A. Northwest							
Domestic	Coal power	Dangjin-si	1(a)	0.0030	0.0157	−0.0431	0.1235
		Taean-gun	1(b)	0.0030	0.0255	−0.0405	0.3574
		Boryeong-si	1(c)	0.0030	0.0164	−0.0180	0.1391

Foreign	China	Dangjin-si	2(a)	0.0027	0.0232	0.0000	0.3387
		Taean-gun	2(b)	0.0027	0.0245	0.0000	0.3396
		Boryeong-si	2(c)	0.0027	0.0239	0.0000	0.3481
Panel B. Southeast							
Domestic	Factory area	Pohang-si	3(a)	0.0002	0.0010	0.0000	0.0072
		Changwon-si	3(b)	0.0002	0.0010	0.0000	0.0076
		Ulsan-si	3(c)	0.0011	0.0059	0.0000	0.0588
Foreign	Japan	Pohang-si	4(a)	0.0007	0.0362	−0.0593	0.5316
		Changwon-si	4(b)	0.0007	0.0357	−0.0386	0.5279
		Ulsan-si	4(c)	0.0034	0.0485	−0.1457	0.4681

Note: The impacts are the percentage changes of air pollution in each city from a 1 percent increase of domestic and foreign factor from Dangjin-si, Taean-gun, Boryeong-si, Pohang-si, Changwon-si and Ulsan-si.

This outcome could be explained by the dynamics of wind in Korea. The prevalent wind direction during highly polluted seasons is the northwestern wind, which blows from the northwest to southeast. Therefore, the impacts of domestic and foreign factors from the northwest appear to diffuse to a farther extent compared with the impacts from the southeast.

With limited information on monthly or daily levels of air pollution, air pollution is difficult to relate with wind direction. Nevertheless, the implication from the results of our analysis with annual air pollution is clear: seasonal heterogeneity appears to lead to spatial heterogeneity observed in these spatial impulse response maps.

V. Conclusion

Identifying which driving forces lead to higher ambient air pollution is crucial for the efficient targeting of the pollution abatement policy. However, pinpointing air pollution with the factors is difficult, particularly for Korea, because we need to consider cross-city and cross-country transboundary pollution effects. This study conducted an in-depth analysis of the factors leading to an increase in ambient air pollution by applying the general specifications of the spatial panel model. For our analysis, our study uses a satellite-based georeferenced dataset to retrieve reliable information on air pollution as the annual mean measurement of PM2.5 for 226 cities in Korea and three foreign countries from 2010 to 2016.

First, we find compelling evidence of spatial effects on ambient air pollution. We note a substantial enhancement in the overall goodness-of-fit of the spatial panel model when we account for these effects. Our empirical findings indicate that vehicles and factory occupation rate are key drivers of air pollution. The results also reveal a significant association of air pollution to climatic factors. Applying the model that restricts the spatial relationship the least improves the identification of the main driving forces and optimizes the performance of the spatial panel model.

Second, the findings confirm that regional pollution levels are not solely attributable to factors within national borders but also to cross-border transboundary air pollution. To investigate this further, we extended the general nesting spatial model to include foreign air pollution based on the distance between foreign sites and domestic cities, revealing the significant impact of foreign air pollution. Moreover, the inclusion of foreign effects in the spatial panel model improved its overall goodness-of-fit and predictive accuracy.

Lastly, we explore spatial heterogeneity in the diffusion of the impact to other cities after the initial spontaneous impact in the northwest and southeast. A comparison of the patterns of impacts from domestic and foreign factors on other cities suggests that influences from the northwest diffused more widely. This outcome implies that targeting pollution abatement in the northwest can increase the abatement of pollution at a national level because more cities are under the influence of the impacts from the northwest.

Based on these circumstances, the Korean government is facing problems in two main aspects. First, the impact of air pollution on population health is amplified by externalities caused by transboundary air pollution. This result highlights the importance of implementing pollution abatement strategies and promoting health development through coordinated efforts among local and nonlocal policy decision makers at the regional and national levels. Second, the findings suggest that the spatial distribution of air pollution is not solely influenced by domestic sources but also by foreign sources. This outcome suggests that the level of impact between countries at an international level should be considered in future studies. In summary, the Korean government needs to address the increasing health risks posed by air pollution by implementing coordinated pollution control.

However, we acknowledge the apparent limitations in our findings and suggest that the presented results be interpreted with caution because of the following reasons. First, we did not account for seasonal variation, which is closely related to the dynamics of air pollution from changes in wind direction. We were able to retrieve only annual data on air pollution and domestic factors. However, if monthly data on satellite-observed air pollution, economic, and geographic factors become available, addressing seasonal heterogeneity on cross-country and cross-city effects and wind direction effects would be an important contribution to the literature, which we leave as an extension of this study. Second, the interregional or international spatial effect could be time varying. Although we assume the interregional spatial effect to be constant, the spatial dynamics of ambient air quality may change in the long-run depending on climatic and geological features. Given the trend in climate change, examining the spatial effect of different periods may be informative for policies of environmental issues at hand.

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대기오염의 결정요인과 공간적 전이효과에 대한 공간패널분석*

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초 록 본 연구는 공간패널분석을 이용하여 한국 대기오염의 결정요인과 공간적 전이효과에 대하여 분석한다. 특히, 초미세먼지(PM2.5) 발생의 경제, 기후, 지리적 결정요인을 밝히고 공간적 전이효과를 측정한다. 또한, 연구의 범위를 확장하여 한국 대기오염의 내부 및 외부 요인을 평가하기 위해 다차원적 접근 방식으로 주변 국가의 전이효과를 분석하고자 한다. 실증분석은 2010~2016년 위성 기반 대기오염, 기상 및 지리 정보를 통합하여 한국과 주변 국가에 걸친 공간패널 자료를 기반으로 한다. 분석한 결과, 대기오염은 다른 지역의 대기 질을 저하시키고 국가 전체로 파급하여 대기 질을 악화하는 것으로 나타났다. 공간적 상호작용에 대한 GNS(General Nesting Spatial) 모형의 분석 결과는 경제 및 기후 요인이 대기오염에 미치는 영향이 유의함을 보였다. 대기오염의 확장모형을 추정하여 주변국들의 대기오염이 국경을 넘어 국내에 파급되는 국가간 전이효과를 얻었다. 또한, 공간적 이질성에 대한 심층 분석은 북서부 지역의 국내 및 해외 요인의 충격이 남동쪽 지역에서 발생하는 충격에 비하여 다른 지역으로 더욱 뚜렷하게 대기오염을 확산하는 결과를 보였다.

핵심 주제어: 공간적 이질성, 공간패널분석, 대기오염, 전이효과, GNS 모형

경제학문헌목록 주제분류: C33, Q53, R11

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