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Spatio-temporal dependence in a hedonic house price model

주택 거래 간 시공간 의존성을 고려한 헤도닉 가격 추정

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< Abstract >

동일 주택 시장 내 유사한 주택들의 거래 가격은 주택 구매자와 판매자에게 있어 가장 접근이 용이하고 용인되기 적합한 참고 가격 중 하나이다. 따라서 시공간적으로 근접한 주택 거래 가격들 간에는 상관관계가 존재할 것이다. 본 연구는 이러한 주택거래가격들 간의 시공간 의존성을 고려한 헤도닉 가격 모델 (Hedonic price model)을 통하여 주택 가격을 추정하고자 한다. 서울 주택 시장 내의 46,000개의 아파트 매매 및 전세 실거래가 데이터를 기반으로 한 본 논문의 실증 분석은 매매가와 전세가에서 모두 유의한 수준의 거래 가격 간 시공간 상호 의존성이 존재함을 나타낸다. 이러한 효과를 고려한 시공간 헤도닉 모델 (Spatio-temporal hedonic price model)은 일반적 헤도닉 모델과 비교하여 향상된 모델 설명력을 제공한다. 본 연구는 또한 시간적 인과관계를 고려하지 않은 주택 거래 가격 간 공간 의존성 측정의 위험성을 지적한다.

주 제 어 : 시공간 의존성, 헤도닉 가격 모델, 아파트 실거래가
Keyword : Spatio-temporal dependence, Hedonic price model, Apartment transaction price

I. 서론

Hedonic price model has taken on a prominent role in housing studies since the model was formalised by Rosen(1974). Hedonic regression estimates a house price as a function of various attributes of the house, and the coefficients pertaining to the respective attributes indicate the implicit(hedonic) prices of the housing characteristics. However, a part of the total variance of house price in the hedonic framework remains unexplained, as measuring and quantifying all relevant characteristics is not practically possible and selecting the best set of hedonic variables is difficult(Cheshire and Sheppard, 1995).

It has been widely suggested that a portion of the unexplained variance might be associated with latent spatial relations. A number of papers have tried to explain the unexplained variance by accounting for spatial dependence(or spatial autocorrelation) in the model. In short, spatial dependence can be defined as 'the coincidence of value similarity with locational similarity (Anselin and Bera, 1998, p. 241).' Applied to housing markets, that means that properties with similar values tend to cluster in a neighbourhood. Indeed, it is commonly observed that when estimating how much their own house is worth,

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market participants use as a reference point the sale price of those nearby houses of a similar value or with similar characteristics.

As one of main causes of the spatial dependence in house price, Anselin(1988) suggests the tendency of market participants to base a housing transaction price on what they observe in the local housing market. In other words, housing sellers and buyers tend to hugely rely on information about transaction prices of nearby properties with comparable characteristics and use them as a reference price to agree upon the price. Incorporating spatial dependence, therefore, closely resembles the practice of the sales comparison approach in real estate appraisal (Can and Megbolugbe, 1997; Small and Steimetz, 2012). Spatial dependence in house prices can be captured in a hedonic price framework by adding an additional explanatory variable of spatially lagged house prices which reflects a correlation between a given house price and its spatially neighbouring house prices. The application accounts for another locational aspect of the properties – which cannot be accounted for in a standard hedonic model which is limited to observable locational explanatory variables – and thus improve the estimation of house prices in a hedonic framework. The crucial role of spatial dependence in a hedonic price framework is well documented by various researchers[1].

The main aim of this study is to consider the spatial dependence in a spatio-temporal hedonic price framework. While most studies assess only the role of spatial dependence in housing markets, it is important to account for the temporal causality; spatial relations only exist between a given transaction and its past transactions, not between a given transaction and its 'non-existing' future transactions. Ignoring the 'arrow of time' in the spatial relations would lead to biased estimation and spurious conclusion. In this study, spatial dependence is measured in a spatio-temporal context in which the spatial relations between housing transactions of different periods weighted for their spatial distance, but controls strictly for the unidirectional temporal reality simultaneously. Incorporating the underlying spatial nature in housing transaction data facilitates to estimate hedonic house price more precisely.

The empirical analysis is conducted on the Seoul apartment market. Using rich apartment transaction data, this study examines the spatio-temporal dependence in sales prices and rents (*jeonse*). The Seoul apartment market has several unique characteristics which facilitate high spatial dependence in house prices through active interaction among market participants (Hwang *et al.*, 2006). First, properties and market structure are homogenous. Apartments are typically constructed within a large complex of multi-storey buildings with highly standardised design, layout and structure. Therefore, market participants compare the properties easily for a given location and characteristics. Second, the market is highly transparent and has easy access to information. There are a large number of real estate brokers in a neighbourhood (even multiple brokers within a single apartment complex), and they provide daily updated information of transaction prices in the local housing market. Potential housing sellers and buyers, therefore, can have easy access to reference prices. Third, the market is liquid and active. Transaction costs are low relative to other metropolitan areas in Western countries (mainly composed of brokerage fees of up to 0.9% of the transaction price). The homogeneity of properties keeps searching costs low as well. Therefore, apartment transactions are relatively frequent and active.

The remainder of this paper is structured as follows. Section 2 provides an overview of the

1) See Elhorst (2003) and Krause and Bitter (2012).

related literature. Section 3 describes methodology and Section 4 the data. Section 5 presents the empirical results and Section 6 a conclusion.

II. Literature review

There have been a number of attempts to account for spatial dependence in the hedonic house price model, using spatial econometric techniques. The empirical process is straightforward. The existence of spatial dependence in the data is examined through the application of diagnostic tests to a non-spatial OLS specification. If spatial dependence is diagnosed in data, then spatial models with a spatially lagged dependent variable, a spatially lagged error term, or both, are applied.

Using 193 single-family houses in Columbus, Ohio, US, Can(1990) find statistically and economically significant estimates for spatial dependence in house prices. The author concludes with the finding that house prices in deteriorating neighbourhood can be raised simply if they are in proximity to higher-prices houses, regardless of the property-specific structural characteristics.

Wilhelmsson(2002) finds that the spatial dependence is hugely influenced by the spatial weight matrices(e.g., inverse distance squared, 600metres threshold, one and four nearest neighbours respectively). A selection of spatial weight matrix also affects the economic interpretation of hedonic variables, particularly parameters of time dummy variables. In contrast, Militino *et al.*(2004) reports comparable spatial effects across application of different spatial weight matrices (e.g., nearest neighbours in 1.5, 2, 2.5 and 3km and inverse distance).

Empirical research on applying spatial econometrics to the hedonic house price model in the Korean housing market has been actively conducted since the early 2000s. Using housing survey data for 1993 for the Seoul housing market, Kim(2000) finds that the spatial models provide best results within 4 kilometres for the owner-occupied houses with 0.55 of spatial parameter in the spatial autoregressive model(SAR) and 9 kilometres for the renter-occupied properties with 0.42. However, the spatial weight matrix is constructed on the basis of distances between the centroids of towns, not of houses, due to data unavailability.

Kim *et al.*,(2003) use the SAR to measure the impact of air quality on house prices. The empirical results based on 512 houses sold in 1993 in the Seoul housing market suggest that capturing spatial dependence(0.469 of coefficient) in house prices considerably decreases estimated coefficients of neighbourhood attributes, such as air quality and income level, compared to a non-spatial model.

Hur(2007) analyses 1,755 apartment price data for 2006 in the Seoul housing market. The spatial analysis is based on the distances between apartment complexes. The model is optimised with a 5km distance band, but the spatial dependence in house prices is economically small when the spatial dependence in error terms is considered simultaneously.

Kim and Chung(2010) use 1,226 apartment transaction data for the Busan housing market from the first quarter of 2006 to the second quarter of 2009. The empirical results suggest outperformance of spatial models based on the distance-based weight matrix over those based on the continuity and distance-continuity combined matrices.

A consensus among previous empirical research using spatial models is that spatial dependence has an important role in the hedonic house price analysis, and capturing the spatial effects improves model performance and efficiency, when compared with non-spatial specifications. However, a crucial limitation in the literature above is that temporal causality in housing transaction is ignored. Housing data collected over time need to be analysed within the spatio-temporal context as only past transaction prices can exert an influence onto a given transaction. Not incorporating such unidirectional temporal information may not only overestimate spatial dependence estimated but also distort estimation of other parameters (Anselin *et al.*, 2008; Lee and Yu, 2009; LeSage and Pace, 2009; Dubé and Legros, 2014a).

Theoretical works show that ignoring unidirectional time dimension causes over-connection(high-density) problems in spatial weight matrices that inevitably leads to biased maximum likelihood estimates of spatial dependence (Farber *et al.*, 2009; Mizruchi and Neuman, 2008; Smith, 2009). As the presence of statistical dependencies essentially reduces the amount of information gained from each observation, less statistical information caused by over-connection should be available for estimation(Smith, 2009).

As a response to overcome these problems, this study constructs a Hadamard spatio-temporal weight matix, following Smith and Wu(2009), Dubé and Legros(2014a) and Thanos *et al.*(2016). They commonly find that the spatial only model yields upward biased spatial dependence, compared to the spatio-temporal specification. Moreover, the time dummy and location dummy variables, which are typically used to build a general price index related to the change in sale prices over time and across location, are highly likely to be erroneously captured by biased spatial dependence in the spatial only framework.

III. Methodology

1. Spatio-temporal weight matrix

Spatial relations are estimated on the basis of spatial and temporal distances between each pair of apartment units. The measurements are typically represented by a $n \times n$ non-negative matrix where n denotes the number of apartment units. At the beginning, all observations are chronically ordered, beginning with the relations between the oldest transactions from the first row and the first column in the matrix. The spatio-temporal weight matrix W' is formed by multiplying spatial weight matrix S and temporal weight matrix T based on a Hadamard produc t[2] as:

$$W' = S \circ T = \begin{pmatrix} 0 & W_{12} & W_{13} & \cdots & W_{1N} \\ W_{21} & 0 & W_{23} & \cdots & W_{2N} \\ W_{31} & W_{32} & 0 & \cdots & W_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & W_{N3} & \cdots & 0 \end{pmatrix}$$

$$= \begin{pmatrix} 0 & S_{12} \times T_{12} & S_{13} \times T_{13} & \cdots & S_{1N} \times T_{1N} \\ S_{21} \times T_{21} & 0 & S_{12} \times T_{12} & \cdots & S_{2N} \times T_{2N} \\ S_{31} \times T_{31} & S_{31} \times T_{31} & 0 & \cdots & S_{3N} \times T_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S_{N1} \times T_{N1} & S_{N2} \times T_{N2} & S_{N3} \times T_{N3} & \cdots & 0 \end{pmatrix} \quad (1)$$

where S_{ij} and T_{ij} are spatial weight and temporal weight between apartment units i and j respectively. Therefore, W_{ij} determines which j's are considered 'neighbours' in space as well as time and the extent of their influence on a given apartment unit i. The value of spatial weight S_{ij} is given as:

$$S_{ij} = \begin{cases} 1/d_{ij}, if\ d_{ij} \le \bar{d} \\ 0, \quad otherwise \end{cases} \quad (2)$$

2) The Hadamard product of two matrices and is defined by simple component- wise multiplication, $[A \cdot B]_{ij} = (a_{ij}) \cdot (b_{ij})$. Unlike the general matrix product, the Hadamard product is associative, distributive and commutative.

where d_{ij} is an Euclidean distance between apartment units i and j using geo-coordinates of each apartment unit and $\bar{d}$ is a critical cut-off value for the spatial relation, beyond which other apartments are assumed to have no direct spatial impacts. The value of temporal distance T_{ij} is given as:

$$T_{ij} = \begin{cases} (v_i - v_j)^{-1}, \ if \ |v_i - v_j| \ \le \bar{v} \\ 0, \ otherwise \ (including \ \ if \ v_i = v_j \ \forall i \neq j) \end{cases} \quad (3)$$

where v_i is a temporal value of a transaction of an apartment unit i in a given time period and $\bar{v}$ is a critical cut-off value for the temporal relation, beyond which other apartments are assumed to have no direct temporal impacts. The value of $v_i - v_j$ represents the time elapsed between transactions of apartment units i and j. The general function in Equation (3) is defined by Smith and Wu(2009), Dubé and Legros(2014b) and Thanos *et al.*(2016) as:

$$v_i = 12 \times (yyyy_i - yyyy_{min}) + mm_i \ \forall i \quad (4)$$

where $yyyy_i$ and mm_i corresponds to a year and a month of transaction i, respectively, and $yyyy_{min}$ is the first year in the data.

The inverse function of weight in Equation (2) and (3) ensures that spatially and temporally closer neighbouring apartment units have larger values(i.e., stronger impacts) respectively. All of the main diagonal elements in the matrix have zero value as these are relations of an observation on itself. Given the chronological order of all elements, based on the main diagonal elements, the upper triangular elements in the matrix describes spatial relations between 'non-existing' future transactions and those past transactions or between transactions in the same month[3]. In order to control for such spurious spatial relations, zero values are assigned to all the upper triangular elements. The spatio-temporal weight matrix is reformed as:

$$W = S \circ T = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ W_{21} & 0 & 0 & \cdots & 0 \\ W_{31} & W_{32} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & W_{N3} & \cdots & 0 \end{pmatrix}$$

$$= \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ S_{21} \times T_{21} & 0 & 0 & \cdots & 0 \\ S_{31} \times T_{31} & S_{31} \times T_{31} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S_{N1} \times T_{N1} & S_{N2} \times T_{N2} & S_{N3} \times T_{N3} & \cdots & 0 \end{pmatrix} \quad (5)$$

Following the common practice in spatial modelling, each weight matrix is normalised to have row sums of unity to form a spatial lag of linear combination of values from neighbouring observations(Can and Megbolugbe, 1997; Kim *et al.*, 2003; Seya *et al.*, 2013; Jeanty *et al.*, 2010; Dubé and Legros, 2014a). Through the row-standardisation, the weight matrix forms a row stochastic matrix and sum of the weights in each row equals to one so that the spatial and temporal relations are measured as a weighted average across the neighbouring properties (Cliff and Ord, 1981; Anselin, 1988).

2. Empirical application

1) Baseline hedonic price model

The baseline model in this study adopts the conventional notion of the hedonic price function that 'goods are valued for their utility-bearing attributes or characteristics'(Rosen, 1974, p. 34). In the hedonic framework, a house price is estimated by a function of the property specific-

3) As the data used in this study define year and month of transaction, it is not possible to make clear the temporal order among transactions in the same month $(v_i = v_j)$.

and locational characteristics attached to the property. The estimated coefficients of the hedonic variables can be interpreted as the implicit prices, that is, the willingness to pay. The baseline hedonic price model (HPM) is specified as:

$$P = c + H\beta + Q\gamma + L\delta + \epsilon \quad (6)$$

where P is a $n \times 1$ vector of apartment unit prices, where n is the number of observations; H is a $n \times k$ matrix of hedonic variables accounting for property specific- and locational characteristics, where k is the number of the variables. Q is a $n \times q$ matrix of quarterly time dummy variables, where q is the number of the variables. L is a $n \times l$ matrix of location dummy variables, where l is the number of the variables. ϵ is a $n \times 1$ vector containing error terms, which are independent and identically distributed with zero mean and variance σ^2. This study uses a semi-logarithm form which is widely used in hedonic house price models. The form allows the value added to vary proportionally with the explanatory variables, and the estimated coefficient has a simple and intuitive interpretation as a measure of percentage change (Malpezzi, 2003; Sirmans *et al.*, 2005).

β, γ and δ are $k \times 1$, $q \times 1$ and $l \times 1$ vectors of coefficients associated with the hedonic (H), time dummy (Q) and location dummy (L) variables respectively.

2) Spatio-temporal autoregressive model

In order to consider spatial dependence in unidirectional temporal context, the HPM is extended by adding an additional spatio-temporally lagged dependent variable in the HPM, forming a spatio-temporal autoregressive model (STAR) as follows:

$$P = c + WP\psi + H\beta + Q\gamma + L\delta + \epsilon \quad (7)$$

where W is a $n \times n$ exogenous spatio- temporal weight matrix defined in Equation (5). The interaction variable is a vector of spatio-temporally lagged dependent variables. The spatio-temporal weight matrix allows the interaction variable to capture the spatial relations between housing transactions of different periods weighted for their spatial distance, but controls strictly for the temporal reality simultaneously. A scalar parameter ψ represents spatial dependence of a given apartment unit price on a linear combination of its neighbouring property prices. If there is no significant spatial dependence in house prices in the data (that is, zero value of the scalar parameter of ψ), the STAR is same with the baseline HPM. For comparison purpose, a spatial autoregressive model (SAR) is formed by:

$$P = c + SP\rho + H\beta + Q\gamma + L\delta + \epsilon \quad (8)$$

where S is a $n \times n$ exogenous spatial weight matrix and an interaction variable SP is a $n \times 1$ vector of spatially lagged dependent variables. A scalar parameter ρ represents spatial dependence of a given apartment unit price on a linear combination of its neighbouring property prices. However, the estimation of the spatial parameter is partly based on spurious spatial relations that 'non-existing' future neighbouring housing transactions exert an influence on a given housing transaction and that all transactions of neighbouring houses are equally influenced each other, rather than more recent transactions of neighbouring houses have greater impacts.

As an OLS estimation of the STAR and SAR could be biased and inconsistent due to an endogeneity in the spatial lag terms, a maximum likelihood estimate is used instead(Anselin, 1988; Kim *et al.*, 2003).

IV. Data

This study analyses apartment sales and rent (*jeonse*) prices in the Seoul housing market. The transaction price data ('sil-georaega' in Korean) come from the Ministry of Land Infrastructure and Transport (MOLIT). Each transaction record in the MOLIT data contains the apartment unit's transaction price, address, floor level, size, construction year and date of transaction. Additional data describing physical and locational characteristics of an apartment for the hedonic analysis which are not available from the MOLIT data are obtained from two residential property websites: Naver Real Estate and R114. 17 variables are included to describe property specific- and locational characteristics which are typical in hedonic house price models, as well as those relating to unique characteristics in the Seoul apartment market. The study period is recent five years, ranging from January 2012 to December 2016. Definitions of the variables are presented in Table 1.

The square of housing age is included to capture the non-linearity generally assumed in housing depreciation(Can and Megbolugbe, 1997; Goodman and Thibodeau, 1995; B. S. Lee *et al.*, 2005). For the CBD variable, two distance measurements are regressed in the preliminary hedonic model respectively – 1) distances from Seolleung station and 2) distances from Gwanghwamun station. While both the two measurements provide statistically and economically significant results, the first one yields better performance overall. Therefore, the first one is used in the final model. The inspection variable reflects to reconstruction expectation effect that apartment prices tend to increase after passing the safety inspection for reconstruction due to future housing value increase after reconstruction(Lee *et al.*, 2005).

A set of borough('Gu' in Korean) dummy variables is included to control for regional heterogeneity according to the location. In addition, in order to represent time fixed effects controlling for differences in the composition of the sample in each time period(Wooldridge, 2010) as well as for temporal heterogeneity, a set of quarterly time dummy variables is included.

A key element for the application of spatial econometrics is the distance between each pair of properties in data. The distances are measured by a geographic information system (GIS), using geographic coordinates (longitude and latitude). Given the nature of apartment units being part of a multi-storey building, the measurement needs to be measured in a 3-dimensional distance to account for the floor level of apartment unit. For the measurement, the value associated with the floor level is added to the last decimal point of geo- coordinates of an apartment building. For example, if apartment units A and B in the same apartment building with 37.330001 of latitude and 126.580001 of longitude are on the 6th and 9th floor respectively, 37.330007 and 126.580007 and 37.330010 and 126.580010 are given to the unit A and the unit B respectively. For repeat sales of the same property during the study period, only the most recent transaction is considered. As apartment units on the same floor in the same building have the same geo-coordinates with the measurement, only one unit is included from the same floor level in the same building.

The final dataset consists of 403,671 transactions for the five years of study period. For the empirical spatial analysis on the dataset, 403,671 $\times$ 403,671 distances need to be measured which implies extremely time-consuming computations and is not possible by the statistic software with a modest size of storage space. Therefore, the analysis is conducted on a sample of 23,000 transactions. The data sampling conducted in proportion to a total number of transactions per

<Table 1> Variable description

Variable	Description
Dependent Variable	
Price	Transaction sale/*jeonse* price of a single apartment unit within the apartment building
Independent Variable	
Size	Gross internal area of an apartment unit in square metres
Rooms	Number of rooms
Bathrooms	Number of bathrooms
Floor	The floor level on which an apartment unit is located within the apartment building
Age	The gap of year between the year of transaction of a given apartment unit and the year of construction of the apartment building
Age sq.	Square of the age
Parking	Number of parking spaces per an apartment unit
CBD	Euclidean distance in kilometres using geographical coordinates from an apartment unit to the central business district
Subway	Euclidean distance in metres using geographical coordinates from an apartment unit to the nearest subway station
Heating+	Equal to one if an apartment building has central heating system and zero otherwise
Complex+	Equal to one if an apartment building is located in an apartment complex consisting of several apartment buildings and zero otherwise
Buildings	Number of buildings in an apartment complex in which the apartment unit is situated
Units	Number of apartment units in an apartment building/complex
Reputation+	Equal to one if an apartment building/complex is constructed by one of the ten largest construction companies (based on average turnover during the study period) and zero otherwise
Public Co.+	Equal to one if an apartment building/complex is constructed by a state-owned construction company and zero otherwise
Low-rental+	Equal to one if low-rental apartment units (equivalent to social housing) are within an apartment building/complex and zero otherwise
Inspection+	Equal to one if an apartment building/complex has passed the safety inspection for reconstruction but before the demolition of the existing apartments has begun and zero otherwise
Time+	Quarterly time dummy variable, equal to one if an apartment unit is sold in the respective quarter and zero otherwise
Location+	Location dummy variable at borough level ('Gu' in Korean), equal to one if an apartment building/complex is located in the respective borough and zero otherwise

Note: +dummy variable.

time(month) first and then region(borough level) from the sample. The measurement provides higher explanation power than random sampling, while the hedonic coefficients estimated are quite comparable.

Descriptive statistics of the sample data are provided in Table 2. The average apartment unit in the data is transacted for about 460 million won and rented for about 310 million won of *jeonse* deposit. The ratio of sale price to *jeonse* in the data is approximately 67% on average. The characteristics of property in sale and *jeonse* data are quite similar each other. The average apartment unit in the sample is about 75 square metres, 17-18 years old and on 9th floor; has about three rooms, more than one bathroom and about one parking space; is located within 6.5 kilometres from the CBD and 530-550 metres from a subway station. About half of the apartment units in the data have a

<Table 2> Descriptive statistics

Variable	Sale (23,000 observations)				*jeonse* (23,000 observations)			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Price (₩10,000)	46,268	27,206	6,200	425,000	31,184	17,503	2,132	230,000
Size (m2)	74.90	27.48	16.96	254.00	79.65	27.17	12.62	244.97
Rooms	2.89	0.67	1	6	2.94	0.70	1	6
Bathrooms	1.51	0.51	1	4	1.54	0.50	1	3
Floor	8.77	5.97	1	66	8.56	5.84	1	54
Age	17.39	8.47	0	48	17.98	10.80	0	45
Age sq.	374.29	335.80	0	2,304	440.05	443.38	0	2,025
Parking	1.05	0.44	0	6.04	1.09	0.47	0	11.96
CBD (km)	6.49	3.41	0.14	57.53	6.34	3.46	0.10	57.53
Subway (m)	549.91	401.96	4	2,800	526.11	409.71	4	2,800
Heating	0.43	0.49	0	1	0.50	0.50	0	1
Complex+	0.85	0.36	0	1	0.86	0.35	0	1
Buildings	15.77	19.15	1	124	16.22	20.89	1	124
Units	1241.40	1201.59	8	6,864	1295.08	1329.85	7	6,864
Reputation+	0.29	0.45	0	1	0.30	0.46	0	1
Public-Co.+	0.14	0.34	0	1	0.12	0.32	0	1
Low-rental+	0.05	0.22	0	1	0.09	0.28	0	1
Inspection+	0.02	0.15	0	1	0.12	0.33	0	1

Note: +dummy variable

central heating system. About 85% of the apartment units are within an apartment complex and the average size of the complex is about 16 apartment buildings and about 1,240-1,300 apartment units. About 30% of the apartments in the data are built by one of the ten biggest construction company, while about 12-14% of the apartments are developed by a public-owned construction company. Most of the apartment units are situated in apartment building/complex which contain no low-rental units. About 2% of apartments in sales data and 12% in *jeonse* data have passed the safety inspection for reconstruction respectively.

V. Empirical Results

The non-spatial HPM and spatial models are operationalised with controls for all the variables, and the results are presented in Table 3. The model fit of the data is reasonable across all models for both sale and lease, explaining over 80% of the variation. Table 3 presents the results of (Robust) Lagrange Multiplier (LM) tests which are commonly used for the spatial dependence diagnostics in the spatial hedonic modelling(Can, 1990; Anselin *et al.*, 1996). Both the LM lag and Robust LM lag tests results reject the null hypothesis of the absence of spatial autocorrelation in sale price as well as *jeonse* data. The results are statistically significant at the 0.01 level. That means that apartment prices

<Table 3> Regression results

Variable	Sale			*jeonse*		
	HPM	STAR	SAR	HPM	STAR	SAR
Size (m^2)	0.003***	0.003***	0.002***	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rooms	0.045***	0.042***	0.036***	0.043***	0.030***	0.011***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Bathrooms	0.036***	0.033***	0.021***	0.015***	0.012***	0.007***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Floor	0.002***	0.002***	0.002***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.014***	-0.013***	-0.009***	-0.009***	-0.006***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age sq.	0.000***	0.000***	0.000***	0.000***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parking	0.025***	0.023***	0.014***	0.023***	0.015***	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
CBD (km)	-0.006***	-0.002***	0.001***	-0.016***	-0.005***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Subway (m)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Heating+	0.011***	0.009***	0.004***	0.032***	0.021***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Complex+	0.051***	0.048***	0.035***	0.029***	0.024***	0.012***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Buildings	0.004***	0.004***	0.003***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Units	-0.000***	-0.000***	-0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reputation+	0.014***	0.014***	0.012***	0.026***	0.019***	0.014***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Public Co.+	0.025***	0.026***	0.029***	-0.047***	-0.026***	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Low-rental+	-0.015***	-0.014***	-0.009***	-0.045***	-0.039***	-0.008***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Inspection+	0.027***	0.025***	0.019***	-0.128***	-0.084***	-0.054***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Psi (ψ)		0.129***			0.334***	
		(0.004)			(0.006)	
Rho (ρ)			0.428***			0.747***
			(0.004)			(0.005)
Constant	8.429***	7.303***	4.748***	8.170***	5.352***	1.928***
	(0.006)	(0.034)	(0.039)	(0.007)	(0.048)	(0.046)

<Table 3> Continued

Variable	Sale			*jeonse*		
	HPM	STAR	SAR	HPM	STAR	SAR
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
(adj)R-squared	0.870	0.886	0.878	0.794	0.823	0.811
Log-likelihood	25087.34	28900.06	25637.37	17885.66	24723.14	19513.79
AIC	-50052.69	-57676.13	-51150.73	-35649.32	-49322.28	-38903.60
BIC	-44178.63	-51794.07	-45268.68	-33450.58	-47115.56	-36696.90
LM lag	512.80***			1257.77***		
Robust-LM lag	502.78***			1189.43***		
Observations	23,000	23,000	23,000	23,000	23,000	23,000

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes: 1) +denotes the dummy variable. 2) Robust standard errors in brackets. 3) R-squared for the spatial models is pseudo R-squared. 4) (Robust) LM tests use the spatio-temporal weight matrix for the STAR, rather than the spatial weight matrix for the SAR. 5) A coefficient of dummy variable indicates an effect in percentage based on [exp (coefficient) -1 by Halvorsen and Palmquist (1980). 6) The spatial cut-off value for the STAR and SAR is 3km and the temporal cut-off value is 12month for the STAR.

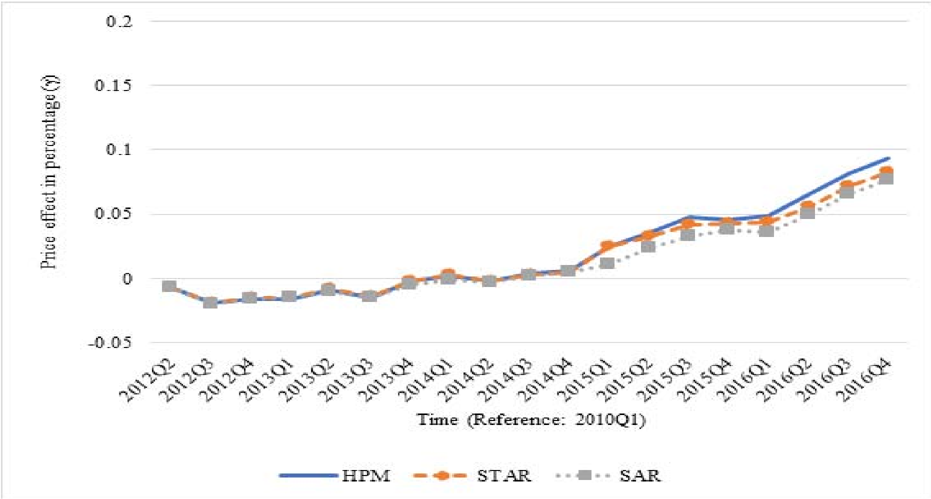
and rents do not vary spatially, but are significantly affected by recent transactions of neighbouring apartments.

In addition, the STAR yields positive and statistically significant spatio-temporal dependence (ψ) in both sale prices and *jeonse*, suggesting a significant role of recent transaction prices of neighbouring apartments. Following the interpretation by Thanos *et al.*(2016), the coefficients ψ of 0.129 and 0.334 suggest that for example, if there is a 10 million Won increase in the average price of comparable apartments located within 3km which are transacted in the past 12 months[4], it would lead to a 1.29 million Won and 3.34 million Won increase in the sales prices and rents as spatio-temporal autoregressive effect respectively. The higher value of spatial effect for rents than sales prices can be explained by the market trend. Hyun and Milcheva(2018) find that due to the market participants' loss aversion tendency, spatial dependence in house prices tends to be stronger in a boom period than in a bust period. The market trends show sharper increase in *jeonse* than sale prices during the study period(Figures 1 and 2). Capturing the significant spatio-temporal dependence in apartment prices improves the model fit in terms of lower values of Akaike information criterion(AIC) and Bayesian information criterion (BIC), compared to the HPM.

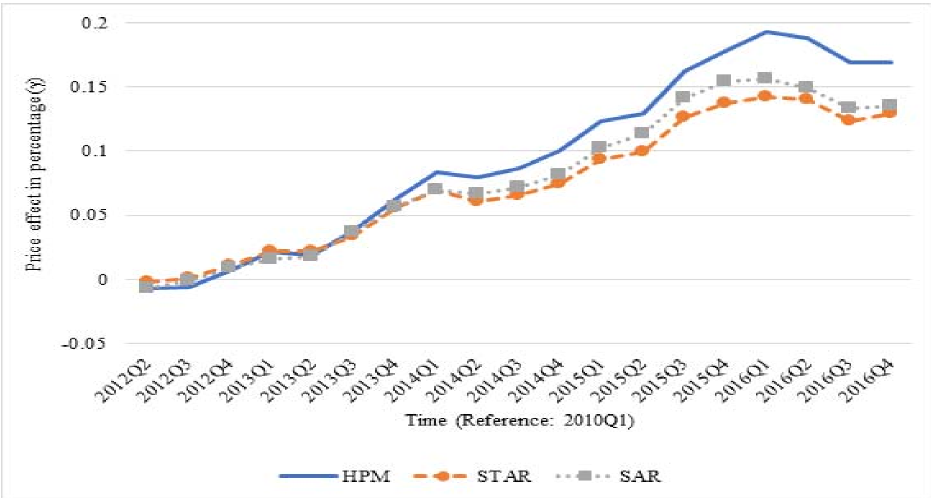
The SAR also yields positive and statistically significant spatial dependence (ρ) in both sale prices and *jeonse*, however the values of the coefficients are much higher than those estimated by the STAR. That implies that the spatial dependence is highly likely to be overestimated by ignoring unidirectional temporal dimension for the housing transaction data pooled over time. In contrast, other hedonic coefficients by the SAR tend to be lower than those by the STAR in general. Overall, the results suggest that considering temporal aspects in housing transactions is necessary for the spatial hedonic modelling, otherwise the overestimated spatial dependence

4) The spatial cut-off value for the STAR is 3km and the temporal cut-off value is 12month as the application yields best model fits. See Table A1 in Appendix for model comparison.

<Figure 1> Time fixed effects for sale prices



<Figure 2> Time fixed effects for *jeonse*



would lead to an inappropriate model specification and spurious estimation. Statistically, the STAR outperforms the SAR in terms of lower values of AIC and BIC.

The STAR results show that most of the hedonic variables are of the expected signs and significant at the 0.01 level. Overall, the property specific- and locational characteristics have similar impacts on the sale prices and *jeonse*. For example, apartment sale prices and *jeonse* tend to increase with the size of the property, number of rooms, bathrooms and parking space, floor level and proximity to the subway station and CBD. Reputation of the construction company has a significant impact on the value of apartment; apartments which are built by one of the biggest construction companies are sold and rent at a higher price than those which are not. Central heating system and being in an apartment complex are positively correlated with sale price as well as *jeonse* respectively. In contrast, the age of apartment is negatively correlated with apartment value; as an apartment is getting old, the property tends to be sold and rented at a lower price. The marginal aging effect tends to increase with the age(i.g., a positive coefficient on the age sq.) although the marginal effect is economically minor. Existence of low-rent units in an apartment building/ complex has a negative impact on the value of apartment in terms of sale prices as well as *jeonse*.

The inspection variable has a significant impact on housing value with conflicting effects on the sale prices and *jeonse* respectively. Apartments which have passed the safety inspection for reconstruction are sold at a premium, but rented at a discount. Such conflicting results imply two effects – 1) the capitalisation effects of expectations about future housing value growth after reconstruction on sales prices and 2) the depreciation effect by confirmation of poor conditions of the property on *jeonse*. Apartments developed by a public construction company tend to be sold at a premium, but rented at a lower price (when compared to apartments developed by a private company). The conflicting impacts of this variable on sale prices and *jeonse* seem to be related to reconstruction expectation effects. The average age of apartments built by a public company is about 28 for both sale price and rent data. However, the Pearson correlation between the public company variable and the inspection variable is not too high – 0.232 and 0.241 in the sale and *jeonse* data respectively.

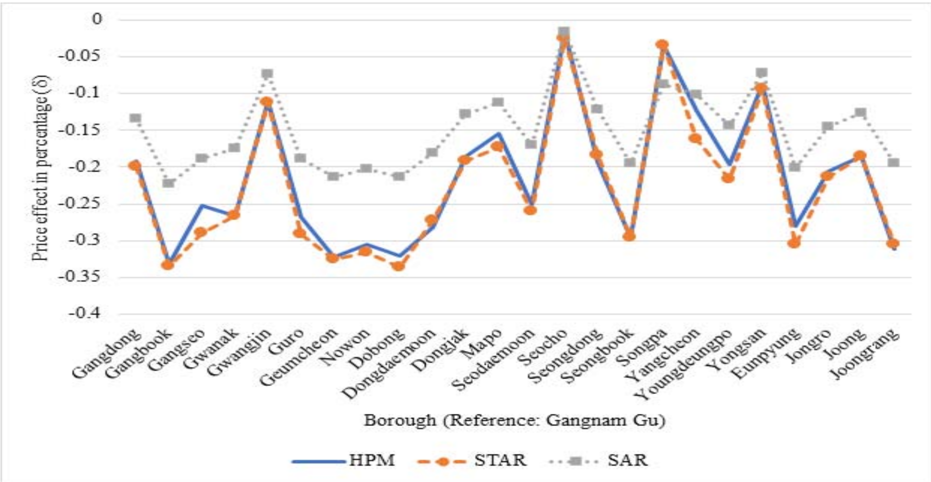
The hedonic coefficients estimated are quite comparable between the STAR and the HPM overall. As well, the time fixed effects which are comprised of coefficients of time dummy variables(i.e., γ in Equations (6), (7) and (8)) are quite comparable across all specifications(Figures 1 and 2). The three models show similar price trends with some differences in the magnitudes of the coefficients. The differences are more noticeable in *jeonse* than Sale prices that has more significant spatio-temporal dependence.

As the spatial dependence is highly likely to be related to locational and neighbourhood characteristics, differences between the spatial model and non-spatial model are commonly found in coefficients for those variables. For example, Kim et al. (2003) find that the spatial model yields lower coefficient values for the neighbourhood attributes, such as income level of residents and air pollution level, compared to the basic hedonic model, while coefficients for the physical characteristics, such as property size and number of rooms and bathrooms are comparable.

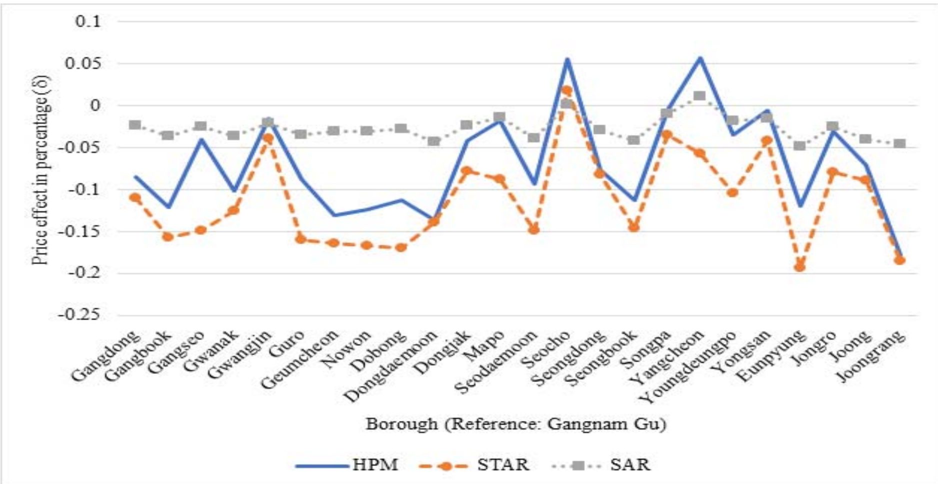
The empirical results in this study show slight differences between the STAR and the HPM in the location dummy variables. Figures 3 and 4 displays the location fixed effects which are comprised of coefficients of location dummy variables(i.e., δ in Equations (6), (7) and (8)). In general, the values of the fixed effects estimated by the STAR are slightly lower than by the HPM. Given the statistically and economically significant spatio-temporal coefficient(ψ of 0.129), the minor differences in the location fixed effects between the STAR and the HPM suggest that apartment transaction prices would be spatially interacted with each other within a more narrow range than 'Gu' in this data and/or that there are still latent spatial interactions in neighbourhood and location characteristics which are not included in this study. The risk of over-connected spatial relations due to spurious multi-directional temporal context is more evidently found in Figure 3. The SAR yields much smaller values of the indices than the STAR.

Figure 3 shows a clear heterogeneity of apartment sales prices according to the borough which is intuitively acceptable. Note that the effects are relative to the reference borough(Gangnam Gu), not absolute values. All the coefficients measured by the STAR are statistically significant at the 0.01 level. For example, holding other factors constant, apartments are sold at the highest price in Gangnam Gu(no positive coefficient is found in Figure 3). Apartments in Seocho Gu and Songpa Gu are the second and third most expensive in the Seoul housing market respectively. The location fixed effects show the so-called 'Gangnam 3 Gu' premium for apartment sales prices. The 'Gangnam 3 Gu' areas are followed by Yonsang Gu, Gwangjin Gu, Yangcheon Gu and Mapo Gu wherein apartments are sold at about 8% - 15% lower price than Gangnam Gu. In contrast, the location fixed effects indicate that apartments are sold at the lowest level in Dobong Gu, Gangbook Gu, Geumcheon Gu, Nowon Gu, Eunpyung Gu and Joongrang Gu in which average apartment

<Figure 3> Location fixed effects for sale prices



<Figure 4> Location fixed effects for *jeonse*



transaction prices are approximately 30% lower than Gangnam Gu.

The location fixed effects for *jeonse* in Figure 4 show roughly comparable patterns with sales prices, but showing more narrow price gaps among boroughs. The STAR yields much higher value of spatio-temporal dependence in *jeonse* than sale prices, and the greater spatial effect seems to influence on the location fixed effects more significantly.

While the fixed effects for sales prices are comparable across the HPM and the STAR, those for *jeonse* between the two models are quite different. For example, the HPM results show a higher *jeonse* level in Yangcheon Gu than Gangnam Gu, whereas Gangnam Gu shows a higher *jeonse* level than Yangcheon Gu when capturing spatio-temporal dependence. In addition, fixed effects patterns are different between the two models overall, although differences in the magnitudes of coefficients are not too big economically; for example, the HPM results suggest that *jeonse* levels are higher in Mapo Gu and Eunpyung Gu than Dongjak Gu and Joongrang Gu respectively, whereas the STAR results suggest the opposite patterns. The risk of over-connected spatial relations by the SAR is also evidently found in these regression results.

Given the clearer differences in the location fixed effects than the time fixed effects between the STAR and the SAR, it can be inferred that the risk of the SAR in this data would be more likely to be reltaed to over-connected relations in the spatial weight matrix due to the spurious influence of the future transactions on a given one. In other words, the STAR improves model performance and capture the spatial dependence more precisely by removing the upper-triangular elements in the spatial wight matrix(i.e., the spurious relation between 'non-existing' future transactions and a given one). LeSage and Pace(2009) suggest that, theoretically, the spatio-temporal modelling might place more emphasis on the temporal relations embodied in time-dependent parameters, and hence produce the spatio-temporal dependence embodied reflecting relatively high temporal dependence and low spatial dependence. The empirical results in this study, however, show different patterns to the suggestion. However, it is practically difficult to address the assumption in this study clearly as it is not possible to included variables that explicitly define spatial and temporal effects respectively(Dubé and Legros, 2014a).

Overall, the empirical results support the significant role of spatio-temporal dependence in a hedonic price framework for apartment sales prices as well as rents in this data. The STAR improves model fits by capturing the spatial effects, compared to the HPM. As can be seen, differences in the empirical estimation between the HPM and the STAR are hugely dependent upon the magnitude of the spaio-temporal dependence as it affects the calculations of the other hedonic variables including the location price indices. However, even if spatio-temporal dependence is low in magnitude, non-spatial hedonic application may introduce bias on the estimated coefficients and lead to an inappropriate price. Another important point is in consideration of spatial dependence in spatio-temporal context. Violations of the temporal causality in spatial modelling for housing data collected over time may result in more serious problems than applying no spatial autoregressive specification.

V. Conclusion

In local housing markets, it is commonly found that properties with similar values tend to cluster, rather than spread randomly. It can be partly explained by the tendency of market participants to base a housing transaction price not only on the fundamentals, but also what they observe in the local housing market. Unsure of the appropriate value of a house given its characteristics, housing buyers and sellers may rely on transaction prices of nearby properties with comparable characteristics to agree upon a price. This paper tries to capture such spatial dependence in house price to estimate house price in the hedonic price framework more accurately and precisely.

Using rich apartment transaction price data on sale as well as *jeonse* from the Seoul housing market, this study finds significant spatio-temporal dependence in transaction prices for both sale and *jeonse*. Capturing the spatial effects provides more appropriate application to estimate housing values in a hedonic framework with more robust model fits. This study uses the spatio-temporal autoregressive model rather than the spatial autoregressive model in order to control for spurious spatial relations between 'non-existing' future housing transactions and a given transaction. Violation of temporal causality in the spatial modelling leads to overestimate spatial dependence. Moreover, the overestimation results in biased estimation on other hedonic variables as well. Therefore, the application of spatial modelling for housing data pooled over time is necessarily conducted in spatio-temporal context.

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Appendix

<Table A1> Model comparison

	Sale					jeonse				
	$\bar{d}$=3km					$\bar{d}$=3km				
	$\bar{v}$=1month	$\bar{v}$=3month	$\bar{v}$=6month	$\bar{v}$=12month	$\bar{v}$=15month	$\bar{v}$=1month	$\bar{v}$=3month	$\bar{v}$=6month	$\bar{v}$=12month	$\bar{v}$=15month
Psi (ψ)	0.089*	0.232	0.102***	0.129***	0.088*	0.109*	0.201*	0.357**	0.334***	0.253**
(adj)R-squared	0.862	0.884	0.887	0.886	0.865	0.798	0.801	0.822	0.823	0.802
Log-likelihood	25630.03	20882.12	27800.01	28900.06	26301.34	20723.32	22232.12	22434.76	24723.14	21345.78
AIC	-51136.06	-41640.24	-55476.02	-57676.12	-52478.68	-41322.64	-44340.24	-44745.52	-49322.28	-42567.56
BIC	-50637.38	-41141.56	-54977.34	-57177.44	-51980.00	-40823.96	-43841.56	-44246.84	-48823.60	-42068.88
	Sale					jeonse				
	$\bar{v}$=12month					$\bar{v}$=12month				
	$\bar{d}$=1km	$\bar{d}$=2km	$\bar{d}$=3km	$\bar{d}$=4km	$\bar{d}$=5km	$\bar{d}$=1km	$\bar{d}$=2km	$\bar{d}$=3km	$\bar{d}$=4km	$\bar{d}$=5km
Psi (ψ)	0.029*	0.031	0.129***	0.109***	0.247*	0.089*	0.301**	0.334***	0.234**	0.412
(adj)R-squared	0.852	0.854	0.886	0.879	0.901	0.798	0.821	0.823	0.823	0.815
Log-likelihood	25630.03	25882.12	28900.06	27081.32	27097.12	20723.32	22232.12	24723.14	22223.3	20109.87
AIC	-51136.06	-51640.24	-57676.12	-54038.64	-54070.24	-41322.64	-44340.24	-49322.28	-44322.60	-40095.74
BIC	-50637.38	-51141.56	-57177.44	-53539.96	-53571.56	-40823.96	-43841.56	-48823.60	-43823.92	-39597.06

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$