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Impacts of Ambient Air Pollution on Health Risk in Korea: A Spatial Panel Model Assessment *

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Abstract This paper investigates the impact of air quality pollution on respiratory health risk in Korea. In particular, we consider transboundary effects of particulate matter (PM10) on the health risk of pneumonia by using the spatial panel model. PM10, generated by natural phenomena and anthropogenic activities, migrates to neighboring areas contributing to not only local but also ambient regional health risks. We employ the spatial panel model to explain the spillover effects of air pollution on the respiratory health risk. The panel data covers environmental, demographic and economic variables that are associated with pneumonia of 120 local districts in Korea during the period from 2010 to 2015. Empirical evidence based on non-spatial and spatial models commonly indicates that the impact of air pollution on pneumonia-related risk is significant. The spatial panel model assessment reveals improvement in explanation and evidences more significant effect of ambient air pollution on pneumonia related hospital visits. As such, evidences of spatial dependence and borderless impacts of air pollution on the health risk of pneumonia are found to be strong. We also investigate the spatial dynamics of the potential association between air pollution and respiratory diseases with respect to variations in wind direction by extending the conventional weight matrix specification. Empirical results imply that transboundary effects of PM10 on health risk are stronger for districts located downwind from Northwest districts than from other directions.

Keywords Air Pollution, Health Risk, Spatial Panel, Transboundary Impacts, Wind Direction

JEL Classification C33, I18, Q53

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1. INTRODUCTION

Recent increase in air pollution poses a threat to human health and economic growth worldwide. According to World Health Organization (WHO), 1.3 million premature deaths worldwide from cardiovascular and respiratory diseases, were attributable to outdoor air pollution. In 2016, this burden of disease increased to 4.2 million deaths, 3.23 times higher than that of 2008. Impacts of ambient air pollution ranges from acute to chronic illnesses resulting in increase of emergency room, hospital visits and sick leave days from work (Portney and Mullahy, 1990; Schwartz, 1994; Medina-Ramón *et al.*, 2006; WHO, 2016). Air pollution also causes cognitive impairment, debilitating productive capability in the workplace (Zivin and Neidell, 2012; Chang *et al.*, 2016). As such, air pollution impacts various aspects of health which is an important part of human capital and key to sustaining labor supply and productivity. Given the trend of worsening air quality, exposure to increased levels of air pollution is expected to increase leading to higher medical costs and productivity loss, posing an economic burden for human population.

Air pollution appears to be particularly high in South-East Asia where excessive development and geographic conditions cause formation and suspension of air pollutants, leading to higher human exposure. Deterioration of overall air quality is particularly a serious issue in Korea. High and persistent interest in air pollution is partly due to the complex and diverse sources of air pollution in Korea that prevents a clear explanation for the higher contributing factors that deteriorates ambient air quality. Anthropogenic sources of air pollutants include transport vehicles, industrial facilities and powerplants. Natural phenomena including climate change, global warming, and deforestation are also known causes of air pollution. During spring and winter, migrated dust of degraded soil from foreign countries are also known as possible contributors to nationwide air pollution in Korea (KORUS-AQ, 2016). Such air pollutants from various sources are suspended in the atmosphere in cities, increasing population exposure. Particulate matter (PM10) lingers between high-level buildings in limited land space of urban areas, and low precipitation during seasons of high PM10 leads to atmospheric stagnation of air pollutants for longer periods. Such formation and suspension of PM10 increases population exposure posing a serious threat to human health.

As population density and atmospheric pollution levels vary over space, population exposure to ambient air pollution has a spatial dimension, which calls for effective local policies aimed at curbing pollution levels in densely populated areas. However, the assessment of air pollution impact is challenging due to transboundary externalities. While air pollutants are emitted and formed from complex processes in the source area, small-sized particulates suspended in the atmosphere dissipate long distances having potentially boundless impacts in neighboring and far away regions. Likely, deterioration in air quality threatens the health and welfare of the population not only in the source region, but also in other regions. Negative externalities of air pollution are closely linked to spatial relationships, and this close association in terms of space needs to be explicitly assessed in studies addressing issues on air pollution (Henderson, 1977).

Without considering the possible impact of air pollution from neighboring districts, the increase in human health risks due to air pollution is potentially understated, leading to improper decisions for air pollution mitigation and health development policies. In addition, identifying the primary contribution of PM10 on respiratory diseases is crucial for effective and efficient air pollution abatement strategies. With higher contribution of PM10 within the borders of the source district on respiratory diseases, policies targeting air pollution of local areas are required. If contributions of spillover PM10 on human health are more significant, coordinated and multilevel efforts of regional facilities are deemed as more crucial. Thus, spatial dependence and transboundary contributions of air pollutants require the assessment of local and transboundary effects of PM10 on health risks. Accordingly, we apply the spatial panel model to empirically assess spatial externalities of air pollution that impose elevated risks on respiratory-related health.

Furthermore, identifying which meteorological or geographic conditions result in higher risk for population health induced from increased levels of air pollution is also required for effective policy designs. For instance, wind transfers air pollutants stagnated in the atmosphere of highly polluted cities, which in turn increases pollution exposure for population in the districts located downwind from the source district. Such dynamics of negative externalities depending on geographic location and changes in wind direction can cause spatial variations in PM10 concentrations and health risks associated with decreased air quality (WHO Europe, 2006).

In this study, we examine the PM10 impacts on pneumonia hospitalizations in South Korea with data including environmental, demographic and economic factors of 120 districts during the period from 2010 to 2015. Empirical evidence based on non-spatial and spatial models commonly indicates that the effect of air pollution on the risk of pneumonia is significant. The spatial panel model assessment reveals improvement in explanation and evidences more significant and higher effects of air pollution on human health risks compared to that of the non-spatial model. We then extend the spillover effects of PM10 on human health risks with respect to wind by using different spatial weight matrices in the spatial panel model. Empirical results of spatial panel models with directional spatial weights imply that transboundary effects of PM10 on pneumonia-related admissions are higher for districts located downwind from Northwest and Southwest direction compared to Northeast and Southeast direction.

This paper is organized as follows. Section 2 summarizes previous studies. Section 3 describes the data and methodology. Section 4 shows empirical results of non-spatial and spatial panel models with several specifications of the spatial weight matrices. Section 5 discusses the policy implication.

2. LITERATURE SURVEY

Previous studies that elicited impact of air pollution on human health focus on individual-level time series analysis. Seo *et al.* (2006) used generalized additive model to adjust for meteorological factors and found that daily particulate matter (PM) increases daily respiratory hospital admissions for age group older than 64. Andersen *et al.* (2007) found that PM increased hospital admissions among the elderly due to respiratory diseases. Yi *et al.* (2010) applied case-crossover design and found that PM increased hospital admissions of cardiovascular and respiratory diseases in Seoul.

Morbidity caused from air pollution also leads to productivity loss through work loss and leave days. Thus, many economic studies have assessed the impact of atmospheric pollution on various measures of morbidity including work days lost (WDL), restricted activity days (RAD), and respiratory related restricted activity days (RRAD). Ostro (1983) and Ostro (1987) found that high levels of air pollution cause temporary illness contributing to lost work hours, RAD and RRAD. Ostro and Rothschild (1988) used fixed effects model to control for intercity differences and showed that fine PM leads to restrictions in activity and work loss due to respiratory conditions. Hanna and Oliva (2015) estimated the effect of decrease in air pollution from closure of large refinery on labor supply. A recent study by Fotourehchi (2016) examined the health impacts of PM10 and air pollutant emissions for developing countries using recursive simultaneous equation model. In the context of Korea, Bae (2016) found that PM2.5 increases number of visiting and admitted patients in hospitals due to respiratory diseases.

While a large body of literature documents studies that associate health risk with deterioration of air quality, studies that utilize spatial-temporal information and spatial econometric models to account for the transboundary property of air pollutants are limited. Portney and Mullahy (1990) used individual-level data and found the association between urban air pollution and chronic respiratory illnesses by matching individuals to air pollution monitors using geographic information. Neidell (2004) investigated the impact of air pollution on asthma-related hospitalizations of children by linking individuals to the weighted average of pollution levels measured by monitors within a 20-mile radius. Lagravinese *et al.* (2014) estimated the impact of air pollution on chronic obstructive pulmonary disease for provinces in Italy using city-level data by allowing for serial correlation and spatial dependence. While these studies include spatial information in the analysis, they do not explicitly assess the health risks induced by air pollutants from external regions.

Spillover models are widely applied for investigating externalities of economic entities (Maddison, 2007; Aklin, 2016; Kim and Kim, 2016; Hyun and Kim, 2017). With increased interest in the health impact of air pollutants farther away from the observed site, recent studies in health economics have applied spillover models in terms of space. Yang *et al.* (2013) used the spatial panel model to identify the leading drivers of mortality rates in the U.S. The study found negative relationship between mortality rates in other districts and social factors such as Hispanic population and social disadvantage. Chen *et al.* (2017) estimated air pollution impact on public health in cities of China and found adverse impact of air pollutants on local and transboundary mortalities from respiratory diseases to be significant. However, this study employed emissions instead of air pollution levels, and mortality rate as the health variable. Although not pertaining to empirical analysis on air pollution, Moscone *et al.* (2007) assessed the determinants of mental health expenditures of England using spatial model and found interdependence of municipalities in spending decisions.

Relating to air pollution, studies have used information on wind direction either as dummy variables or instrumental variables, as lightweight air pollutants are prone to long-range transport by wind. Lee *et al.* (2017) applied the spatial panel model to assess the leading factors of daily PM2.5 in Seoul, and included dummy variables for four cardinal directions, and found that wind blown from the Northwest direction increases air pollution level in Seoul. Deryugina *et al.* (2019) estimated the causal effects of PM2.5 on daily mortality, health care use, and medical costs, and revealed significant impact of PM2.5 on healthcare use and medical costs. This study used wind direction as instrumental variables to resolve bias arising from measurement error due to daily variations in air pollution induced by wind blown from different directions. However, merely including dummy variables in the model cannot capture the decaying effect of air pollution for cities farther away. Therefore, we apply the spatial panel model and experiment with different specifications of spatial weight matrices for 120 cities in Korea, which captures transboundary effects of other cities regardless of distance.

Recent increase in scale and importance of health impact from ambient air pollution requires accurate assessment of PM10 health risks by properly reflecting properties of air pollutants. Through this study, we attempt to elicit effects of PM10 on human health risks and also find evidences of stronger relationship and transboundary impacts of PM10 on respiratory diseases through spatial panel models. We also investigate the spatial dynamics of the potential association between PM10 and respiratory diseases with respect to wind by experimenting with various spatial weight matrices in our model. Such use of spatial weight matrices reflecting spillover effects of wind in the spatial panel model is a vital contribution to the literature because it considers which wind direction contributes to spatial variations in the effect of air pollutants on human health. Our study is the first to evaluate the spatial dynamics of air pollution spillovers on respiratory health with respect to wind direction, which would provide important references for effective pollution abatement strategies.

3. METHODOLOGY

3.1. DATA

For our main analysis, we use annual data of 120 cities (si-gun-gu) in South Korea for the period from 2010 to 2015. The sample for this study does not include all cities as districts with no air quality monitors or missing measurements were not considered. Description of the variables are outlined in Table 1.

Health data The dependent variable is the number of hospital admissions of pneumonia patients per 1,000 people obtained from National Health Insurance Service (NHIS). Based on area of residence, NHIS provides city-level data on hospital visits, hospital admissions, medical expenses, out-of-pocket expenses, and pharmaceutical expenses. The reason for focusing on the number pneumonia-related hospitalizations is twofold. Pneumonia is one of the most frequently diagnosed respiratory diseases with contagious viruses. Pneumonia is also one of the diseases that can lead to death in excessive cases along with cancer and cardiovascular diseases for susceptible age groups. Furthermore, we use number of pneumonia-related hospitalizations instead of mortality rates to avoid under- or over-stating the effect of air pollution on population health risks.

Table 1: Explanation of variables

Variables		Unit	Description
Health	Pneumonia	Per 1,000 people	Number of pneumonia patients
Environmental	PM10	Days	Number of days with high PM10
	Temperature	Celsius	Yearly average temperature
	Precipitation	mm	Total precipitation
Demographic	PoplOld	Per 1,000 people	Rate of 65+ years old population
	PoplYoung	Per 1,000 people	Rate of 10- years old population
	Smoking	Percent	Smoking rate of each district
Economic	Manufacture	Won per capita	Per capita production of the manufacturing sector

Environment data For the air pollution indicator, number of days with PM10 daily average exceeding $150\mu g/m^3$ is used to assess the impact of excessive cases of air pollution on pneumonia-related hospitalizations. The criterion was chosen according to the standard set out by the Ministry of Environment, which signals alerts of "very bad" level of PM10 when its daily average exceeds $150\mu g/m^3$. For comparison, we experimented with other criteria for air pollution, and the results using $200\mu g/m^3$ as the threshold were not conspicuously different from our main results.

Data for air pollution was obtained from AirKorea (http://www.airkorea.or.kr/) managed by Korea Environment Corporation which offers hourly measures of various air pollutants from a network of 398 air quality monitoring sites. The WHO air quality guideline states that health impact of air pollution should be estimated using measures from monitoring sites that are representative of population exposures. Following this guideline, data from monitoring sites in cities, or residential areas were included, and national background, non-residential, or road-side monitoring sites were not included. If there was more than one monitoring site in a district, the average of readings from all the monitors were used.

For confounding environment variables, yearly average temperature and total precipitation were retrieved from Korea Meteorological Association. These variables are also used to compare the transboundary effects, as these are less prone to impact other cities' health risks as they do not have transboundary properties as opposed to air pollutants which are easily transmitted by wind.

Demographic and economic data Proportion of susceptible age groups (i.e., people aged 65 years old or older and people aged 10 years old or younger) was retrieved from Korea Statistics and measured as per 1,000 people. Smoking rate

Table 2: Summary statistics

Variables	Mean	Std. Dev.	Min	Max	Observation
Pneumonia	6.794	3.524	2.226	40.496	720
PM10	2.936	2.848	0.000	21.000	720
Temperature	13.123	1.301	9.600	17.400	720
Precipitation	1,340.656	414.709	51.500	2,618.100	720
PoplOld	120.021	39.479	52.516	285.339	720
PoplYoung	90.581	17.640	47.582	153.067	720
Smoking	38.954	2.904	26.265	47.508	720
Manufacture	8.109	12.951	0.076	75.282	720

was obtained from the Community Health Survey conducted by Korea Centers for Diseases Control and Prevention (KCDC). The survey data was used to calculate number of respondents that have been or is smoking cigarettes and then weighted to represent the total smoking rate of each district. For economic confounding factor, we retrieved the total production of the manufacturing sector per capita from Korea Statistics. The standard price of 2010 was used to determine the variations in resulting products exempt the price effect.

The summary statistics are reported in Table 2. Amount of production in the manufacturing sector and PM10 demonstrates high variation relative to the mean. This reflects the situation in Korea where the level of development is particularly high in urban cities. Such difference in production level and the geographic location causes variations in regional air pollution level. We attempted to include as many variables as possible in the model, and additionally accounted for the unobserved city-specific effects in the panel data model.

In Figure 1, the 120 cities included in the sample are highlighted with respect to the 2015 population of each city. As shown, the population is concentrated in regions of urban areas rather than in non-urban regions. Cities from Seoul, Incheon and Gyeonggi-do are enlarged in the figure. As shown, many of the sample cities in this study are located in the enlarged portion of the map. As we could not include all cities due to absence of monitors with accurate measurements of PM10, we also estimated the results including 55 cities of the enlarged portion where there are fewer missing regions. The results did not reveal any noticeable difference with those from our main analysis with 120 districts; transboundary effects of PM10 on pneumonia-related admissions appeared to be positive and significant.

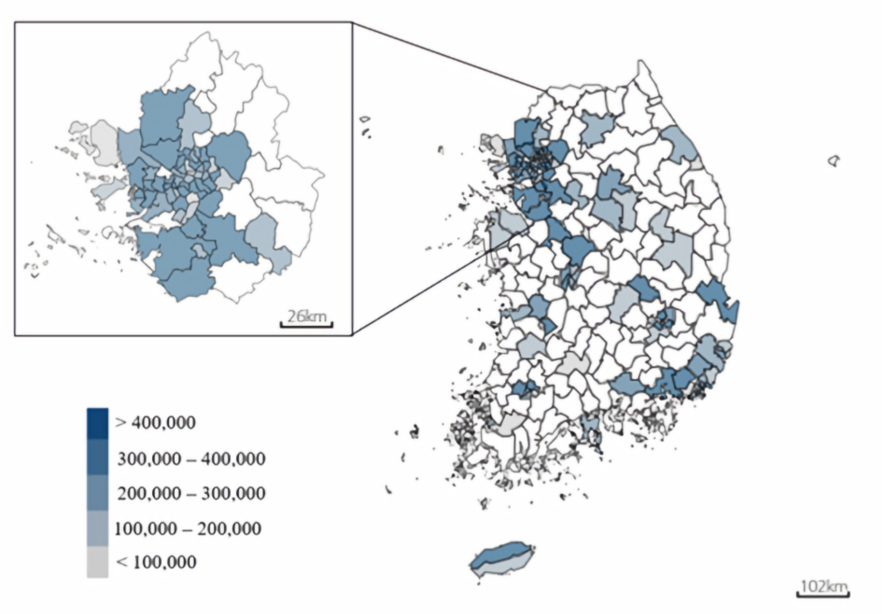

Figure 1: Cities included in the sample

Spatial weights matrix For our first result, we used the matrix where the elements are binary with $w_{ij} = 1$ if i and j are neighbors and $w_{ij} = 0$ otherwise. Following Anselin *et al.* (2008), the rows of matrices are normalized equalizing the impacts from all other units. In our panel data setting, spatial relationships are constant over time as geographical locations are time-invariant.

Furthermore, we experimented with four different types of spatial dependence that represent variations in wind direction. The intuition behind this experiment is that the magnitude and strength of spatial dependence may vary between observations from different cardinal directions due to geographic location and variations in wind direction. Accordingly, we use spatial weight matrices representing the direction of the neighboring district. Directional weights matrices (M) with elements expressing neighboring districts in the Northwest, Southwest, Northeast and Southeast directions are specified to reflect spillover effects of PM10 with respect to wind direction. Relative to the centroid of each district, cardinal directions are divided into 4 planes (Northeast: 0^o- 90^o, Southeast: 90^o- 180^o, Southwest: 180^o- 270^o, Northwest: 270^o- 360^o). For the spatial weight matrix representing Northwest neighboring districts, $m_{ij} = 1$ if district j has its centroid within the Northwest plane and is neighbor to district i, and

Table 3: Moran's I statistic of health risk and air pollution

	2010	2011	2012	2013	2014	2015
Pneumonia	0.637***	0.306***	0.655***	0.693***	0.749***	0.655***
PM10	0.406***	0.420***	-0.014	0.124***	0.273***	0.436***

Note: *, **, *** indicates statistically significant at 1%, 5%, and 10% level, respectively.

$m_{ij} = 0$, otherwise. Specifications of spatial weight matrix representing other directions were retrieved following the same procedure.

As a descriptive measure, we apply Moran's I statistic to examine whether pneumonia-related hospital admissions and PM10 exhibit spatial interaction behavior.

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

where w_{ij} is the element in the spatial weight matrix of district i and j. In addition, y_i and y_j are the observations of interest for district i and j, respectively.

Moran's I of pneumonia-related hospital admissions and PM10 are reported in Table 3. The statistics of pneumonia hospitalizations for all years are positive and significant. For PM10, the statistics are positive and significant for all years except 2012. The statistic is negative in 2012 but not significant. This indicates that both variables are spatially dependent and show similar patterns for trans-boundary regions. The spatial dependence appears to be stronger for the number of pneumonia hospitalizations than for PM10. While existence of spatial dependence is found from Moran's I statistic, further estimation using the spatial panel model is required to assess whether accounting for the spatial dependence better explains the data.

3.2. MODEL

For our empirical analysis, the baseline model is the non-spatial panel data specification with city-specific effect:

$$Y_{it} = \beta A_{it} + \gamma' X_{it} + u_{it}, \tag{2}$$

$$u_{it} = \mu_i + \varepsilon_{it}$$

where i denotes district, t represents year, Y_{it} is health risks measured by number of pneumonia patients in district i at time t, A_{it} represents PM10 and X_{it}

includes other environmental, demographic and socioeconomic factors, u_{it} is the time-invariant city-specific effect μ_i and stochastic error term ε_{it}. The parameter β and γ denotes the impact of air pollution and other explanatory variables, respectively. To treat city-specific effect, we apply fixed effect estimator for the non-spatial panel data model.

Following Grossman (1972), we construct current stock of health capital as accumulation of investments. As an expanded perspective on health production, Leibowitz (2004) suggested including environmental factors or lifestyle, such as ambient air quality, high crime rate, or healthy diet that contributes to health capital. Accordingly, we use the Grossman model to assess the relationship between changes in air quality and health capital stock at a city-level.

The stacked form of Eq (2) by cross-sections and time periods is as follows:

$$Y = A\beta + X\gamma + u \tag{3}$$

where Y denotes NT-dimensional vector of dependent variable, A represents NT-dimensional vector of PM10 and X is an $NT \times K$ matrix of other variables, u denotes NT-dimensional vector of city-specific effects and the error term. Here, β measures the health impact of air pollution.

In the non-spatial panel model, however, potential interregional spatial effects are not accounted for. From Moran's I test, spatial dependency was positive for air pollution and pneumonia-related hospitalizations, and such spatial relationship is likely to indicate underestimation if not accounted for in the model. Accordingly, we apply the spatial autoregressive (SAR) model and account for spatial interaction effects of all studied variables. We also briefly explain the results for the spatial model with spatially lagged dependent and independent variables, the spatial Durbin model (SDM) and the model with only spatially lagged explanatory variables (SLX)[1]

Following Anselin *et al.* (2008), our spatial panel model for health risk is as follows:

$$Y = \rho(I_T \otimes W_N)Y + A\beta + X\gamma + u \tag{4}$$

where I_T is the identity matrix with T dimension, W_N is the $N \times N$ spatial weights matrix reflecting adjacent districts, the Kronecker product $I_T \otimes W_N$ becomes $NT \times NT$ spatial lag matrix, and ρ is the spatial autoregressive parameter.

The stacked SAR model can be rearranged to Eq (5):

$$Y = [I_T \otimes (I_N - \rho W_N)^{-1}](A\beta + X\gamma) + [I_T \otimes (I_N - \rho W_N)^{-1}]u \tag{5}$$

[1]For representation on SDM and SLX models, refer to LeSage and Pace (2009).

Taking the expectation of the the reduced form for each $N \times 1$ cross-section at time t yields the following equation:

$$E(Y_t) = (I_N - \rho W_N)^{-1}(\beta A_t + X_t \gamma) \tag{6}$$

$$= (I_N + \rho W_N + \rho^2 W_N^2 + \rho^3 W_N^3 + \cdots)(\beta A_t + X_t \gamma)$$

Through the expanded geometric series, high-order matrices of ρW_N capture the decaying effect of air pollution on pneumonia-related admissions. From high-order matrices, we can observe that spatial relationships spread out, including impacts from districts farther away from i. Also, the impacts decrease, or decay, with higher order spatial weight matrices, capturing the decaying effect of air pollution farther away from i (Kelejian and Piras, 2017).

Taking the partial derivatives of Eq (6) with respect to air pollution, A, yields marginal impacts of atmospheric pollution on the dependent variable as follows:

$$\begin{bmatrix} \frac{\partial E(Y_{1t})}{\partial A_{1t}} & \cdots & \frac{\partial E(Y_{1t})}{\partial A_{Nt}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(Y_{Nt})}{\partial A_{1t}} & \cdots & \frac{\partial E(Y_{Nt})}{\partial A_{Nt}} \end{bmatrix} = \begin{bmatrix} S(W)_{11} & \cdots & S(W)_{1N} \\ \vdots & \ddots & \vdots \\ S(W)_{N1} & \cdots & S(W)_{NN} \end{bmatrix} \tag{7}$$

$$S(W)_{ii} = \frac{\partial E(Y_{it})}{\partial A_{it}} \quad for \quad i = 1, 2, \ldots, N, \tag{8}$$

$$S(W)_{ij} = \frac{\partial E(Y_{it})}{\partial A_{jt}} \quad for \quad i \neq j, \tag{9}$$

$$where\ S(W) = (I - \rho W)^{-1}\beta$$

With the spatial effect parameter and spatial weight matrix, we can decompose marginal effects into local and transboundary effects. In the SAR model, local effects are the impacts of air pollution within the city which is measured by the average of $S(W)_{ii}$, that is, the diagonal elements. Transboundary effects include the impacts of air pollution from neighboring and far away cities and is measured as the average of the off-diagonal elements, $S(W)_{ij}$. The sum of local and transboundary impacts yields total impacts.

We estimated the spatial autoregressive parameter with city fixed effects using the quasi-maximum likelihood method following Lee and Yu (2010).

4. MAIN RESULTS

4.1. REGRESSION RESULTS OF THE NON-SPATIAL AND SPATIAL PANEL MODELS

Table 4 compares regression results of the non-spatial and spatial panel models. The results of the non-spatial and spatial panel models unanimously show PM10 and pneumonia-related admissions to be positively associated at statistically significant levels. For the SAR and non-spatial model, PM10 increased pneumonia-related risks, and for SDM and SLX, the spatially lagged of PM10 is positive and statistically significant. Although the impact of PM10 on pneumonia-related risks may be understated or overstated, as there are discrepancies in admissions to the hospital and actual pneumonia-related incidents, we were able to resolve the potential downward bias arising from not accounting for the spatial effect of PM10 from cities other than the source region. In overall, the impact of PM10 on pneumonia admissions is positive and statistically significant.

For all spatial models, the spatial dependence between city-level health risks and air pollution could be found. The spatial effect parameters are all positive and statistically significant implying that pneumonia-related health risks and their driving factors, be it environmental, demographic, or socioeconomic, are geographically connected impacting each other cities' pneumonia admissions. This implies that the transboundary impacts of air pollution results in increase in pneumonia admissions of other districts.

As presented in Table 4, the results from SAR and SDM are comparable. When we compare the results from the non-spatial and SAR model, the log-likelihood (-1,365.891 to -1,167.711), Akaike information criterion (2,474.782 to 2,353.241), and Schwarz information criterion (2,784.416 to 2,394.635) show significant improvement in explanation in spatial panel model compared to the non-spatial model. However, when we compare SAR to the models with spatially lagged PM10, the indicators merely show any noticeable improvement in explanation. Thus, results from both models, SAR and SDM, are comparable, and we pertain to SAR model for further analysis in latter parts of this paper.

The Hausman test is used to assess the mean independence of city-specific effect. As the test rejects the null hypothesis, mean independence is rejected, thus, we present results of panel models with city fixed effects.

For robustness check, we elicited results for not only cities from all over the nation, but also for metropolitan areas from Seoul, Incheon and Gyeonggi-do. From comparison, we found the results for 55 cities from metropolitan areas to be in alignment in terms of direction and significance of PM10 with those

Table 4: Regression results of non-spatial and spatial models

	Spatial						Non-Spatial	
	SAR		SDM		SLX			
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
W*Y	0.299***	0.040	0.291***	0.040				
W*PM10			0.098**	0.047	0.132***	0.049		
PM10	0.073***	0.029	0.018	0.039	0.026	0.042	0.101***	0.031
Temperature	0.257	0.212	0.235	0.211	0.291	0.223	0.323	0.225
Precipitation	0.001**	0.000	0.001**	0.000	0.001***	0.000	0.001***	0.000
PoplOld	0.029***	0.008	0.032***	0.008	0.041***	0.008	0.038***	0.008
PoplYoung	0.042**	0.021	0.041*	0.021	0.042*	0.022	0.044**	0.022
Smoking	0.083**	0.035	0.083**	0.035	0.085**	0.037	0.084**	0.037
Manufacturing	0.076**	0.038	0.076**	0.038	0.083**	0.040	0.082**	0.040
Log-likelihood	-1,167.711		-1,165.512		-1,189.375		-1,365.891	
AIC	2,353.241		2,351.025		2,396.750		2,474.782	
BIC	2,394.635		2,396.817		2,437.963		2,784.416	

Note: *, **, *** indicates statistically significant at 1%, 5%, and 10% level, respectively.

of our main analysis including cities of Korea. Additionally, we estimated the results by using different criteria for measurements of PM10. Using $200\mu g/m^3$ as the threshold for severe air pollution level showed positive and statistically significant association between PM10 and pneumonia-related admissions.

The local, transboundary and total effects of PM10 on pneumonia-related hospitalizations are presented in Table 5. Total marginal effects of PM10 on pneumonia admissions estimated based on regression results of non-spatial and spatial panel models are all positive and statistically significant. While positive local effects of spatial models are ambiguous in terms of significance, transboundary impacts for all spatial panel models are in align, showing PM10 from other cities to be a significant driving factor in increasing pneumonia admissions. Based on the result from SAR, pneumonia-related hospitalizations are increased by 0.075 (74.3% of total effect) due to one-day increase of severely polluted days within the district and by 0.026 (25.7% of total effect) due to one-day increase of severely polluted days from other cities. While internal air pollution is found to be more of a risk for pneumonia patients, air quality degradation results in negative externalities where cities emitting pollutants and the ones bearing the health risks are different. This implies that not only local, but also coordinated efforts for air quality and health improvement policies are imperative.

Other environmental variables also appear to be positively associated with pneumonia-related admissions. The local effect of precipitation on number of pneumonia patients is positive and significant. This is because higher precipita-

Table 5: Decomposition: local, transboundary, and total effects

	Spatial						Non-Spatial	
	SAR		SDM		SLX			
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Local effects								
PM10	0.075***	0.030	0.028	0.037	0.026	0.042		
Temperature	0.266	0.218	0.242	0.218	0.291	0.223		
Precipitation	0.001**	0.000	0.001**	0.000	0.001**	0.000		
PoplOld	0.030***	0.008	0.033***	0.008	0.041***	0.008		
PoplYoung	0.044**	0.022	0.042*	0.022	0.042*	0.022		
Smoking	0.085**	0.036	0.086**	0.036	0.085**	0.037		
Manufacturing	0.078**	0.039	0.079**	0.039	0.083**	0.040		
Transboundary effects								
PM10	0.026**	0.011	0.121***	0.047	0.120***	0.045		
Temperature	0.091	0.076	0.080	0.073				
Precipitation	1.933E-4**	0.000	1.856E-4**	0.000				
PoplOld	0.010***	0.003	0.011***	0.003				
PoplYoung	0.015*	0.008	0.014*	0.008				
Smoking	0.029**	0.013	0.028**	0.013				
Manufacturing	0.027*	0.014	0.026*	0.014				
Total effects								
PM10	0.101***	0.041	0.150***	0.046	0.146***	0.035	0.101***	0.031
Temperature	0.357	0.293	0.322	0.290	0.291	0.223	0.323	0.225
Precipitation	0.001**	0.000	0.001**	0.000	0.001**	0.000	0.001**	0.000
PoplOld	0.041***	0.011	0.044***	0.011	0.041***	0.008	0.038***	0.008
PoplYoung	0.059**	0.029	0.056*	0.029	0.042*	0.022	0.044**	0.022
Smoking	0.114**	0.049	0.114**	0.048	0.085**	0.037	0.084**	0.037
Manufacturing	0.105**	0.052	0.105**	0.052	0.083**	0.040	0.082**	0.040

Note: *, **, *** indicates statistically significant at 1%, 5%, and 10% level, respectively.

tion increases respiratory health risks including aggravation of asthma and respiratory infections such as pneumonia. For temperature, both the local and transboundary effects are positive, yet insignificant. In overall, compared to other environmental factors, air pollution is found to impose considerable health risks in other cities farther away from the source region.

For demographic variables, the elderly population is more susceptible to pneumonia-related risks as demonstrated by the positive and statistically significant association. The local effects are higher than impacts from other districts. The local and transboundary effects of the proportion of the young population is also positive and significant. Although not reported in this paper, we also estimated results with the proportion of the age group 40-49, for which the rate of economically active population is the highest compared to other age groups. The proportion of the elderly and children were still positively associated with pneumonia hospitalizations. Higher proportion of the age group in their 40s appeared to decrease pneumonia-related admissions. As such, proportion of susceptible age groups increase pneumonia-related health risks, rather than other age groups that are less vulnerable. Smoking rate is also found to be positive and significant. As smoking has negative impact on respiratory health, higher smoking rate in a region leads to higher risk for the area to experience increased hospitalizations due to pneumonia.

As for the economic variable, the production of the manufacturing sector is positively associated with pneumonia admissions. Production of the manufacturing sector is an indicator of economic development in districts, with better environmental amenities. Conversely, production in the manufacturing sector increases emissions from industrial facilities, energy consumption and transportation. From the result, both local and transboundary effects are positive and statistically significant as emissions from industrial facilities not only lead to higher PM10, but also other air pollutants from external districts, and increased exposure to such air pollutants lead to pneumonia-related risks.

4.2. REGRESSION RESULTS FOR SPATIAL PANEL MODELS WITH RESPECT TO WIND DIRECTION

The results of the spatial model with different spatial weight matrices representing variations of wind directions are outlined in Table 6. According to the results from all spatial weight specifications, increase in days with severe levels of PM10 is positively associated with increased pneumonia hospitalizations.

The parameter of spatially lagged variable is positive and statistically significant for results with each directional spatial weight matrix. This indicates that spatial effect exists for all cardinal directions, hinting on the existence of positive transboundary effects of PM10 on pneumonia-related admissions. Listing the cardinal directions in the order of highest spatial effect demonstrates that spatial dependency is strongest in the following order: Northwest, Southwest, Northeast, and Southeast. This reflects the stronger contagious effect of pneumonia from neighboring districts in the Northwest direction because major cities with higher population density, transport and industries along with less forestation are primarily located in Northwest Korea. The contagious effect is also heightened when the wind from the Northwest direction transfers domestic and foreign air pollutants during dry and highly polluted seasons. Additionally, the pronounced spatial effect in the Southwest direction may be attributable to periods of high pollution levels during spring and winter primarily due to dust blown from overseas. As such, the spatial interrelationship of various factors, includ-

Table 6: Regression results with directional spatial weight matrices

	Spatial							
	Northwest		Southwest		Northeast		Southeast	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
M*Y	0.636***	0.074	0.479***	0.075	0.373***	0.065	0.208***	0.046
PM10	0.063**	0.030	0.060*	0.031	0.078**	0.030	0.084***	0.031
Temperature	0.238	0.211	0.296	0.217	0.224	0.219	0.314	0.220
Precipitation	0.001**	0.000	0.001**	0.000	0.001**	0.000	0.001**	0.000
PoplOld	0.023***	0.008	0.024***	0.008	0.033***	0.008	0.034***	0.008
PoplYoung	0.024	0.021	0.042*	0.022	0.046**	0.022	0.044**	0.022
Smoking	0.077**	0.035	0.063*	0.036	0.081**	0.036	0.086**	0.036
Manufacturing	0.091**	0.038	0.070*	0.039	0.068*	0.039	0.076*	0.039
Log-likelihood	-1,158.042		-1,173.303		-1,176.894		-1,182.869	
AIC	2,334.083		2,364.607		2,371.788		2,383.739	
BIC	2,375.296		2,405.820		2,413.001		2,424.952	

Note: *, **, *** indicates statistically significant at 1%, 5%, and 10% level, respectively.

ing air pollution, leads to the spatial dependency of the dependent variable, or pneumonia hospitalizations.

Moreover, the log-likelihood is highest, and Akaike information criterion and Schwarz information criterion are lowest for the results with the spatial weight matrix for districts adjacent in the Northwest direction. This indicates that including the spatial effect from other districts located in the Northwest direction improves explanation of the spatial panel model.

Table 7 presents the local, transboundary and total effects of PM10 on pneumonia related admissions to the hospital. All results unanimously show total marginal effects of PM10 on pneumonia-related admissions to be positive and statistically significant. While both local and transboundary effects of PM10 for all results are positive and significant, the proportion of the internal and external air pollution differs depending on which direction of the spatial effect is accounted for in the model. When including the spatial effect from the Northwest, pneumonia-related admissions are increased by 0.063 (57.8 percent of total effects) due to one-day increase of severely polluted days within the city, and by 0.046 (42.2 percent of total effects) due to a day increase with high PM10 in other districts. With the spatial effect from the Southwest, hospital admissions are increased by 0.060 (71.4 percent of total effects), and by 0.024 (28.6 percent of total effects) due to one-day increase of PM10 in other cities. For the Northeast direction, a one-day increase of high PM10 in its own district and other districts increased pneumonia patients by 0.078 (77.2 percent of total effect) and 0.024 (23.8 percent of total effect), respectively. In the results with spatial effects

Table 7: Decomposition: local, transboundary, and total effects

	Spatial							
	Northwest		Southwest		Northeast		Southeast	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Local effects								
PM10	0.063**	0.030	0.060*	0.031	0.078***	0.030	0.084***	0.031
Temperature	0.238	0.211	0.296	0.217	0.224	0.219	0314	0.220
Precipitation	0.001**	0.000	0.001**	0.000	0.001**	0.000	0.001***	0.000
PoplOld	0.023***	0.008	0.024***	0.008	0.033***	0.008	0.034***	0.008
PoplYoung	0.024	0.021	0.042*	0.022	0.046**	0.022	0.044**	0.022
Smoking	0.077**	0.035	0.063*	0.036	0.081**	0.036	0.086**	0.036
Manufacturing	0.091**	0.038	0.070*	0.039	0.068*	0.039	0.076*	0.039
Transboundary effects								
PM10	0.046**	0.022	0.024*	0.012	0.024**	0.010	0.013**	0.005
Temperature	0.175	0.158	0.119	0.091	0.068	0.068	0.049	0.036
Precipitation	4.611E-4**	0.000	2.293E-4**	0.000	1.808E-4**	0.000	1.070E-4**	0.000
PoplOld	0.017***	0.006	0.010***	0.003	0.010***	0.003	0.005***	0.002
PoplYoung	0.017	0.016	0.017*	0.009	0.014*	0.007	0.007*	0.004
Smoking	0.057**	0.028	0.025*	0.015	0.025**	0.012	0.013**	0.007
Manufacturing	0.067**	0.031	0.028*	0.016	0.021*	0.013	0.012*	0.007
Total effects								
PM10	0.109**	0.051	0.084**	0.042	0.101***	0.039	0.097***	0.035
Temperature	0.413	0.367	0.415	0.305	0.292	0.285	0.363	0.254
Precipitation	0.001**	0.000	0.001**	0.000	0.001**	0.000	0.001***	0.000
PoplOld	0.040***	0.013	0.034***	0.011	0.043***	0.010	0.039***	0.009
PoplYoung	0.041	0.036	0.058*	0.030	0.060**	0.029	0.050**	0.025
Smoking	0.135**	0.061	0.088*	0.050	0.106**	0.047	0.099**	0.042
Manufacturing	0.158**	0.067	0.098*	0.054	0.089*	0.051	0.088*	0.045

Note: *, **, *** indicates statistically significant at 1%, 5%, and 10% level, respectively.

from the Southeast, 0.084 (86.6 percent of total effect) pneumonia-related hospitalizations per 1,000 persons increased due to a one-day increase of "very bad" PM10 within the district and 0.013 (13.4 percent of total effect) hospitalizations due to a one-day increase of high PM10 in outer districts.

The contribution of transboundary effects (42.2 percent of total effect) is highest for air pollution from the Northwest, followed by from the Southwest (28.6 percent of total effect). In overall, impacts of air pollution from outer districts when including spatial effects from the west are found to be high contributors to pneumonia-related hospital admissions. This is attributable to the highest levels of air pollution from industrial facilities, transport and foreign dust in metropolitan areas including Seoul, Incheon and Gyeonggi-do which are primarily located in the northwestern portion of the peninsula. Also, Northwest is the prevalent wind direction during periods of severely polluted seasons.

The Northwest wind migrates the air pollutants accumulated in Seoul and urban cities, mainly in the northwestern Korea, to other districts located downwind of these cities, posing risks at a national level.

As for control variables, local and transboundary effects are all positive and statistically significant except for temperature. Compared to precipitation and temperature, air pollution appears to have strong and significant transboundary effects, since air pollutants are easily transported by wind. Also, in cities with high proportion of the elderly population, pneumonia-related admissions to the hospital are higher. Additionally, increased production from the manufacturing sector is positively associated with increased risks related to pneumonia. As such, increased emissions from industrial facilities not only contribute to higher hospital admissions of pneumonia in the source district, but also to those of other cities as well.

Although not presented in this paper, the estimation results from SDM are comparable to those from our main analysis. The results from the SDM show transboundary effects in the Northwest and Southwest directions to be particularly strong, and local effects to be significant when accounting for spatial effects from the Northeast and Southeast directions.

5. CONCLUSION

Frequent exposure to ambient air pollution caused from natural and anthropogenic sources may lead to higher human health risks. Specifically, PM10 may aggravate respiratory-related morbidity, resulting in increased emergency room or hospital admissions negatively impacting human capital. As health is an important part of human capital, comprehensive assessment of air pollution impact on human health is required for effective exposure reduction strategies. Through this study, we used spatial panel models to estimate impacts of PM10 on human health and evidences of stronger association and spillover effects of PM10 on morbidity.

This study estimates the impact of PM10 on pneumonia patients with the non-spatial and spatial panel models. Empirical evidence based on non-spatial and spatial panel models commonly indicate that air pollution increases city-level health risks. The spatial panel model assessment reveals improvement in explanation and evidences stronger transboundary effects of air pollution on human health risks, revealing that air pollution imposes boundless risks at a national level. We further extend our spatial panel model analysis by utilizing various spatial weight matrices to investigate the spatial dynamics of PM10 impacts on respiratory health with respect to wind direction. We find that spatial spillovers of PM10 on pneumonia-related admissions are stronger and more pronounced for districts located downwind in the Northwest and Southwest direction than from other directions.

In overall, we have shown that spatial dependency yields negative externalities in terms of space, which requires policy designs expanded to include not only local, but also non-local efforts. The results from this paper begets two main policy implications imperative for the current situation in Korea relating to air pollution. First, we require global efforts for air pollution abatement strategies as clearing pollutants for a single district does not suffice, since air pollution transmitted from other cities are likely to have detrimental impacts on population health. Second, significant transboundary impacts of air pollution call for policy strategies that focus on Seoul and metropolitan areas of Korea. The results clearly reveal that the impact of air pollution goes beyond the city border and have repercussions for the health of the population at a national level. With intervention from the government specifically focusing on districts in the northwestern regions of Korea, or Seoul and metropolitan areas, we can expect positive spatial spillover effects of policies on abatement of air pollution and health risks at a national level.

Our study is the first to evaluate which wind direction causes the most severe negative externalities of air pollution on health risk. Assessing which wind direction contributes to stronger transboundary effects of air pollution on human health poses critical policy implications. As one of global efforts to attenuate ambient air pollution, designing and building skyscraper-sized air purifiers in highly polluted cities are being carried out. Large-scale towers have recently been built in Xi'an of Northwest China and more recently in South Delhi of India. According to the Institute of Earth Environment at the Chinese Academy of Sciences, air purifying towers are deemed as effective, as improvement in ambient air quality of an area of 3.86 square miles was observed in Xi'an. And yet these towers are spacious and costly, and a single air purifier would not suffice to curb national air pollution. Thus, decisions on targeting of geographical locations that would incur the crucial local and transboundary air quality improvement in terms of population health are needed. And our study could be used as a reference for effective strategies regarding geographic locations of future air filtering systems and industrial facilities.

This study could be improved by addressing the following shortcomings. First, the limitation of data for pneumonia-related risks should be addressed. Pneumonia is a chronic illness and patients are likely to have been diagnosed with pneumonia prior to being hospitalized. Hospital admissions for pneumonia patients might have increased due to worsening symptoms of already incurred respiratory-related ailments rather than exposure to higher levels of pollution. Moreover, biased results may arise as there are discrepancies in numbers between observed patients and patients in reality not included in the data. With more data available, we could better explain the association of recently increased air pollution and pneumonia incidents for future research.

Second, this study used air pollution data measured at ground level. Each administrative district has at most one or two stations measuring air pollution level. It is not accurate as how to associate which air pollution monitors with districts. A monitor in a district may be closer in distance to another district. To circumvent this limitation, the polygon-averaged measurement of satellite data can be used to better associate exposure to air pollution with district of residence. For this, high resolution satellite measure of air pollution is needed which is left for future research.

Third, assessing the extent to which spatial dependence between districts remains significant would have meaningful policy implications. As for the extent to which distance poses significant transboundary effects of air pollution, we need to experiment with various applications of the spatial weight matrix with different distance thresholds, and we leave this task for the future.

Fourth, empirical results suggest that contributions of PM10 on pneumonia are borderless due to spatial dependence between domestic districts. The spread of ambient air pollutants is not necessarily bounded by national borders. Considering the serious air pollution level in East Asia and complications of foreign contributions, research on this matter is imperative. As for now, we resort to domestic pollution contributors to population health, and leave the investigation of foreign factors for future research.

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