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Spatial Effects of Air Pollution on the Housing Market: Evidence from South Korea

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ABSTRACT
This paper examines the spatial relationship between the ambient air pollution level of an apartment and its property value in the housing market of South Korea. Using detailed transaction data for 2015–2018, we construct the air pollution index and estimate a two-stage spatial Durbin error model that controls for both direct and spillover effects. We find that, holding other factors equal, a 1% increase in the air pollution level can, on average, cause a decrease in the value of a local real property by 0.32% ($879). Spatially heterogeneous effects of air pollution on housing prices are investigated, and air pollution is found to have a more significant direct impact on the urban housing market than in rural areas. Moreover, rising air pollution levels in urban centers can raise housing prices in suburban and rural areas, suggesting a strong spillover effect of air pollution and potential migration towards better air quality. The findings in this paper have profound implications for analyzing the spatial impacts of air pollution on housing prices and urban development.

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Introduction

The valuation of the accrued benefits of improved air quality has long been the main focus in assessing the effectiveness of environmental policies that aim to address air pollution (Freeman et al., 2014). Due to the absence of a formal and explicit market for clean air, some typical nonmarket valuation techniques have been proposed and widely used to estimate its value. These modeling methods include hedonic pricing, contingent valuation, conjoint analysis, and discrete choice model, and most estimates have been made in the context of real estate markets.[1] Given the attributes of available transaction records of residential properties and measurements of air pollution levels, this paper adopts the methodology of the hedonic pricing model to estimate an implicit cost for air pollution. The rationale behind this approach is that homebuyers are willing to pay less for the residences with a higher air pollution level, ceteris paribus. Thus, air pollution would be capitalized into the property value and reflected in a lower sales price. Using the hedonic approach, we can elicit homebuyers' preferences for air quality by observing their choice behaviors.

Since the 1980s, South Korea has experienced rapid industrialization, and, as reported by the Korea Environment Institute, the levels of air pollution, such as ozone and fine particulate, have largely increased.[2] Concurrently, the fast-growing development and large-scale urbanization have dramatically driven up housing prices in the real estate market. Given the rising income level and economic growth in South Korea, more attention has been given to the quality of the living environment, especially the ambient air quality that influences everyone' s welfare. This surrounding public good has become an essential factor in the decision-making of a potential home buyer. Thus, the relationship between air pollution and housing prices in the nation with a fast-growing housing market is worthy of study. This is the first paper, to the best of our knowledge, that comprehensively explores how air pollution influences the housing market in entire South Korea.[3] Another aspect of potential improvement in the existing research arises from the measurements of air pollution in South Korea. Over the study period, there only exist readings of individual air pollutions, other than an indicator of overall air pollution.[4] In this paper, we construct the air pollution index (API) ourselves and use the constructed API to measure the influence of air pollution more generally.

From the perspective of urban planning, accurate economic evaluations of air quality improvement require a correct identification and consistent estimation of the implicit price of air quality. Using a hedonic pricing model, numerous researches have provided empirical pieces of evidence about the value of air quality reflected in the housing price.[5] However, the influence proves to be region-specific, and there has been no consensus on its magnitude and even direction of the influence. The ambiguity can be attributed to the lack of considering the spatial effects of air pollution on housing prices in a non-spatial hedonic model. The ambient air pollution level of a particular unit influences not only its property value but also the values of other properties in a locality or other nearby housing markets. It is since home buyers typically perceive both temporal and geographic variations in air quality when choosing among alternative housing units in a city or locality. Therefore, the spillover effects of air pollution need to be controlled for when evaluating its influence on the housing market. The use of a spatial pricing model in this paper accounts for the strong spillover influence among other housing and locational attributes. Given the high-density built environment in most residential areas, the magnitude of these spatial interactions can be more significant in South Korea than in other nations. In the high-density urban area, the height of a residence influences not only its scenic view and property value but also the amenities, like a view of open space and sunlight, for other nearby apartments. Another aspect of spatial interactions in the hedonic setup comes from the dependent variable, housing price. The purchase behaviors of home buyers are likely to be influenced by other bidders, which implies that housing prices can be spatially related. To fully capture the spatial dependence of various types, this paper adopts a spatial Durbin error model (SDEM) that incorporates spatial variables in property values, air pollution, and other housing and locational attributes. Utilizing this spatial modeling technique, we pursue a comprehensive empirical analysis on the relationship between air quality and property values, providing the estimates of direct, spillover, and total effects of air pollution in this paper.

Apart from spatial dependence, the issue of endogeneity in air pollution variables needs to be fixed in estimating a spatial pricing model. Due to the budget and technological constraints in the monitoring system of air quality, there commonly exists a mismatch between locations of residences with price information and sites of monitoring stations. Some data interpolation techniques are required to get around the data limitation and obtain interpolated values for the locations in which housing prices are observed.[6] However, all these geostatistical methods bring unexpected endogeneity in constructing the environmental variables, referred to as errors-in-variables (Anselin & Lozano-Gracia, 2008). It is primarily due to spatially interpolated values that have a prediction error correlated with the idiosyncratic error in the spatial hedonic pricing model. The correlation between two spatial error terms leads to simultaneity bias in the estimation. To address the issue of endogeneity, we use an instrumental variable for the interpolated air pollution variable in a spatial two-stage least square model (S2SLS) to correct the bias.

This paper documents the relationship between air pollution and housing price and contributes to the existing literature as follows. Firstly, using the detailed nationwide housing and air pollution data, this is the first research that provides estimates on the influence of air pollution on the housing market of entire South Korea. Secondly, we construct an air pollution index in this paper to analyze the influence of overall air pollution. The index incorporates more information on air pollution and can be used to capture the perception of air pollution levels better when making a home purchase decision. Lastly, this paper reports the new estimates using the up-to-date two-stage spatial hedonic pricing model. Compared to related literature in the context of South Korea's real estate market, we address the endogeneity of interpolated air pollution variables and largely improve the accuracy in estimating the value of improved air quality due to the advanced methodology.

The main findings in this paper are as follows: (1) There exist heterogeneous effects of air pollution on the housing market. Specifically, households in urban areas with a higher level of air pollution have a higher marginal willingness to pay (MWTP) for improved air quality than those living in rural areas. (2) The central urban air pollutions have a more substantial spillover effect on suburban and rural housing prices than that in the opposite direction. The rest of this paper is organized as follows. We review the related studies in the section of literature review and describe the empirical background and data in the next section. The spatial pricing model is introduced in the section of spatial two-stage least square model, followed by the empirical results outlined in section of estimation results. The final section concludes the paper.

Literature Review

In the area of nonmarket valuation, the hedonic pricing model has long been the primary methodology, and this modeling method can be traced back to consumer theory by Lancaster (1966) and the implicit market model by Rosen (1974). Since then, many studies have widely adopted the model in estimating the values of air quality improvement in the context of residential property markets. To describe the vast body of related literature, two meta-analyses that summarize empirical findings regarding the influence of air quality on housing prices are first mentioned here. Smith and Huang (1995) conducted a meta-analysis that covers 37 studies on air pollution and compares 86 estimates of marginal willingness to pay (MWTP) for air quality improvement. They found that a 0.05–0.10% increase in property values results from improving air quality by one unit. In more recent work, Chay and Greenstone (2005) argue that the true relationship between property value and air pollution is primarily obscured by some unobserved attributes influencing both in a non-spatial analysis.[7] The casual ambiguity about how air quality is capitalized into a property value warrants further investigation using a more advanced modeling technique. Thus, a spatial Durbin error model (SDEM) is proposed soon after.[8] The SDEM accommodates a more flexible spatial dependence pattern and enables researchers to analyze the direct, spillover, and total effects of some environmental attribute (LeSage & Pace, 2009). Many empirical studies also showed that it yields a better fit to the data than a traditional non-spatial hedonic price model (Osland, 2010).

The development of a spatial modeling approach largely facilitates the evaluation of an air quality improvement, and numerous empirical estimates are provided in the context of housing markets. In the U.S. housing market, some focus on a local urban area (Anselin & Le Gallo, 2006; Brasington & Hite, 2005), while others estimate its hedonic value over the national housing market (Chay & Greenstone, 2005). In the non-U.S. regions, there is also a fast-growing body of studies that cover various places worldwide. These study areas include, but are not limited to, Madrid (Fernández-Avilés et al., 2012), Indonesia (Yusuf & Resosudarmo, 2009), mainland China (Li et al., 2014), and Seoul in South Korea (Jun, 2018; Kim et al., 2003). Model identification is a focal point for an accurate estimate of willingness to pay for air quality improvement. Much effort has been made to identify and avoid potential endogeneity in pollution variables from multiple sources. Chay and Greenstone (2005) argue that, when there exists preference heterogeneity in air quality, environmental indicators can be endogenous due to a residential sorting by house purchasers. Bayer et al. (2009) point out the possibility of local air pollution being correlated with unobserved local locational attributes, which can be addressed using the influence of distant sources to local air pollution as an instrument. Moreover, the endogeneity in air pollution measurement can also be generated in the data interpolation process. Anselin and Lozano-Gracia (2008) propose that data interpolation leads to unexpected endogeneity if there exists a spatial correlation between locally interpolated air pollution variables and errors in the main pricing model. In an attempt to fix endogenous air pollution data, many studies use instrumental variables in a spatial modeling technique and estimate the values of school quality (Fernández-Avilés et al., 2012), park amenities (McGranahan et al., 2010), and an ambient power plant (Hoen et al., 2009).

Empirical Background and Data

Air Pollution in South Korea

Over the past decade, the rising air pollution level has become a primary public concern about environmental quality in South Korea, especially for households living in urban areas. The residential housing market in South Korea is influenced by the nationwide air pollution issue, and property values thus change in response to the environmental amenity. Due to technological advancement and the universal use of a mobile device, the public has easy access to real-time air quality data all over the entire country. The free information flow of air quality is of critical importance, in the sense that the impact of air quality reflected in the housing price depends on how much is known about it (Clark & Allison, 1999). The accuracy of empirical evidence based on revealed preferences could be reduced mainly by the limited perceived information. Therefore, in the context of the housing market in South Korea, almost complete information on air pollution eliminates the potential concern, which makes it reliable to estimate the value of improved air quality in light of the price differentials in property values

Geography of the Study Area

The study area of this paper is the entirety of South Korea, comprised of 250 counties and county-equivalents.[9] Figure 1 illustrates the boundaries of geographical units and spatial distribution of the monitoring system in South Korea. The green areas represent the metropolitan cities constituted by a couple of counties. It can be seen that there are more monitoring stations in metropolitan cities than in rural areas. A total of 398 monitoring stations are located over the entire study area, even if no monitors are sited in a few rural counties. Thus, a data interpolation method is required to estimate the air pollution level in these places without direct measurements.

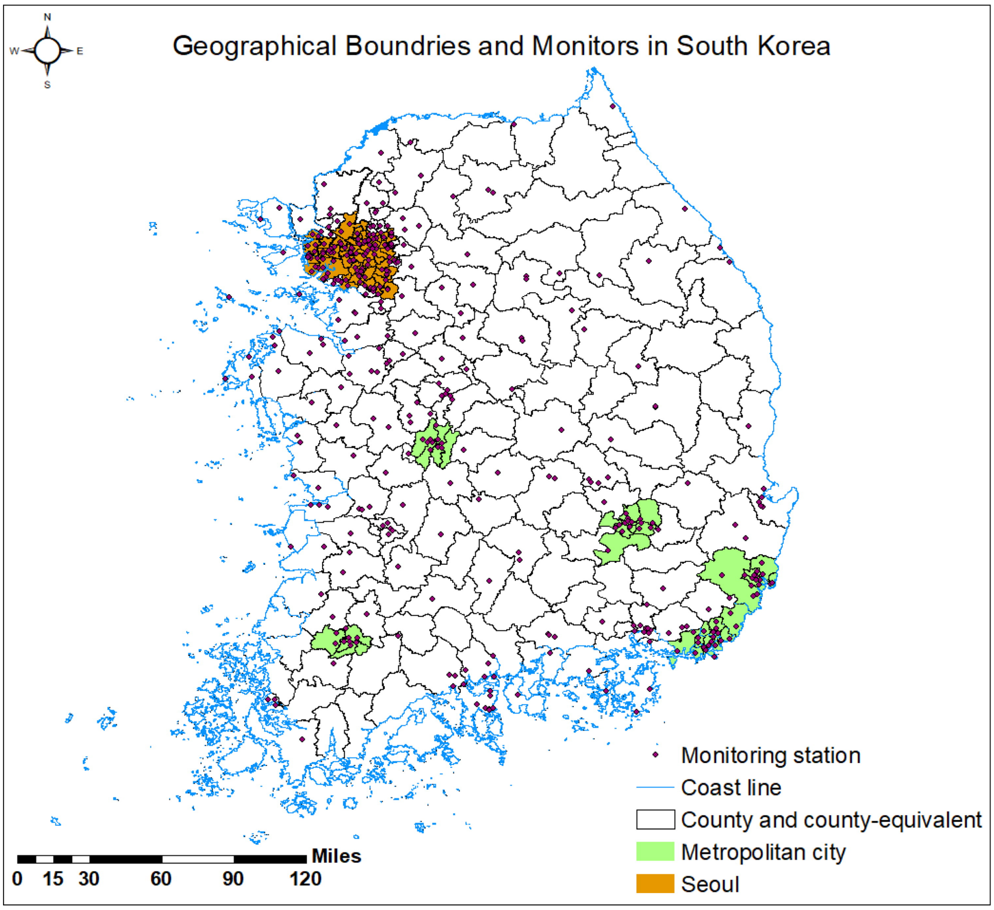


Figure 1. Geographical boundaries and stations in South Korea.

Real Estate Data

This paper is conducted with a comprehensive dataset that includes real estate data, air quality, and locational attributes. The first data source, real estate data, comes from the database provided by the Ministry of Land, Infrastructure, and Transport, which includes the transaction records of residential properties and housing attributes.[10] In the database, we obtain sales information of 1,765,631 apartments in 2015–2018, including transaction price, floor area, specific address, the floor of an apartment in the building, year of construction, transaction date (month). There exist a total of 35,821 buildings in our sample, and they are densely distributed across geographic areas. Panel (a) in Figure 2 presents the geographic variations in housing prices over the entire nation, and it can be found that metropolitan cities feature much higher housing prices than the remaining areas.

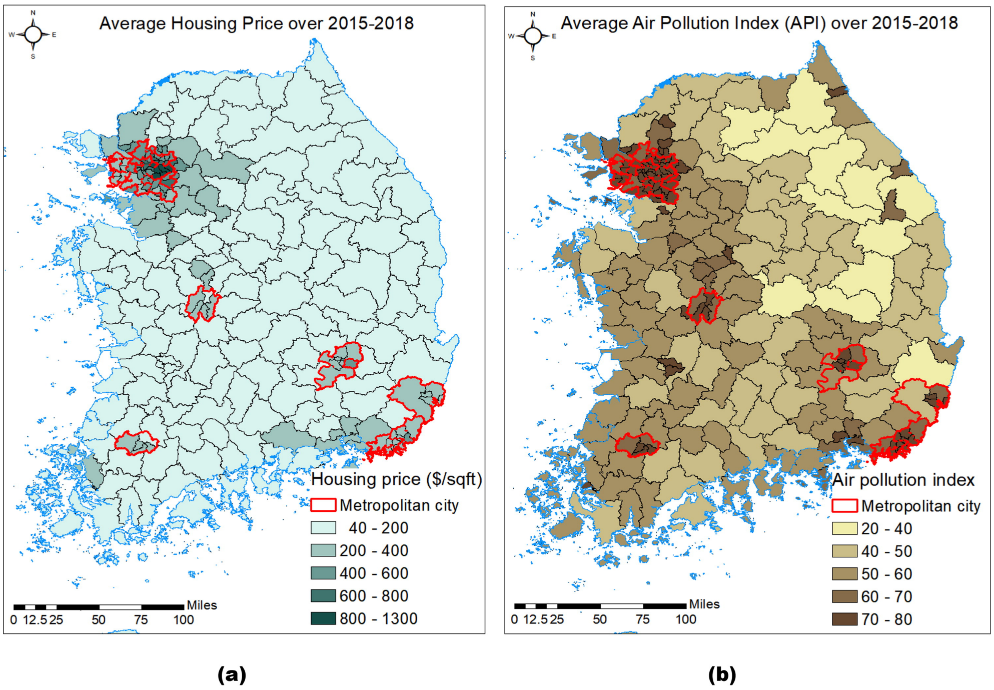


Figure 2. Average housing price and air pollution index over 2015–2018 in South Korea. (a) Housing price. (b) Air pollution index

Air Quality

Air pollution data used in this paper are measured on an hourly basis and obtained from the Korean Ministry of Environment in South Korea.[11] Figure 1 shows the spatial distribution of all 398 stations. They report six common air pollutants, i.e., sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2), particulate matter (PM2.5 and PM10).[12] Rather than estimating the influence of two specific air pollutants on housing prices (Kim et al., 2003), we fully utilize the rich information of the air pollution data and construct a new air pollution index (API).[13] The index can be used to estimate how much residents value the overall air quality in South Korea. Let $\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_6$ be the levels of six pollutants, the API measured at a site $\boldsymbol{s}_i$ is given by the weighted mean:

$$\mathrm{API}\left(\boldsymbol{s}_i\right) = \sum_{k=1}^{6} a_k X_k(\boldsymbol{s}_i) = \boldsymbol{A}'\boldsymbol{X}, \tag{1}$$

where $X_k(\boldsymbol{s}_i)$ is the value of air pollutant $\boldsymbol{k}$ measured at the site $\boldsymbol{s}_i$ and $\boldsymbol{A}$ is the vector of loadings of all pollutants. We use the principal component analysis (PCA) to obtain the weights.

Due to the financial constraint, it is impossible to measure the air pollution level at every location, which makes it necessary to interpolate the pollution data at the given locations of apartments. Based on the physical attributes of air pollutants, this paper adopts the ordinary kriging (OK) method assuming a constant local level of air pollution.[14] This interpolation procedure first estimates a spatial variance-covariance structure by fitting a variogram function of distances and observed values. Then, the kriging weights of nearby values are calculated by the fitted variogram function. The ordinary kriging estimator at any particular location becomes a linear combination of the surrounding values with these kriging weights.[15] Given the techniques of data construction and interpolation, there are essentially two alternative ways of constructing air pollution levels at the locations of apartments. The two options are 1) to construct the API at each location of monitors and then obtain the kriged estimates of API at locations where housing prices are observed but pollution levels are unknown;[16] 2) to krige the values of each air pollutant separately in the locations of apartments and then form the API in these locations.[17] Following the proof by Myers (1983), we take the second option with a less prediction error by first kriging the air pollution levels and then forming the API with the weights of principal components.[18] Table 1 displays the results of fitting variogram functions for each air pollutant and the principal component analysis in constructing the API. Given the fitted semivariogram, we first calculate the kriging weights and interpolate the pollution levels in all locations of apartments for each air pollutant. It is seen that PM10 is given a much higher weight than other air pollutants, due partially to the fact that it is the only visible pollutant that has a large perceived risk to health.

Given the weights on principal component and kriged air pollution levels, we calculate the apartment-specific air pollution index. Panel (b) in Figure 2 shows the geographic variations in the overall air pollution levels across counties over 2015–2018. It displays that most urban areas are heavily polluted, while rural counties have relatively lower air pollution levels.

Locational Attributes

In a hedonic pricing model, all price determinants need to be controlled to attain an accurate estimate of the coefficient on the variable of interest. To this end, we collect a broad range of locational attributes at the county level. All attributes are obtained from the Korean Statistical Information Service (KOSIS).[19] It includes unemployment rate, gross regional domestic product, number of residents, number of cars, severe crime, number of elementary schools. These variables are measured yearly and capture the annually time-varying effects that locational fixed effect cannot in our main identification equation.

Summary Statistics

Table 2 presents the summary statistics of all the variables used in estimating the spatial hedonic pricing model, including the real estate data, air pollution, housing, and locational attributes. The economic variables, i.e., housing prices and GDP per capita, are measured in 2018 U.S. dollars.[20] It is shown that the average value of an apartment is in South Korea comparable with that in the U.S. and that household income is slightly lower than U.S. household income. As for the floor level, we can observe that most apartments are in high-rise buildings and relatively new. The locational attributes are all in normal ranges and provide much information for local housing prices.

Spatial Two-Stage Least Square Model (S2SLS)

To estimate the influence of air pollution on housing prices, this paper adopts the up-to-date spatial two-stage least square model (S2SLS) under the framework of a spatial Durbin error model (SDEM). The spatial Durbin error model includes spatial lags of both explanatory variables and error terms as follows (LeSage & Pace, 2009)[21]:

$$\begin{array}{l} \ln(P_{ibct}) = X_{ict}\Theta_1 + WX_{ict}\Theta_2 + \lambda_t + L_b + \mu_{ibct} \\ \mu = \eta W\mu + \epsilon;\ \epsilon \sim N(0, \sigma_\epsilon^2 I_N) \end{array}, \tag{2}$$

where $\ln(P_{ibct})$ is the natural log of unit price of the apartment i of building b in county c sold in month t. The vector, X_{ict}, denotes all independent variables, including air pollution index (API), apartment-specific characteristics, and all other observed locational attributes. The coefficients on these independent variables, Θ_1 and Θ_2, represent direct and spillover effects, respectively. The monthly fixed effect, λ_t, captures the monthly pattern and other time-variant changes that influence the entire housing market. Given the large sample and exact address of each building, this spatial model incorporates building fixed effects, L_b, controlling for all other local unobserved locational attributes at the lowest possible level. The error term, μ_{ibct}, could be spatially correlated, and μ is the vector of the error terms.[22] The spatial autoregressive parameter, η, measures the existing spatial dependence of unobserved idiosyncratic errors that influence the property values between nearby areas. The key component in the spatial hedonic pricing model is the spatial weighting matrix, W, that controls for local spillovers to neighboring observations and describes spatial influences between nearby apartments as follows:

$$W = \begin{bmatrix} 0 & w_{12} & \dots & w_{1n} \\ w_{21} & 0 & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & 0 \end{bmatrix} \tag{3}$$

The diagonal elements of the matrix are set to zero since there exist no spillover effects on itself. To fully capture the spatial effects of air pollution, housing, and locational attributes in the high-density residential areas, we use the most robust double-power distance weights defined on the following criteria:

$$w_{ij} = \begin{cases} \left[1 - (d_{ij}/d)^k\right]^k, 0 \le d_{ij} \le d \\ 0, d_{ij} > d \end{cases}, \tag{4}$$

where d_{ij} is the distance between two apartments. d denotes the maximum radius of influence (bandwidth), and k is the integer that takes the typical value, 2 (Dou et al., 2016).[23] Given the density of a residential area, the value of the maximum radius is required to be context-specific. To obtain the radius that well describes the range of spatial effects in South Korea, we test a few values and find that the radius of 10 miles can best fit the data in estimating the spillover influence.[24] Given the elements $\boldsymbol{w_{ij}}$, the symmetric weighting matrix is row-standardized, such that $\sum_j \boldsymbol{w_{ij}} = \mathbf{1}$. After the row standardization, the weighting matrix becomes asymmetric and is then used in the spatial model.

Given the structure form in Equation (2), we derive the reduced form of the spatial hedonic model and use the following matrix to represent the spatial effects of $\boldsymbol{r}$-th independent variable on housing prices:

$$\frac{\partial y_i}{\partial x_{jr}} = (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1} (I_n \theta_{1r} + \boldsymbol{W} \theta_{2r})_{ij} = S_r \left(\boldsymbol{W} \right)_{ij}, \tag{5}$$

where $\boldsymbol{\theta_{1r}} \in \boldsymbol{\Theta_1}$ and $\boldsymbol{\theta_{2r}} \in \boldsymbol{\Theta_2}$ are the coefficients on the $\boldsymbol{r}$-th independent variable. The diagonal elements of $\boldsymbol{S_r(W)_{ij}}$ are the direct effects. The sum of off-diagonal elements across each row represents the indirect effect of one unit change in $\boldsymbol{r}$-th independent variable across all spatially correlated observations on the $\boldsymbol{i}$ th housing price.

If we assume that all regressors, except for spatially lagged error terms, are exogenous, the standard spatial hedonic pricing model, which regresses housing prices on air pollution index and other control variables, can be estimated using the classic Maximum Likelihood (ML) procedure. However, the use of interpolated air pollution levels results in prediction error that is spatially correlated with the overall error term in the spatial hedonic pricing model (Anselin & Lozano-Gracia, 2008). Therefore, an instrumental variable (IV) for API is used to estimate the spatial effects of air pollution on housing prices in a spatial two-stage least square model (S2SLS). Following the choice of IV by Fernández-Avilés et al. (2012), we adopt spatial coordinates and lagged APIs to instrument the endogenous air pollution levels. The latitude and longitude are able to largely proxy the global spatial trend of air pollution, and they are unlikely to be correlated with the error term in the hedonic model. The lagged APIs are strongly correlated with the current APIs and can substantially improve the precision of the instrumented API.

Estimation Results

This section presents the main estimation results of the hedonic pricing models introduced before and explores the possible heterogeneous effects of air pollution on local housing markets.

Spatial Hedonic Pricing Models

In an attempt to examine the impacts of air pollution on local property values, we first test for the possible spatial dependence using an LM-spatial lag test in which a non-spatial hedonic model is assumed to be the null hypothesis (H_0) against a spatial Durbin error model (H_1). The non-spatial model is rejected at the 1% level, showing strong spatial interactions in price determinants of apartments. Table 3 presents the estimation results of the non-spatial and spatial models. To interpret the results, we report the estimated effects in Equation (5), instead of the estimates of coefficients.[25] All spatial models allow for the remaining spatial autocorrelation and heteroskedasticity of an unspecified nature using the HAC standard errors (Kelejian & Prucha, 2007). Column [1] reports the estimation results of the non-spatial hedonic pricing model. It can be seen that, without controlling for the spatial effects, a higher level of air pollution is expected to increase a local housing price, ceteris paribus. The coefficient on the air pollution index is largely biased, and some other coefficients can also be misleading in the non-spatial model, which proves the incompleteness of the naïve OLS method.

Table 3. Estimation results of non-spatial and spatial hedonic pricing models. (Table view)

Dependent variable: $\ln(P_{ibct})$							
	Non-spatial	SLX and SDEM with ln(API) instrumented					
	OLS	Spatial lag of *X* model			Spatial Durbin error model		
	Direct	Direct	Spillover	Total	Direct	Spillover	Total
Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]
ln(API)	0.3783***	−0.3264***	0.2555**	−0.0709***	−0.3201***	0.2391**	−0.0810***
	(0.0112)	(0.0223)	(0.1213)	(0.0101)	(0.0124)	(0.1114)	(0.0122)
Floor	0.0551**	0.0301**	0.0201***	0.0502**	0.0441***	0.0237***	0.0678**
	(0.0230)	(0.0148)	(0.0026)	(0.0243)	(0.0025)	(0.0058)	(0.0321)
Floor^2	−0.0032**	−0.0311**	0.0529***	0.0218**	−0.0213***	0.0424***	0.0211**
	(0.0013)	(0.0148)	(0.0046)	(0.0102)	(0.0078)	(0.0026)	(0.0109)
Age	−0.2485***	0.2233***	0.2858***	0.5091***	0.4911***	0.7100***	1.2011***
	(0.0135)	(0.0165)	(0.0231)	(0.0485)	(0.0718)	(0.0423)	(0.0592)
Unemploy	−0.0902***	−0.8023**	−0.1289**	−0.9312**	−0.8023**	−0.0898**	−0.8921**
	(0.0316)	(0.3619)	(0.0596)	(0.4346)	(0.4218)	(0.0432)	(0.4190)
Gdpper	0.1102**	0.5940***	0.0674***	0.6614**	0.5498**	0.0715***	0.6213**
	(0.0459)	(0.1291)	(0.0023)	(0.0197)	(0.2882)	(0.0109)	(0.3121)
Popden	0.0202**	0.2440***	0.3051**	0.5491**	0.2132**	0.3309**	0.5441**
	(0.0084)	(0.0070)	(0.1284)	(0.2130)	(0.1084)	(0.1612)	(0.2381)
Carden	−0.0102**	0.5520**	0.9608***	1.5128**	0.7134***	0.5487***	1.2621**
	(0.0043)	(0.2227)	(0.0174)	(0.7529)	(0.2133)	(0.0218)	(0.5221)
Crime	−0.1002***	−0.7711**	−0.6401***	−1.4112***	−0.7789**	−0.6728**	−1.4517**
	(0.0209)	(0.3326)	(0.0297)	(0.1312)	(0.3341)	(0.3094)	(0.6221)
School	1.2342***	0.2489**	0.7123**	0.9612**	0.2210***	0.7202***	0.9412**
	(0.1956)	(0.1219)	(0.3446)	(0.4182)	(0.0482)	(0.0322)	(0.4613)
Month FE	Y		Y			Y	
Building FE	Y		Y			Y	
N	1,765,631		1,765,631			1,765,631	
Adjusted R^2	0.1827		0.2043			0.2591	

Notes: Columns [1] presents the coefficient estimates of the non-spatial hedonic pricing model. Columns [2–4] show the estimation results of the spatial lag of *X* model. Columns [5–7] show the results of the spatial Durbin error model. The spatial models are estimated with a radius of 10 miles in the weighting matrix. The direct and indirect effects are the estimates averaged over all observations arising from changes in each variable. The robust HAC standard errors are presented in parentheses and are clustered by county and month. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Before estimating the spatial hedonic pricing models, we first attempt to identify the potential endogeneity in interpolated air pollution levels as a result of spatial correlation with the disturbance of the spatial model. To this end, we adopt the Durbin-Wu-Hausman test and reject the hypothesis of exogenous API (Anselin & Lozano-Gracia, 2008).[26] To address the endogeneity, we instrument the endogenous air pollution index in a spatial two-stage least square model (S2SLS) and estimate the economic value of improved air quality. The validity of the IVs chosen in this paper is tested and confirmed in the first-stage regression.[27] The remaining columns in Table 3 present the estimation results of the spatial hedonic pricing models with In(API) instrumented. The spatial models are estimated with a radius of 10 miles in the weighting matrix, and the robust HAC standard errors are presented in parentheses and are clustered by county and month. Columns [2 - 4] and [5 - 7] show the estimation results of the spatial lag of X model (SLX) and the spatial Durbin error model (SDEM), respectively. It can be seen that the two models have parameter estimates similar to each other. Since the SDEM has a higher adjusted R^2 and controls for the potential spatial dependence in the idiosyncratic errors, we mainly focus on the empirical estimates of SDEM.

Compared with the non-spatial model, the estimates on air pollution from spatial models become in line with conventional wisdom. In column [5], we find that holding other factors equal, a 1% increase in the air pollution level can, on average, reduce the value of the real property by nearly 0.32%. Given the average property value of $274,012, the marginal willingness to pay (MWTP) for a 1% decrease in air pollution level is nearly $879 in each dwelling unit. The spillover effect implies a higher air pollution level by 1% across all nearby areas can increase the property value of this particular apartment by around 0.24% ($655), holding the air pollution level of this apartment fixed. It shows more severe air pollution in surrounding areas makes the given residence more valuable, which in some sense offsets the negative impact of local air pollution on the property value. The combination of a negative impact of local air pollution and a smaller positive spillover effect of nearby air pollution yields a much smaller total effect of regional air pollution. It implies that the higher air pollution level in South Korea essentially has a significantly negative influence on each apartment but a smaller influence on the national housing price, which largely contributes to the simultaneous upward trends in both housing price and air pollution levels.

Besides the overall air pollution, I estimate the influence of individual air pollutants on property values in the S2SLS model (2) as a robustness check. Table 4 presents that there exist large variations in the magnitudes of home price elasticity to individual air pollutants. The visible particulate matter (PM10) and smelly SO_2 have a larger impact on housing prices than the others, due largely to the fact that they are more perceptible than other air pollutants. The estimates on other air pollutants are barely significant, suggesting that potential homebuyers in South Korea do not perceive any risk and respond to these types of air pollution. It also implies that estimating the spatial model with a single air pollutant can bias the empirical results. Therefore, this paper adopts the air pollution index for the main analysis.

Table 4. Estimation results of the spatial model with individual air pollutants. (Table view)

Dependent variable: $\ln(P_{ibct})$			
	Direct	Spillover	Total

Dependent variable: ln(P_{ibct})

	Direct		Spillover		Total	
Air pollutant	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
ln(PM10)	−0.4203***	(0.0209)	0.3002***	(0.0302)	−0.1201***	(0.0209)
ln(NO_2)	−0.2211*	(0.1212)	0.1609**	(0.0828)	−0.0602*	(0.0354)
ln(PM2.5)	−0.1492	(0.2082)	0.1808	(0.1712)	−0.0287	(0.1098)
ln(SO_2)	−0.3763***	(0.0587)	0.0858***	(0.0246)	−0.0405***	(0.0149)
ln(CO)	−0.1831	(0.1931)	0.1309	(0.1209)	−0.0522	(0.1207)
ln(O_3)	−0.1639	(0.1801)	0.1301	(0.2772)	−0.0332	(0.2002
ln(API)	−0.3310***	(0.0341)	0.2482***	(0.0901)	−0.0828***	(0.0682)

Notes: This table shows the estimation results of the spatial two-stage least square model with individual air pollutants. The robust HAC standard errors are presented in parentheses and are clustered by county and month. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Apart from air pollution, the influence of housing attributes is examined. In the SDEM, we find that there exists a nonlinear relationship between the height and value of an apartment and that the dwellings in the middle of buildings, holding other attributes equal, are priced higher than those in the bottom and top.[28] As for locational attributes, it is found that a higher unemployment rate and local crime rate can decrease a poverty value, while a higher density in households and cars, higher income, and school quality are positively correlated to local housing prices.

As mentioned before, the hedonic value of air quality improvement obtained from a spatial model might be sensitive to the model specification. We assess the robustness of the estimated values by carrying out the model estimation with different specifications. First, to address the potential spatial interactions among dependent variables, we estimate the standard spatial Durbin model (SDM) that specifies such spatial dependence in housing prices across geographical areas.[29] Table A1 in Appendix presents the estimation results of the SDM. Given different assumptions of the air pollution variable, two estimation methods are used in estimating the spatial Durbin model. Firstly, assuming the exogeneity of the air pollution index interpolated by the ordinary kriging method, we use maximum likelihood estimation (MLE) to attain the consistent coefficients, as reported in columns [2 - 4]. Columns [5 - 7] show the results of the spatial two-stage least square model with spatial coordinates and lagged API as instruments for endogenous API.[30] The significance in the autoregressive coefficient, ρ, suggests that there exist spatial interactions among local housing prices. However, since ρ^2 is less than 0.04, there exist strong local spillover effects, but the global spillovers are relatively weak. In addition, the estimated coefficients in the spatial Durbin model are close to those in the spatial lag of X model (SLX) and spatial Durbin error model (SDEM). Therefore, the empirical results are mainly discussed with the two local spatial spillover specifications.

Table A1. Estimation results of non-spatial and alternative spatial hedonic pricing models. (Table view)

Dependent variable: ln(P_{ibct})

	Non-spatial	Spatial Durbin Model with a radius of 10 miles in the weighting matrix					
	OLS	Exogenous API with ML			Endogenous API with S2SLS		
	Direct	Direct	Spillover	Total	Direct	Spillover	Total

Dependent variable: ln(P_{ibct})	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Non-spatial	Spatial Durbin Model with a radius of 10 miles in the weighting matrix					
	OLS	Exogenous API with ML			Endogenous API with S2SLS		
	Direct	Direct	Spillover	Total	Direct	Spillover	Total
Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]
ρ		0.1672***			0.1982***		
		(0.0121)			(0.0241)		
ln(API)	0.3783***	−0.2314***	0.2083***	−0.0231***	−0.3310***	0.2482***	−0.0828***
	(0.0112)	(0.0213)	(0.0023)	(0.0122)	(0.0341)	(0.0901)	(0.0682)
Floor	0.0551**	0.0525**	0.0171**	0.0696**	0.0345***	0.0113***	0.0458**
	(0.0230)	(0.0228)	(0.0086)	(0.0348)	(0.0115)	(0.0028)	(0.0231)
Floor2	−0.0032**	−0.0203**	0.1021**	0.0818**	−0.0293***	0.0624**	0.0331***
	(0.0013)	(0.0088)	(0.0516)	(0.0409)	(0.0098)	(0.0316)	(0.0043)
Age	−0.2485***	−0.1233**	0.8203**	0.6970**	0.5933**	0.5760***	1.1693**
	(0.0135)	(0.0536)	(0.4143)	(0.3485)	(0.1978)	(0.1440)	(0.5905)
Unemploy	−0.0902***	−0.0849**	0.4941**	0.4093**	−0.9055**	−0.0369**	−0.9424**
	(0.0316)	(0.0369)	(0.2496)	(0.2046)	(0.3018)	(0.0092)	(0.4760)
Gdpper	0.1102**	0.0940***	0.3174**	0.4114**	0.6954**	0.0307**	0.7261**
	(0.0459)	(0.0409)	(0.1603)	(0.2057)	(0.2318)	(0.0077)	(0.3667)
Popden	0.0202**	0.8440**	0.8838**	1.7279**	0.2021**	0.4090**	0.6111**
	(0.0084)	(0.3670)	(0.4464)	(0.8639)	(0.0674)	(0.1022)	(0.3087)
Carden	−0.0102**	−0.8550**	0.3512**	−0.5038**	0.8831***	0.8831***	1.7662**
	(0.0043)	(0.3717)	(0.1774)	(0.2519)	(0.2944)	(0.2208)	(0.8920)
Crime	−0.1002***	−0.7617**	0.8859**	0.1241***	−0.8039**	−0.8667**	−1.6707**
	(0.0209)	(0.1656)	(0.2237)	(0.0310)	(0.1340)	(0.1083)	(0.4219)
School	1.2342***	0.8404**	0.2692**	1.1096**	0.3580**	0.6794***	1.0374**
	(0.1956)	(0.2811)	(0.1046)	(0.4268)	(0.0918)	(0.1307)	(0.4030)
Month FE	Y		Y			Y	
Building FE	Y		Y			Y	
N	1,765,631		1,765,631			1,765,631	
Adjusted R^2	0.1827		0.2443			0.2709	

Notes: Columns [1] presents the coefficient estimates of the non-spatial hedonic pricing model. Columns [2–4] show the estimation results of the spatial Durbin model with exogenous API using ML estimation. Columns [5–7] show the results of the spatial two-stage least square model with spatial coordinates and lagged API as instruments for endogenous API. The direct and indirect effects are the estimates averaged over all observations arising from changes in each variable. The robust HAC standard errors are presented in parentheses and are clustered by county and month. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Apart from the main spatial model, we further check the robustness of models with different spatial weighting matrix settings. Figure 3 shows the geographic scale of metropolitan Seoul and the dense residential area. It can be seen that the area within a radius of 10 miles is large enough to cover most buildings in this urban area. It can be seen in the right panel that, within a radius of 100 meters, there are many buildings located close to each other. The high-density urban area requires an accurate setting of a spatial matrix.

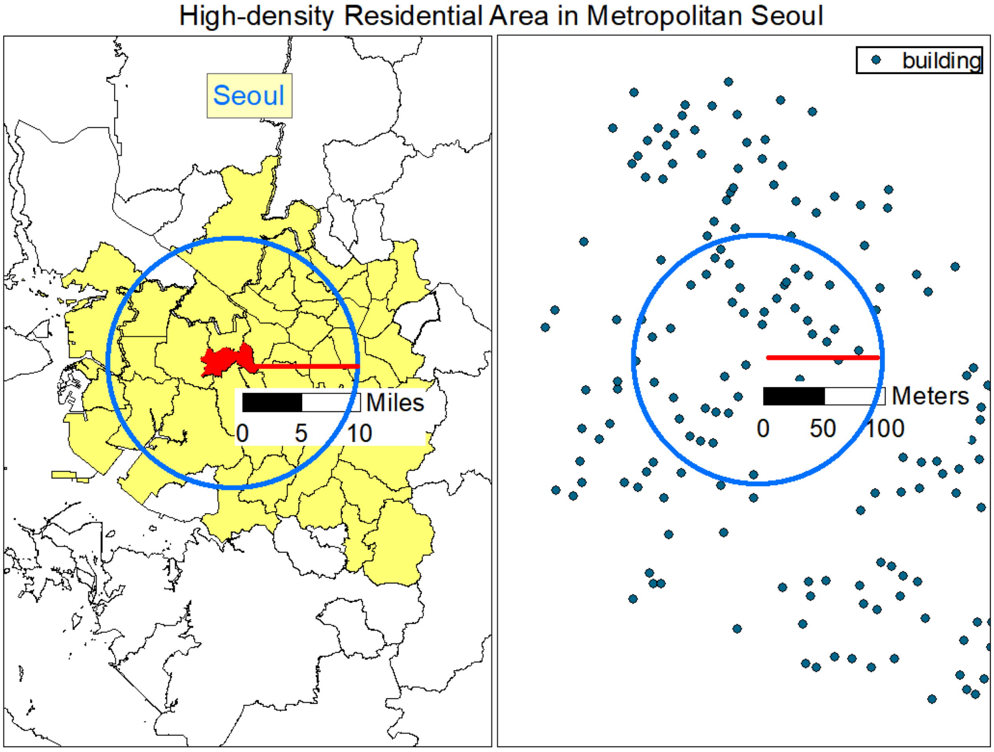


Figure 3. High-density urban residential areas in South Korea.

Table 5 reports the estimated coefficients on the air pollution index with alternative ranges in the spatial weighting matrix. It shows that the spillover effects are sensitive to the setting of range in the spatial weighting matrix, while the estimated direct effects are robust to the range. As a result of sensitivity in spillover effects, the total influence of air pollution on housing prices could be even positive under a radius of 20 miles, an unreasonably large range that exceeds the limit of potential spatial impact in dense urban areas in the South Korea. The goodness of fit confirms that 10 miles yield the best fit to the data. Therefore, we take the estimations with 10 miles as the main results to report in Table 3.

Table 5. Sensitivity to the alternative radius of the weighting matrix. (Table view)

Dependent variable: ln(P_{ibct}), S2SLS in SDEM with double-power distance weights					
	Model 1	Model 2	Model 3	Model 4	Model 5
Maximum radius (miles)	1	5	10	15	20
ln(API)	Estimate	Estimate	Estimate	Estimate	Estimate
Direct	−0.3587	−0.3231	−0.3201	−0.3903	−0.3219
Spillover	0.1298	0.1344	0.2391	0.3194	0.4215
Total	−0.2289	−0.1887	−0.081	−0.0709	0.0996
Apartment characteristics	Y	Y	Y	Y	Y
Locational attributes	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Building FE	Y	Y	Y	Y	Y
Adjusted R^2	0.1098	0.1278	0.2591	0.201	0.1814
# of observations	1,765,631	1,765,631	1,765,631	1,765,631	1,765,631

Notes: The maximum radius represents the longest distance in which air pollution has a spatial influence, measured in miles.

Another factor that potentially influences the estimation results is the choice of timing in the air pollution level. We explore the time-variant influence of air pollution on property values and plot time-lagged direct effects in Figure 4. It shows that a time lag of air pollution up to 12 months has an insignificant impact on the willingness to pay for better air quality, suggesting that homebuyers in South Korea are forward-looking. It might also be the case that differences in air pollution levels come primarily from the geographical, rather than temporal, variations, and the spatial distribution of air pollution remain almost the same over the entire study period.

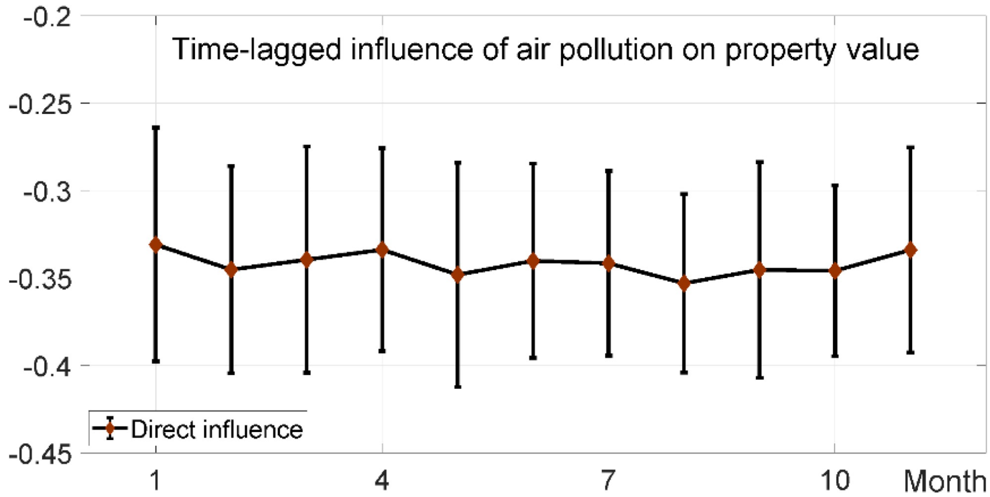
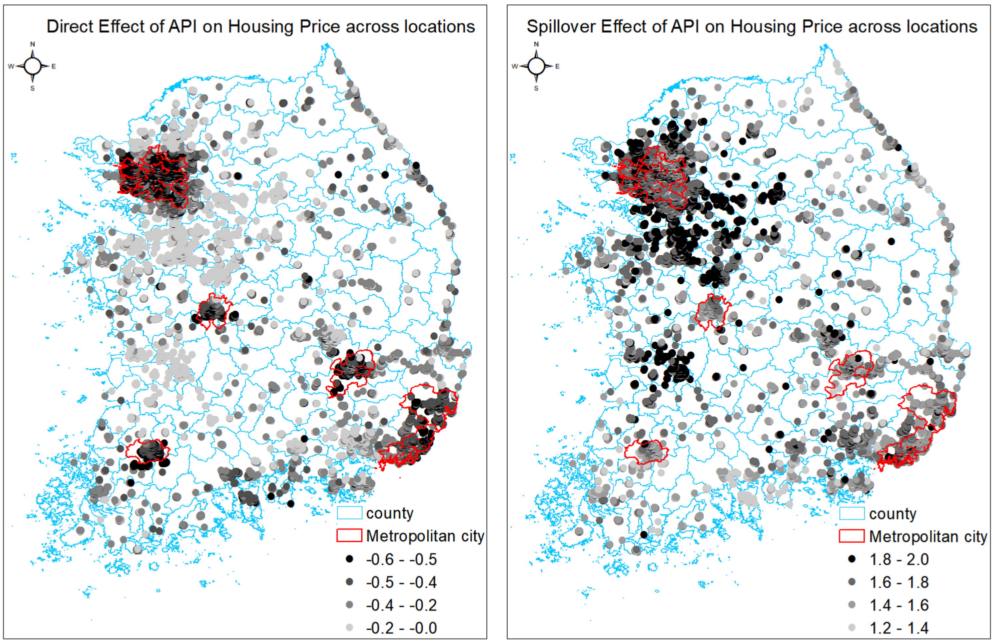


Figure 4. Time-lagged influence of air pollution on property value. Each bar represents the 95% confidence interval of time lag-specific coefficients.

Spatially Heterogeneous Effects

Table 3 describes the estimates of average direct and spillover effects of air pollution on housing prices. Given the complicated spatial relationship between air pollution and property value, we further investigate the heterogeneous effects of air quality in the housing market. Using the spatial matrix, $\boldsymbol{S}_r(\boldsymbol{W})_{ij}$, estimated before, we describe the location-specific relationship between air pollution and housing price and explore the spatial pattern in the direct and spillover effects of air pollution on local housing markets.

Figure 5 presents the location-specific direct and spillover impacts of air pollution on a local housing price. Panel (a) shows that air pollution has a more considerable direct impact on property value in urban than in rural areas. It implies that urban households with a higher income on average have a higher demand for better air quality, and thus, they are willing to pay more for the environmental amenity. Panel (b) presents the spillover effects that vary by location. It can be seen that a higher level of air pollution in the metropolitan area makes the nearby alternative residences in rural areas much more valuable, while urban housing prices are not influenced mainly by changing the air pollution level of surrounding areas. The spatial interactions between urban and rural housing prices imply that, given an equal increase in the surrounding air pollution level, urban households are more likely to move to a suburban or rural area for better air quality than rural households moving to urban areas. Urban households have a stronger incentive to purchase an alternative apartment in nearby areas. The spatial pattern of spillover effects predicts an unbalanced urban-rural migration tendency driven by the long-run environmental concern.



(a) **(b)**

Figure 5. Direct and spillover effects of air pollution on local housing prices. (a) Direct impact of API. (b) Spillover impact of API.

Conclusion

This paper investigates the spatial relationship between the value of the real property and its ambient air pollution in the context of the residential housing market in South Korea. Using detailed transaction data in 2015–2018, we provide new empirical evidence regarding the capitalization of air quality in property value and how air pollution has a spatial influence on the housing market. We first construct a new air pollution index that incorporates more information on air pollution. It can be more representative of the perceived air pollution when making a home purchase decision and thus help evaluate an environmental policy for general air quality. Estimation results of the up-to-date two-stage spatial Durbin error model present that, holding other factors equal, a 1% increase in the air pollution level can, on average, reduce a local housing price by 0.32% ($879). In contrast, the increases in nearby air pollution levels by 1% raise the property value of the particular apartment by 0.24% ($655). The positive spillover effect due to the higher level of air pollution largely offsets its direct negative impact, which yields a smaller total effect of regional air pollution. Therefore, it necessitates the separation of direct and spillover effects when analyzing the influence of air pollution on the housing price at a larger scale.

Another contribution we make to the existing literature is to explore spatially heterogeneous effects of air pollution on local housing prices. Air pollution is found to have a more significant direct impact on urban housing markets than that on rural markets, showing a higher marginal willingness to pay for better environmental quality by urban households. Moreover, a rising air pollution level in urban centers raises housing prices in suburban and rural areas, which implies a strong spillover effect of urban air pollution on rural housing markets. However, rural air pollution has little influence on urban property values. The spatial heterogeneity in spillover effects of air pollution suggests that urban households have a stronger incentive to purchase an apartment in nearby areas when relocating to a suburban or rural area for better air quality than rural households moving in the opposite direction. The unbalanced spatial influence on the housing market can influence numerous locational choices made by households, which eventually contributes to a large-scale residential sorting driven by air pollution in South Korea.

The empirical findings in this paper have profound implications for housing market development and urban planning. First, we find that long-lasting air pollution plays a critical role in future housing prices. The estimated value of air quality improvement or pollution-related discount in the sales price provides potential home buyers and real estate developers much information in the decision-making process. From an urban planner's perspective, the amenity-driven residential sorting and resulting migration flow between urban and rural areas can be of great importance to both the labor market and city development.

Notes

1. All these nonmarket valuation techniques and their applications are introduced and summarized by Bishop and Boyle (2017).
2. http://www.kei.re.kr/eng/main.kei
3. The estimates of values of air quality improvement presented in previous studies are either obtained from the survey involved in-person interviews (Kim et al., 2003) or restricted in the metro area of Seoul (Jun, 2018).
4. It is not until recently that Korean environmental agency reports a Comprehensive air-quality index (CAI). https://www.airkorea.or.kr/eng/khaiInfo?pMENU_NO=166
5. Many papers are summarized in the two meta-analyses (Simons & Saginor, 2006; Smith & Huang, 1995).
6. The widely used interpolative alternatives include Thiessen polygon (Anselin & Le Gallo, 2006), inverse distance method (Luechinger, 2009), splines (Luechinger, 2009), kriging (univariate) (Neill et al., 2007), and co-kriging (multivariate) (Lu, 2018).
7. An example is that economic activities in a local area can impact both property value and air pollution.
8. In an analogy to the time series fitting model proposed by Durbin (1960), Anselin (1988) named it as the spatial Durbin error model.
9. We drop the sample in some islands, such as Jeju Island, in this paper since few monitors and buildings are located in them, and they are distant from the main continent of South Korea. Including these outliers can bias the estimation of spatial dependence.
10. All real estate transactions are reported to the government in South Korea. This database was released publicly in 2006 by the government agency. See: http://www.mlit.go.jp/en/index.html
11. http://eng.me.go.kr/eng/web/main.do
12. All the six air pollutants pose a threat to health. Among them, nitrogen oxides (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), PM2.5, and ozone are invisible, while only PM10 is a visible pollutant.
13. Apart from the overall air pollution level, we test the influence of each air pollution individually and report the estimation results in Table 4.
14. Rather than a constant mean over the entire area in simple kriging, the average air pollution level in ordinary kriging is allowed to vary locally by limiting the domain of stationarity (Anselin & Lozano-Gracia, 2008).
15. In reality, wind direction, strength, and seasonality can also be relevant to local air pollution levels. Some recent paper utilizes air pollution from the cities in the upwind direction to construct the instrumental variable (Zheng et al., 2019).
16. $\mathrm{API}^{*}\left(s_i\right) = \sum_{j=1}^{n} \lambda_j \mathrm{API}\left(s_j\right) = \sum_{j=1}^{n} \lambda_j \sum_{k=1}^{6} a_k X_k\left(s_j\right)$, where λ_j is the weight of the air pollution value measured at the monitoring station at the site s_j.

17. $\widehat{\mathrm{API}}(s_i) = \sum_{k=1}^{6} a_k \widehat{X_k}(s_j) = \sum_{k=1}^{6} a_k \sum_{j=1}^{n_i} \lambda_j^k X_k(s_j)$, where λ_j^k represents the weight of the k-th air pollutant level at monitoring station j.
18. Myers (1983) proves that $\mathrm{Var}\left[\mathrm{API}^*(s_i) - \mathrm{API}(s_i)\right] > \mathrm{Var}\left[\widehat{\mathrm{API}}(s_i) - \mathrm{API}(s_i)\right]$.
19. http://kosis.kr/eng/aboutKosis/Introduction.do
20. Average exchange rates are obtained from the World Bank. https://data.worldbank.org/indicator/pa.nus.fcrf
21. To address the potential spatial interactions among dependent variables, the standard spatial Durbin model (SDM) that specifies such spatial dependence is also introduced later and estimated as robustness checks (LeSage, 2014).
22. If there exist no spatial dependence in the vector of error terms, μ, i.e., $\mu \sim N(0, \sigma_\epsilon^2 I_N)$, the spatial Durbin error model (SDEM) reduces to the spatial lag of X model (SLX) (LeSage, 2014).
23. Some different values of k are also taken and the estimates are found to be robust to the value of k. Thus, we report only the results with k being 2.
24. Table 5 reports the estimates with other ranges, and it turns out to be important in estimating the value of air quality improvement.
25. The direct and indirect effects are the estimates averaged over all observations arising from changes in each variable.
26. The Durbin-Wu-Hausman test statistic is 20.90(0.00), which implies the rejection of the null hypothesis that the API is exogenous.
27. Due to the overidentifying restrictions, we use J-test and find that we do not reject the null hypothesis of instrument exogeneity (Sargan, 1958). The J statistic$= mF = 2.019 < 3.841$ (critical value of χ_1^2 at 5% significance level). Then, we perform a F test to examine the relevance of the instrument. The API is found to be jointly and significantly correlated to instrumental variables and exogenous regressors.
28. The main reason that residents generally prefer the units in the middle of a building over those at the bottom and top is that lower floors usually suffer more noise pollution or are more humid on rainy days, and, for safety purposes, it is harder to get down to the ground in the case of a fire at the top of a building (Lo et al., 2001).
29. The spatial Durbin model (SDM) equals the spatial Durbin error model (SDEM), except for the inclusion of a spatial lag of the dependent variable defined as follows (LeSage, 2014):

$$\mathrm{In}(P_{ibct}) = X_{ict}\Theta_1 + W\left[\rho\,\mathrm{In}(P_{ibct}) + X_{ict}\Theta_2\right] + \lambda_t + L_b + \mu_{ibct}\mu = \eta W \mu + \epsilon;\ \epsilon \sim N(0, \sigma_\epsilon^2 I_N) \quad (6)$$

where $\rho W\,\mathrm{In}(P_{ibct})$ is the spatial lag of housing prices. ρ is spatial autoregressive parameter measuring the existing spatial dependence of housing prices between nearby areas.
30. We also estimate the spatial model with ML applied to the instrumented regressors and find that the estimated coefficients are close to those in S2SLS model. It implies that the bias mainly comes from the endogenous variables, rather than the estimation method itself. The results are omitted due to space limitation.

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Appendix

Table 1. Fitting results of variogram functions and principal components for pollutants. (Table view)

		Variogram			Principal component analysis		
Pollutant	Semivariogram	Nugget	Sill	Range	Weights	Eigenvector	% of variance
PM10	Spherical	0.72	0.14	289.98	0.88	8.49	75.93
NO_2	Circular	0.22	0.00	200.37	0.17	1.14	10.19
PM2.5	Exponential	0.32	1.00	140.71	0.08	0.73	6.53
SO_2	Exponential	1.00	1.09	208.92	0.26	0.46	4.11
CO	Spherical	0.15	1.10	215.09	0.17	0.27	2.41
O_3	Gaussian	1.00	0.00	180.03	0.26	0.09	0.83

Note: The functional forms of valid semivariogram are selected using the ML method.

Table 2. Summary statistics of apartment characteristics and locational attributes. (Table view)

Variable	Description	N	Mean	SD	Min	Max
Apartment-specific characteristics						
Unitp	Unit price in $/sqft	1,765,631	331.51	210.66	6.16	4,585.11
API	Air pollution index	1,765,631	60.44	9.39	14.13	134.1
Price	Total price in $	1,765,631	274,012	221,368	3,500	8,200,000
Area	Total floor area in feet^2	1,765,631	808.51	288.82	99.67	4,567.34
Floor	Floor level of residence	1,765,631	8.75	6.05	1	79
Age	Apartment age in years	1,765,631	16.4	8.56	0	57
Locational attributes at the county level						
Unemploy	Unemployment rate (%)	750	3.52	1.91	2.22	6.93
Gdpper	GDP per capita in $	750	30,957	8,420	19,643	64,438
Popden	Population density (p/mile^2)	750	4,813	4,604	1,115	16,549
Carden	Cars per mile^2	750	1,762	1,319	498	5,058
Crime	Crimes per 1,000 persons	750	0.49	0.08	0.35	0.76
School	# of schools per 100,000	750	11.53	4.91	5.97	22.67

Note: Economic variables are measured in 2018 U.S. dollars.