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Analysis of Spatial Interaction Effect of Retail Gasoline Price in Seoul: A Spatial Econometric Approach*

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There has been a continued criticism that the retail gasoline market shows a typical impaired market due to the lack of price competition and that local gas stations maintain their shares based on inelastic demand of oil products. Accordingly, several policy measures have been suggested to reduce likely market distortions and finally to lower retail price. Taking such circumstances into consideration, this paper attempts to investigate existence of competitive pricing mechanism and regional interconnections in the price discovery process. Spatial econometrics models are adopted to capture regional interaction effects on retail gasoline price and to identify pricing mechanism. An empirical analysis of spatial fixed effects model based on monthly data of retail gasoline prices in Seoul, Korea shows that the regional interaction effect exists as a reaction in response to the price changes of adjacent regions and that a pricing mechanism is thus associated with geographical location. The paper concludes that the price formation could be affected by the direct and indirect effects caused by their locations which property is important in establishing related policy measures for retail gas prices.

JEL Classification: D43, C33, R12

Keywords: retail gasoline price, spatial econometrics, spatial interaction effect, spatial Durbin model, direct and indirect effects

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1. INTRODUCTION

The role of automobiles is increasingly important as a primary mean of transportations as reflected by the fact that the expenditure on gasoline has steadily increased to be one of the largest portions in household expenditures in 2012. Despite the retail gasoline has many economic aspects to be examined, most research conducted in Korea more likely focus on macro-level, mainly because Korea economy is substantially sensitive, among OECD countries, to energy prices and supply conditions.[1)] However, a need for micro-level research is growing as we cannot control international oil price but are in a limited way able to manage retail markets.

Among a variety of energy sources, gasoline has been recognized as one of the most necessary ones. In particular, its price formation in Seoul metropolitan is highly emphasized because about half of national population is clustered into this area. In this regard, retail gasoline price that is set at the level of gas station needs to be studied to identify price discovery process and to discuss possible related polices to improve the standard of living quality.

Although price of gasoline is fundamentally based on the importing crude oil price, it is also true that we observe spatially quite different ranges of gasoline price between regions. Notably, a gasoline market, well known as a location-based oligopolistic market, shows the price discrimination in regional level. According to the many studies of marketing strategy of gas stations, individual station tends to show a keen interest to consider pricing strategies of competing adjacent stations and to attract more consumers in order to increase their profits. Indeed, an amount of traffic flow is quite considered as one of important components to explain the profit of gas station. We suppose that such a tendency can be extended toward regional gasoline market.

In this paper, we attempt to show the existence of such pricing strategies by incorporating spatial interactions that recognize consumers' likely

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[1)] Korea has one of the lowest self-sufficiency rates in energy which shows less than 10%.

responses to different prices across the area. As a result, a regional pricing strategy is affected by neighbor's pricing behavior and other associated factors. For example, land price, the number of vehicles as a potential size of incoming consumers, a level of traffic congestion around the station and population density of area could be possible candidates for such critical factors in determining their gas price and be applied the extension of regional level.

To consider variables related to the socio-economic and geographic factors, we employ the spatial econometric method as a tool for displaying the regional linkages. We test existence of the regional interaction effect, spatial dependence, and the direct and indirect effects. Using (Robust) LM test, LR test and Wald test, we examine which spatial model is best suitable for the analysis. We expect that this paper can provide useful and interesting information on pricing mechanism in gasoline retail market.

The rest of this study is organized as follows. In section 2, we introduce the background to the spatial econometric method by reviewing the literature. In section 3, we summarize studies related with our subject. The method of spatial econometrics and empirical models constructed is presented in section 4. The empirical analysis and results are discussed in section 5. The conclusion and policy recommendations are presented in section 6.

2. LITERATURE REVIEW

"Everything is related to everything else, but near things are more related than distant things."[2] This phrase is to be a basic motivation of this paper to explain the geographically interconnected economic events. However, only a few research were conducted in Korea with spatial econometric methods for gasoline market study. Indeed, the previous study of retail gasoline market is more likely focused on specific subjects, for example, unbalanced demand and supply caused by its market structure. In order to understand a pricing

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[2] The first law of geography that was advocated by Waldo Tobler (1970).

mechanism and spatial interaction effects in the market, we review two strands of literatures. The first review is about the study on retail gasoline market and the second part is for general review on the methodology of spatial econometric models.

For understanding the retail gasoline market mechanism in Korea, Kim and Kim (2009, 2010) shed light on the role of customers' searching cost and purchase frequency that are linked to the price dispersion event. They suggested that reducing searing cost for finding the lowest price of gasoline could diminish the retail price dispersion. Kim (2004) applied a GIS method to identify the sales area and the location of gas stations. After she analyzed the locational features of gas stations, she indicated that traffic and land use significantly affected profits of gas station, respectively, in positive and negative ways. To examine the pricing mechanism of gas station in Seoul, Yoon and Lee (2008) introduced variables in order to consider market size of each gas station. According to their research, land price and distance between regional competitors are significant to explain a price mechanism. Lee and Lee (2001) estimated gasoline price elasticity of demand for automobile fuel efficiency in Korea, using a hedonic price model. Based on their analysis, they concluded that the high gasoline price policy could induce the lower demand of retail gasoline in the long term.

Son and Na (2002) also attempted to find the retail gasoline pricing mechanism to focus on macro-economic variables such as the importing price, exchange rate and tax. Using a graph theory coupled with time series models, Pearl (2000), and Spirtes, Glymour and Scheines (2000) showed that it is important to understand existence of locational information flows in gas markets. And another approach to checking the relationship between tax regulation and gasoline price was examined by Parry and Small (2005) to show the need of introduction of differential fuel tax based on traffic burdens across regions. And Kang (2010) analyzed asymmetry U.S retail gas market and tax regulation treatment.

Most of research that adopt the spatial econometric models in Korean are in general concentrated in the real estate market study and the industry clustering policy analysis. There are no papers, up to our knowledge, on the retail gasoline price or market mechanism that apply the spatial econometric method. Thus, we employ spatial panel econometric models to discuss possible spatial linkages, interaction effects and the pricing mechanism in gasoline retail markets in Seoul. Whereas several literature deals with the single equation cross-sectional setting that is a primary method of the spatial econometrics for a long time, recent studies have more interests in finding appropriate models. In general, panel data model allows researchers to extend the model to analyze their subjects based on more sufficient information (Elhorst, 2012).

To highlight spatial relationship with market and price competition, Netz and Taylor (2002) suggested that higher level of spatially differentiated market could lead the mitigation of price competition. They said if the gasoline supplied by small independent retailers is perceived as inferior to gasoline supplied by more branded stations, an increase in the percentage of the market supplied by the independents might instead represent a decline in price competition. In Austria gasoline market, Clemenz and Gugler (2006) had interest on connection with the locational choice of individual station and price of retail gasoline market. They carried out analysis which a higher station density reduces average prices and spatial competition is a suitable standard of judgment of intensity of competition in the retail gasoline market. Benson *et al*. (1992) suggested the concepts for constructing the spatial weighted matrix and indicated that sellers tend to recognize only the nearest neighbors as relevant competitors in most spatial markets. Indeed, among researchers who are concerned with both spatial econometric method and retail gasoline market, Pennerstorfer and Weiss (2013) studied the impact of local market power and ‘spatial clustering’ on prices in Austrian retail gasoline market. He suggested that spatial clustering of gasoline stations lessens the degree of competition between firms and increases equilibrium prices. Indeed, he suggested that the competition and composition effects among the branded and unbranded station could bring retail gasoline price down (Pennerstorfer, 2009). In this study, we try to find regional interaction effect on the lower price of retail gasoline market with spatial panel econometric model. At this point, our study can contribute to comprehensively understanding retail gasoline market at different view from conventional perspective and model.

3. MODEL FRAMEWORK

Cliff and Ord (1970) who were one of pioneers in the development of spatial econometric suggested many of the spatial econometrical concepts such as the spatial autocorrelation concept and testing methods to determine the spatial autocorrelation regression (SAR). Based on SAR model concept, spatial econometric models have been extended to the spatial error model (SEM), spatial Durbin model (SDM), spatial Durbin error model (SDEM), Kelejian-Prucha model (1998), Manski model (1993), and Dynamic model.[3)] Thus, the spatial econometric has been regression models for cross-sectional and panel data (Anselin and Baltagi, 2001). We generally follow the recommendation of Elhorst (2012) and LeSage and Pace (2009) to utilize the spatial panel models. The (robust) LM test is employed to inspect spatial dependences and spatial heterogeneity, and then Lagrange Ratio test, Wald test, and Hausman test are carried out to find the appropriate model for our analysis. For amplifying the spatial/regional interaction effects with the testing results, we consider three general models: spatial autoregressive model, spatial error model and spatial Durbin model with spatial and/or fixed effect.

As a first model, SAR model that contains a spatially autoregressive dependent variable as explanatory variable for capturing the spatial interaction effect on dependent variable can be written as[4)]

[3)] Because we constructed monthly data set, we determined that dynamic spatial model was not proper model.

[4)] Basically, this equation follows the notation of Elhorst (2010b, 2012).

$$y_{it} = c_{SAR} + \delta \sum_{j=1}^{N} W_{ij} y_{jt} + X_{it}\beta + \mu_i + \theta_t + \varepsilon_{it}, \tag{1}$$

where i is an index for the spatial units, with $i = 1, \dots, N$, and t is an index for the time, with $t = 1, \dots, T$. The observations on the dependent variable represent as y_{it}, c_{SAR} is the constant parameter, and X_{it} is $1 \times K$ row vector of observations on the independent variables, and β is $K \times 1$ coefficient vector of X_{it}. Error term, represented as ε_{it}, follows an independently and identically distribution for i and t with zero mean and variance σ^2, while μ_i denotes a spatial fixed effect and θ_t is time fixed effect.

Spatial fixed effect controls for all space-specific but time-invariant variables preventing from biased the estimates in a typical cross-sectional study, while time fixed effect controls for all time-specific misleading in a typical time-series study (Baltagi, 2005; Hsiao *et al*., 2002).

To apply the feature of individual spatial unit, time-invariant variables such as size of area, square of road are utilized commonly. However, it has problem to interpret because the role of these time-invariant variables would be the same as that of spatial fixed effects. In order to make any biased estimation, we transformed equation by demeaning procedure following Plümper and Troeger (2007). Notably, X_{it} can be divided into time varying and invariant variable.

$$\hat{y}_i = c_{SAR} + \delta \sum_{j=1}^{N} W_{ij} \hat{y}_j + \hat{K}_i \beta + Z_i \sigma + \mu_i + \theta_t + \hat{\varepsilon}_i, \tag{2}$$

where $\hat{y}_{it} = (1/T)\sum_{t=1}^{T} y_{it}$, $\hat{x}_i = (1/T)\sum_{t=1}^{T} x_i$, $\hat{\varepsilon}_i = (1/T)\sum_{t=1}^{T} \varepsilon_i$, and K_{it} is time varying variables, Z_{it} represents time-invariant variables and e stands for the residual of the estimated model. Through equation (2) is subtracted from equation (1), the spatial fixed effects μ_i and the time-invariant variables Z_i can be removed such as following demeaned equation (3).

$$\begin{aligned} (y_{it} - \hat{y}_i) &= \delta \sum_{j=1}^{N} W_{ij} (y_{it} - \hat{y}_i) + (K_{it} - \hat{K}_i)\beta + (\varepsilon_i - \hat{\varepsilon}_i) \\ &= \delta \sum_{j=1}^{N} W_{ij} \dot{y}_i + \dot{K}_i \beta + \dot{\varepsilon}_i. \end{aligned} \tag{3}$$

We use equation (3) to check the spatial unit effects μ_i. At this point, μ_i should be considered as 'estimated spatial unit effects'. To include time-invariant variables, the constant parameter, and the mean effects of the time varying variables *K*, we equate as follow:

$$\hat{\mu}_i = \hat{y}_i - \sum_{j=1}^{N} W_{ij} \dot{y}_i + \dot{K}_i \beta^{Fixed} + \hat{\varepsilon}_i, \tag{4}$$

where β^{Fixed} is an estimate of the demeaned model. In this equation (4), $\hat{\mu}_i$ can be calculated without the observed spatial features Z_i. Based on demeaning procedure, we resolve the problem to use time-invariant variable in spatial fixed effect model.

The spatial weight matrix, *W*, is assumed that a pre-specified non-negative matrix of order *N*. The $\sum_{j=1}^{N} W_{it} y_{it}$ term addresses the interaction effect of the dependent variable by considering spatially adjacent regions so that δ is treated as the spatial autoregressive coefficient. And W_{ij} describes the spatial arrangement of the units in the sample. To express and consider the spatial linkage of sample area, two methods are mainly considered such as distance and contiguity criteria. The way using distance criteria, for example K-nearest neighbor distance, Radial distance, Power distance, Double-power distance and Exponential distance, has advantage in that it represents the different impact graded according to the distance. While the advantage of contiguity criteria is that there is easy computing step to express boundary condition of spatial units. Accordingly, the standard of choice mostly depends on sample data condition.

To avoid the critical misleading to interpret the results, we distribute the different weight to every contiguity region. The row standardization is as follows:

$$W_{ij}^{*} = \frac{w_{ij}}{\sum_j w_{ij}}, \text{ s.t. } \sum_j W_{ij}^{*} = 1, \tag{5}$$

where W_{ij}^{*} represents the normalized value so that the sum of normalized value equals to 1.[5] And $1/\omega_{\min} < \delta < 1/\omega_{\max}$ is the necessary condition to be stationarity, where $\omega_{\min}$ and $\omega_{\max}$ mean the minimum and maximum characteristic roots of the matrix W.[6]

To know the detail features of SAR model, it is transformed to equation (6) as follow:

$$
\begin{aligned}
y_{it} = {} & \left(I_N - \delta \sum_{j=1}^{N} W_{ij} \right)^{-1} c_{SAR} + \left(I_N - \delta \sum_{j=1}^{N} W_{ij} \right)^{-1} X_{it}\beta \\
& + \left(I_N - \delta \sum_{j=1}^{N} W_{ij} \right)^{-1} \mu_i + \left(I_N - \delta \sum_{j=1}^{N} W_{ij} \right)^{-1} \theta_t \\
& + \left(I_N - \delta \sum_{j=1}^{N} W_{ij} \right)^{-1} \varepsilon_{it}, \qquad (6)
\end{aligned}
$$

$$\varepsilon_{it} \sim N(0,\ \delta^2 I_N).$$

As equation (1) is transformed into equation (6), it shows the decomposition of effects. In the RHS of equation (6), $(I_N - \delta \sum_{j=1}^{N} W_{ij})^{-1}\beta$ represents the coefficient of independent which includes the total effect,[7] and $(I_N - \delta \sum_{j=1}^{N} W_{ij})^{-1}$ indicates the spatial multiplier.

As mention before, we adopt MLE to estimate the coefficients so that the log-likelihood function for SAR model is written as follows:

$$
\begin{aligned}
\ln L = {} & -\frac{NT}{2}\ln(2\pi\sigma^2) + T\ln(I_n - \delta W) \\
& - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}[y'_{it} - \delta(\sum_{j=1}^{N} W_{ij} y'_{it}) - X'_{it}\beta]^2, \qquad (7)
\end{aligned}
$$

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5) Because all of spatial weighted matrix are normalized, we drop the superscript * in the models.

6) Generally, the literature suggested that δ should be constrained between the interval (–1, +1). This logic is also adjusted to SEM and SDM, similarly.

7) This is discussed in more detail in direct and indirect effect part in this paper.

where $y'_{it} = y_{it} - (1/T)\sum_{t=1}^{T} y_{it}$ and $X'_{it} = X_{it} - (1/T)\sum_{t=1}^{T} x_{it}$ for the fixed effect. Note that, for the random effect model can expressed as $y'_{it} = y_{it}$ $-(1/\eta)(1-T)\sum_{t=1}^{T} y_{it}$ and $X'_{it} = X_{it} - (1-\eta)(1/T)\sum_{t=1}^{T} X_{it}$ with η which is the weight imposing to the spatial units of data and which follows the condition that $0 \le \eta^2 = \sigma^2 / (T\sigma_u + \sigma) \le 1$.

As a second model, the spatial error model (SEM) is specified as in equation (8) and equation (9). The first equation posits that the dependent variable is affected by a set of characteristics of one region with spatial and time fixed effect term. The second equation shows that the model may embody a spatial autoregressive process in the error term. It is indirectly correlated across the space by specifying as follows:

$$y_{it} = c_{sem} + X_{it}\beta + \mu_i + \theta_t + \lambda_{it}, \tag{8}$$

$$\lambda_{it} = \rho \sum_{j=1}^{N} W_{ij} \lambda_{jt} + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0,\ \delta^2 I_N), \tag{9}$$

where c_{sem} is the constant parameter, λ_{it} is the spatial autoregressive error term and ρ is the spatial autocorrelation coefficient. The error term of i is affected by the error terms of neighboring units j according to the spatial weighted matrix W and ε_{it}.

$$y_{it} = c_{sem} + X_{it}\beta + \mu_i + \theta_t + (I_N - \rho \sum_{j=1}^{N} W_{ij})^{-1} \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\ \delta^2 I_N). \tag{10}$$

In the same manner with SAR panel model, equation of error term is transformed and put into equation (7) for decomposition of its meanings. Thus, β is the regression coefficient on X_{it} and $(I_N - \rho \sum_{j=1}^{N} W_{ij})^{-1}$ indicates the spatial multiplier and stationarity of spatial error model requires $1/w_{\min} < \rho < 1/w_{\max}$. The log-likelihood function for the spatial error model is represented as below:

$$\ln L = -\frac{NT}{2}\ln(2\pi\sigma^2) + T\ln(I_n - \delta W) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}[y'_{it} - \delta(\sum_{j=1}^{N} W_{ij} y'_{it}) - (X'_{it} - \rho(\sum_{j=1}^{N} W_{ij} X'_{it})\beta]^2. \quad (11)$$

To find appropriate models which are best suitable for the data, the (Robust) Lagrange multiplier test is performed as suggested in Elhorst (2010a). Both ways of tests are using the errors of the non-spatial model[8] with or without spatial and/or time fixed effects which follow a chi-square distribution with one degree of freedom. LeSage and Pace (2009, Chapter.6) recommend the spatial Durbin model, if the following test result supports the specific conditions. The spatial Durbin model, SDM, is originated from SAR with spatially lagged independent variables

$$y_{it} = c_{SDM} + \delta\sum_{j=1}^{N} W_{ij} y_{jt} + X_{it}\beta + \sum_{j=1}^{N} W_{ij} X_{jt}\gamma + \mu_i + \theta_t + \varepsilon_{it}, \quad (12)$$

where c_{SDM} is the constant parameters, X_{it} is $1\times K$ row vector of observations on the independent variables of neighboring region and γ is a $K\times 1$ vector of parameters. To utilize SDM, investigations into the hypotheses $H_0 : \gamma = 0$ and $H_0 : \gamma + \delta\beta = 0$ are needed using the LR test and Wald test. The results of test mean that if each hypothesis is rejected, then SDM is more appropriate than SAR and SEM, respectively. The advantage of panel data set offers the chance to highlight the direct and indirect effect[9] that can be called respectively as feedback effect and spillover effect among neighboring regions. For representing as before, the equation (12) can be transformed as follows:

[8] In this case, an ordinary least square (OLS) is used as a non-spatial model.
[9] The spatial econometric model using cross-section data is able to mislead the result in terms of the existence of spillover effect (LeSage and Pace, 2009).

$$y_{it}=\left(I_N-\delta\sum_{j=1}^{N}W_{ij}\right)^{-1}c_{SDM}+\left(I_N-\delta\sum_{j=1}^{N}W_{ij}\right)^{-1}X_{it}\beta$$
$$+\left(I_N-\delta\sum_{j=1}^{N}W_{ij}\right)^{-1}WX_{jt}\gamma+\left(I_N-\delta\sum_{j=1}^{N}W_{ij}\right)^{-1}\mu_i$$
$$+\left(I_N-\delta\sum_{j=1}^{N}W_{ij}\right)^{-1}\theta_t+\left(I_n-\delta\sum_{j=1}^{N}W_{ij}\right)^{-1}\varepsilon_{it}, \tag{13}$$

$$\varepsilon_{it}\sim N(0,\ \delta^2 I_N).$$

And rearrangement as a vector form is

$$Y_t=(I-\delta W)^{-1}c_{SDM}l_N+(I-\delta W)^{-1}(X_t\beta+WX_t\gamma)+(I-\delta W)^{-1}\varepsilon_t^*, \tag{14}$$

where l_N is the a K by K identical vector of parameters and the error term ε_t^* contains ε_t and spatial and/or time fixed effects term.[10] To analyze and represent direct and indirect panel effect, the matrix form is more convenient than numerical form. The elements of matrix are made of partial derivatives of the dependent variable in the different units with respect to the *k*th explanatory variable in the different units at a particular point in time (Elhorst, 2012). The direct effect value is different from the coefficient of the SAR model and SDM, because this effect is the result of impacts passing through neighboring regions and back to one's region itself. And the indirect effect or spillover effect capture the impact on the dependent variable of one region from changing an explanatory variable in all other regions, or the impact of changing an exogenous variable in one region on the dependent variable of all other regions (Seldadyo *et al*., 2010).

[10] It does not make any difference between the reduced form and original form.

$$\begin{aligned}\left[\frac{\partial Y}{\partial X_{ik}}\cdots\frac{\partial Y}{\partial X_{NK}}\right] &= \begin{bmatrix} \frac{\partial Y_1}{\partial X_{1k}} & \cdots & \frac{\partial Y_1}{\partial X_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial Y_N}{\partial X_{1k}} & \cdots & \frac{\partial Y_N}{\partial X_{Nk}} \end{bmatrix} \\ &= (1-\delta W)^{-1}\begin{bmatrix} \beta_k & W_{12}\gamma_k & \cdots & W_{1N}\gamma_k \\ W_{21}\gamma_k & \beta_k & & W_{2N}\gamma_k \\ \vdots & & \ddots & \vdots \\ W_{N1}\gamma_k & W_{N2}\gamma_k & \cdots & \beta_k \end{bmatrix}.\end{aligned} \tag{15}$$

LeSage and Pace (2009) suggested the intuitive method to calculate these effects. The direct effect is the mean of the diagonal elements of matrix on the right hand side of equation (15) and the indirect effect is represented by the mean of row sums of the off diagonal elements of matrix.[11)] These effects are applied to SAR and SDM, not SEM. Because SEM does not have the element of γ_k, the off-diagonal terms converges to the zero. Therefore, the direct effect and indirect effect of SEM are the same as in the non-spatial model.

4. MODEL ANALYSIS

To consider the importance of spatial interaction effects, we model a panel type dataset that specifies the administrative districts level of data across regions and across times.[12)] A monthly average retail average price is used as a dependent variable and variety sets of data including socio-economical and geographical information as independent variables. Figure 1 shows a map of Seoul with the quartile of price analysis.

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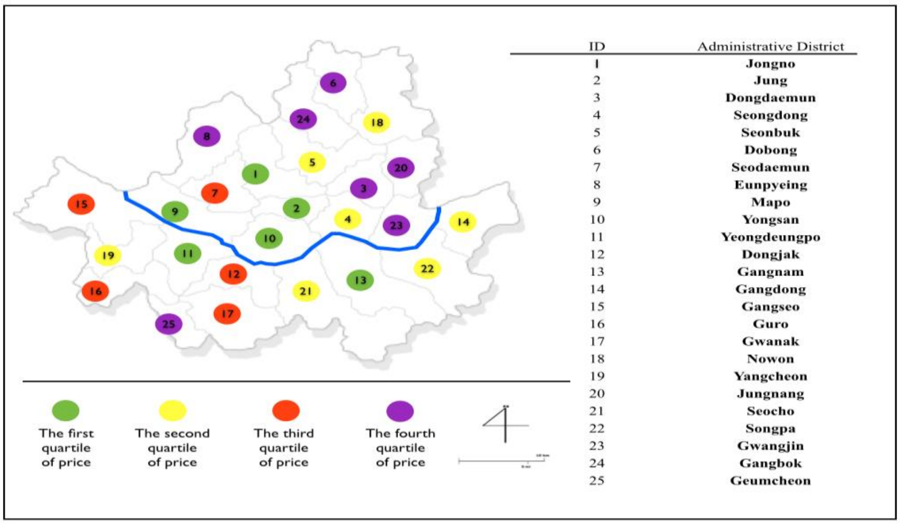
11) The average of the column sums of off-diagonal elements of matrix is also to be the indirect effect.

12) As we study using regional level units, spatial can be interpreted same meaning as regional.

Figure 1 A Map of Seoul with the Quartile Price Analysis



According to the figure 1, there is the certain pattern of distribution of gasoline price. Seoul is greatly divided into northern and southern area around the Hangang (River) and it is not a poly-centric, but a multi-centric city. The four types of color ball stand for the quartile of average price and it shows the feature of Seoul clearly. The first quartile of price is clustered into Gangnam, Jongno, Jung and the nearby regions because there are main central business districts (CBD). And we can intuitively surmise that the sprawl phenomena may exist in the gasoline market. The source of a monthly average retail price at each administrative district is obtained from the OPINET website that is organized by the Korea National Oil Corporation.[13] The OPINET offers the monthly average retail price information for every 25 administrative districts from Jan. 2010 to Dec. 2012.[14]

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13) To set balance panel data, we choose a monthly price not a daily price. And In this case, station level analysis is impossible due to the aggregated data form.

14) In spatial panel analysis, the small number of spatial unit leads to inconsistent estimation and biased result. Avoiding such a problem, we use the bias correction procedure proposed by Lee and Yu (2010), and adapt a logical background of statistical consistency in small samples suggested by Anselin and Florax (1995).

Socio-economical variables as independent variables consist of number of cars, population density, number of stations and land price change rate. In addition, variables for the urbanization rate, road area, and accessibility to the highway are employed for explaining the geographical characteristics.

To justify the employment of variables, we use the result of previous literatures above mentioned such as Kim (2004), Yoon and Lee (2008). Kim examined that proper gas station location to make higher profit exists and analyzed effect of people per gas station, traffic flow, population density and land use status.[15)] Also, Yoon and Lee emphasized significant meaning of traffic inflow of spatial unit. Based on such previous literatures, we construct data set which is extracted from the Korean Statistical Information Service and the Seoul statistics. Among variables, highway is measured by the existence of ramps and it represents the one of determinant of traffic inflow of spatial units. As analogous logic, the network intensity is specified by two components, the number of parking lots and car registrations. If the ratio of a number of parking lots to the number of registered cars exceeds 1, it demonstrated that such a region is regarded as highly connected regions with other regions. And the area per station means the sales coverage of each station. The cars per the number of residents is a proxy variable to propose the car density.

Table 1 provides the descriptive statistics of the data. Detailed values grouped by administrative district are listed in Appendix A1. In detail, the monthly average retail gasoline price and its standard deviation are 1,942 Korean won and 140 Korean won, respectively. And a monthly average retail gasoline quantity (PQ) is reported at 5,605.63won. The average value of URBANIZATION[16)] in Seoul is 0.65% and HIGHWAY is a dummy variable: 1 for the existence of ramps, and 0 for otherwise. And the average of CAR is 119.19 with high standard deviation value. According to Appendix A1, Gangnam and Jung have the largest and smallest the number

15) In the study of Kim (2004), land use status is divided into business, residential, CBD and manufacturing area.

16) The urban area is the sum of residential, business and manufacturing area, and URBANIZATION is the percentage of urban area per administrative area.

Table 1 Descriptive Statistics

Variables	Total		Regions				Unit
			Average		Standard Deviation		
	Average	Std	Max	Min	Max	Min	
PP	1,942.00	140.66	2,058.30	1,862.53	170.56	107.73	Korean Won
PQ	5,605.63	3,705.29	17,783.36	1,821.72	1,308.11	203.15	KL
URBANI -ZATION	0.65	0.18	1.00	0.37	0.01	0.00	
ROAD	3.31	0.94	5.54	1.88	0.14	0.00	km^2
HIGHWAY	0.32	0.47	1	0	0	0	
CAR	119.19	46.35	245.700	55.510	8.305	0.229	Thousand
NETWORK	1.18	0.21	1.69	0.93	0.30	0.01	
POPDEN	174.19	48.20	280.21	73.21	5.65	0.42	Hundred / km^2
STATION	26.59	10.41	51.00	10.33	1.91	0.00	
LAND PRICE	1.06	0.17	1.12	1.00	0.30	0.05	Change Ratio
AREA PER STATION	0.98	0.42	2.33	0.55	0.23	0.00	km^2 / Station
POP PER CAR	3.46	0.64	4.57	2.04	0.42	0.03	
CAR PER STATION	4.63	1.26	9.14	3.13	0.77	0.01	Thousand
CAR PER AREA	5.09	1.31	8.43	2.32	0.35	0.01	Thousand / km^2

of the registered cars, respectively. The average value of NETWORK is 1.18, indicating that Seoul has feature of closely connection with nearby regions. Among the administrative districts, Jung has the highest value of network 1.69 and Jungnang has the smallest value of network, 0.93. The number of stations in Seoul is distributed quite differently at each region ranged from 53 to 10. LANDPRICE is the ratio of monthly land price. When LANDPRICE is over 1, it can be regarded as a bullish real estate market.

Jung, one of the CBD in Seoul, has a highest average price of gasoline in the sample period and a peak gasoline price is 2,286 won at Sep. 2012 in Jongno. The average number of car registered to the administrative district is 119.19. Specifically, Gangnam has the largest and Jongro has the smallest values in the number of car registrations. Because Gangnam has an important role in Seoul as a central of business and residential area, Gangnam also has the largest number of private parking lots and gas stations.

Intuitively, the analysis in terms of retail gasoline price may have a necessity of using the spatial econometric method because the pricing of any region may be affected by price of adjacent regions. To check our hypothesis whether it correct or not, we should regress on retail gasoline price using OLS method with spatial and/or time fixed effect as a benchmark model. Table 2 shows the result of estimation using MATLAB.

The following result reports that the spatial econometric models, SAR or SEM, are more appropriate than a pooled OLS. The first column shows the result of pooled OLS model and the rest of columns provide results of spatial and/or fixed effects compared to the OLS model. To find appropriate model, we employ LM test and robust LM test.[17)] Both tests are based on the residuals of the OLS model and follow a chi-squared distribution with one degree of freedom. The (Robust) LM tests rejects a hypothesis of no spatially lagged dependent variable at 1 percent significance at all of models. It implies that SAR model could be more appropriate model than OLS model with any fixed effects. On contrary, the hypothesis of no spatially autoregressive error term must be rejected at 1 percent significance with time fixed effect or both fixed effect. It indicates that SEM is more relevant than non-spatial model when adopting the no fixed or time fixed effect model. Hence, it is suitable to include spatial interaction effect into the model. Indeed, SAR model and SEM except the spatial fixed effect model are possible to be converted into spatial Durbin model.

Before finding the proper models, we should set up the spatial weighted matrix. To introduce regional interaction effect on the price, the contiguity

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[17)] Because the existence of one type of spatial dependence does not bias the test for the other type of spatial dependence, we call it robust LM test.

Table 2 Results for the Non-Spatial Model with the Spatial and/or Time Fixed Effect

Variable	Coefficient			
	Pool OLS	Spatial Fixed Effect	Time Fixed Effect	Spatial Fixed Effect Time Fixed Effect
CONSTANT	3.161843*** (63.917088)			
LNPQ	0.008964 (0.942701)	0.008421 (0.008421)	0.057598*** (3.85714)	0.059341*** (3.955884)
URBANICATION	–0.001703 (–0.158723)	–0.002143 (–0.002143)	0.003187 (0.158096)	0.003159 (0.15646)
ROAD	0.012015*** (4.045129)	0.012132*** (0.012132)	–0.015496*** (–3.502613)	–0.016927*** (–3.790663)
HIGHWAY	–0.004102 (–1.2413)	–0.003996 (–0.003996)	–0.02789*** (–4.844335)	–0.028283*** (–4.907414)
CAR	0.000277** (2.213976)	0.000268** (0.000268)	0.001683*** (9.578044)	0.001716*** (9.698611)
NETWORK	0.032025*** (4.125487)	0.032527*** (0.032527)	0.084065*** (9.034015)	0.084*** (8.978905)
POPDEN	–0.00047*** (–3.060771)	–0.000475*** (–0.000475)	–0.000082 (–0.344839)	–0.000083 (–0.346438)
STATION	–0.002569*** (–4.611181)	–0.002538*** (–0.002538)	–0.007035*** (–8.843274)	–0.007043*** (–8.826286)
LANDPRICE	0.020266*** (3.586305)	0.020742*** (0.020742)	0.01554*** (3.278694)	0.016442*** (3.441855)
AREA PER STATION	0.010884 (1.398573)	0.010058 (0.010058)	0.130393*** (10.926979)	0.132923*** (10.972663)
POP PER CAR	0.012805 (1.606961)	0.013072 (0.013072)	–0.018036 (–1.436739)	–0.018049 (–1.432543)
CAR PER STATION	–0.007607** (–2.451156)	–0.007296** (–0.007296)	–0.046031*** (–9.980133)	–0.046738*** (–9.986587)
CAR PER AREA	0.018278*** (3.397007)	0.018391*** (0.018391)	0.020751*** (2.603367)	0.020796*** (2.59974)
Log-likelihood	1,954.3	1,954.9	2,154.2	2,157.2
R-squared	0.2415	0.2422	0.3799	0.3837
LM Test No Spatial Autoregressive	104.4948***	103.9966***	35.6161***	35.6836***
Robust LM Test No Spatial Autoregressive	33.2084***	33.5321***	0.3746***	0.2247***
LM Test No Spatial Error	166.9723***	166.4748	44.2002***	45.6422***
Robust LM Test No Spatial Error	95.6859***	96.0103	8.9587***	10.1833***

Notes: 1) ***, **, * significant at 1%, 5% and 10%, respectively. 2) The numbers in parentheses refer to *t*-statistic.

method is appropriate than the distance standard methods. Among the contiguity method, we select queen contiguity weights method which is defined as follow:

$$W_{ij} = \begin{Bmatrix} 1, \text{ boundary of spatial unit } i \cap \text{boundary of spatial unit } j \neq \phi \\ 0, \text{ boundary of spatial unit } i \cap \text{boundary of spatial unit } j \neq \phi \end{Bmatrix}. \quad (16)$$

We only consider first order adjacent spatial unit, even second or higher order spatial unit can be employed. The first reason to use first order contiguity is that data set only consists of 25 spatial units which are not large size to use higher order contiguity. And second reason is that the very contiguous region is most significant impacts on each region. To discuss suitability of second reason, we employ detailed traffic flow data reported in 2006.[18] According to the third column in Appendix A2, the close regions tend to impact more than far regions. Indeed, we only consider Seoul not Gyeonggi province that surrounds Seoul. According to the Appendix A2, traffic comes from Gyeonggi province is not more than inner traffic flows of Seoul. As a result, the first order contiguity weight matrix with only considering spatial units of Seoul sufficiently stands on reason to analyze spatial interaction effect in this study.

After discussion on spatial weight matrix, we spell over model specification. Generally, SDM tells more than SAR or SEM as aspect of employing socio-economic variables in an objective equation. We adopt the LR test and the Wald test to determine whether SDM can be simplified to SAR model or SEM. As mentioned before, we adjust the procedure to test the hypothesis whether the spatial Durbin model can be simplified to the spatial autoregressive model and the spatial error model, i.e., $H_0 : \gamma = 0$ and $H_0 : \gamma + \delta\beta = 0$, respectively.

[18] We use recent data that is reported in 2006, therefore we could employ it as a components of panel data set. However, this data is able to give an evidence to use the first order contiguity spatial weights matrix.

Table 3 Test Result of Model Specification

Spatial Durbin Specification			
Time Fixed Effect		Spatial and Time Fixed Effect	
Wald Spatial Autoregressive	32.3841*** (0.0021)	Wald Spatial Autoregressive	35.6985*** (0.00066074)
LR Spatial Autoregressive	32.2637*** (0.0022)	LR Spatial Autoregressive	34.5623*** (0.00098807)
Wald Spatial Error	23.8319** (0.0327)	Wald Spatial Error	25.9069** (0.0175)
LR Spatial Error	24.6953** (0.0253)	LR Spatial Error	25.7078** (0.0186)
Hausman Test Statistic	2.271300 (1)	Hausman Test Statistic	189.487*** (0)

Notes: 1) ***, **, * significant at 1%, 5%, and 10%, respectively. 2) The numbers in parentheses refer to probability.

Table 3 reports that all of test results of spatial Durbin model specification are significant in 5% confidence level so that SDM with time fixed effect and spatial/time fixed effect can be determined as a proper model than SAR or SEM. However, the Hausman test derive different result that SDM with time fixed effect is rejected to use spatial fixed effect model, while SDM with spatial/time fixed effect is appropriated using fixed effect model in favor of random effects. Then, we utilize SDM spatial random model with time fixed effect and SDM with spatial/time fixed effect. Based on model specification result, we generate three models such as 1) SAR model with the spatial fixed effect, 2) SDM with spatial random effect and time fixed effect, and 3) SDM with both the spatial and fixed effect. Of course, the rest of combination of models with any effects can be selected by intuitive interpretation of researchers, however we follow the steps which is suggestion of LeSage and Pace (2009) and Elhorst (2003, 2010a).

Table 4 shows the comprehensive results of those models using MATLAB. The results of estimation presented at table 4 are compatible with our prior predictions and intuitions.

Table 4 Results for the Three Models

Model	(Model 1) SAR Spatial Fixed Effect		(Model 2) SDM Spatial Random Effect Time Fixed Effect		(Model 3) SDM Spatial Fixed Effect Time Fixed Effect	
Dependent Variable	LNPP		LNPP		LNPP	
R-squared	0.3287		0.5551		0.5628	
Corr-squared	0.2049		0.3957		0.3995	
sigma^2	0.0007		0.0005		0.0005	
Nobs	900		900		900	
Log-likelihood	1,996.227		2,186.0765		2,190.6109	
Variable	Coefficient	Asymptotic *t*-stat	Coefficient	Asymptotic *t*-stat	Coefficient	Asymptotic *t*-stat
LNPQ	0.01	1.33	0.049925***	3.44	0.052051***	3.57
URBANICATION	0.00	–0.38	–0.01	–0.53	–0.01	–0.58
ROAD	0.007639***	2.69	–0.014819***	–3.26	–0.016763***	–3.63
HIGHWAY	–0.005566*	–1.77	–0.035672***	–6.06	–0.036364***	–6.18
CAR	0.000342***	2.86	0.001848***	10.35	0.001883***	10.48
NETWORK	0.026449***	3.54	0.07435***	7.89	0.074785***	7.91
POPDEN	–0.00037**	–2.53	0.00	0.45	0.00	0.51
STATION	–0.002403***	–4.46	–0.007443***	–9.10	–0.007402***	–9.02
LANDPRICE	0.019732***	3.65	0.013319***	2.86	0.013997***	2.99
AREA_PER STATION	0.012632*	1.69	0.120837***	9.51	0.123511***	9.61
POP_PER_CAR	0.01	1.43	–0.03164**	–2.43	–0.032283**	–2.48
CAR_PER STATION	–0.008691***	–2.91	–0.046173***	–9.73	–0.046732***	–9.73
CAR_PER AREA	0.014946***	2.91	0.01	1.51	0.01	1.45
W*LNPQ	-	-	0.051462*	1.88	0.050142*	1.82
W* URBANIZATION	-	-	0.05	1.37	0.05	1.42
W*ROAD	-	-	0.00	–0.46	0.00	–0.14
W*HIGHWAY	-	-	0.029974***	3.09	0.030628***	3.16
W*CAR	-	-	–0.000832***	–2.79	–0.000838***	–2.80
W*NETWORK	-	-	0.01	0.93	0.01	0.81
W*POPDEN	-	-	0.00	–0.53	0.00	–0.43
W*STATION	-	-	0.002642*	1.95	0.002449*	1.80
W*LANDPRICE	-	-	0.00	–0.48	–0.01	–0.65
W*AREA_PER STATION	-	-	–0.01	–0.70	–0.02	–0.77
W*POP_PER CAR	-	-	0.03	1.50	0.03	1.43
W*CAR_PER STATION	-	-	0.016499**	2.01	0.015987*	1.92
W*CAR_PER AREA	-	-	0.01	0.38	0.00	0.29
W*dep.var.	0.336998***	9.06	0.261956***	6.34	0.26498***	6.43
phi	-	-	0.996894***	6.96	-	-

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

Our major findings are in order. First, the spatial autoregressive parameter in the each model amounts to 0.34, 0.26 and 0.26, respectively and are significant. It means that when the setting retail gasoline price at regional level, individual region considers neighbor's price and then reflect it into one's price. This result supports implicitly the regional interaction effect on price exists and works well. Also, it may be interpreted as a kind of the elasticity of substitution or the competition effect because of logarithm form.

And second, the elasticity of quantity is measured 0.049 and 0.052 in model 2 and model 3, respectively. We can get meaningful interpretation that price and quantity have positive relation but the inelastic relationship. The coefficient parameter of NETWORK is estimated positively and significantly. It suggests that when value of NETWORK increases, the gasoline price change rate is augmented as amount of coefficient, 0.24%, 0.74% and 0.74%. Thus, we can relate this estimation result to the general behavior of consumers. Because a parking lot can be considered as a infrastructure of individual region, we derive that it has effect on visitors came from other regions and it also relates price of gasoline at second hand.

While we can interpret that the number of station affects to the retail gasoline price change rate negatively as amount of its coefficient. These results of estimation account for the impact that the selling coverage of each station and level of demand change on price. When any region has more stations which cover large area to sell or gets more market power, such a region is likely to have high level of price change rate of increase and when demand for gasoline per station of regions increases, the rate of price change will be down.[19] Likewise result of Yoon and Lee (2008), it can be inferred that each station has incentive to control the price change rate for maintaining or expanding one's revenue when the coverage to sell and the demand size are fluctuated.

Fourth, Model 2 and Model 3 can explain more things to employ $\sum_{j=1}^{N} W_{ij} y_{ij} \gamma$ term. As applying feedback, spillover effect and total effect to

[19] According to the many of micro level study about asymmetric price change, individual station change price of gasoline to react on demand for gasoline.

gasoline price, the some characteristics of neighboring regions affect one's gasoline price and each variable generally shows more strengthened estimates. Among them, the coefficient of variables, W*CAR, W*HIGHWAY and W*STATION, show the opposite sign to its coefficient of non-spatial independent variables. Such results also could be strong evidence in terms of the existence of interaction effect so that we try to look more closely into this result by using the direct effect and indirect effect.

As ignoring the direct effect and indirect effect, pooled OLS tends to underestimate than the results of the spatial econometric models. The one of answers for underestimation problem is obtained from the estimates of those effects as listed in Appendix A3. As mentioned before, when a region has relationship with adjacent regions, the gasoline price is affected by not only components of one's region but that of its neighbors. Besides, the empirical results of direct effect are not far from our prior intuition by supporting the existence of influential effects across regions. Hence, the direct effect should be considered as an important factor when policy is to be introduced in order to manage the retail gasoline price.

Fifth, three models indicate not far from each other result. The coefficients of SDM model show the slightly bigger than estimates of SAR, because the SDM considers the impact of feedback and spillover effect.

5. CONCLUSION

This paper conducted a study in order to examine the presence of regional interaction effects in the retail gasoline price in Seoul. For this purpose, a couple of spatial econometric models were employed to understand associated pricing mechanisms. Three different spatial econometric models were estimated to incorporate the direct and indirect effects. Our findings show that three different models lead to the almost same conclusion such that the price of one region is more likely linked to the neighboring regions. The result implies the need of more market oriented policy to incorporate network effects between adjacent regions in regards to price formation. In addition, it could be helpful to provide spatial information to let consumers facilitate their decision-making on the choice of proper gas stations.

By employing various explanatory variables, we could understand a pricing mechanism behind the retail gasoline markets. Many previous literatures reinforce that price is influenced by the quantity of sales and that the gasoline is considered as one of the typical inelastic products. We confirmed those general arguments and also showed additional findings such as the effect of coverage to the sales, the network intensity or car density as proxy variables. The estimation results of direct and indirect effects explain the existence of influence of neighbors consistently.

In addition, this paper would contribute to spatial econometrics research by extending its area to retail gasoline markets. Various model specifications were studied coupled with the tests for identifying spatial dependency. In addition, we suggested that non-spatial model could estimate biased parameters when the spatial dependency is prevalent but ignored.

The presence of regional interactions can suggest the important policy implication. Current policy of gasoline price is strongly curbed by central government in order to maintain price sufficiently. However, to maintain and induce lower price of gasoline, government has pushed industry and energy firms with political issues. Such direct price control methods give rise to much more conflicts between consumers, energy industry and government. To avoid such difficulty and problems in the price control process, it is necessary to consider the incentive of price discrimination at the regional level while keeping market-oriented approaches. Furthermore, offering price information system can be one of way to stimulate price differentiation using internet posting or advertisement at public place that is supported by Kim and Kim (2010).[20] When positive regional interaction effect on gasoline price exists, price differentiation and information delivery

[20] They empirically found the effects of the reduction of consumers' search costs using a panel dataset on the Korean gasoline market. They concluded that a reduction in consumers' search costs decreases price dispersion and margin. Notably, result is more clearly shown at metropolitan.

can be easy and effective approach to making lower price compare to government control.

Several limitations in this paper need to be mentioned for the prominent future research. First, because we focused on the administrative districts level of data, brand effects were not covered which is another very important issue. In addition, due to the currently available limited data, price discovery process in Gyeonggi province was not studied in this paper where the one of substantial portion of residents are commuters to Seoul. Third, we couldn’t consider sufficient time effect because this analysis was conducted using monthly data. It could be interesting to analyze the disaggregated data such as weekly or real time data which provide more crucial information regarding price formation. These issues are rendered to future research.

APPENDIX

Table A1 Descriptive Statistics by Regions

ID	REGION	Gasoline Price	Gasoline Quantity	URBANIZATION	ROAD	HIGHWAY	CAR	STATION	LAND PRICE	NETWORK	POPDEN	AREA PER STATION	POP PER CAR	CAR PER STATION	`CAR PER AREA
1	Jongno	2,050.73 (170.56)	1,821.72 (203.15)	0.53 (0)	2.67 (0)	0 (0)	55.51 (8.31)	10.33 (0.96)	1.05 (0.11)	1.55 (0.3)	73.21 (1.64)	2.33 (0.23)	3.21 (0.42)	5.4 (0.77)	2.32 (0.35)
2	Jung	2,058.3 (157.21)	2,871.97 (504.42)	1 (0)	1.88 (0)	0 (0)	61.89 (2.98)	14.67 (0.48)	1.05 (0.09)	1.69 (0.14)	126.27 (2.23)	0.68 (0.02)	2.04 (0.14)	4.23 (0.3)	6.21 (0.3)
3	Dong -daemun	1,883.13 (126.37)	4,630.94 (338.59)	0.99 (0)	3.08 (0.02)	0 (0)	91.39 (0.92)	24.67 (0.48)	1.1 (0.26)	1.25 (0.05)	251.73 (1.64)	0.58 (0.01)	3.91 (0.06)	3.71 (0.1)	6.44 (0.06)
4	Seongdong	1,939.32 (126.4)	4,336 (378.31)	0.73 (0)	3.01 (0)	0 (0)	86.93 (0.61)	24 (1.66)	1.05 (0.25)	1.13 (0.06)	180.23 (1.73)	0.71 (0.05)	3.49 (0.04)	3.64 (0.25)	5.16 (0.04)
5	Seonbuk	1,939.08 (124.47)	4,955.33 (319.16)	0.73 (0)	4.01 (0)	0 (0)	115.47 (1.49)	31.33 (0.96)	1.03 (0.09)	1.17 (0.07)	189.75 (1.61)	0.78 (0.02)	4.04 (0.09)	3.69 (0.14)	4.7 (0.06)
6	Dobong	1,884.78 (123.88)	3,515.08 (233.7)	0.59 (0)	2.33 (0)	0 (0)	94.11 (0.23)	24 (0)	1.05 (0.2)	1.11 (0.01)	174.08 (2.17)	0.86 (0)	3.83 (0.05)	3.92 (0.01)	4.55 (0.01)
7	Seo -daemun	1,928.6 (107.73)	2,753 (494.6)	0.89 (0)	2.67 (0)	0 (0)	79.02 (0.98)	19.33 (0.48)	1.04 (0.18)	1.02 (0.12)	177.44 (4.91)	0.91 (0.02)	3.95 (0.06)	4.09 (0.06)	4.49 (0.06)
8	Eunpyeing	1,888.38 (123.94)	4,476.47 (418.92)	0.51 (0)	3.07 (0.01)	0 (0)	117.41 (3.45)	30.67 (0.48)	1.05 (0.28)	1.05 (0.08)	156.95 (0.91)	0.97 (0.02)	3.97 (0.12)	3.83 (0.16)	3.95 (0.12)
9	Mapo	1,982.13 (131.34)	3,165.92 (259.37)	0.53 (0)	4.04 (0.01)	0 (0)	110.57 (0.96)	19 (0)	1.03 (0.05)	1.22 (0.03)	159.25 (1.51)	1.26 (0)	3.44 (0.05)	5.82 (0.05)	4.64 (0.04)
10	Yongsan	2,039.9 (153.81)	5,317.36 (939.25)	0.59 (0)	3.14 (0)	0 (0)	76.26 (0.6)	21 (0)	1.05 (0.13)	1.28 (0.14)	102.28 (3.55)	1.04 (0)	2.93 (0.12)	3.63 (0.03)	3.49 (0.03)
11	Yeongdeung -po	1,958.61 (136.47)	9,067.72 (596.95)	0.72 (0)	4.4 (0)	0 (0)	141.01 (3.1)	45 (0.83)	1.04 (0.08)	1.09 (0.09)	162.49 (2.08)	0.55 (0.01)	2.83 (0.03)	3.13 (0.02)	5.74 (0.12)

12	Dongjak	1,920.94 (115)	3,496.86 (679.32)	0.96 (0)	2.68 (0.01)	0 (0)	96.95 (0.74)	15 (0)	1.05 (0.08)	1.15 (0.01)	240.65 (1.39)	1.09 (0)	4.06 (0.05)	6.46 (0.05)	5.93 (0.05)
13	Gangnam	2,041.45 (141.91)	14,092.69 (1052.66)	0.61 (0.01)	5.54 (0.06)	1 (0)	245.7 (8.1)	51 (1.43)	1.09 (0.15)	1.52 (0.07)	140.18 (1.5)	0.78 (0.02)	2.26 (0.07)	4.82 (0.22)	6.22 (0.2)
14	Gangdong	1,954.79 (118.36)	4,514.33 (322.67)	0.56 (0)	3.17 (0.02)	1 (0)	140.44 (1.38)	25 (0)	1.04 (0.09)	1.04 (0.04)	196.03 (1.71)	0.98 (0)	3.43 (0.05)	5.62 (0.06)	5.71 (0.06)
15	Gangseo	1,938.31 (129.07)	5,733.58 (326.43)	0.44 (0)	4.42 (0)	1 (0)	178.85 (2.02)	35.33 (1.91)	1.04 (0.17)	1.13 (0.08)	135.19 (1.68)	1.18 (0.06)	3.13 (0.05)	5.08 (0.28)	4.32 (0.05)
16	Guro	1,925.25 (130.71)	3,306.64 (318.24)	0.71 (0)	3.04 (0.07)	0 (0)	135.53 (3.33)	25 (0)	1.01 (0.07)	1.13 (0.02)	206.46 (1.41)	0.8 (0)	3.07 (0.08)	5.42 (0.13)	6.74 (0.17)
17	Gwanak	1,925.03 (124.76)	4,534.72 (347.01)	0.4 (0)	2.76 (0)	0 (0)	119.41 (0.26)	23 (1.66)	1 (0.17)	1.13 (0.02)	175.02 (2.26)	1.29 (0.09)	4.33 (0.06)	5.22 (0.37)	4.04 (0.01)
18	Nowon	1,939.32 (136.69)	4,113.42 (285.06)	0.37 (0)	3.69 (0)	1 (0)	155.42 (0.47)	17 (0)	1.03 (0.07)	1.05 (0.01)	168.5 (2.3)	2.08 (0)	3.84 (0.05)	9.14 (0.03)	4.39 (0.01)
19	Yang -cheon	1,940 (132.79)	6,244.58 (629.45)	0.75 (0)	3.59 (0.14)	1 (0)	146.73 (0.25)	31.67 (0.48)	1.04 (0.07)	0.97 (0.02)	280.21 (5.65)	0.55 (0.01)	3.32 (0.07)	4.63 (0.07)	8.43 (0.01)
20	Jungnang	1,862.53 (127.97)	4,530.86 (340.25)	0.58 (0)	2.69 (0)	0 (0)	103.98 (0.38)	24 (0)	1.1 (0.28)	0.93 (0.05)	229.37 (1.15)	0.77 (0)	4.08 (0.03)	4.33 (0.02)	5.62 (0.02)
21	Seocho	1,941.17 (132.46)	17,783.36 (1308.11)	0.42 (0)	4.96 (0)	1 (0)	171.28 (1.16)	46 (0.83)	1.11 (0.17)	1.49 (0.1)	90.13 (0.42)	1.02 (0.02)	2.47 (0.03)	3.73 (0.09)	3.64 (0.02)
22	Songpa	1,957.52 (130.63)	9,324.19 (683.5)	0.7 (0)	4.67 (0.02)	1 (0)	214.51 (1.15)	44.33 (1.26)	1.12 (0.13)	1.17 (0.01)	198.59 (1.74)	0.76 (0.02)	3.14 (0.04)	4.84 (0.16)	6.33 (0.03)
23	Gwangjin	1,874.55 (113.91)	9,511.31 (675.83)	0.68 (0)	3.39 (0)	0 (0)	94.04 (0.67)	24 (1.43)	1.11 (0.3)	1.11 (0.02)	214.26 (2.49)	0.71 (0.04)	3.89 (0.07)	3.93 (0.24)	5.51 (0.04)
24	Gangbok	1,867.79 (125.3)	2,966.92 (278.39)	0.4 (0)	1.97 (0)	0 (0)	73.91 (0.89)	20.33 (0.48)	1.06 (0.12)	1.03 (0.06)	143.06 (0.68)	1.16 (0.03)	4.57 (0.07)	3.64 (0.12)	3.13 (0.04)
25	Geum -cheon	1,908.33 (121.84)	3,075.69 (305.35)	0.81 (0)	1.94 (0)	1 (0)	73.55 (1.25)	19 (0)	1.06 (0.11)	1.16 (0.13)	183.46 (2.12)	0.68 (0)	3.24 (0.09)	3.87 (0.07)	5.66 (0.1)

Note: The numbers in parenthesis refer to the standard deviation.

Table A2 Traffic Flow by Car from Adjacent Regions per Day

Region	Traffic Flow per day between Spatial Unit in Seoul	Percentage of Traffic Inflow between Adjacent Regions	Traffic Flow per day came from Gyeonggi	Percentage of Traffic Inflow came from Gyeonggi
Jongno	154,240	31.47%	11,486	7.45%
Jung	177,618	33.80%	Not Exist any Adjacent Regions	
Dongdaemun	106,700	55.13%	Not Exist any Adjacent Regions	
Seongdong	88,682	51.94%	Not Exist any Adjacent Regions	
Seonbuk	90,249	58.83%	2,003	2.22%
Dobong	54,283	49.04%	11,556	21.29%
Seodaemun	359,468	51.60%	Not Exist any Adjacent Regions	
Eunpyeing	75,884	35.32%	Not Exist any Adjacent Regions	
Mapo	116,066	52.20%	17,309	14.91%
Yongsan	87,867	59.84%	Not Exist any Adjacent Regions	
Yeongdeungpo	181,410	51.98%	Not Exist any Adjacent Regions	
Dongjak	96,261	50.07%	Not Exist any Adjacent Regions	
Gangnam	359,468	50.10%	36,902	10.27%
Gangdong	115,259	30.55%	18,661	16.19%
Gangseo	108,097	45.71%	17,851	16.51%
Guro	108,998	45.87%	28,409	26.06%
Gwanak	93,824	55.49%	6,118	6.52%
Nowon	95,362	49.05%	28,694	30.09%
Yangcheon	115,835	59.86%	15,496	13.38%
Jungnang	68,370	50.11%	7,482	10.94%
Seocho	223,820	40.13%	28,185	12.59%
Songpa	228,279	54.73%	39,247	17.19%
Gwangjin	83,500	61.43%	5,290	6.34%
Gangbok	59,539	51.65%	1,340	2.25%
Geumcheon	53,658	44.45%	22,151	41.28%
Average	132,109	48.81%	17,540	15.03%
Standard Deviation	83,006	8.73%	11,691	10.20%

Source: traffic.seoul.go.kr

Table A3 The Result of Direct and Indirect Effects

Model	SAR Spatial Fixed Effect		SDM Spatial Random Effect Time Fixed Effect		SDM Spatial Fixed Effect Time Fixed Effect	
Dep. Variable	LNPP		LNPP		LNPP	
R-squared	0.3287		0.5551		0.5628	
corr-squared	0.2049		0.3957		0.3995	
sigma^2	0.0007		0.0005		0.0005	
Nobs	900		900		900	
Loglikelihood	1,996.227		2,186.0765		2,190.6109	
Variable	Coefficient	Asymptotic *t*-stat	Coefficient	Asymptotic *t*-stat	Coefficient	Asymptotic *t*-stat
Direct Effect						
LNPQ	0.01239	1.36	0.053775***	3.59	0.05625***	3.94
URBANICATION	–0.004178	–0.40	–0.007404	–0.38	–0.008241	–0.42
ROAD	0.008048**	2.69	–0.015133***	–3.32	–0.017008***	–3.87
HIGHWAY	–0.005845*	–1.75	–0.034307***	–5.78	–0.034984***	–6.16
CAR	0.000357***	2.88	0.001825***	10.17	0.001865***	10.33
NETWORK	0.027204***	3.47	0.076457***	8.10	0.076816***	8.06
POPDEN	–0.000385**	–2.60	0.00009	0.36	0.000111	0.46
STATION	–0.002508***	–4.61	–0.007398***	–9.21	–0.007396***	–9.29
LANDPRICE	0.020271***	3.70	0.013625**	2.77	0.013914**	2.78
AREA_PER STATION	0.013238	1.70	0.121405***	9.60	0.123767***	9.62
POP_PER_CAR	0.011299	1.46	–0.029671**	–2.26	–0.030586**	–2.38
CAR_PER STATION	–0.009119***	–2.97	–0.045783***	–9.80	–0.046437***	–9.47
CAR_PER AREA	0.015548***	2.97	0.012997	1.56	0.012315	1.49
Indirect Effect						
LNPQ	0.005775	1.31	0.081912**	2.37	0.082068**	2.38
URBANICATION	–0.001912	–0.39	0.05674	1.36	0.057969	1.36
ROAD	0.003735**	2.55	–0.009732	–0.98	–0.007632	–0.81
HIGHWAY	–0.002702	–1.70	0.026903**	2.25	0.0272**	2.29
CAR	0.000166**	2.68	–0.000461	–1.25	–0.000435	–1.24
NETWORK	0.012619***	3.20	0.044741**	2.22	0.042629**	2.20
POPDEN	–0.000179**	–2.46	–0.000255	–0.46	–0.000191	–0.36
STATION	–0.001165***	–4.00	0.000964	0.57	0.000676	0.42
LANDPRICE	0.009487***	3.07	–0.001055	–0.09	–0.002885	–0.23
AREA_PER STATION	0.00616	1.64	0.021129	0.81	0.02208	0.87
POP_PER_CAR	0.005262	1.43	0.032116	1.15	0.029348	1.07
CAR_PER STATION	–0.004239**	–2.75	0.005976	0.58	0.004558	0.45
CAR_PER AREA	0.007228**	2.77	0.011064	0.62	0.009279	0.52

Total Effect						
LNPQ	0.018165	1.35	0.135687***	3.34	0.138318***	3.53
URBANICATION	–0.00609	–0.40	0.049335	1.05	0.049728	1.01
ROAD	0.011783**	2.69	–0.024865**	–2.32	–0.02464**	–2.47
HIGHWAY	–0.008548*	–1.75	–0.007403	–0.57	–0.007784	–0.60
CAR	0.000523***	2.88	0.001364***	3.31	0.00143***	3.75
NETWORK	0.039822***	3.47	0.121198***	5.59	0.119445***	5.54
POPDEN	–0.000564**	–2.60	–0.000165	–0.26	–0.00008	–0.13
STATION	–0.003673***	–4.61	–0.006434***	–3.51	–0.006719***	–3.94
LANDPRICE	0.029758***	3.58	0.012569	0.83	0.011029	0.72
AREA_PER STATION	0.019398	1.69	0.142533***	5.19	0.145846***	5.47
POP_PER_CAR	0.016562	1.46	0.002445	0.08	–0.001238	–0.04
CAR_PER STATION	–0.013358***	–2.96	–0.039807***	–3.61	–0.041879***	–3.91
CAR_PER AREA	0.022776***	2.97	0.024061	1.18	0.021594	1.07

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

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