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Effects of Air Pollution on Assaults: Findings from South Korea

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Abstract: This study investigates the effects of concentration of air pollution on assault rates for 204 police districts of South Korea from 2001 to 2018. A series of panel spatial Durbin models for the concentration of ozone, fine dust, and nitrogen dioxide—three key air pollutants of the country—identify the significant impacts of air pollution on assault rates that vary from each other. Ozone is expected to induce more assaults both locally and regionally. Fine dust decreases assault rates of an area and also in neighboring areas. Nitrogen dioxide yields positive effects on the surrounding areas' assault rates but not in area of pollution itself. Findings of this study suggest the need to incorporate active measures on air pollution and violent crime at both city and inter-city levels. They also propose the active sharing of information on air pollution and crime between cities and regions as a collaborative response.

Keywords: air pollution; assaults; panel spatial Durbin model; South Korea

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1. Introduction

Since the advent of fossil fuel-based combustion engines in the 18th century, cities around the world have enriched themselves through the mass production of goods. However, small particles generated from the engines' operation have polluted the earth's near-surface atmosphere, putting the natural ecosystem and the human species at great risk. The Muse Valley fog of Belgium in 1930, the photochemical smog of Los Angeles in the 1940s, and the Great Smog of London in 1952 are some of the most remembered air pollution incidents that caused countless casualties and damages.

Chronic exposure to air pollution is widely known to adversely affect people's health [1,2]. Ozone induces chest pain, coughing, and nausea. It also exacerbates bronchitis, heart disease, emphysema, and asthma [3,4]. Fine dust, or particulate matter, penetrates inhaled alveoli and causes serious cardiovascular and respiratory diseases [5–7]. High concentrations of nitrogen dioxide lead to chronic bronchitis, pneumonia, pulmonary hemorrhage, and even pulmonary edema. In 2016, the World Health Organization (WHO) estimated 4.2 million premature deaths occurred from air pollution worldwide [8].

Another effect of air pollution is on people's aggressive behavior and misjudgment, mainly through psychological and biological changes, leading to violent crime outbreaks [9–11]. Many psychology studies report that air pollution impedes cognitive function. Abilities for language learning, memory, and self-control are negatively affected; and depression and anxiety symptoms may appear [12–14]. Losing self-control and the reduction of individual work capacity [15] and productivity [16] are found. Effects on depression, mental health, and even suicides are also identified [17–21]. Furthermore, a number of biological studies argue that air pollution may cause a reduction in hormones that make humans happy, and cause inflammation in the central nervous system [22–25]. They suggest that ozone significantly reduces serotonin, also known as the "happiness hormone", so also increases aggression [26,27], and that exposure to air pollution may cause oxidative stress and neuroinflammation along with changes in cerebrovascular damage, neurodegenerative pathology, and neuronal cells as the central nervous system is damaged [23–25,28]. Air pollution may also affect the oxygen transported in the blood and trigger physical discomfort and cognitive impartment [29].

Recent studies identify significant links between exposure to air pollution and crime. Burkhardt et al. [9] unveil the relationship between increased air pollution levels and violent crime rates in the United States and note the overlooked social costs. Herrnstadt and Muehlegger [30], based on an extensive analysis of data on more than 2 million crimes, air pollution, and climate conditions reported over 12 years in Chicago, United States, suggest that higher carbon monoxide levels result in increased daily crime rates. Lu et al. [31], using a panel analysis of nine years of six major air pollutants and crime data in 9360 cities in the United States, argue that criminal activities are positively associated with high air pollution concentrations. Chen and Li [11], from the NOx Budget trading program operated by the United States Environmental Protection Agency, report that lowering air pollution levels significantly reduces criminal activities. Bondy et al. [32], using air quality data and criminal records of London, United Kingdom, also unveils the positive relationship between the two.

In spite of these efforts, it is clear that the current literature looks into a limited part of the world and that further investigation is required. For better development of policies and strategies for managing air pollution and violent crime in diverse contexts, their intricate relationship should be further explored by adopting methods that take a wider range of causes into consideration.

This study looks into South Korea where high concentrations of air pollution, which frequently exceed WHO's recommended standards, persist [33,34]. It is also where the number of assaults, among the five official violent crime types in South Korea, does not present a clear declining trend unlike the other four, which are burglary, rape and sexual assault, robbery, and homicide, as Figure 1 illustrates, despite years of crime prevention efforts implemented at the national and local level [35]. More specifically, we use panel spatial Durbin models to empirically analyze the effects of concentrations of ozone, fine dust, and nitrogen dioxide on assault rates. Findings of this study may help identify the relationship between air pollution and crime for the first time in South Korea. It may also inform local and regional policy makers to secure environmental sustainability and safety.

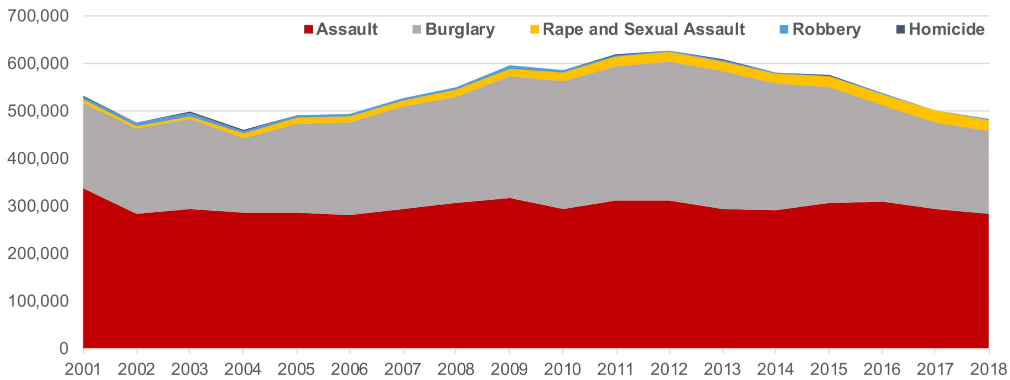
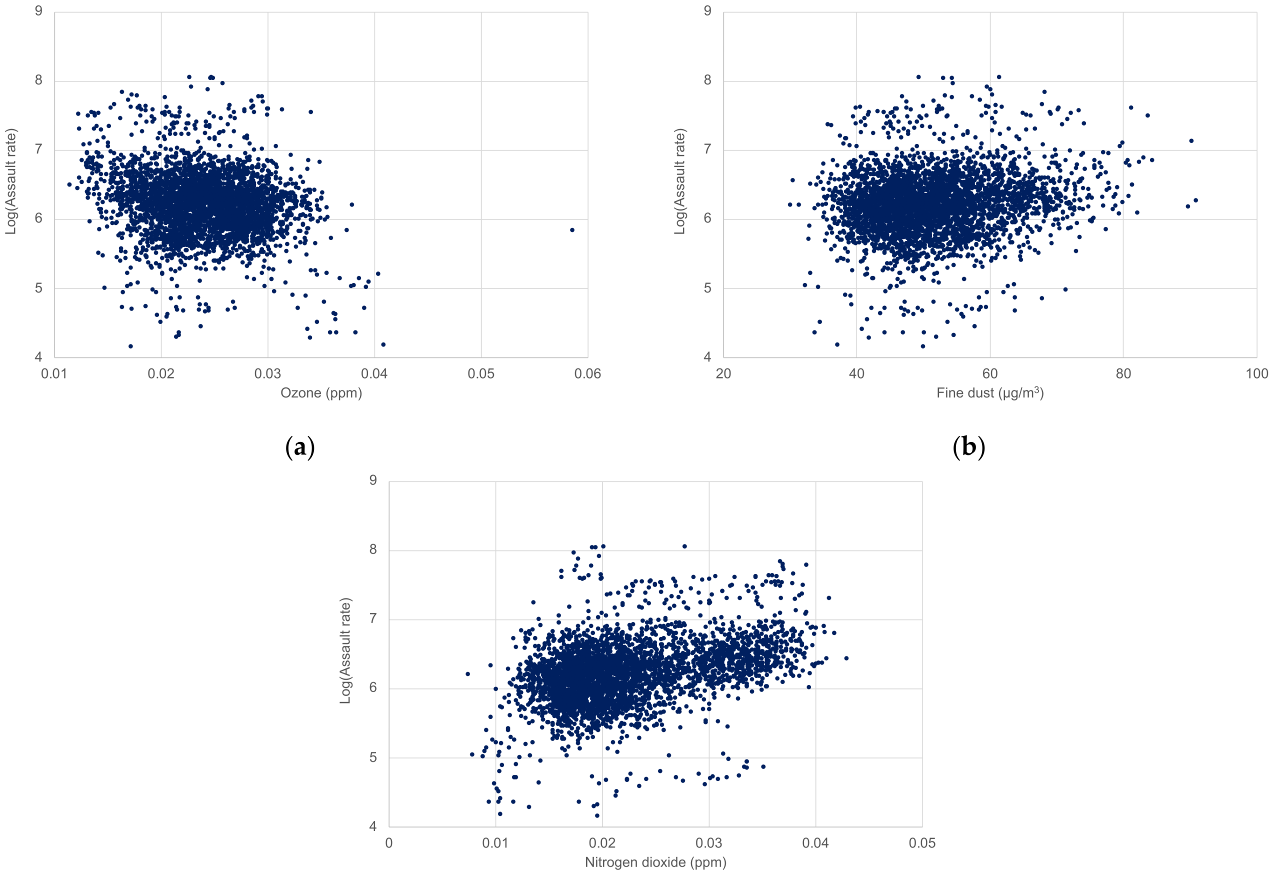


Figure 1. Reported numbers of the five types of violent crime (assault, burglary, rape and sexual assault, robbery, and homicide) in South Korea from 2001 to 2018 (Data source: National Police Agency of South Korea).

2. Materials

The dependent variable of our investigation is the assault rate. Assault in local terms includes aggression, injury, confinement, threat and blackmailing, kidnapping, and malicious mischief. We calculate the annual number of assaults per 100,000 residents using panel data for 204 police districts across the country for eighteen years from 2001 to 2018 based on data availability. The data is obtained through a special request from the Korean National Policy Agency (https://www.police.go.kr/ accessed on 4 March 2021).

Our key independent variables are concentrations of ozone (O_3), fine dust (PM_{10}), and nitrogen dioxide (NO_2). They are the three most representative air pollutants of South Korea and increasingly fail to satisfy the country's environmental standards in many cities. We use data offered by AirKorea (https://www.airkorea.or.kr/ accessed on 4 March 2021), a public website run by the Korean Ministry of Environment and the Korea Environment Corporation. The website plays an active role in providing access to data on concentrations of various air pollutants acquired from hundreds of monitoring stations established across the country. We calculate the annual mean concentrations of ozone, fine dust, and nitrogen dioxide from 2001 to 2018 for each of the 204 police districts. For ten districts without any monitoring stations, interpolations using geographic information systems are applied to generate reliable estimates. Figure 2 delivers the relationships between each of the independent variables and the log-transformed dependent variable for the 18 years. An initial observation implies some correlations between the variables but suggests further analysis is required.



(**c**)

Figure 2. Correlations between log-transformed assault rate and concentrations of (**a**) ozone, (**b**) fine dust, and (**c**) nitrogen dioxide (Data sources: National Police Agency of South Korea and AirKorea).

We also adopt a number of control variables that may yield non-negligible impacts on crime so as to avoid any confounding relationships between the dependent and independent variables. First, we look at climate characteristics by drawing from related literature [36–39], which include mean, minimum, and maximum temperatures, precipitation, and wind speeds. Relevant data is acquired from the Korea National Climate Data Center (https://data.kma.go.kr/ accessed on 4 March 2021). Interpolated values are computed for the ten police districts without specific data. Second, following previous research attempts [40–44], we include population characteristics such as population density and shares of children, elderly, and foreign populations. Lastly, to incorporate socioeconomic conditions of each district, data for property tax revenue, and unemployment rates, as some studies suggest [45,46], are adopted. The density of commercial facilities, which represent retail vibrancy as suggested by local literature [47], is also included. Population and socioeconomic data are downloaded from by the Korean Statistical Information Service (https://kosis.kr accessed on 4 March 2021).

Table 1 presents a descriptive summary of variables used in this study. Assault rate, population density, and property tax variables are logged to minimize skewness and increase normality. The log-transformed assault rates range between 4.15 and 8.05 with a mean of 6.21. Concentrations of ozone, fine dust, and nitrogen dioxide average at 0.024 ppm, 51.61 μg/m^3, and 0.023 ppm, respectively. The mean values of average, minimum, and maximum temperatures are 12.57 °C, −14.31 °C, and 35.41 °C, respectively. Those for precipitation and wind speeds are 1307 mm and 1.85 m/s, respectively. As for population characteristics, the logged population densities average at 6.35 persons per square meter and range from 2.97 to 10.27. The mean ratios of child, elderly, and foreign populations are 7.36, 15.54, and 1.55 percent, respectively. Regarding socioeconomic characteristics, the logged property taxes average at 67.1 million Korean Won; unemployment rates range between 1.3 and 5.7 percent with a mean of 3.13; and the average density of commercial facilities is 12.03 per 100 residents.

Table 1. Summary statistics.

Variable (Unit)	Observations	Mean	Standard Deviation	Minimum	Maximum
Dependent					
Assault rate (logged) (cases per 100,000 persons)	3672	6.21	0.46	4.15	8.05
Concentration of air pollution					
Ozone (ppm)	3672	0.024	0.005	0.012	0.059
Fine dust (μg/m^3)	3672	51.61	8.73	30.12	90.95
Nitrogen dioxide (ppm)	3672	0.023	0.007	0.008	0.043
Climate characteristics					
Average temperature (°C)	3672	12.57	1.33	8.14	16.34
Minimum temperature (°C)	3672	−14.31	4.25	−29.14	−2.57
Maximum temperature (°C)	3672	35.41	1.32	31.50	40.26
Precipitation (100 mm)	3672	13.07	3.38	1.02	31.90
Wind speed (m/s)	3672	1.85	0.52	0.89	4.27
Population characteristics					
Population density (logged) (persons/km^2)	3672	6.35	2.16	2.97	10.27
Child population ratio (%)	3672	7.36	2.15	2.78	17.14
Elderly population ratio (%)	3672	15.54	7.57	2.53	38.64
Foreign population ratio (%)	3672	1.55	1.49	0.06	10.60
Socioeconomic characteristics					
Property tax (logged) (10 million Korean Won)	3672	6.71	1.69	2.01	11.14
Unemployment rate (%)	3672	3.13	0.90	1.30	5.70
Density of commercial facilities (locations per 1000 persons)	3672	12.03	16.44	6.63	158.74

Note: Bold texts are used to differentiate variable types from the actual variables.

3. Methods

We first identify the spatial autocorrelation of assault rates for each year and select a spatial econometric model based on likelihood ratio (LR) and Wald tests. The Hausman test [48] is applied to each model to decide whether the model with fixed effect or the model with random effect is employed.

It is widely shared that spatial data is subject to spatial dependence and heterogeneity. Such effects, when identified as significant, violate basic assumptions of the ordinary least square (OLS) estimation of regression models and may generate unreliable results [49]. Accordingly, we verify spatial autocorrelation of assault rates for each of the eighteen-year periods by computing Moran's I statistic [50]. Results, as shown in Table 2, verify that the rates yield positive spatial autocorrelation that is statistically significant at the 0.1 percent level for all the eighteen years. They suggest the need for adopting spatial panel econometric models for analysis to take into account the spatial effects.

Table 2. Moran's I calculations of violent crime rates for each year.

Year	Moran's I	*p*-Value
2001	0.292 ***	<0.001
2002	0.325 ***	<0.001
2003	0.285 ***	<0.001
2004	0.278 ***	<0.001
2005	0.273 ***	<0.001
2006	0.232 ***	<0.001
2007	0.283 ***	<0.001
2008	0.262 ***	<0.001
2009	0.306 ***	<0.001
2010	0.253 ***	<0.001
2011	0.284 ***	<0.001
2012	0.263 ***	<0.001
2013	0.252 ***	<0.001
2014	0.243 ***	<0.001
2015	0.199 ***	<0.001
2016	0.186 ***	<0.001
2017	0.188 ***	<0.001
2018	0.168 ***	<0.001

*** $p < 0.01$.

Spatial econometric models are classified based on the different spatial dependencies considered. Spatial error models (SEMs) incorporate the spatial autocorrelation of the error term. Spatial lag models (SLMs), or spatial autoregression models, capture the spatial autocorrelation of the dependent variable. Spatial Durbin models (SDMs) introduce spatial spillover effects by recognizing the spatial lag terms of the dependent variables and the spatial lag term of the error of independent variables [51].

LR and Wald tests provide guidance to selecting the appropriate model [52,53]. As presented in Table 3, both the LR and Wald test results reject the hypothesis that the SDM can be simplified to an SEM or SLM at the 0.1 percent significance level, suggesting the applicability of SDM to this analysis. We use the panel SDM henceforth to effectively respond to the nature of the variables.

Table 3. Results of LR and Wald tests.

Air Pollutant	LR Test		Wald Test	
	Chi-Square	*p*	Chi-Square	*p*
Ozone	78.49	<0.001	81.41	<0.001
Fine dust	46.75	<0.001	53.79	<0.001
Nitrogen dioxide	32.12	<0.001	36.67	<0.001

The panel SDM can be expressed as follows:

$$Y_t = \rho W Y_t + X_t \beta + \theta W X_t + \varepsilon_{it} \quad (1)$$

where Y_t is the dependent variable at year t; ρ is the spatial lag coefficient of Y_t; X_t is the matrix of independent variables; β is the coefficient of the independent variables; θ is the spatial lag coefficient of the independent variables; W represents the spatial weight matrix; and ε_{it} represents random errors.

Unlike other spatial econometric models, panel SDMs capture direct and indirect effects [49,54,55]. The direct effect implies that the assault rate of an area is affected by the variations in the explanatory variables of the area. It also includes the potential effect of feedback loops where the impacts pass through neighboring areas back to the original area [51]. The indirect effect exhibits spillover effects caused by the explanatory variables of surrounding areas. The total effect is the sum of the direct and indirect effects. These effects provide a better interpretation of the results as the coefficients of SDMs may not directly reflect the marginal effects of each explanatory variable on the dependent variable [49,54]. SDMs successfully examine the influence of the independent variables on the dependent variable in local and surrounding areas and test spatial, temporal, and spatiotemporal dependences of the dependent variable [56]. For these reasons, many studies on air pollution or crime rates actively adopt SDMs to incorporate and identify spillover effects in their analyses [49,57–59].

We establish three panel SDMs each for the concentration of ozone, fine dust, and nitrogen dioxide, since they commonly yield relatively high levels of correlation among them (ozone and fine dust: −0.672; ozone and nitrogen dioxide: −0.675; and fine dust and nitrogen dioxide: 0.524) all of which are significant at the 0.01 level. Among the control variables, we do not include average temperature, population density, and child population ratio in all three models, and additionally unemployment rate in the nitrogen dioxide model, for their high levels of correlation, significant at the 0.01 level, with other variables.

4. Results

4.1. Ozone Impacts on Assault Rates

The Hausman test statistics for the ozone model is 47.21 ($p < 0.001$). We reject the random effect model and select the fixed effect model. Table 4 presents estimation results for ozone based on the panel SDM. Results suggest that the coefficient of concentration of ozone is 7.706 ($p < 0.05$), indicating that it positively affects assault rates at the local level. Among the control variables, minimum temperature, precipitation, wind speed, property tax, unemployment rate, and density of commercial facilities increase the rates, while the elderly population ratio decreases them. When spillover effects are considered, results differ slightly. The table shows that the concentration of ozone yields no significant impact but that minimum temperature, precipitation, elderly population ratio, and unemployment rate negatively affect the rates. The spatial rho value, which represents spatial interdependency, explains that a 1 percent increase in the surrounding areas' assault rates is associated with a 0.247 percent increase in local rates.

Table 5 demonstrates direct and indirect effects also generated from the panel SDM. Results are generally in line with what Table 4 provides. The direct effects are in general similar to the coefficients, and the indirect effects to those that consider spillover effects. The direct and indirect effects of the concentration of ozone are both significantly positive. This suggests that not only the ozone concentration of an area but also of its surrounding areas simultaneously increase the area's assault rates, similar to what previous studies have found. Among the climate variables, minimum temperature's negative indirect effect overcomes its positive direct effect, resulting in a negative total effect. Precipitation yields significantly positive direct and negative indirect effects at the same time, but the two effects seem to offset each other when combined. Wind speed exhibits only a significantly positive direct effect. Among the population variables, the direct and indirect effects of the elderly population ratio are both significantly negative. As for the socioeconomic variables, property tax, and unemployment rate present significantly positive direct effects but not significant indirect effects. The direct and indirect effects of the density of commercial facilities are both significantly positive.

4.2. Fine Dust Impacts on Assault Rates

The Hausman test statistics of the fine dust model is 46.20 ($p < 0.001$) and suggest the fixed effect model for analysis. As the panel SDM in Table 6 illustrates, the coefficient of concentration of fine dust, −0.003 ($p < 0.1$), presents a significantly negative impact on assault rates. Among the control variables, minimum temperature, precipitation, wind speed, property tax, unemployment rate, and density of commercial facilities increase the rates, while the elderly population ratio decreases them. When spillover effects are taken into consideration, the coefficient of concentration of fine dust is 0.006 ($p < 0.01$), exhibiting a significantly negative impact. Minimum temperature, precipitation, elderly population ratio, property tax, and unemployment rate negatively affect the rates. The spatial rho value presents that a 1 percent increase in the surrounding areas' assault rates is associated with a 0.247 percent increase in local rates.

Table 4. Estimation results for ozone.

Variables	Coefficient	*p*
Concentration of Ozone	7.706 **	0.013
Minimum temperature	0.026 ***	0.000
Maximum temperature	0.006	0.490
Precipitation	0.010 **	0.004
Wind speed	0.155 ***	0.000
Elderly population ratio	−0.006 ***	0.001
Foreign population ratio	0.005	0.249
Property tax (logged)	0.051 ***	0.000
Unemployment rate	0.100 ***	0.000
Density of commercial facilities	0.013 ***	0.000
*W** (Concentration of Ozone)	7.038	0.110
*W** (Minimum temperature)	−0.037 ***	0.000
*W** (Maximum temperature)	0.009	0.200
*W** (Precipitation)	−0.009 **	0.046
*W** (Wind speed)	−0.004	0.911
*W** (Elderly population ratio)	−0.009 **	0.007
*W** (Foreign population ratio)	−0.006	0.498
*W** (Property tax (logged))	−0.026	0.125
*W** (Unemployment rate)	−0.051 **	0.016
*W** (Density of commercial facilities)	−0.001	0.463
Spatial rho	0.247 ***	0.000
R^2	0.389	

** $p < 0.05$, *** $p < 0.01$.

Table 5. Direct, indirect, and total effects (ozone).

Variables	Direct Effect	Indirect Effect	Total Effects
Concentration of ozone	8.104 **	11.590 **	19.700 ***
Minimum temperature	0.024 ***	−0.039 ***	−0.015 ***
Maximum temperature	0.007	0.013	0.020 *
Precipitation	0.010 **	−0.008 *	0.002
Wind speed	0.158 ***	0.042	0.200 ***
Elderly population ratio	−0.007 ***	−0.013 ***	−0.020 ***
Foreign population ratio	0.005	−0.006	−0.001
Property tax (logged)	0.050 ***	−0.016	0.034
Unemployment rate	0.098 ***	−0.034	0.064 ***
Density of commercial facilities	0.013 ***	0.003 *	0.015 ***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Direct and indirect effects, as Table 7 presents, are again in line with what the panel SDM estimates in Table 6. The direct effects are almost identical to the coefficients, and the indirect effects are generally similar to the coefficients that incorporate spillover effects. The direct effect of concentration of fine dust is significantly negative but its indirect effect is significantly positive, presenting a significantly positive overall effect. This can be interpreted that an area's concentration of fine dust may negatively affect assault rates, but its surrounding areas' concentrations may positively affect the area's rates, resulting in an overall increase. Minimum temperature and unemployment rate commonly yield significantly positive direct and negative indirect effects at the same time. Precipitation and property tax present significantly positive direct effects. Wind speed and density of commercial facilities show significant positive direct and indirect effects, while the elderly population ratio exhibits significantly negative effects directly and indirectly.

Table 6. Estimation results for fine dust.

Variables	Coefficient	*p*
Concentration of fine dust	−0.003 *	0.076
Minimum temperature	0.028 ***	0.000
Maximum temperature	0.002	0.769
Precipitation	0.010 ***	0.007
Wind speed	0.159 ***	0.000
Elderly population ratio	−0.006 ***	0.001
Foreign population ratio	0.005	0.243
Property tax (logged)	0.049 ***	0.000
Unemployment rate	0.090 ***	0.000
Density of commercial facilities	0.013 ***	0.000
*W** (Concentration of fine dust)	0.006 ***	0.008
*W** (Minimum temperature)	−0.033 ***	0.000
*W** (Maximum temperature)	0.01	0.147
*W** (Precipitation)	−0.007 *	0.099
*W** (Wind speed)	0.006	0.854
*W** (Elderly population ratio)	−0.009 ***	0.005
*W** (Foreign population ratio)	−0.013	0.180
*W** (Property tax (logged))	−0.039 **	0.019
*W** (Unemployment rate)	−0.069 ***	0.001
*W** (Density of commercial facilities)	−0.001	0.517
Spatial rho	0.247 ***	0.000
R^2	0.403	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Direct, indirect, and total effects (fine dust).

Variables	Direct Effect	Indirect Effect	Total Effect
Concentration of fine dust	−0.003 *	0.007 ***	0.004 *
Minimum temperature	0.027 ***	−0.033 ***	−0.006
Maximum temperature	0.003	0.013 *	0.017
Precipitation	0.009 ***	−0.006	0.003
Wind speed	0.162 ***	0.056 *	0.219 ***
Elderly population ratio	−0.007 ***	−0.014 ***	−0.020 ***
Foreign population ratio	0.005	−0.014	−0.009
Property tax (logged)	0.047 ***	−0.033	0.014
Unemployment rate	0.088 ***	−0.060 ***	0.028
Density of commercial facilities	0.013 ***	0.003 *	0.015 ***

* $p < 0.1$, *** $p < 0.01$.

4.3. Nitrogen Dioxide Impacts on Assault Rates

The Hausman test statistics of the nitrogen dioxide model is 38.07 ($p < 0.01$) and suggests selecting the fixed effect model as opposed to the random effect model. As Table 8 shows, the panel SDM suggests that the concentration of nitrogen dioxide does not yield any significant impacts on local assault rates. Among the control variables, minimum temperature, precipitation, wind speed, property tax, and density of commercial facilities show positive effects; and elderly population negative exhibit effects, similar to what the two other models provide. When spillover effects are considered, results differ in general. The coefficient of concentration of nitrogen dioxide is 7.441 ($p < 0.05$), presenting a significantly positive impact on the rates. This can be interpreted that an area's assault rates are less affected by local concentration of nitrogen dioxide but more by those of the surroundings. Among other variables, minimum temperature, elderly population ratio, and property tax yield significantly negative impacts. The spatial rho is 0.247, suggesting that the surrounding areas' violent crime rates are associated with a 0.247 percent increase in local rates.

Table 8. Estimation results for nitrogen dioxide.

Variables	Coefficient	*p*
Concentration of nitrogen dioxide	−3.904	0.149
Minimum temperature	0.028 ***	0.000
Maximum temperature	0.006	0.502
Precipitation	0.006 *	0.085
Wind speed	0.157 ***	0.000
Elderly population ratio	−0.005 ***	0.003
Foreign population ratio	0.003	0.528
Property tax (logged)	0.055 ***	0.000
Density of commercial facilities	0.013 ***	0.000
*W** (Concentration of nitrogen dioxide)	7.441 **	0.026
*W** (Minimum temperature)	−0.034 ***	0.000
*W** (Maximum temperature)	0.008	0.272
*W** (Precipitation)	−0.004	0.339
*W** (Wind speed)	0.022	0.524
*W** (Elderly population ratio)	−0.011 ***	0.002
*W** (Foreign population ratio)	−0.015	0.132
*W** (Property tax (logged))	−0.039 **	0.024
*W** (Density of commercial facilities)	−0.002	0.301
Spatial rho	0.247 ***	0.001
R^2	0.404	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9 provides the direct and indirect effects of the nitrogen dioxide panel SDM. Again, the direct effects for each variable are similar to the coefficients from Table 8, and the indirect effects to those that consider spillover effects. Only the indirect effect is statistically significant for the concentration of nitrogen dioxide, suggesting that the spatial spillover effect of nitrogen dioxide of adjacent areas exhibit positive impacts on increasing assault rates. Among the climate variables, minimum temperature presents a significantly positive direct effect and a negative effect at the same time, resulting in an overall negative effect. Maximum temperature yields a significantly positive indirect effect, and precipitation a direct effect. Wind speed demonstrates significantly positive direct and indirect effects. Among the population variables, the elderly population presents negative direct and indirect effects. Among socioeconomic variables, property tax and the density of commercial facilities show significantly positive direct effects.

Table 9. Direct, indirect, and total effects (nitrogen dioxide).

Variables	Direct Effect	Indirect Effect	Total Effect
Concentration of nitrogen dioxide	−3.652	8.266 **	4.614 *
Minimum temperature	0.027 ***	−0.034 ***	−0.008 **
Maximum temperature	0.007	0.012 *	0.018 *
Precipitation	0.006 *	−0.003	0.003
Wind speed	0.161 ***	0.075 **	0.236 ***
Elderly population ratio	−0.006 ***	−0.015 ***	−0.021 ***
Foreign population ratio	0.002	−0.018	−0.016
Property tax (logged)	0.053 ***	−0.032	0.022
Density of commercial facilities	0.013 ***	0.002	0.015 ***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Disscussion

The results suggest several issues for discussion. First, we are able to identify the significant impacts of air pollution on assault rates, but the impacts differ by air pollutant type. An increase in the concentration of ozone would not only escalate the rates of an area but also increase in surrounding areas and in the end return to the area as feedback. Expanded ozone discharged into the atmosphere, largely caused by vehicle emissions and rising temperatures observed globally [60,61], is expected to induce more assaults both locally and regionally. On the other hand, an increase in the concentration of fine dust is expected to decrease assault cases of an area, while at the same time increasing in neighboring areas. The decreasing effect may relate to previous empirical findings that fine dust discourages outdoor activities [33,62,63], thus decreasing any likelihood of crime occurrence. The increasing impact may reflect the spillover effects that have been less perceived so far. In the case of nitrogen dioxide, only positive effects on the surrounding areas' assault rates are identified, raising concerns about its spillover effect, while not yielding any significant local impacts.

Some noteworthy impacts can also be identified from the control variables. Among the climate characteristics, rising minimum temperatures introduce higher assault rates at the local level. This is largely in line with empirical findings from existing studies that prove temperature impacts on crime [38,64,65]. Precipitation and wind speeds are found to increase assault rates at the local level in most cases. Regarding population characteristics, an evident finding is the negative impact of the elderly population on assault rates, yielding both local and spillover effects for all three air pollutant types. Although this may sound counterintuitive as some research identifies the elderly population as being more vulnerable to violent crime [66–68], it may represent that assault more frequently targets relatively younger population groups in our study context. Unlike researchers who identify relationships between foreign population and violent crime [44,69,70], we find no significant evidence in this analysis. Among socioeconomic characteristics, property tax and unemployment in general rate increase assault rates at the local level. It can be interpreted that more affluent areas, as represented by larger property tax revenues, and economically stagnant areas, as described by higher unemployment rates, at the same time may provoke assaults. This may illustrate the positive impact of economic inequality on crime also experienced in other contexts [46,71–73]. Commercial facilities are found to present positive impacts on assault rates at the local level. A higher concentration of retail, which often draws a larger number of people, may attract violent crime.

5. Conclusions and Policy Implications

Using a series of panel SDMs that build on data between 2001 and 2018 from South Korea, we find that air pollution yields significant impacts on assault rates. More specifically, concentrations of ozone, fine dust, and nitrogen dioxide, three of the most representative air pollutants in South Korea, exhibit either positive or negative impacts. They also present local and spillover effects at the same time.

There are several shortcomings in this study. First, our analysis carried out at the police district level, which is in general similar to the city level, may not detect specific locations of assaults that may be influenced by directly adjacent settings like building configurations, land use, and accessibility. Second, using yearly data may not accommodate seasonal or monthly fluctuations which may also influence crime. Third, as some climate data were missing, interpolations had to be made for statistical analysis.

However, several policy implications for creating safer and sustainable environments can be drawn. First, the identified impacts alarm cities with higher air pollution levels to adopt measures that are more preemptive and comprehensive to combat crime. The close connection between air pollution and assault should be reflected in local environmental and crime policies and be widely shared by policymakers. Second, the spatial spillover effects, identified for all three air pollutants, call for the need to adopt regional approaches that build on close inter-city collaboration. Coordinated policy responses against air pollution and assault should be promoted. Information on local air pollution levels and crime occurrences could be instantly shared between neighboring cities. Third, more active measures are required for ozone. The concentration of ozone is continuously rising nationwide and presents the most critical impacts on assault among the three air pollutants. It is also receiving less societal and policy concerns than fine dust, for which a wide range of strategies are being already established and implemented.

Future studies may benefit from the findings of this study and carry out more in-depth analyses. Air pollution impacts on other violent crime types can be investigated, and seasonal or monthly influences can be identified. Similar approaches in diverse contexts may generate practical findings that would benefit local policymakers devoted to making safer and more sustainable dwelling environments for people.

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