PACIFIC RIM PROPERTY RESEARCH JOURNAL
2019, VOL. 25, NO. 2, 101–124
https://doi.org/10.1080/14445921.2019.1610595

Routledge
Taylor & Francis Group

A comparative study on the value of scenic views between an inland and a coastal city in Korea

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ABSTRACT

This study estimates hedonic house price models for an inland city of Seoul and a coastal city of Pusan using spatial regression with successful bidding price data of court auction during the period from January 2006 to December 2014. Among hedonic attributes such as floor area, building age, total floor level, living floor level, direction of the window of the living room, proximity to natural environment, scenic views and others employed in this study, our main focus is on scenic views. As a result of our empirical analysis, the most preferred view turns out to be a water-related view such as a broad river view in Seoul or an ocean view in Pusan. A mountain view, affecting negatively in a coastal city like Pusan which is adjacent to the beautiful ocean, has positive influence in Seoul, since it is an inland city with no ocean in sight with only a river running across the heart of the city which is surrounded by mountains serving as its boundary. While a building view in Seoul has negative effect on the price, it affects positively in Pusan.

ARTICLE HISTORY
Received 22 November 2018
Accepted 19 April 2019

KEYWORDS
Korean housing market; scenic view; spatial regression

Introduction

The value of the house can be determined by both its internal properties (structural attributes) and external characteristics (locational and environmental factors). Internal attributes of a house such as floor area, floor level, building age and so on do matter in house purchases.

However, with economic development and income growth, home buyers tend to consider more about the external characteristics of a house such as good environmental conditions and quality amenities given good internal attributes of a house in making their house purchase decisions.

Scenic views, among such environmental attributes, seem to mean a lot to home buyers as they tend to pay increasingly high prices for houses with good views (Baranzini & Schaerer, 2011; Bond, Seiler, & Seiler, 2002; Chen & Jim, 2010; Conroy & Milosch, 2011; Jim & Chen, 2009; Kim, Park, Lee, & Xue, 2015). For example, a river view in Netherlands increases the house price by 8–10% (Luttik, 2000). A wide view of a nearby park raises the price of houses by 8–20% in the United States (Crompton, 2001), and seaport or ocean view in Hong Kong increases the house price by 2.97% (Jim & Chen, 2009).

Likewise, high-rise apartments with park views close to the Central Park in Manhattan, New York are priced high (Oh, 2015), and skyscrapers near Haeundae Beach which provide nice ocean views in Pusan, Korea are also priced high compared to their counterparts

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without the views in the same region. Similarly, the buildings located along the riverside of the Han River in Seoul which provide nice river views are also of high value and tend to attract premium-seeking investors even in real estate recession times.

Considering these previous studies regarding views, we carefully designed this research to provide evidence to our initial assumption that scenic views affect house prices and that the degree of impact of scenic views on the house price may differ depending on the location and the price segment to which each unit belongs.

We choose the two cities, namely, Seoul and Pusan, as our subjects. As shown in Figure 1, most premium apartments in an inland city, Seoul are located in or around

Figure 1. Maps of Seoul and Pusan. Source: Korean Government.

places where they can get the view of the Han River or mountains, whereas in a coastal city, Pusan, ocean views are valued most. And then we compare the values of views between an inland and a coastal city within a country, Korea. To the best of our knowledge, few studies have conducted this kind of comparative researches within the same country. Thus our study may fill the gap in the literature.

Kim et al. (2015) who studied Seoul apartments showed that mountain views have positive impact on the house price in Seoul. On the contrary, Jim and Chen (2009) who explored the case of Hong Kong revealed that mountain views affect house prices negatively while ocean views have positive effect on the house price. Likewise, Lee (2008) and Jeong and Park (2016) who studied Pusan apartment showed that ocean views raise the price. The reason for this different results among the cities aforementioned such as an inland city and two coastal cities can be that while Hong Kong and Pusan are coastal cities where ocean views are most preferred, Seoul is an inland city where ocean views are not existent with only other types of views such as mountain views and river views available.

In our study, we chose, more specifically, as our subject areas, Gangnam-gu and Seocho-gu in Seoul where premium apartments with those views of our interest are quite abundant and Haeundae-gu and Sooyoung-gu in Pusan where there are plenty of premium apartments with ocean views, which facilitated our data collection process.

Although our study is basically in line with Kim et al. (2015) on Seoul, and Lee (2008) and Jeong and Park (2016) on Pusan, a major difference of ours from their studies is that our study considers spatial autocorrelation which their studies are missing. This can also be one of our main contributions to the literature.

Spatial dependence occurs when the price of a house at one location depends on that of a neighbouring house. Since house prices seem to involve spatial dependence, housing research may also be required to adopt the spatial econometric technique (Li & Saphores, 2012; Liao & Wang, 2012; Wyman, Hutchison, & Tiwari, 2014). In Korea, house transaction prices have been reported to the government, and the government has made these prices posted online publicly since 2006. In housing transactions, each party (seller and buyer) tends to check the actual transaction price of the nearby apartment with similar characteristics using the online site and consider it as an important reference for making his or her decision of selling or buying a house. Hence, the influence of the price of neighbouring apartments with trading history cannot be disregarded.

In consideration of this spatial dependence, we conducted Global Moran's I test to assess the degree of the house price randomness using ArcGIS. In order to identify the spatial autocorrelation of our data, we also performed all kinds of Lagrange Multiplier tests using GeoDa. Finally, after investigating the hedonic characteristics of each house in our sample, we examined how each factor influences the price in the traditional Ordinary Least Square (OLS), spatial lag model and spatial error model using GeoDaSpace, and compared the results for both of the cities.

Using all possible techniques aforementioned, we tried to analyse the impact of scenic views on house price in Seoul and Pusan. Unlike the literature, however, we attempted to classify these types of views more specifically into mountain, village, ocean, river, street and building view, and also the direction of the window in the living room towards the east, the west, the south and the north. This specification of views in our research can also contribute to literature.

In the next section, we examine the literature and then introduce a theoretical model to derive the key house price drivers and describe the empirical models and the dataset in the research model and data section. The empirical results section presents the empirical results and compares the value of scenic views between houses in Seoul and those in Pusan while the conclusion section concludes.

Literature review

Plenty of studies exist on the economic value of scenic views as house price determinants. For instance, Benson, Hansen, Schwartz and Smersh (1998), Seiler, Bond and Seiler (2001), Bond et al. (2002), Bourassa, Hoesli and Sun (2004), Jim and Chen (2006, 2007, 2009), Hui, Chau, Pun and Law (2007), Kong, Yin and Nakagoshi (2007), Shultz and Schmitz (2008), Chen and Jim (2010), Baranzini and Schaerer (2011), Damigos and Anyfantis (2011) and Wyman et al. (2014) revealed that ocean or river (lake) views have positive effect on the price.

Benson et al. (1998) which study real estate market in Bellingham from 1984 to 1994 showed that a high-quality ocean view raises the price by 60% while a low-quality ocean view raises it only by 8%. Bond et al. (2002) exhibited a significant water view premium in their study of homes on Lake Erie; that is, having a lake view adds $256,544.72 to the value of a home. Bourassa et al. (2004) who studied various types of homes in Auckland, New Zealand disclosed that wide waterfront views are found to add an average of 59% to property values.

Jim and Chen (2009) who studied apartments located in the Quarry Bay District in Hong Kong Island showed that ocean views increase the price by 2.97% while mountain views and street views decrease the price of apartments by 6.7% and 3.7%, respectively. However, building views do not show any significant effect according to their research. Chen and Jim (2010) whose study was conducted on Shenzhen, China in 2008 concluded that city park views raise the house price by 17.2%. Moreover, they found that views have bigger impact on the house price than proximity or accessibility. Baranzini and Schaerer (2011) who conducted their study on Geneva, Switzerland in 2005 revealed that river or lake views increase the house price by 57%.

Wyman et al. (2014) who examined the vacant lots in South Carolina in the United States determined that the water view increases the price by 91% while the combined water and Blue Ridge Mountain view increases the price by 126%.

Meanwhile, Kim and Choi (2012) conducted a survey on residents of Seoul and Pusan in 2010, which proved that respondents have higher willingness to pay additional money for river, lake or park views rather than for mountain or ocean views. In contrast, Kim, Lee, Cho and Park (2007) studied properties in Bundang, Seoul from January to June in 2006 with 912 real transaction price samples in which views can be observed. They proved that mountain views hike up the price by 6% while river or lake views raise it by 4%. Likewise, Kim et al. (2015) concluded that mountain views in inland Seoul have positive effect on the price. This may be because mountain views rather than other views can give potential home buyers as well as existing homeowners in crowded Seoul tranquillity or pleasure since mountains give us relaxation and the vistas provided by mountains change with the season in an inland city where ocean views are not existent.

Research model and data

Hedonic characteristics used in this research include structural and environmental characteristics and accessibility. Structural factors include variables such as floor area, total floor level, living floor level, building age, household number, parking space and construction firm.[1] Proximity or distance to subway, high school, sub-centre of the city and highway IC are used as accessibility variables. Direction of living room and the proximity to mountain, river or ocean and scenic views are used as environmental aspect variables of a house. We also include the regional dummy variable to control the effect of house market segmentation.

House prices often involve positive spatial autocorrelation, which means that the prices of houses in the same neighbourhood tend to be similar due to the spatial dependence of house prices (Sun, Tu, & Yu, 2005). When the data generating process encounters spatial dependence, OLS estimators can have inefficient and biased results. In such a case, spatial econometric modelling becomes necessary (Anselin & Lozano-Gracia, 2011). One common approach is to model spatial dependence through a spatial weight matrix, and housing studies often incorporate this into either a spatial-lag model or a spatial error model (Liao & Wang, 2012). A nonparametric approach such as locally weighted regression is also used (McMillen, 1996).

The spatial lag model is appropriate where the price of a house at any location is a function of the price of a house at a nearby location. The spatial lag model implies that there are correlated errors that affect the dependent variables. This is also known as the spatial spillover effect (Suriatini, 2007; Wyman et al., 2014).

In a spatial error model, the error terms of a regression are spatially auto-correlated: the error of the price of a house at any location is a function of the error of the price of a house at a nearby location (Wyman et al., 2014). Odland (1988) argues that the presence of spatial autocorrelation in regression residuals violates the assumption of independence of the errors.

This study adopts both a spatial-lag model and a spatial error model. The spatial weights are a key component in spatial dependence. They are an essential element in the specifications of the spatial variables in a model, such as the spatial lag and spatial error models. Spatial weights express the neighbour structure between the observations as N × N matrix **W** in which the elements W_{ij} of the matrix are the spatial weights:

$$W = \begin{bmatrix} w_{11} w_{12} \cdots w_{1n} \\ w_{21} w_{22} \cdots w_{2n} \\ \vdots \vdots \ddots \vdots \\ w_{n1} w_{n2} \cdots w_{nn} \end{bmatrix}$$

The spatial weights are non-zero when i and j are neighbours and zero if otherwise. The self-neighbour relation is excluded, so that the diagonal elements of **W** are zero.

In the operational approach of neighbourhood relation, the inverse distance weight is adopted. The inverse distance weight ensures the distance-decay function that spatially closer neighbouring apartments are given relatively greater weights with the spatial weights decreasing with spatial distance (Hyun & Milcheva, 2018).

For the spatial-lag model, its general form can be written as indicated below:

$$p_i = \rho W_i p_i + X_i\beta + \varepsilon_i$$

where p_i is a vector of dependent variable, W_i is an $N \times N$ spatial weight matrix, $W_i p_i$ is a spatially lagged dependent variable, and ρ indicates the degree of the spatial autocorrelation and is a parameter to be estimated. If ρ is positive, the spatial autocorrelation is positive, and prices of nearby houses tend to be similar. On the other hand, if ρ is negative, the spatial autocorrelation is negative, and prices of nearby houses tend to be dissimilar. X_i is a matrix of the values of explanatory variables, β is a vector of unknown regression parameters, and ε_i is an error term.

For the spatial error model, its general form can be written as:

$$p_i = X_i\beta + u_i,$$

$$u_i = \lambda W_i u_i + \varepsilon_i$$

where p_i is a vector of dependent variable, W_i is an $N \times N$ spatial weight matrix, $W_i u_i$ is the spatially lagged error terms, λ is the parameter for the spatial error dependence. Note that λ is interpreted either as the nuisance because of measurement errors in the linear model or as the omission of a spatially correlated variable from the matrix, X_i (Plummer, 2010). Therefore, ignoring the spatial structure of the error term leads to biased estimates of the standard errors. Lastly, ε_i is an error term (Anselin & Bera, 1998).

Here, maximum likelihood is used as the estimation method of the spatial lag and spatial error model.

Table 1 shows the definition of variables. The dependent variable is the log value of the real auction price of an apartment in Korean won. FLOOR AREA represents the size of an apartment in square metres. AGE represents the age of an apartment in years, which can be measured by the difference between the date of issue of the occupation permit after construction and the date of the auction transaction. TFL represents the number of total floor levels of an apartment building to which a specific unit belongs. The reason TFL is considered as a variable is that high-rise apartments tend to be valued higher in Korea since they are built up to provide more space in the ground for other amenities for the residents such as a gym, a park or a pond inside the complex which are valued by most home purchasers. LFL represents the living floor level of a house. That is, if an apartment unit is on the second floor in a 30-story apartment building, its TFL is 30 and LFL is 2. SQLFL represents the squared value of the living floor level of a house and SQAGE represents the squared value of the age. We also include SQLFL and SQAGE in our hedonic price equation to reflect the quadratic effects on the price.

HOUSEHOLD NUMBER represents the total number of apartment units or households in the apartment complex. PARKING SPACE represents the number of cars per household which can be parked in the parking lot, meaning the capacity of the parking lot within the apartment complex.

Meanwhile, SUBWAY dummy represents the distance from an apartment to the nearest subway station; it equals 1 if one can walk to the nearest subway station in 10 min from an apartment unit and 0 otherwise. SCHOOL dummy represents the distance from an apartment to the nearest high school; it equals 1 if one can walk to the nearest high school in 10 min from an apartment unit and 0 otherwise.

Table 1. Definition of variables.

Variables	Definition
Log Price	Logarithm of house price
FLOOR AREA (m^2)	Floor area of an apartment unit
AGE (year)	Age of an apartment building
SQAGE	Squared age of an apartment building
TFL	Total floors of an apartment building
LFL	Floor level of the building on which an apartment unit is located.
SQLFL	Squared floor level of an apartment unit
HOUSEHOLD NUMBER	The number of households in the apartment complex
PARKING SPACE	The number of parking spaces per household in the apartment complex
BRAND Dummy	It equals 1 if an apartment unit is constructed by major construction firm and 0 otherwise.
SUBWAY Dummy	It equals 1 if one can walk to the nearest subway station in 10 min and 0 otherwise
SCHOOL Dummy	It equals 1 if one can walk to the nearest high school in 10 min and 0 otherwise
INVERSE DISTANCE to SUBCENTRE (km)	Inverse distance to the nearest sub-centre from an apartment unit
INVERSE DISTANCE to HIGHWAY IC (km)	Inverse distance to the nearest highway IC (km) from an apartment unit
SOUTH Dummy	It equals 1 if the living room faces south and 0 otherwise.
EAST Dummy	It equals 1 if the living room faces south and 0 otherwise.
WEST Dummy	It equals 1 if the living room faces west and 0 otherwise.
BROAD RIVER VIEW Dummy	It equals 1 if an apartment unit has a broad river view and 0 otherwise.
PARTIAL RIVER VIEW Dummy	It equals 1 if an apartment unit has a confined river view and 0 otherwise.
RIVER VIEW Dummy	It equals 1 if an apartment unit has a river view and 0 otherwise. (This variable applies only to Pusan.)
BROAD OCEAN VIEW Dummy	It equals 1 if an apartment unit has a broad ocean view and 0 otherwise.
PARTIAL OCEAN VIEW Dummy	It equals 1 if an apartment unit has a confined ocean view and 0 otherwise.
MOUNTAIN VIEW Dummy	It equals 1 if an apartment unit has a mountain view and 0 otherwise.
VILLAGE VIEW Dummy	It equals 1 if an apartment unit has a village view and 0 otherwise.
BUILDING VIEW Dummy	It equals 1 if an apartment unit has a building view and 0 otherwise.
RIVER DISTANCE Dummy	It equals 1 if an apartment unit is located within 500 m from the Han river or 300 m within the Yangjae creek and 0 otherwise
OCEAN DISTANCE Dummy	It equals 1 if an apartment unit is located within 500 m from ocean and 0 otherwise.
MOUNTAIN DISTANCE Dummy	It equals 1 if an apartment unit is located within 1 km from the nearest mountain and 0 otherwise
Seocho Gu Dummy	It equals 1 if an apartment unit is located in Seocho Gu and 0 otherwise.
Sooyoung Gu Dummy	It equals 1 if an apartment unit is located in Sooyoung Gu and 0 otherwise

INVERSE DISTANT to SUB-CENTRE and INVERSE DISTANCE to HIGHWAY IC represent the inverse of distance (km) from an apartment to the nearest sub-centre of the city or highway IC. Kangnam Subway Station or Kangnam Express Bus Terminal is the sub-centre of city in Seoul, while in Pusan it is the Pusan International Convention Center. The inverse of distance is used so that the value of the coefficient becomes positive when the apartment price rises with proximity to urban amenities.

SOUTH dummy represents that the window of living room is facing the south; it equals 1 if the window of living room faces towards the south and 0 otherwise. The reason SOUTH is included as an explanatory variable in this study is that as Korea is located in the northern hemisphere, south facing houses or apartments are much preferred since the south frontage means more sunlight in the winter and more cool wind in the hot summer season, thus resulting in a considerable amount of savings in the cost of heating or cooling of the house. Also there are apartments where the windows of the living rooms face towards the East or the West; it equals 1 if the window of living room is facing either of the directions and 0 otherwise. NORTH is a reference variable. MOUNTAIN DISTANCE dummy represents the distance from the nearest mountain in Seoul: it equals 1 if a house is located within 1 km from the nearest mountain and 0 otherwise. RIVER DISTANCE dummy represents distance from the Han River or the Yangjae Creek in Seoul: it equals 1 if a house is located within 500 m from the Han River or within 300 m from the Yangjae Creek and 0 otherwise. The Yangjae Creek is a small river or stream with a small range of amenity. OCEAN DISTANCE dummy represents the distance of an apartment from the ocean in Pusan: it equals 1 if a house is located within 500 m from the ocean and 0 otherwise.

MOUNTAIN, BROAD RIVER, PARTIAL RIVER, BUILDING, VILLAGE, BROAD OCEAN and PARTIAL OCEAN dummy represent the dummy variables for the scenic view; it equals 1 if a property has such a view and 0 otherwise. In reference to the study by Jim and Chen (2009), water view such as river view or ocean view is divided into broad view and partial view in this study. However, for Pusan, a river view cannot be divided into a broad river view or a partial river view due to the limited number of apartments with a river view in Pusan. A street view is a reference variable.

Seocho Gu Regional dummy in Seoul equals 1 if an apartment is located in Seocho Gu and 0 otherwise. Suyoung Gu Regional dummy in Pusan equals 1 if an apartment is located in Sooyoung Gu and 0 otherwise.

As for data, this research involved data gathered from apartments in the Gangnam Gu (henceforth referred to as Gangnam) and Seocho Gu (henceforth referred to as Seocho) of Seoul, an inland city, and those in the areas of Sooyoung Gu (henceforth referred to as Sooyoung) and Haeundae Gu (henceforth referred to as Haeundae) of Pusan, a coastal city. Gangnam and Seocho are relatively newly constructed residential submarkets in Seoul which provide a good educational and residential environment, thus attracting premium-seeking house purchasers. Haeundae and Sooyoung in Pusan are two regions well known for their beautiful scenery of the beach and the ocean and for mild climate conditions throughout the year since these are located in the southern area near the ocean in Korea. The reason we chose these four subregions as our study subjects is that most of the premium apartments of each city are clustered in these regions, respectively, even though the two cities have different attributes of natural environment, which therefore facilitates comparison analysis on scenic views of our main interest.

Housing transactions in Korea are normally conducted through real estate agents. Real estate agents usually work for a company in developed countries like Australia and Japan, whereas in Korea most of them are self-employed and work separately and independently. So, it may be an extremely difficult job to obtain sufficient housing transaction data needed for this kind of research from scattered individual agents in Korea (Kim et al., 2015). In 2006, however, the Korean government implemented a law making it compulsory for realtors to report a transaction price to the Ministry of Land and Transportation, and made the data posted online, thus making it possible for the public to access to the data for free.

Only since then, have we gotten access to the data of house transaction. But even so, only a few pieces of general information – such as the name of the apartment complex to which a specific apartment unit belongs, floor level, floor area and the price – are all we can come by except for the exact address of the apartment (Kim et al., 2015). These data alone may not suffice for this kind of study on hedonic price modelling, since they contain and indicate only limited pieces of information on the traits of a certain apartment. We need more specific information on hedonic attributes of each apartment unit such as the direction of living room window and the views.

Unlike the online data of Korean government, though, court auction data which we rely on for this research provide exact address information of an apartment unit which government data do not provide and which we definitely need for our study even though auction data generally deal with distressed properties (Kim et al., 2015). This is the main reason we use auction data instead of government data of transaction prices for our study.

Yet, many studies concerning auction markets for houses focus on comparison between the auction price and the normal market price as their main themes. Most studies empirically find that the auction prices of houses tend to be discounted from their normal market prices (Allen & Swisher, 2000; Andersen & Nielsen, 2013; Brasington & Sarama, 2008; Campbell, Giglio, & Pathak, 2011; Carroll, Clauretie, & Neill, 1997; Clauretie & Daneshvary, 2009; Donner, Song, & Wilhelmsson, 2016; Harding, Rosenblatt, & Yao, 2009; Mocking & Overvest, 2017; Seo & Mikelbank, 2017; Zhou, Yuan, Lako, Sklarz, & McKinney, 2015), while other studies find that auction prices are higher than market prices (Qu & Liu, 2012; Quan, 2002). Frino, Peat and Wright (2012) find no statistically significant difference between the auction price and market price of a house. Regardless of some difference which may exist as literature argues between auction price and market price, we have no choice but to use auction data of prices rather than normal market prices for our research because as described above, they contain the exact address information necessary for our study.

So we collected these kinds of information of our data manually from private domains since no dataset of these kinds for the Korean housing market is established or existent. We obtained these kinds of information on individual properties from auction results from Seoul and Pusan District Court which was compiled by a private auction information provider (www.goodauction.com) during the period from January 2006 through December 2014. This website has provided essential information on exact address, auction price, floor area, age, number of total floors and floor level.

A typical Korean apartment complex consists of more than 10 building blocks on the average, and each building contains 60 units on the average. Each unit has different hedonic characteristics in terms of floor area, floor level, direction and scenic view (which may include a mountain, river, ocean, street or building view). In other words, even if they look similar, no identical units exist in terms of scenic view and distance from urban infrastructure (e.g. the nearest high school, subway station or highway IC). That is, if two units indicated with the same floor level belong to different buildings, they are not the same in terms of scenic view and the distance from the nearest high school, subway station or high way IC can also differ from unit to unit (Kim et al., 2015).

For more details regarding the hedonic characteristics of each apartment such as its longitude and latitude, we used Google maps to identify them. These geographic coordinates allow us to make the distance weight panel to create the spatial weight matrix and to calculate the distance from each house to the nearest subway station, high school, sub-centre of city and highway IC by using ArcGIS. We collected data for the directions and scenic view of each house via fieldwork and Google map analysis. We dropped from our analysis, the observations with missing data for any of the variables and those with big gaps between bidding price and appraiser's price due to more than four times of bidding failure even without a tenant with an opposing power.

All told, we obtained a sample of 4962 housing transactions (2459 apartment units in Seoul and 2503 apartment units in Pusan). To control for the possible time effect over the nine-year observation period of this study, we used real house prices instead of nominal house prices. The real house prices are calculated by deflating the auction prices by the monthly regional apartment price index of Kookmin Bank.

Empirical results

Table 2 shows descriptive statistics for apartment price, structural, accessibility and environmental variables in the two cities. The average house price in Seoul was 837,000 thousand Korean won, and the highest one was 5,100,000 thousand won. The average age of houses was 14.66 years, and the average floor area was 119.88 m^2. The average number of total floors was 14.55, and the average number of living floor levels was 7.51. House prices and floor area in Pusan, on the other hand, were lower and smaller than those in Seoul. The average house price in Pusan was 210,000 thousand Korean won, and its highest one was 2,550,000 thousand won. The average age of houses in Pusan was 12.31 years, and the average floor area was 86.05 m^2. The average number of total floors was 17.76, and the average number of living floor levels was 8.4.

The spatial autocorrelation diagnostics are presented in Table 3. We carried out Global Moran's I test using ArcGIS to assess the degree to which the house price pattern deviates from the null hypothesis of house price randomness. If Moran's I is close to 1, it represents clustering, while if it is close to 0, it represents randomness. In order to test for spatial dependence, we calculated Moran's I for residual spatial autocorrelation. Moran's I statistics turned out to be significant at the 1% level of significance, and Moran's I for Pusan is bigger than that for Seoul. This implies that apartment prices in Pusan are more clustered and affected by neighbouring apartments than in Seoul.

To identify the spatial autocorrelation of our data, we also conducted all kinds of Lagrange Multiplier tests using GeoDa which provides spatial diagnostics of LM-Lag, LM-Error, Robust LM-Lag, Robust LM-Error and LM (SARMA) test statistics for the original OLS model. All LM test statistics for these two regions are statistically significant at the 1% level.

We examine the overall spatial diagnostics to confirm relative model fit by comparing the spatial diagnostics of the standard OLS model, spatial lag model and spatial error model. The regression diagnostics for Seoul indicate that R^2 improved from 0.7476 (OLS) to 0.7677 (spatial lag), to 0.7757 (spatial error). The regression diagnostics for Pusan indicate that R^2 increased from 0.8170 (OLS) to 0.8448 (spatial lag), to 0.8699 (spatial error). However, Anselin (2005) mentioned that the R^2 for the spatial models are effectively a pseudo-R^2 and that the R^2 result is not directly comparable to the OLS model. Instead, Anselin (2005) recommended using three spatial diagnostics – log likelihood, Akaike information criterion (AIC) and the Schwarz criterion (SC) – to provide comparative information on relative model fit.

Table 2. Basic statistics of variables for Seoul and Pusan.

	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Number of observations
Panel A: Seoul							
Price (thousand won)	837,000	5,100,000	44,191	493,000	2.03	11.32	2459
FLOOR AREA (㎡)	119.88	301.47	16.53	50.79	0.63	2.90	2459
AGE (years)	14.66	40	1	10.5	0.6	1.96	2459
TFL	14.55	69	3	9.56	2.54	11.29	2459
LFL	7.51	55	1	6.71	2.47	12.80	2459
HOUSEHOLD NUMBER	572.03	6075	5	944.65	3.14	14.11	2459
PARKING SPACE	1.55	7.36	0.16	0.86	1.96	9.84	2459
BRNAD Dummy	0.18	1	0	0.38	1.71	3.92	2459
SUBWAY Dummy	0.33	1	0	0.47	0.73	−1.47	2459
SCHOOL Dummy	0.38	1	0	0.48	0.51	1.26	2459
INVERSE DISTANCE to SUBCENTRE	0.52	3.57	0.12	0.44	2.68	11.95	2459
INVERSE DISTANCE to IC	0.70	9.28	0.18	0.70	4.44	34.09	2459
SOUTH Dummy	0.79	1	0	0.41	−1.44	3.07	2459
EAST Dummy	0.10	1	0	0.3	2.62	7.87	2459
WEST Dummy	0.08	1	0	0.27	3.11	10.70	2459
BROAD RIVER VIEW Dummy	0.04	1	0	0.19	4.94	25.36	2459
PARTIAL RIVER VIEW Dummy	0.02	1	0	0.12	7.75	61.07	2459
BUILDING View Dummy	0.77	1	0	0.42	−1.31	2.71	2459
MOUNTAIN View Dummy	0.04	1	0	0.2	4.68	22.88	2459
MOUNTAIN DISTANCE Dummy	0.18	1	0	0.39	1.64	3.69	2459
RIVER DISTANCE Dummy	0.31	1	0	0.46	0.83	1.68	2459
Seocho Gu Dummy	0.45	1	0	0.50	0.19	1.04	2459
Panel B: Pusan							
PRICE (thousand won)	210,000	2,550,000	15,587	159,000	3.44	30.40	2503
FLOOR AREA (㎡)	86.05	244.97	9.86	37.88	1.05	4.22	2503
AGE (years)	12.31	41	1	7.28	0.81	3.3	2503

(*Continued*)

Table 2. (Continued).

	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Number of observations
TFL	17.76	80	2	8.69	0.85	5.50	2503
LFL	8.4	60	1	6.76	1.5	7.07	2503
HOUSEHOLD NUMBER	609.3	3,060	5	621.14	1.66	6.24	2503
PARKING SPACE	1.06	4.92	0.12	0.48	1.97	11.14	2503
BRAND Dummy	0.22	1	0	0.42	1.34	2.79	2503
SUBWAY Dummy	0.35	1	0	0.48	0.61	1.37	2503
SCHOOL Dummy	0.21	1	0	0.4	1.45	3.1	2503
INVERSE DISTANCE to SUBCENTRE	0.35	2.88	0.10	0.29	4.49	30.23	2503
INVERSE DISTANCE to IC	0.15	0.59	0.06	0.06	2.10	11.85	2503
SOUTH Dummy	0.61	1	0	0.49	−0.45	1.2	2503
EAST Dummy	0.22	1	0	0.42	1.32	2.75	2503
WEST Dummy	0.13	1	0	0.34	2.15	5.63	2503
BROAD OCEAN VIEW Dummy	0.05	1	0	0.22	4.17	18.40	2503
PARTAL OCEAN VIEW Dummy	0.39	1	0	0.49	0.44	1.20	2503
MOUNTAIN VIEW Dummy	0.08	1	0	0.27	3.13	10.79	2503
VILLAGE VIEW Dummy	0.13	1	0	0.34	2.18	5.76	2503
RIVER VIEW Dummy	0.02	1	0	0.15	6.59	44.37	2503
BUILDING VIEW Dummy	0.66	1	0	0.47	−0.69	1.48	2503
OCEAM DISTANCE Dummy	0.21	1	0	0.4	1.46	3.13	2503
Sooyoung Gu Dummy	0.28	1	0	0.45	0.97	1.95	2503

Table 3. Diagnostic for spatial autocorrelation.

Test	Panel 1: Seoul			Panel 2: Pusan		
	MI/*df*	Value	Significance	MI/*df*	Value	Significance
Moran's Index	0.0678	27.8723	0.00	0.2232	55.2072	0.00
Lagrange Multiplier (lag)	1	230.6931	0.00	1	511.6914	0.00
Robust LM (lag)	1	107.4649	0.00	1	101.8476	0.00
Lagrange Multiplier (error)	1	184.8154	0.00	1	1157.3226	0.00
Robust LM (error)	1	61.5872	0.00	1	747.4788	0.00
Lagrange Multiplier (SARMA)	2	292.2803	0.00	2	1259.1702	0.00

MI: Moran's I; *df*: degree of freedom.

First, a higher value for the log likelihood indicated an improved goodness-of-fit. The log likelihood of Seoul increased from 1636.61 (OLS) to 1735.78 (spatial lag), to 1757.15 (spatial error). The log likelihood of Pusan, on the other hand, increased from 1759.27 (OLS) to 1960.08 (spatial lag), to 2134.88 (spatial error). Second, however, a lower value for the AIC indicated an improved model fit. Again, the AIC for Seoul decreased with the following values obtained for each model: −3225.23 (OLS), −3421.56 (spatial lag) and −3466.29 (spatial error). The AIC for Pusan also decreased: −3468.54 (OLS), −3868.15 (spatial lag) and −4219.75 (spatial error). Third, a lower value for the SC also indicated a comparative improvement in model fit. Once more, the SC for Seoul decreased: −3085.85 (OLS), −3276.37 (spatial lag) and −3326.91 (spatial error). The SC for Pusan likewise decreased as follows: −3322.9 (OLS), −3716.7 (spatial lag) and −4074.12 (spatial error).

Overall, spatial diagnostics clearly indicated that the spatial error model is a better model fit than the standard OLS model or the spatial lag model.

The coefficient (ρ) of spatially lagged prices in the spatial lag model is statistically significant at the 0.01 level in both regions, that is 0.4359 for Seoul and 0.3902 for Pusan, implying that the price of each apartment unit can be affected by that of a neighbouring apartment. Following the interpretations of Thanos, Dube and Legros (2016) and Hyun and Milcheva (2018), the coefficient of spatially weighted prices of neighbouring apartments of 0.4359 for Seoul suggests that a \$100 increase in the average selling price of a neighbouring apartment leads to an increase of \$43 in the price of a given apartment unit.

In the spatial error model, the lambda coefficient (λ) is positive at 0.9127 for Seoul and 0.8717 for Pusan and significant at the 1% level of significance, implying the presence of spatial autocorrelation in the error terms.

For the purpose of comparison, we provide the OLS estimates. These are reported in the first columns of Table 4. Though coefficient and their statistical significance of the spatial models are slightly different with the OLS, the OLS and spatial models have similar results. The test results for Seoul and Pusan can be seen that most variables are statistically significant at conventional levels and appear to have the expected signs.

The AGE variable incorporates quadratic effects in the model because their impacts might have non-linear patterns on apartment prices. For Pusan, the coefficient of the AGE variable shows a negative sign, while the coefficient of SQAGE variable displays a positive sign. These suggest that the apartment once constructed gets depreciated until it reaches a certain age, but after reaching such an age, the trend is reversed and the property gains more value. In fact,

Table 4. Empirical test results.

Variable	OLS		Spatial lag model		Spatial error model	
	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics
Panel 1: Seoul						
Constant	18.7612***	301.1873	4.3439***	17.9959	8.1991***	231.6620
Spatially lagged prices			0.4359***	15.8059		
FLOOR AREA	0.0079***	34.4546	0.0034***	55.1999	0.0034***	56.0209
AGE	0.0188***	5.1847	0.0075***	6.8388	0.0079***	6.6666
SQAGE	−0.0001	−1.5978	−0.0001***	−2.6150	−0.0001***	−3.0252
TFL	0.0076***	6.8324	0.0024***	5.6889	0.0026***	6.1826
LFL	0.0083***	4.1283	0.0042***	4.9194	0.0041***	4.9757
SQLFL	−0.0002***	−3.3428	−0.0001***	−3.7768	−0.0001***	−3.4280
HOUSEHOLD NUMBER	0.0001***	12.5338	0.00004***	13.0796	0.0001***	12.2049
PARKING SPACE	−0.0034	−0.2947	−0.0056	−1.4865	−0.0051	−1.3412
BRAND Dummy	0.1811***	8.8915	0.0800***	11.1259	0.0786***	10.8960
SUBWAY Dummy	0.0059	0.4720	−0.0001	−0.0195	0.0032	0.5453
SCHOOL Dummy	0.0269*	1.9419	0.0029	0.5088	−0.0018	−0.3010
INVERSE DISTANCE to SUBCENTRE	−0.0085	−0.5402	−0.0023	−0.3450	−0.0117	−0.9920
INVERSE DISTANCE to IC	−0.019**	−2.1346	0.0066	1.5955	−0.0006	−0.1057
SOUTH Dummy	0.2467***	4.7700	0.1019***	6.4838	0.1126***	7.1071
EAST Dummy	0.2653***	4.9462	0.1079***	6.2918	0.1122***	6.5725
WEST Dummy	0.1511***	2.7801	0.0667***	3.8056	0.0777***	4.3842
BROAD RIVER View	0.1298***	3.6772	0.0441***	2.9373	0.0453***	3.0743
PARTIAL RIVER View	0.0236	0.5335	0.0117	0.5686	−0.0128	−0.6136
MOUNTAIN View	0.1017***	3.0238	0.0380***	2.7307	0.0373***	2.6990
BUILDING View	−0.0346*	−1.8664	−0.0206***	−2.7588	−0.0197***	−2.6409
MOUNTAIN DISTANCE Dummy	0.0025	0.1494	0.0217***	2.8878	0.0130	1.1301
RIVER DISTANCE Dummy	0.1370***	9.2633	0.0232***	3.5722	−0.0102	−1.0047
Seocho Gu Dummy	−0.0858***	−4.9886	−0.0454***	−7.3279	−0.0342**	−1.9683
Lambda					0.9127***	41.1483
R^2	0.7476		0.7677		0.7757	

(Continued)

Table 4. (Continued).

	OLS		Spatial lag model		Spatial error model	
Variable	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics
Log likelihood	1636.61		1735.78		1757.15	
AIC	−3225.23		−3421.56		−3466.29	
SC	−3085.85		−3276.37		−3326.91	
Panel 2: Pusan						
Constant	17.3421***	357.3632	4.4572***	30.2840	7.6304***	265.045
Spatially lagged prices	-		0.3902***	21.0769		
FLOOR AREA	0.0111***	46.3488	0.0045***	60.6948	0.0045***	65.4061
AGE	−0.0278***	−8.4399	−0.0098***	−8.4152	−0.0089***	−7.2248
SQAGE	0.0007***	5.8408	0.0002***	6.5355	0.0002***	4.8346
TFL	0.0146***	13.8787	0.0039***	9.2866	0.0052***	11.1305
LFL	0.0162***	8.7852	0.0071***	9.1834	0.0052***	7.1865
SQLFL	−0.0005***	−7.5371	−0.0002***	−8.0060	−0.0001***	−5.7709
HOUSEHOLD NUMBER	0.0002***	18.0147	0.0001***	14.5011	0.0001***	10.0970
PARKING SPACE	0.0192	1.1517	−0.0087	−1.4573	0.0107*	1.7560
BRAND Dummy	−0.0189	−1.2186	−0.0084	−1.1968	0.0080	1.4375
SUBWAY Dummy	0.1568***	9.9258	0.0530***	9.8605	0.0094	1.1066
SCHOOL Dummy	−0.0061	−0.4190	−0.0216***	−3.5665	−0.0208**	−2.5717
INVERSE DISTANCE to SUBCENTRE	0.1101***	6.1269	0.0156*	1.8091	−0.0035	−0.1526
INVERSE DISTANCE to IC	0.1753*	1.7637	0.0491	1.1431	0.1650**	2.1443
SOUTH Dummy	0.0925***	3.3456	0.0334***	2.6506	0.0222*	1.9192
EAST Dummy	0.0853***	3.0839	0.0274**	2.0804	0.0130	1.0681
WEST Dummy	0.0252	0.8413	0.0085	0.6180	0.0141	1.1235
BROAD OCEAN View	0.3798***	11.4161	0.1588***	13.5171	0.1873***	16.6096
PARTIAL OCEAN View	0.1151***	7.4590	0.0536***	9.5193	0.0813***	14.3908
MOUNTAIN View	−0.0752**	−2.4526	−0.0057	−0.5136	0.0160	1.4394
VILLAGE View	0.0172	0.6467	0.0205**	2.0962	0.0251***	2.6439
RIVER View	0.0260	0.4913	−0.0125	−0.7127	−0.0001	−0.0059
BUILDING View	0.1202***	5.2425	0.0380***	4.5654	0.0387***	4.7847

(*Continued*)

Table 4. (Continued).

	OLS		Spatial lag model		Spatial error model	
Variable	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
OCEAN DISTANCE Dummy	0.1740***	9.5871	0.0094	1.3718	0.0139	1.1627
Sooyoung Gu Dummy	−0.0181	−1.2357	−0.0087	−1.5025	−0.0147***	−2.7398
Lambda					0.8717***	51.5340
R^2	0.8170		0.8448		0.8699	
Log likelihood	1759.27		1960.08		2134.88	
AIC	−3468.54		−3868.15		−4219.75	
SC	−3322.9		−3716.7		−4074.12	

*, ** and *** indicate statistical significance at the 10%, 5% and 1% confidence levels, respectively.

apartment aging over time usually leads to depreciation but at the same time the possibility for its redevelopment increases with aging, which, in turn, may result in high expectations for capital gain from the price rise through redevelopment of the house. This expectation for redevelopment can also be reflected in the price of an old house. In Korea where the land is quite small and the sites for new constructions are limited, redevelopment of old residential housing area or apartment complexes is common and normally accompanied by an increase in structural density and improvements in residential conditions, all of which may lead to price upheaval and eventually results in capital gains for the homeowners. More specifically, an increase in structural density means an increased number of apartment units for sale, which may in turn contribute to the capital gains for the homeowners. In addition, new construction of apartments tends to add more pleasantness and amenity to residents by not allowing car passage on the ground, making garages underground and decorating ground space with gardens and ponds instead. These improved living conditions from redevelopment will increase demand, resulting in price appreciation accordingly. Therefore, expectations for redevelopment in the near future have a strong positive impact on the current price of housing (Kim et al., 2015; Lee, Chung, & Kim, 2004).

For Seoul, the coefficient of AGE is positive and significant while the coefficient of SQAGE is negative and significant except OLS model. This means a continuous rise in the price of the apartment after new construction of it. We can see this phenomenon quite evident from considering a number of apartments in the sample which are planned or expected to be redeveloped in the near future in Seoul.

The TOTAL FLOOR LEVEL (TFL) variable is also statistically positive at a 1% significance level. This result is consistent with empirical findings from Hong Kong (Choy, Ho, & Mak, 2012; Jayantha & Lam, 2015; Jim & Chen, 2009) and Guangzhou, China (Jim & Chen, 2006). In contrast, in Western countries such as the Netherlands (Bengochea-Morancho, 2003), total floor level may not have significant effect on house prices. For widely dispersed single-family houses in Western countries, total floor level would not mean a lot. TFL has higher coefficients for Pusan than for Seoul. The possible reason for this may be heights and the comparatively narrow location of the apartments, like in Pusan, most of the premium apartments are located around the Haeundae beach where they can have better view of the ocean.

LIVING FLOOR LEVEL (LFL) variable and its squared terms are found to be statistically significant at the 1% level of significance and the LFL variable shows a positive sign, whereas its squared terms show a negative sign. This implies that the LFL variable has a non-linear effect on prices. It first keeps raising the price to a certain floor level but eventually the price decreases with the increasing number of floors, from a certain point. This result is likely to be the same as Lee (2016), who studied Seoul apartments, Conroy, Narwold and Sandy (2013), who focused on condominiums in San Diego, California, and Choy, Mak and Ho (2007), who conducted a study on condominiums in Hong Kong.

Economic theory implies that there may be two competing forces affecting the decision to live on higher levels of a condominium. On one hand, higher level of floors is associated with longer travel time within a given building and hence, higher implicit travel costs. On the other hand, there may also be positive amenities associated with living higher up such as better scenic view, less noise and air pollution from the street (Conroy et al., 2013).

Variables for household number in apartment complexes are positive and statistically significant at the 1% significance level in both of the cities. This may be because the more are the households in a single complex, the lower will be the management or the maintenance fee, according to economies of scale and more often, the existence of a high level of facilitation and amenities is insured in such complexes. This result is consistent with empirical findings from Korea (Jung, 2006; Lee & Ko, 2011).

The parking space per household is negative or statistically not significant in the case of Seoul, whereas in the case of Pusan, spatial error model shows a significant positive coefficient in the 10% significance level while OLS model and the spatial lag model displays an insignificant coefficient. In fact, apartment prices in Korea increase when the parking space of the apartment building can hold more cars per household. This unexpected result may be attributed to the fact that in Korea some old apartment buildings, despite having narrow parking spaces, are valued high due to the expectations of their redevelopment. In Lee and Moon's (2007) study on Gangnam, Seoul, parking space did not affect apartment prices significantly. However, Kim's (2014) study for the nationwide apartment shows that parking space has a significant positive influence on an apartment price.

BRAND dummy is significant and positive in the case of Seoul, while in case of Pusan, it is not significant. The possible reason that brand does not have positive impact on price in Pusan can be that in Pusan where the apartments are located near the beach having sea view have relatively high prices regardless of the brand name of the construction companies.

For Seoul, the coefficient of accessibility variable such as the SUBWAY dummy, SCHOOL dummy, REVERSE SUB-CENTRE and REVERSE IC DISTANCE is negative or statistically insignificant. This may be because Seoul has such a well-organized subway system and lines that one can go to almost every part of the city using the subway except for a few remote areas. The bus system in Seoul is also well organized, providing service efficiently and extensively. The distance from one bus stop to the next on a bus line is almost within a 10-min walk. Buses run every 15 min, with a good transit system between the metros and buses around the city. As a result, locations of houses may not matter in terms of access or accessibility (Kim et al., 2015). However, in the study of Jun and Kim (2017), which focuses on Seoul as a whole rather than Gangnam and Seocho in Seoul, accessibility has positive effect on apartment rent.

Unlike in Seoul, however, the subway and the bus system in Pusan has not been well established and networked yet; however, proximity to subway, sub-centre of the city and highway IC have significant positive influence on the apartment price in Pusan for some models.

For Pusan, the SCHOOL dummy shows an insignificant coefficient in OLS model, while the spatial lag model and the spatial error model display negative and significant coefficients. This result is consistent with empirical findings from the same region (Jeong & Park, 2016). This is probably because some high schools are located near a low-priced apartment complex in Pusan. The coefficient of the SOUTH dummy is positive and statistically significant for Seoul and Pusan. South frontage is generally considered an important price determinant in the Korean housing market. If a house faces the south, it can get more sunlight, which means more savings in heating, lighting and even cooling costs. The coefficient of the EAST dummy is positive and statistically significant for Seoul, while it is positive but insignificant in the spatial error model for Pusan. This strange result in the case of Pusan may be because in some east-facing apartments in Pusan which are located along the coast, people's sleep can be disrupted by strong sunlight in the morning.

BROAD RIVER VIEW proves to have the most positive and significant impact in the case of Seoul while PARTIAL RIVER VIEW is not significant there. We can infer from this result that in Seoul where people cannot see the ocean, the Han River serves pretty much as a proxy for the ocean that provides people with fresh air and a nice view as well as good recreational area. Actually, the Han River is the biggest river in Korea and runs across the heart of Seoul like the Seine River of Paris and the Hudson River of New York providing a nice view as well as a resting place for people who get tired from crowded metropolitan city life.

It may also inferred that partial river view is not significant because an apartment with a partial view is blocked in substantial part by other buildings and thus such a view can not be recognized as a river view. A river view in Pusan also does not have significant impact because the river of our interest in Pusan is quite narrow compared to the Han River and does not provide the good leisure space like the Han River and the Yangjae creek in Seoul.

After all, the most favourite view in Pusan is the ocean view. BROAD OCEAN VIEW shows the biggest and significant coefficient. PARTIAL OCEAN VIEW also shows positive and significant coefficient. From these results, we can confirm that people prefer water views such as a river view or an ocean view to other types of views. This result is the same as in Gordon, Winkier, Barrett and Zampano (2013), who studied the case of condominiums along the Gulf Coast of Alabama, and in Wyman et al. (2014), whose study focused on single-family homes in Southern California.

Building views have negative coefficients at the 1% or 10% significance level in the case of Seoul. From the outcome of the dummy criteria, we can see that house purchasers would rather choose street views than building views. Building views where views are commonly blocked by other buildings in a crowded city packed with apartment buildings as is the case in Seoul have some drawbacks, namely insufficient sunlight and bad ventilation. Although street views also tend to decrease the quality of life with noise and dust resulting from being located alongside the roads, they may not have such problems as not enough sunlight or bad ventilation as observed in building views.

Unlike in Seoul, however, house purchasers in Pusan seem to mind street views more than building views. This may be because some high-price apartments near the ocean in Haeundae are constructed as the tower-type apartments which have building views in front rather than street views.

While a mountain view positively affects house prices in Seoul, it shows insignificant or negative impact in Pusan. Apartments with mountain views in Pusan are usually located far away from the coast and belong to a cluster of low-priced apartments. This result is identical with the findings of Jim and Chen (2009), who studied a coastal city, Hong Kong.

Apartments with ocean views are usually located along coastal side so that the residents can have a clear view of the ocean or can hear the sound of the waves, while most of the apartments with mountain views are located quite far from the mountains so the residents cannot see the view clearly, which result in low level of enjoyment for the residents compared to the high level of enjoyment for the residents having the water view. This can be the reason for the high value of the apartments with water views compared to those with unclear faraway mountain views as witnessed in our research.

MOUTAIN DISTANCE dummy, which applies only to Seoul, shows positive but significant coefficient in the spatial lag model only. Generally, an apartment close to a mountain has a better view of the landscape (Wen, Zhang, & Zhang, 2015) and comparatively, healthy and fresh air. Also, residents can easily go for hiking in the nearby mountains. The mountains in the suburbs of Seoul are low in height and the terrains are soft, so most of the pedestrians often enjoy hiking. Therefore, apartments close to the mountains tend to have increased prices.

RIVER DISTANCE dummy, which applies only to Seoul, shows positive and significant coefficients except for the spatial error model. Waterside parks built on the banks of the Han River and Yangjae Creek in Seoul provide residents with good leisure space, so the apartments near the river tend to rise in price (Bae, Jo, & Lee, 2018; Wen et al., 2015). OCEAN DISTANCE dummy, which applies only to Pusan, shows positive coefficients in all three models but statistically significant in OLS model only. Conroy and Milosch (2011) show that a 10% increase in distance from the ocean is associated with a 1.46% decline in price. This can probably be explained with the fact that the air quality close to the sea is superior. Moreover, most particularly in summer, it may be comparatively cool because of the fresh wind blowing from the sea side. For these or other reasons, most high-priced apartments are located near the coast in Pusan.

Conclusion

This research aims to find the differences among the impacts of the variables regarding the view on the price of apartments in an inland city of Seoul and a coastal city of Pusan. Our study targets two sub-regions of each city, named Gangnam and Seocho in Seoul and Haeundae and Sooyoung in Pusan where most premium apartments are known to be located and clustered, thus facilitating this kind of comparative research. As hedonic attributes, we include such variables as floor area, building age, total floor level, living floor level, household number and parking space, distance from subway and high school, direction of window of the living room, scenic view and the proximity to environmental factors. Our data sample comprises 4962 court auction cases traded during the period from 2006 to 2014.

In conducting our empirical analysis, we find that apartment price tends to converge with the test result of spatial randomness with Global Moran's I because the price of an apartment may be affected by that of its neighbouring apartment. The LM test results are the same as Global Moran's I. We subsequently applied some models, namely the traditional OLS, spatial lag and spatial error models with results showing that the spatial error model provides an improved fit compared to a conventional OLS model or a spatial lag model.

As a result, water views such as broad river views for Seoul or ocean views for Pusan turned out to be the most favoured views. However, mountain views affect the house price differently between an inland city and a coastal city. While a mountain view in the inland city of Seoul has positive effect on the price, it affects house price negatively or insignificantly in Pusan. This may be because apartments with mountain views are mostly amassed in comparatively low-priced areas in Pusan where ocean views are available and preferred. Most premium apartments are located near Haeundae beach or along the coast not just because they provide good ocean views but because they provide a good natural environment with fresh air from the ocean and mild weather. The prestige the residents of those premium apartments might feel with living in one of those premium apartments might also be reflected in the price. Generally, the proximity to natural environment such as mountain, river or ocean tends to increase the price.

While a building view in Seoul has negative impact on the price, such a view affects house prices positively in Pusan. Building views where views are blocked by other buildings in Seoul might have some drawbacks. They might not get enough sunlight and ventilation, since Seoul is a super crowded metropolitan city packed with apartment buildings. By contrast, though, the tower-type apartment with building views in front near the ocean in Haeundae is still priced high probably because the residents of the apartments in this area value the honour of living there and they might enjoy fresh air from the ocean, more than the actual ocean views even if they do not have a clear sight of the ocean from inside their apartments.

The number of total floors has positive influence on the house price in the cases of both Seoul and Pusan. However, living floor shows non-linearity, meaning that the house price keeps rising with the floor level going up, but after that point up, the price rather falls.

While proximity to the subway, sub-centre of city and highway IC does not affect the house price in Seoul, it affects the house price positively in Pusan. This may be because Seoul has well-organized subway, bus and transit system and so the proximity to those means of transportation or sub-centre may not count. In contrast, the proximity to the subway and highway IC may matter in Pusan since the subway and bus system in Pusan have not been well established yet compared to Seoul.

The spatial relations in housing prices occur from recently sold houses to future transactions and not vice versa. The violation of temporal direction of causality may cause over-connection in the spatial weight matrix, so further researches may need to consider the temporal direction of causality.

Note

1. We include a dummy variable representing the construction firm as a proxy for brand value. If an apartment was constructed by 1 of 10 largest firms, it is regarded as a premium apartment. These 10 firms are selected as the largest construction firms in a construction capability evaluation conducted by Korean government every year.

Disclosure statement

No potential conflict of interest was reported by the authors.

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