Spatial dependence in apartment transaction prices during boom and bust

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ABSTRACT

Due to the illiquid and intransparent nature of housing markets, property sellers and buyers may hugely rely on information about transaction prices of nearby properties with comparable characteristics to agree upon a transaction price. We show that the spatial dependence in house prices is more pronounced in a rising housing market than in a falling market and can be associated with behavioural biases such as sellers' loss aversion tendency or herding of buyers. Using a spatio-temporal autoregressive model for 30,541 apartment transactions in Seoul, South Korea between 2006 and 2015, we find that spatial dependence in house prices is eight time higher in a boom as opposed to a bust. This shows huge asymmetric spatial effects across apartment transactions which suggests that neighbouring property prices can serve as an appropriate benchmark during a rising market but they may not be suitable to capture the housing market dynamics in a falling market. This implies that behavioural aspects such as sellers' loss aversion should be taken into account in the price formation when house prices are falling.

JEL classification: C21, D12, E32, R15, R21, R31

Keywords: Spatio-temporal autoregressive model, hedonic house price, spatial dependence, loss aversion, boom and bust.

1. Introduction

Housing transaction prices reflect not only hedonic characteristics of the property fundamentals but also capture the dynamics of neighbouring property transactions thus accounting for unobserved characteristics and local dynamics. The housing market is highly illiquid and market participants may not easily assess the true value of their houses given their characteristics. In order to agree upon a transaction price, buyers and sellers may hugely rely on information about historical prices of nearby properties with comparable characteristics (Can and Megbolugbe, 1997; Small and Steimetz, 2012). However, this spatial dependence across housing prices may vary across time depending on the point in the housing cycle in which the transaction takes place. The spatial dependence can be defined as "the coincidence of value similarity with locational similarity" (Anselin and Bera, 1998 , p.241), and is represented as a spatial correlation between a given house price and its nearby property prices. The fundamental notion of the method is based on Tobler's first law of geography that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970 , p.236).

On the one hand, in a boom period, the housing market can be driven by the sellers and is known as a 'seller's market' thus buyers easily willing to accept house prices similar to house prices of similar properties recently transacted. This can be due to overly optimistic buyers and herding behaviour. In this case we should observe strong spatial correlation among housing transactions. On the other hand, in a market downturn, housing sellers may be hesitant to sell their property at a lower price than what they perceive the value of the property. This is aligned with the prospect theory and the seller's loss aversion tendency (Genesove and Mayer, 2001; Haurin et al., 2013; Haurin et al., 2010) in specifically. Therefore, we would expect sellers to pay less attention on information of neighbouring transaction prices when benchmarking their house. Therefore, given the dynamics on the housing market, we can observe that a housing transaction is likely to occur at a price similar to recent transaction prices of nearby properties in a rising market, however not in a falling market. This means that the spatial correlation across property transactions is higher in a boom than in a bust.

The theoretical mechanism embodied in the argument is based on the prospect theory by Kahneman and Tversky (1979). The prospect theory can explain the asymmetric relationship described above. The theory argues that under uncertainty, investor's choice is associated with an aversion to the realisation of a loss. When outcomes are represented as either gains or losses relative to a neutral reference point, losses tend to loom larger than gains. This would suggest that from a seller's point of view, a sale during a downturn may have stronger effects as is associated with a loss and thus agents may not benchmark their properties against neighbouring transaction prices to the same extent as during a boom. Shefrin and Statman (1985) also suggest a positive theory of capital gain and loss realisation in which investors tend to sell winning stocks too early, but hold losing stocks too long. There are a number of studies (Anenberg, 2011; Case and Shiller, 1988, 2003; Cutler et al., 1991; Engelhardt, 2003; Genesove and Mayer, 2001; Grenadier, 1995; Haurin et al., 2013; Lamont and Stein, 1999; Stein, 1995) which look at the effects on the housing market. When a housing market is in an upside, expectations about capital gains from increases in the nominal house price give rise to enough motivation for homeowners to sell their property, and buyers also easily accept the sellers' list price due to an expectation about continuous appreciation. The sellers' behaviour during a boom is also supported by theoretical studies of optimal seller strategy by DeGroot (1970) and its application into the housing market by Haurin (1988) that sellers set a reservation price and accept the first offer that exceeds it. In contrast, loss-aversion homeowners will delay a transaction or decide not to sell their property when the market is cooling down until the market price recovers as close to the level of the price they initially paid for the house.

In this paper, we estimate a spatio-temporal autoregressive (STAR) model using a large number of housing transactions on the Seoul market between 2006 and 2015 to demonstrate that the spatial linkages vary considerably during a boom and bust. The Seoul housing market is associated with high market efficiency[1] and homogeneity providing a good testing ground of above hypothesis. In order to formally measure the spatial dependence, a spatially lagged dependent variable obtained on the basis of a spatio-temporal weight matrix is added in a hedonic price model. The spatial dependence in house prices is well documented by various researchers[2] who show that adding a spatial term improves the performance of the hedonic price model by capturing a portion of the unexplained variance associated with latent spatial relations. While most studies focus on the spatial relationship, when using transaction level data it is crucial to consider the temporal causality. Market participants could be influenced by price information of neighbouring properties which have been transacted, but not which will be transacted. In other words, spatial dependence can be defined as an unidirectional effect from the past transactions to the current transaction, but not from future transactions to the current one. The spatio-temporal weight matrix used in this study accounts for both, the spatial and the temporal effects across transactions.

We find that the spatial dependence in transaction prices is eight time higher in a boom than in a bust. This shows evidence for huge asymmetric spatial effects across apartment transactions over time which suggests that neighbouring property prices can serve as an appropriate benchmark during a rising market but they may not be suitable to capture the housing market dynamics in a falling market. This implies that behavioural aspects such as sellers' loss aversion should be taken into account in the price formation when house prices are falling. We would expect that in a rising market, sellers and buyers would be willing to agree on a transaction price similar to the prices of comparable nearby properties, whereas ignore recent transaction prices in a market downturn.

The remainder of this paper is structured as follows. Section 2 presents the prospect theory and reviews related empirical literature. Section 3 covers the methodology used in this study and Section 4 describes the data used. Section 5 presents the results. Section 6 concludes.

[1] The Seoul housing market is defined by several characteristics. First, the market is homogeneous. Apartments are typically constructed within a large complex of multi-storey buildings with highly standardised floor plans, building materials and structures and complex amenities. Second, the market is liquid. Transaction costs are relatively low (mainly composed of brokerage fees of up to 0.9% of the transaction price) and the homogeneity of property keeps searching costs low, hence transactions are quite frequent. Third, the market is highly transparent in terms of high availability of information on individual housing transactions. As a large number of real estate brokers provide daily information of transaction prices in neighbourhoods (multiple brokers within a single apartment complex), potential sellers and buyers have easy access to reference prices (Hwang et al., 2006).

[2] See Elhorst (2003) and Krause and Bitter (2012).

2. The prospect theory

In order to explain the difference in the spatial dependence in house prices in a boom and a bust, we could borrow some concepts from behavioural economics. In particular, relevance for the spatial econometrics model would be to explain why neighbouring prices may not serve as a good benchmark during a bust given that they incorporate a set of local market characteristics and unobserved hedonic variables. We argue that if investors assess the value of property as a gain or a loss from a reference value, asymmetric responses to changes in surrounding housing prices could be observed depending on if a gain or a loss is expected. This is related to the loss aversion concept which is a central feature of the prospect theory developed by Kahneman and Tversky (1979). The prospect theory argues that investors make decisions under uncertainty based on changes in wealth (i.e. the value of potential gains and losses from a determined reference point, rather than the final outcome). A decision maker orders outcomes of a decision according to their probabilities and then evaluates each of the edited prospects choosing the prospect with the highest value. In the case of two prospects x and y, one receives x with a known probability p, y with a probability q, and nothing with a probability $(1-p-q)$, with $p+q \leq 1$. The overall value or expected utility of the expected outcomes, *V*, to the decision maker is given as:

$$V(x,p;y,q) = \pi(p)v(x) + \pi(q)v(y) \qquad (1)$$

where $\pi(p)$ and $\pi(q)$ are decision weights each with a probability of p and q respectively which reflect the impact of p and q on the overall value of the prospect respectively. $v(x)$ and $v(y)$ reflect the subjective value of each outcome x and y respectively. The prospect theory assumes that the evaluation of monetary changes is a concave function. That is, the marginal value of gains and losses generally decreases with their magnitude. The value function for changes of wealth is nominally concave above the reference point ($v''(x) < 0$, for $x > 0$) and convex below it ($v''(x) > 0$, for $x < 0$) (see Figure 1). What is key for the use of the prospect theory to explain asymmetric spatial coefficients lies in its salient characteristics of attitudes to changes in welfare. More specifically, the aggravation associated with losing a sum of money appears to be greater than the pleasure associated with gaining the same amount. Symmetric bets of the form $(x, 0.5; -x, 0.5)$ may be distinctly unattractive. Moreover, as seen in Fig.

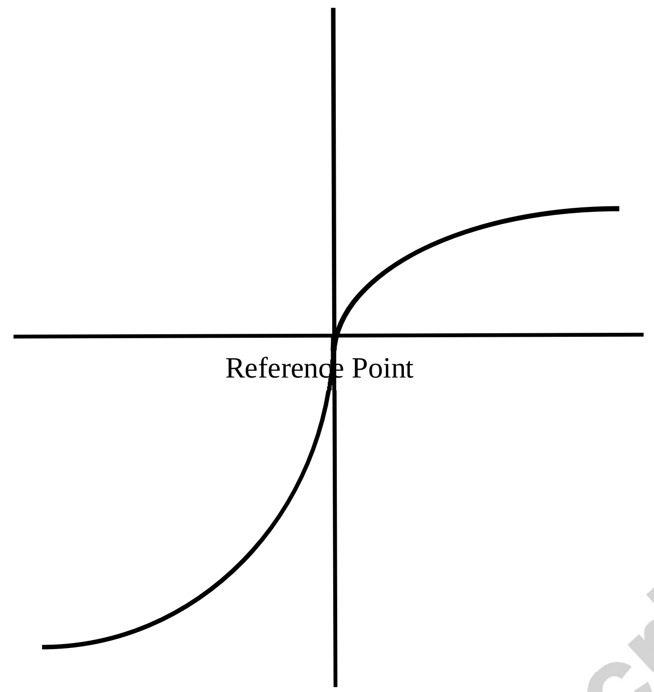


Fig. 1. The form of the value function in the prospect theory. Note: The figure is replicated from Kahneman and Tversky (1979) and Genesove and Mayer (2001).

1, the value function for losses is steeper than the value function for gains reflecting asymmetric risk attitudes with risk aversion in the domain of gains and risk seeking in the domain of losses.

Following Kahneman and Tversky (1979), Shefrin and Statman (1985) develop a positive theory of capital gain and loss realisation in a market setting, labelled as the disposition effect. The disposition effect is the investors' tendency to "sell winners too early and ride losers too long" (Shefrin and Statman, 1985, p.778). That is, they may have value functions like those described in the prospect theory. This applied to the housing market would suggest that buyers are more willing to buy quickly at the asking price in a rising market. Whereas in a falling market, sellers are not willing to sell and keep their properties for longer than needed. This applied to a spatial context would suggest that the information based on surrounding property prices is more pronounced in a boom than in a bust.

Odean (1998) supports the disposition effect by showing that investors tend to realise their profitable stocks investments at a much higher rate than their unprofitable ones. The extent of this behaviour significantly depends on the trading activities of other market participants such as professional traders and institutional investors. In particular, various features of housing transactions such as infrequency of house purchases (thus, lack of experience and expertise), heterogeneity on the housing market and no centralised trading, difficulty to obtain information and high transaction costs would increase the impact of other market participants' trading activities in housing markets (Scott and Lizieri, 2012). Case and Shiller (2003) report evidence of disposition effects from interviews with homeowners in housing markets during boom and bust periods. Sellers have reservation prices below which they tend not to sell and do not lower the price even if they are unable to sell.

One of the first studies to apply the prospect theory to the housing market is Genesove and Mayer (2001). They suggest that loss aversion homeowners would have an incentive to attenuate losses by deciding upon a reservation price that exceeds the level they would set in the absence of a loss. They look at the correlation between the list price at the date of entry, the transaction price and the time on the market, using data from the Boston condominium market. The empirical results show that when house prices fall following a boom period, condominium owners subject to nominal losses tend to set higher asking prices of 25-30% of the difference between the property's expected selling price and their original purchase price and attain higher selling prices of 3-18% of that difference. Another finding is that owner-occupiers exhibit a much lower hazard rate of sale (i.e. a longer time on the market) than investors although both of them behave in a loss-averse fashion.

Engelhardt (2003) examines the effect of nominal loss aversion on household mobility. The study focuses on young households who are supposed to be the most mobile as well as most leveraged group, hence they are most likely to be equity-constrained when the housing market is in a downturn. Using house price data from 149 US metropolitan areas, the results suggest economically large and statistically significant effects of nominal losses on mobility. A 5% nominal loss is associated with a 30-44% reduction in the probability of a move. Anenberg (2011) examines the effects of seller's loss aversion and equity constraints on selling prices using panel data from the San Francisco housing market. The author finds that a seller facing a 10% prospective nominal loss receives a 3.55% higher price, on average, while a seller with a 100% LTV ratio receives a 3.3% higher price than a seller with an 80% LTV ratio. Combining with the results from Genesove and Mayer (1997, 2001), Anenberg (2011) concludes that sellers become locked into their houses because of loss aversion during market downturns. However, transaction prices do not drop quickly as sellers are reluctant to accept lower prices in order to avoid nominal losses on their housing transactions. These findings are supported by Haurin et al. (2013) who use housing sales data from the Belfast metropolitan area, to find that sellers' loss-aversion behaviour is reflected in the high list–to-sale price ratio. Sellers' price expectations are not adjusted downwards or sellers set a relatively high list price and are waiting for demand to return to normal levels. The list–to-sale price ratio is unusually high during a sustained housing bust.

Above empirical applications of the prospect theory provide evidence of the existence of behavioural anomalies that can explain the dynamics of house prices during booms and busts. We go one step further by exploring if we can find asymmetries in the way market participants approach of surrounding property prices in a rising versus a falling market. Those asymmetries can then well be explained by behavioural theories such as the prospect theory outlined above. Our goal is to demonstrate if there is an asymmetric effect but not to identify the channel, which goes beyond the scope of this research but is an important next step in support of the prospect theory.

3. Methodology

3.1. Spatio-temporal hedonic price model

The theoretical support for the application of spatial models into a hedonic price analysis is established in Anselin (1988), Anselin et al. (1996) and LeSage and Pace (2009). One of key feature of spatial housing data is its unidirectional temporal causality. The spatial relations in housing transactions have a direction and occur from recently sold properties to future transactions and not vice versa. In the majority of the applications of spatial hedonic modelling, that distinction is not made, treating housing transaction data as cross-sectional when constructing the spatial weight matrix (e.g. Basu and Thibodeau, 1998; Cohen and Coughlin, 2008; Conway et al., 2010; Kim et al., 2003; Militino et al., 2004; Osland, 2010; Wilhelmsson, 2002). Theoretical works show that the violation of temporal direction of causality causes over-connection in the spatial weight matrices, hence inevitably introduces considerable biases into both the testing and estimating of spatial dependence (Farber et al., 2009; Mizruchi and Neuman, 2008; Smith, 2009). The risk of a mis-specified spatial weight matrix is also found in empirical research (Dubé and Legros, 2014; Thanos et al., 2015; Thanos et al., 2016). Spatio-temporal models have been proposed as means to consider the unidirectional temporal dimension. They are generally used in two ways[3], 1) through the filtering process and 2) through a Hadamard product.

The underlying approach of the filtering process introduced by Pace et al. (1998) is to deconstruct a weight matrix into different matrices accounting for temporal, spatial, temporal-spatial (product of temporal and spatial weight matrix) and spatial-temporal (product of spatial and temporal weight matrix) links respectively. Smith and Wu (2009), however, point out that the filtering process treats the spatio-temporal relations as a compound effect involving indirect influences[4], rather than as a spatio-temporal interaction effect. They suggest the Hadamard product[5] as an alternative method to allow for the interaction effect. A key to this application is the recognition of the unequal spacing between individual housing sales over time, preserving lower triangularity for the unidirectional time dimension. Thanos et al. (2016) also suggest that the filtering process could be inefficient as it often

[3] Thanos et al. (2016) provide comprehensive review of spatio-temporal applications in housing studies.
[4] Distinct spatial and temporal autoregressive terms mean that house *i* can be dependent on the spatially weighted observation of house *h* and at the same time on the temporally weighted observation of house *h*. Whereas, house *i* can be dependent on the spatially weighted observation of house *j*, but not on the temporally weighted observation of house *j* and vice versa (Thanos et al., 2016, p.83).
[5] The Hadamard product of two matrices A and B 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.

produces negative and rarely significant spatial coefficients. They conclude that given that the spatio-temporal distance is calculated by the product of the function of spatial distance and the function of temporal distance, using a single spatio-temporal weight matrix based on the Hadamard product is more efficient and appropriate than the filtering process for a hedonic analysis in housing studies. Following the suggestion of Smith and Wu (2009) and Thanos et al. (2016), we use a single spatio-temporal weight matrix based on the Hadamard product.

3.2. Spatio-temporal weight matrix

Spatial modelling in this study is based on spatial as well as temporal distances between each pair of apartment units. The measurements are typically represented by a $n \times n$ non-negative matrix where n denotes a number of observations. A spatio-temporal weight matrix is constructed stepwise; first, we construct a spatial weight matrix and a temporal weight matrix separately; second, the two matrices are multiplied using the Hadamard product. At the beginning in each step, all observations are chronically ordered, beginning with the oldest one, hence all elements of a matrix are also chronically ordered in each matrix, beginning with the distance between the oldest transactions from the first row and the first column. The construction of the spatio-temporal weight matrix in this section follows the work of Dubé and Legros (2014) and Thanos et al. (2016).

Spatial weight matrix

The spatial weight S_{ij} between apartment units *i* and *j*[6] is defined as:

$$S_{ij} = \begin{cases} 1 / d_{ij}, & if\ d_{ij} \leq \bar{d} \\ 0, & otherwise \end{cases} \tag{2}$$

where d_{ij} is the Euclidean distance between i and j and $\bar{d}$ is the critical distance band for the spatial relation, beyond which properties are assumed to have no direct spatial relations, therefore defined as non-neighbours. The inverse distance function ensures the distance-decay function that spatially closer neighbouring houses are given relatively greater weights with the spatial weights decreasing with a spatial distance. Pooling all the spatial weights S_{ij} into a single matrix produces a $n \times n$ spatial weight matrix S:

$$S = \begin{pmatrix} 0 & S_{12} & S_{13} & \cdots & S_{1N} \\ S_{21} & 0 & S_{23} & \cdots & S_{2N} \\ S_{31} & S_{32} & 0 & \cdots & S_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S_{N1} & S_{N2} & S_{N3} & \ldots & 0 \end{pmatrix} \tag{3}$$

[6] Property index (e.g. *i* and *j*) identifies the same apartment in all of the spatial, temporal and spatio-temporal weight matrices in this section.

All of the main diagonal elements have zero values, as these are distances of an observation on itself. Following the common practice in spatial modelling, the spatial 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; Dubé and Legros, 2014; Jeanty et al., 2010; Kim et al., 2003; Seya et al., 2013). Through the row-standardisation, the spatial weight matrix forms a row stochastic matrix and sum of the weights in each row equals to one so that the spatial relations are measured as a weighted average across the neighbouring properties.

Temporal weight matrix

The temporal weight T_{ij} between apartment units *i* and *j* is defined as:

$$T_{ij} = \begin{cases} 1/(v_i - v_j), & if\ |v_i - v_j| \le \bar{v} \\ 0, & otherwise\ (including\ if\ v_i = v_j\ \forall i \ne j) \end{cases} \quad (4)$$

where v_i is a temporal value of observation *i* at a given time and $\bar{v}$ is a critical distance band for the temporal relations, beyond which properties are assumed to have no direct temporal relations, therefore defined as non-neighbours. The value of $v_i - v_j$ represents time elapsed between transactions of houses *i* and *j*. The inverse distance function ensures the distance-decay function that more recent transactions are given relatively greater weights with the temporal weight diminishing with a temporal distance. The general function v_i can be defined by Dubé and Legros (2013, 2014) as:

$$v_i = 12 \times (yyyy_i - yyyy_{min}) + mm_i \ \ \forall i$$
(5)

where $yyyy_i$ and mm_i are the year and month when house i is transacted, respectively, and $yyyy_{min}$ is the earliest year among the observations in data. Pooling all the temporal relations T_{ij} into a single matrix produces a $n \times n$ spatial weight matrix, T':

$$T' = \begin{pmatrix} 0 & T_{12} & T_{13} & \cdots & T_{1N} \\ T_{21} & 0 & T_{23} & \cdots & T_{2N} \\ T_{31} & T_{32} & 0 & \cdots & T_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ T_{N1} & T_{N2} & T_{N3} & \ldots & 0 \end{pmatrix} \quad (6)$$

Like the spatial weight matrix, all the main diagonal elements in the matrix T' have a zero value, so observations are not considered neighbours to themselves (i.e. $T'_{ii} = 0$). The temporal weight matrix is also row-standardised. Given the chronological order of all elements, based on the main diagonal elements, the upper triangular elements have negative values (i.e. the temporal influence of future transactions on a given transaction), whereas the lower triangular elements have positive values (i.e. the temporal influence of past transactions on a given transaction). In order to rule out the spurious temporal relations, all the upper triangular elements are assigned zero value. Therefore, the temporal weight matrix, T', is reformed as:

$$T = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ T_{21} & 0 & 0 & \cdots & 0 \\ T_{31} & T_{32} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ T_{N1} & T_{N2} & T_{N3} & \dots & 0 \end{pmatrix} \quad (7)$$

Spatio-temporal weight matrix

A spatio-temporal weight matrix W is formed by multiplying the spatial weight matrix S defined in Equation (3) and the temporal weight matrix T defined in Equation (7) using the Hadamard product. The spatio-temporal weight matrix W is defined in the form of a $n \times n$ matrix as:

$$W = S \circ T = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ W_{21} & 0 & 0 & \cdots & 0 \\ W_{31} & W_{32} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & W_{N3} & \dots & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ S_{21} \times T_{21} & 0 & 0 & \cdots & 0 \\ S_{31} \times T_{31} & S_{32} \times T_{32} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S_{N1} \times T_{N1} & S_{N2} \times T_{N2} & S_{N3} \times T_{N3} & \dots & 0 \end{pmatrix} \quad (8)$$

Finally, the spaio-temporal weight matrix is row-standardised.

3.3. Empirical application

In the first step, we develop a baseline hedonic price model, exploiting a set of structural, neighbourhood characteristics as well as time and location fixed effects. In the second step, the baseline model is extended by a spatially lagged dependent variable based on a spatio-temporal weight matrix. This model is called a spatio-temporal autoregressive (STAR) model. For comparison, we estimate a spatial autoregressive (SAR) model based on a spatial weight matrix.

Baseline hedonic price model (HPM)

This study adopts the conventional notion of the hedonic analysis that 'goods are valued for their utility-bearing attributes or characteristics' (Rosen, 1974, p.34). In this framework, a house price is assessed by a function of the levels of all observable characteristics of the property. The hedonic price equation takes the following form:

$$P = c + \beta H + \delta Q + \varphi L + \varepsilon \quad (9)$$

where P is a $n \times 1$ vector of apartment unit prices, with n the number of observations. H is a $n \times k$ matrix of hedonic variables accounting for the property specific and locational characteristics, with k the number of hedonic variables. Q is a $n \times q$ matrix of quarterly time dummy variables, with q the number of time periods. L is a $n \times l$ matrix of location dummy variables, with l the number of locations. ε is a $n \times 1$ vector containing error terms which are independent and identically distributed with a zero mean and a variance σ^2. β, δ and φ are coefficients associated with the hedonic variables (H), the time dummy variables (Q) and the location dummy variables (L) respectively. We use a semi-logarithmic form which is common in hedonic house price models. This allows the value added to vary proportionally with the characteristics of the property, and the estimated coefficient to have a simple and intuitive interpretation (i.e. as a measure of percentage change) (Malpezzi, 2003; Sirmans et al., 2005).

Spatio-temporal autoregressive model (STAR)

The STAR is formalised by adding a spatio-temporally lagged dependent variable in the baseline HPM as follows:

$$P = c + \psi WP + \beta H + \delta Q + \varphi L + \varepsilon \quad (10)$$

where W is a $n \times n$ exogenous spatio-temporal weight matrix defined in Equation (8). WP is a $n \times 1$ vector of spatio-temporally lagged dependent variables. A scalar parameter ψ reflects spatial dependence in apartment prices which considers only the spatial relations from past transactions. If the scalar parameter of ψ has a value of zero (that is, no spatial dependence), the STAR is same as the baseline HPM.

Spatial autoregressive (SAR) model

Like the STAR, the SAR extends the baseline HPM by including an additional spatially lagged dependent variable based on the spatial weight matrix in which temporal causality is ignored. The SAR is formalised as:

$$P = c + \rho SP + \beta H + \delta Q + \varphi L + \varepsilon \quad (11)$$

where S is a $n \times n$ exogenous spatial weight matrix defined in Equation (3). A scalar parameter ρ reflects the spatial dependence in apartment prices which considers the spatial relations in the spurious multidirectional temporal context.

4. Data

4.1. Market description

This study examines spatial dependence in apartment transaction prices in the Seoul housing market, South Korea. The apartment transactions account for the vast majority of residential properties in Seoul, comprising approximately 60% of the total number of residential properties as of 2010.[7] Fig. 2 depicts a trend of average apartment unit prices per square metre during a recent housing cycle between 2006 and 2015 which is based on 687,809 transactions reported to the Ministry of Land (MOL) under the Real Estate Transaction Reporting system[8]. After strong volatility in 2006, apartment prices rapidly accelerated and peaked in January 2010, then slowly drop to a trough in July 2013. Prices have begun rising again since March 2014. We find evidence for seasonal trends in the data; sparing months from March to May tend to see stronger price rises in general as documented in other housing studies. In addition, increasing prices are found in autumn months between August and November. In contrast, apartments tend to be transacted at a lower price in January.

Fig. 2 shows an overall positive correlation between transaction prices and the volume of transactions which can be explained by market fundamentals as shown in previous research (e.g. Chan, 2001; Genesove and Mayer, 1997; Himmelberg et al., 2005; Linneman and Wachter, 1989; Ortalo-Magne and Rady, 2006; Stein, 1995). However, negative correlations are found in 2006 and 2008 with prices going up and volumes down. Based on fitting a linear trend in apartment prices, we define a boom as the period between January 2007 and January 2010, which was characterised by rapid and significant increase in the apartment transaction prices. The boom is mainly driven by mortgage expansion with low interest rates, low housing transaction taxes and a relaxation of apartment reconstruction restrictions. A bust is defined as the period between February 2010 and March 2014 in which transaction prices show a decreasing trend. Two factors are pointed out as main causes of the market downturn, 1) sluggish new apartment sales due to oversupply of new apartments in the short term in the outskirts of Seoul and 2) an increase in mortgage rates due to a rise in the default rates of project finance borrowers such as developers.

One could say that a bust has started in March 2008 when a trend of a significant reduction of transaction volume sets on or in January 2009 when house prices dropped for the first time in the cycle. In order to identify the break point in the housing price series, we conduct a Chow test. As shown in Table 1, the Chow test results define a trend in January 2010. For the entire study period, from January 2007 to March 2014, the average apartment unit price is approximately $5,080[9] per

[7] Based on the latest Population and Housing Census by the Korea National Statistical Office in 2010.
[8] Once a real estate transaction is completed, the seller or buyer must report the transaction price to the district tax office within 30 days. The reported transaction price is used as a standard for the transaction and registration tax of each transaction for both sellers and buyers.
[9] The average annual closing exchange rate in 2014 was 1,126 KRW for one USD.

square metre. Fig. 3 depicts the linear trend of apartment prices for the two periods – the boom and the bust. In nominal terms, the price increased by 73.47% during the boom period and decreased by 28.87% during the bust.

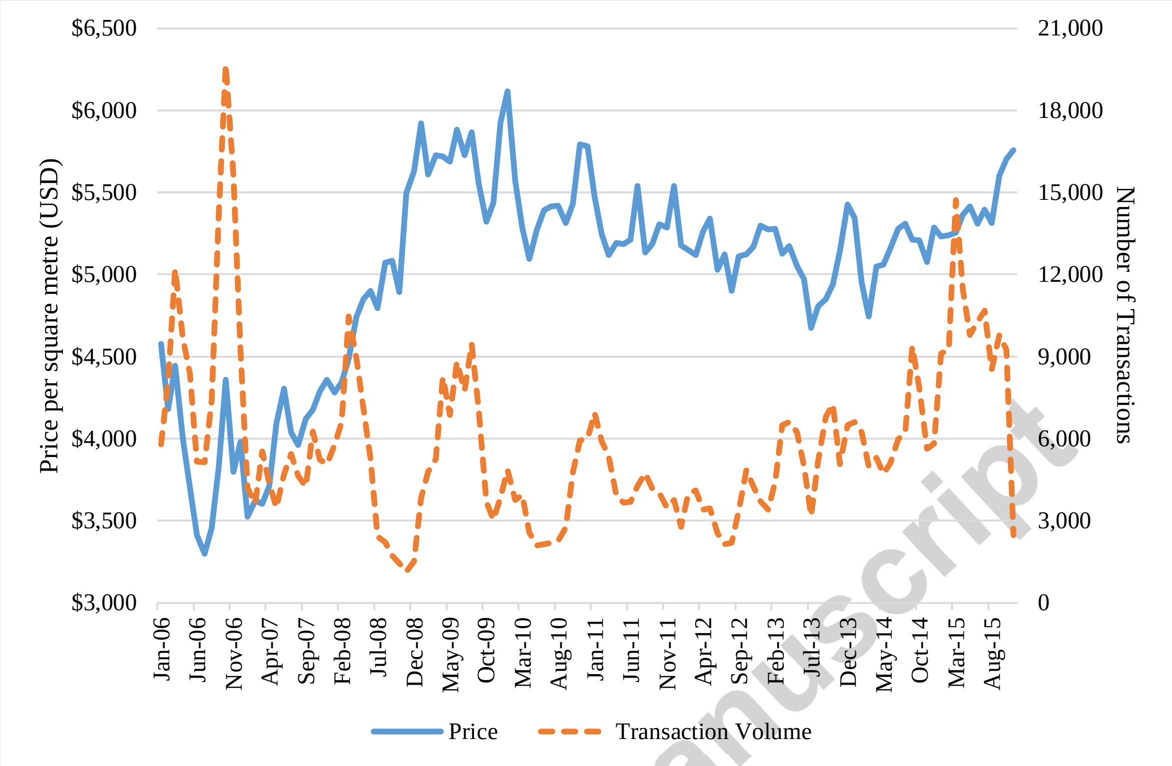


Fig. 2. The Seoul apartment market between January 2006 and December 2015.

4.2. Data

Apartment transaction price data come from the MOL. The data contains every apartment transaction price reported in the Real Estate Transaction Reporting System between January 2007 and March 2014. The final dataset consists of 406,033 transactions. For the empirical application, a 406,033 × 406,033 matrix needs to be built which implies that computations could be extremely time-consuming and not possible by the statistic software with a modest size of storage space. Therefore, we randomly sample 30,541 transactions, 17,290 for the boom period and 13,251 for the bust instead of using the entire dataset. The data sampling is in proportion to the total number of transactions per time period (monthly) and region (borough level).

A key element for the spatial analysis is the distance between each pair of properties. The measurement of the distance is conducted using the geographic information system (GIS), based on geographic coordinates (longitude and latitude). Given the nature of apartments being part of a multi-storey building, a 3-dimensional distance needs to be measured accounting for the floor level. We measure the longitude and latitude at a building level, and then account for the floor level of the apartment by adding the value associated with the floor to the last decimal point of the latitude and longitude of the building to distinguish properties at an apartment unit level. If there is a repeated sale of the same property during the study period, we only consider the most recent transaction.

Table 1 *Chow test results for data split.*

Boom	Bust	F-statistic
January 2007 – February 2008	March 2008 – March 2014	93.54
January 2007 – December 2008	January 2009 – March 2014	137.54**
January 2007 – January 2010	February 2010 – March 2014	284.27***

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

For the baseline hedonic price model, we include 17 apartment characteristics at various levels to cover housing attributes which are commonly used in hedonic housing studies as well as unique characteristics of the Seoul apartment market. The 'Age squared' is included to capture the nonlinearity generally assumed in housing depreciation (Can and Megbolugbe, 1997; Goodman and Thibodeau, 1995). 'Permission' reflects the expected capital gain from future housing value growth after a reconstruction[10]. Property characteristics which are not available from the MOL dataset are obtained from three Korean property websites covering the residential property market: Naver Real Estate, R114 and DrApt.

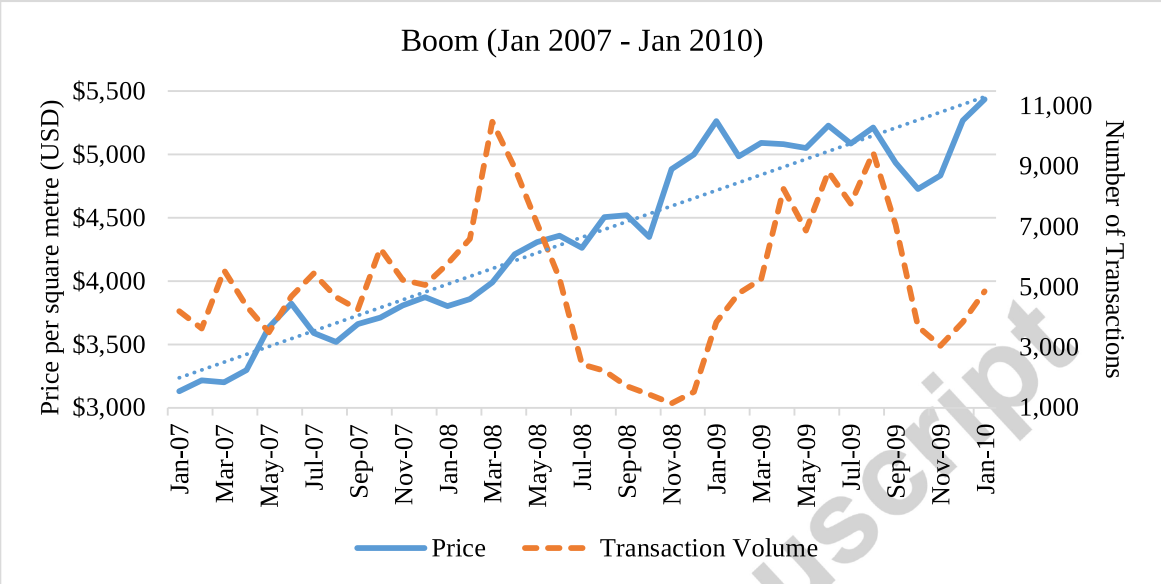
In order to control for the temporal heterogeneity, such as market conditions that are common to the study area, we use a set of quarterly time dummy variables (Wooldridge, 2010). A set of local jurisdictional boundary dummies at a borough level is included to control for regional heterogeneity. A list of variables and their definitions is provided in Table 2 and descriptive statistics are in Table 3. The average transaction price for the sample is approximately $263,800 higher for the boom period than the bust period. Other average house characteristics are similar for the two periods.

5. Results

The HPM and STAR are operationalised with controls for all the variables, and the results for the entire study period are presented in Table 4. For comparison purposes, the results of the SAR model are also shown. The model fit of the data is reasonable across all models, explaining over 87% of the variation. Most of the coefficients are of the expected signs and significant at the 0.01 confidence level. Apartment prices tend to increase with the size of the property, number of rooms, bathrooms and parking space, floor level and proximity to a subway station and the central business district (CBD). The price of an apartment falls with its age, with a positive marginal aging effect. The reputation of the construction company that has built the apartment complex has a significant impact

[10] Reconstruction of apartment (complex) defines that: in accordance with the procedures described in existing laws, existing owners of multi-family housing voluntarily form an association for redevelopment, demolish deteriorated existing housing and construct new housing jointly with construction firms on the site where existing multi-family homes were built (Lee et al., 2005, p.59).

on the apartment price. Apartments which are built by one of the biggest construction companies are sold at significantly higher prices than the reminder. Apartment units which have central heating systems and which are in an apartment complex sell at higher prices as well. The existence of low-rent units in the building or complex has a negative impact on the value of the apartment units in that building or complex. Apartments which have been approved for reconstruction are sold at a premium.



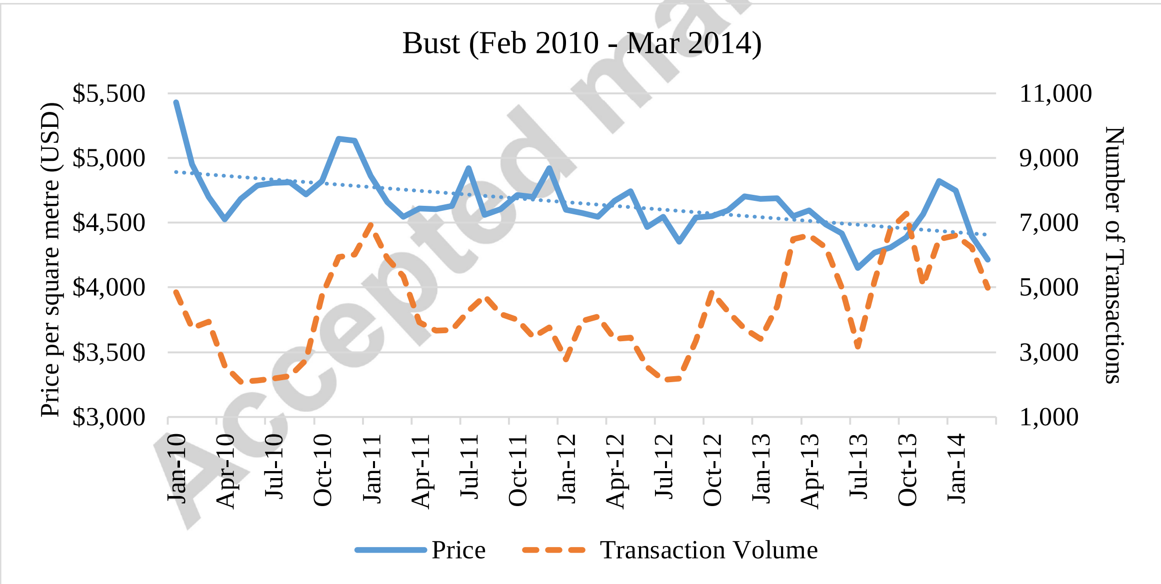


Fig. 3a. The Seoul apartment market during a boom period. **Fig. 3b.** The Seoul apartment market during a bust period.

5.1. Model comparison

A crucial methodological issue is to identify spatial dependence in either the dependent variable or error terms (Thanos et al., 2015). For that purpose, we use the Lagrange Multiplier (LM) tests commonly used in the spatial modelling (Anselin et al., 1996; Can, 1990). The results of the LM tests in Table 4 suggest the presence of a spatial dependence in both the dependent variable and the error terms. The LM diagnostic statistics are significant at the 0.01 level for both terms, however a higher value of the statistic is observed for the dependent variable. Moreover, the robust LM test rejects the null hypothesis of an absence of spatial dependence only for the dependent variable, not for the error terms. Therefore, we conclude that the application of the STAR model is appropriate for this data.

Table 2 Variable description.

Variab	Description
Dependent Variable	
(Log)	(Logarithm of) transaction price of a single apartment unit within an apartment building
Independent Variable	
Size	Gross internal area of an apartment unit in square metres
Room	Number of rooms
Bathro	Number of bathrooms
Floor	The floor level on which an apartment unit is located within the apartment building
Age	The difference between the year of transaction of the given apartment unit and the year of
Age	Square of the age
Parkin	Number of parking spaces per an apartment unit
Heatin +	Equal to one if the building has central heating system and zero otherwise
Subwa	Euclidean distance in metres using geographical coordinates from the apartment unit to the
CBD	Euclidean distance in kilometres using geographical coordinates from the apartment unit to the central point of the central business district
Compl +	Equal to one if an apartment unit is located in an apartment complex consisting of several
Buildi ngs	Number of buildings in the apartment complex in which the apartment unit is situated. In case the apartment unit is not part of a complex, the value is one
Units	Number of apartment units in the apartment complex/building
Reput ation+	Equal to one if the apartment building/complex is constructed by one of the ten largest construction companies (all of them are domestic developers) and zero otherwise
Public +	Equal to one if the apartment building/complex is constructed by a publicly owned
Low-rental+	Equal to one if registered as a low rental apartment unit (equivalent to social housing) within the apartment building/complex and zero otherwise
Permis sion+	Equal to one if the apartment building/complex had obtained a permission for reconstruction but before the reconstruction has begun and zero otherwise
Quarte +	Quarterly time dummy variable, equal to one if an apartment unit sold in the time period and
Locati +	Location dummy variable (25 boroughs in Seoul), equal to one if an apartment is located in

Note: + dummy variable.

Table 3 Descriptive statistics.

Variable	Boom (17,290 observations)				Bust (13,251 observations)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Price (USD)	686,500	570,159	35,524	5,017,761	422,735	319,715	55,062	3,774,423
Size (m^2)	97	42	16	273	96	29	19	266
Rooms	3.213	0.864	1	7	3.178	0.837	1	7
Bathrooms	1.706	0.534	1	4	1.506	0.511	1	4
Floor	9.086	6.112	1	66	8.949	6.032	1	68
Age	12.577	9.620	0	41	12.773	9.952	0	45
Age squared	225	212	0	1681	237	208	0	2025
Parking	1.072	0.456	0	12	1.065	0.467	0	9.890
Heating$^+$	0.492	0.500	0	1	0.461	0.499	0	1
Subway (m)	535	419	4	2,800	545	419	4	2,800
CBD (km)	10.306	5.597	0.169	22.726	10.085	5.307	0.168	22.743
Complex$^+$	0.775	0.418	0	1	0.849	0.358	0	1
Buildings	13.488	18.454	1	124	13.562	18.295	1	124
Units	1,102	1,215	6	6,864	1,105	12,15	8	6,864
Reputation$^+$	0.303	0.478	0	1	0.308	0.462	0	1
Public Co.$^+$	0.118	0.323	0	1	0.111	0.314	0	1
Low-rental$^+$	0.048	0.214	0	1	0.052	0.223	0	1
Permission$^+$	0.044	0.217	0	1	0.042	0.201	0	1

Note: $^+$dummy variable

Table 4 Regression results for the entire study period.

VARIABLES	HPM Equation (9)	STAR Equation (10)	SAR Equation (11)
Size (m^2)	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)
Rooms	0.064***	0.061***	0.030***
	(0.002)	(0.002)	(0.002)
Bathrooms	0.046***	0.044***	0.021***
	(0.003)	(0.003)	(0.002)
Floor	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)
Age	-0.007***	-0.007***	-0.001***
	(0.000)	(0.000)	(0.000)
Age squared	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Parking	0.028***	0.027***	0.016***
	(0.002)	(0.002)	(0.002)
Heating$^+$	0.024***	0.023***	0.015***
	(0.003)	(0.003)	(0.002)
Subway (m)	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
CBD (km)	-0.002***	-0.004***	-0.000
	(0.000)	(0.000)	(0.000)
Complex$^+$	0.103***	0.098***	0.066***

VARIABLES	HPM Equation (9)	STAR Equation (10)	SAR Equation (11)
	(0.003)	(0.003)	(0.002)
Buildings	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Units	-0.000	-0.000	0.000***
	(0.000)	(0.000)	(0.000)
Reputation⁺	0.015***	0.014***	0.012***
	(0.003)	(0.002)	(0.002)
Public Co.⁺	-0.003	-0.004	0.014***
	(0.004)	(0.004)	(0.003)
Low-rental⁺	-0.035***	-0.037***	-0.012***
	(0.005)	(0.005)	(0.004)
Permission⁺	0.081***	0.079***	0.050***
	(0.006)	(0.006)	(0.005)
Psi (ψ)		0.061***	
		(0.004)	
Rho (ρ)			0.604***
			(0.007)
Constant	8.168***	7.177***	3.066***
	(0.010)	(0.022)	(0.061)
Time fixed effect	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes
(Adjusted) R-squared	0.876	0.901	0.898
Log-likelihood		38,377.236	36,048.315
AIC	-51,929.682	-76,612.472	-71,954.630
BIC	-51,346.790	-76,021.253	-71,363.411
LM_lag	210.926***		
Robust-LM_lag	101.032***		
LM_error	75.871***		
Robust LM_error	0.702		
Observations	30,541	30,541	30,541

Notes:
1) Dependent variable is log of transaction price of apartment unit in all specifications.
2) ⁺denotes the dummy variable.
3) Robust standard errors in brackets.
4) A coefficient of dummy variable indicates an effect in percentage based on [exp (coefficient) –1] by Halvorsen and Palmquist (1980).
5) The spatial cut-off value for the STAR and SAR is 3km and the temporal cut-off value is 12month for the STAR.
Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

The STAR model yields a statistically as well as economically significant coefficient (ψ) for the spatio-temporal dependence, suggesting that apartment unit prices are partly determined by recently sold neighbouring apartment prices. Following the interpretation of Thanos et al. (2016), a spatial coefficient of 0.061 suggests that, for example, a $10,000 increase in the average transaction price of neighbouring apartment units which are 3km away from the given apartment unit leads to an increase of $610 in the given apartment unit. Capturing the spatial effect improves the model fit as can be evidenced by a lower value of the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), compared to the baseline model.

While Table 4 indicates comparable coefficients for most variables across the STAR and the HPM, clear differences are found in the coefficients for the time and location dummy variables (Figs. 4 and 5). The findings which are in line with other empirical research (e.g., Dubé and Legros, 2014; Kim et al., 2003) imply that the spatio-temporally lagged dependent variable captures a part of the time and location variation of the price determination process that is, otherwise, hiddened by the coefficients of the dummy variables. The differences between the two models are more evident in the coefficients for the time dummy variables than the location dummy variables. LeSage and Pace (2009) point out that theoretically, the spatio-temporal modelling is likely to place more emphasis on the temporal relations embodied in time-dependent parameters, hence yield a spatio-temporal effect reflecting relatively high temporal dependence and low spatial dependence. The sample size or omitted variables could create this problem as argued by (Dubé and Legros, 2014). However, it is difficult to clearly address this assumption because, practically, it is not possible to include variables that explicitly define spatial and temporal effects respectively.

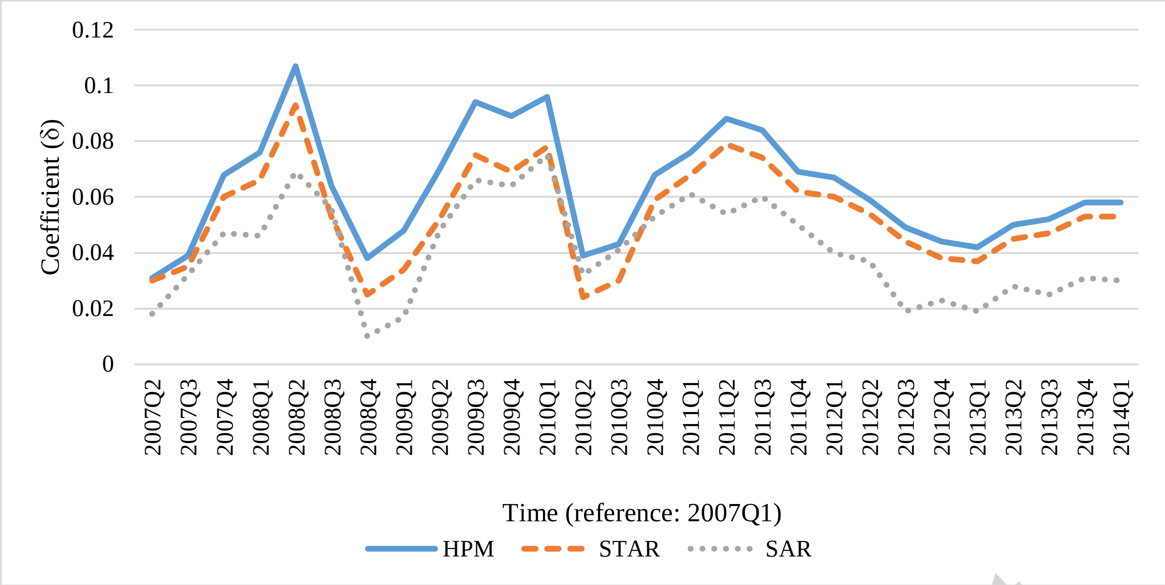


Fig. 4. Time fixed effect for the entire study period.

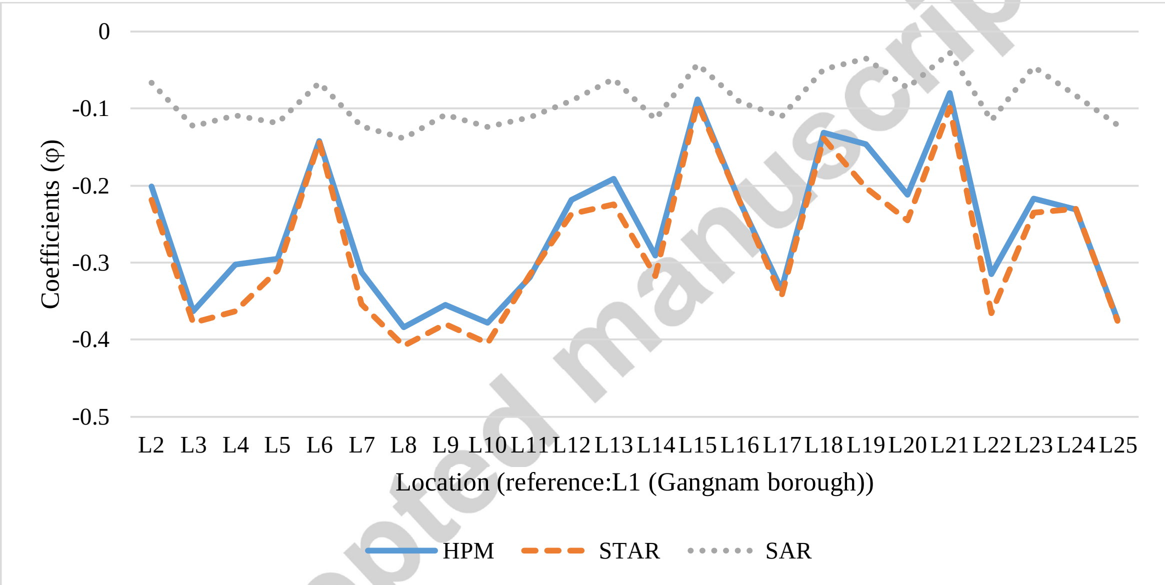


Fig. 5. Location fixed effect for the entire study period.

We find clear differences between the STAR and the SAR in Table 4, and it strongly supports the importance of time causality in the spatial modelling. The spatial dependence measured by the SAR is approximately ten times higher compared to the spatial dependence in the STAR. In contrast, the hedonic coefficients are lower in the SAR, as compared to the STAR. In particular, huge differences between the two spatial models are found in the coefficients for the location dummy variables (Fig. 5). Such discrepancies suggest that overstating the effect of the spatial relations by ignoring time causality produces biased inferences that lead to an inappropriate model specification and spurious estimations. Based on the information criteria, such as the AIC and BIC, the STAR outperforms the SAR.

5.2. Spatial dependence during a boom and a bust

Table 5 compares the regression results between the boom and the bust. The presence of

Table 5 Regression results for the boom and the bust period

	Boom		Bust	
VARIABLES	HPM Equation (9)	STAR Equation (10)	HPM Equation (9)	STAR Equation (10)
Size (m^2)	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Rooms	0.065***	0.056***	0.044***	0.038***
	(0.002)	(0.002)	(0.002)	(0.002)
Bathrooms	0.053***	0.047***	0.032***	0.028***
	(0.003)	(0.003)	(0.002)	(0.002)
Floor	0.004***	0.004***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.006***	-0.005***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.000)	(0.000)
Age squared	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Parking	0.033***	0.028***	0.029***	0.026***
	(0.002)	(0.002)	(0.002)	(0.002)
Heating+	0.022***	0.021***	0.022***	0.021***
	(0.003)	(0.003)	(0.002)	(0.002)
Subway (m)	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
CBD (km)	-0.002***	-0.003***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Complex+	0.129***	0.115***	0.068***	0.064***
	(0.003)	(0.003)	(0.002)	(0.002)
Buildings	0.002***	0.002***	0.003***	0.003***
	(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)
Reputation+	0.017***	0.015***	0.016***	0.015***
	(0.003)	(0.003)	(0.002)	(0.002)
Public Co.+	0.002	0.004	0.004	0.005*
	(0.005)	(0.005)	(0.003)	(0.003)
Low-rental+	-0.067***	-0.059***	-0.017***	-0.017***
	(0.006)	(0.006)	(0.004)	(0.003)
Permission+	0.071***	0.068***	0.047***	0.047***

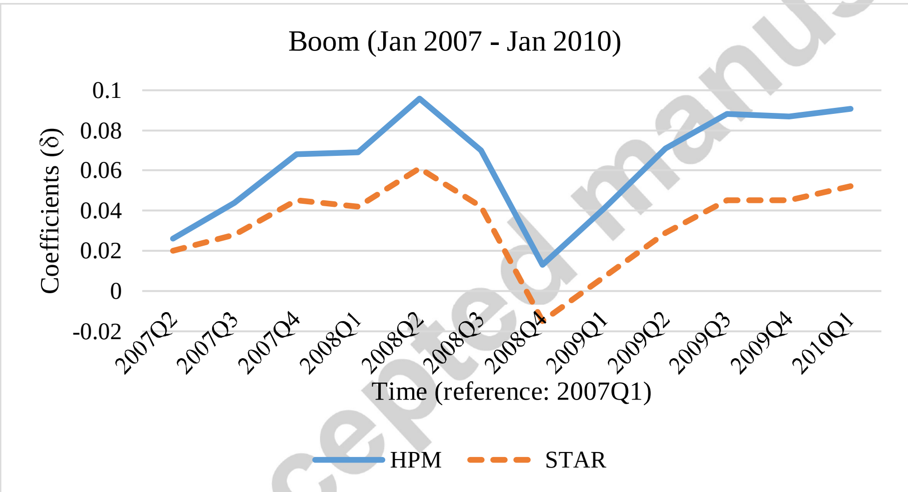
VARIABLES	Boom		Bust	
	HPM Equation (9)	STAR Equation (10)	HPM Equation (9)	STAR Equation (10)
	(0.006)	(0.006)	(0.004)	(0.004)
Psi (ψ)		0.176***		0.021***
		(0.006)		(0.005)
Constant	8.116***	6.182***	8.387***	7.058***
	(0.008)	(0.051)	(0.008)	(0.042)
Time fixed effect+	Yes	Yes	Yes	Yes
Location fixed effect+	Yes	Yes	Yes	Yes
(Adjusted) R-squared	0.874	0.909	0.877	0.905
Log-likelihood		20,220.867		19,088.386
AIC	-25,931.279	-40,329.734	-20,849.048	-38,058.722
BIC	-25,504.596	-39,895.293	-20,414.496	-37,616.727
LM_lag	1137.023***		120.592***	
Robust LM_lag	910.954***		89.51***	
LM_error	133.451***		46.981***	
Robust LM_error	0.943		0.463	
Observations	17,290	17,290	13,251	13,251

Notes:
1) Dependent variable is log of transaction price of apartment unit in all specifications.
2) +denotes the dummy variable.
3) Robust standard errors in brackets.
4) A coefficient of dummy variable indicates an effect in percentage based on [exp (coefficient) –1] by Halvorsen and Palmquist (1980).
5) The spatial and temporal cut-off value for the STAR is 3km and 12month respectively.
Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

spatial dependence in apartment prices is diagnosed by the LM tests for both the boom and bust periods. The STAR model yields statistically significant coefficients for the spatial dependence for both periods. As expected, the results indicate asymmetric spatial dependence in apartment prices. The spatial coefficient for the boom period is about eight times higher than for the bust period. The considerable difference in the spatial dependence between the two periods could be explained by the loss aversion behaviour hypothesis. When housing sellers and buyers expect capital gain from housing transactions by observing increases in neighbouring house prices, they are willing to transact for a price similar to the price of a comparable neighbouring apartment. This means, they are likely to consider the recent transaction prices in the local housing market as an appropriate benchmark in a boom period. On the contrary, the loss aversion leads the spatial dependence in house prices to be economically marginal when the market is cooling down as sellers tend to be reluctant to sell at a loss because of a perceived entitlement to their initial purchase price. Housing sellers, therefore, rely less on information of transaction prices in the relevant neighbourhood.

The spatial coefficient of 0.176 for the boom period suggests that for example, a $10,000 increase in transaction prices of comparable apartment units sold in the last 12 months within a distance of 3km would result in an approximately $1,760 increase in a given transaction price. Given an average appreciation of $165,200 during the boom period, the total spatial effect is estimated to be approximately $29,100 per apartment unit. On the contrary, the spatial coefficient of 0.021 for the bust period suggests much smaller pecuniary effect – an approximate $3,370 decrease from an average depreciation of $160,500 during the bust period.

The coefficients for the hedonic variables are comparable across the boom and bust periods. The expected signs are observed for most of other variables and the values of the parameters are similar to those obtained for the entire sample period as shown in Table 4. This suggests that market conditions have a significant impact on sellers' and buyers' property value perception, whereas preferences regarding property-specific and neighbouring characteristics are rather idiosyncratic in nature. Fig. 6 shows the cross-section variation of the coefficients for the time fixed and location fixed effects. The former follows a similar pattern across the STAR and the HPM during the boom and the bust periods, however, at different magnitude. Accounting for spatial dynamics reduces the impact from time fixed effects which is in line with Can and Megbolugbe (1997) and Dubé et al. (2014) . The coefficients for the location fixed effects are similar across the boom and the bust (Fig. 7), providing evidence for the clear spatial heterogeneity in apartment prices across 25 boroughs in Seoul.



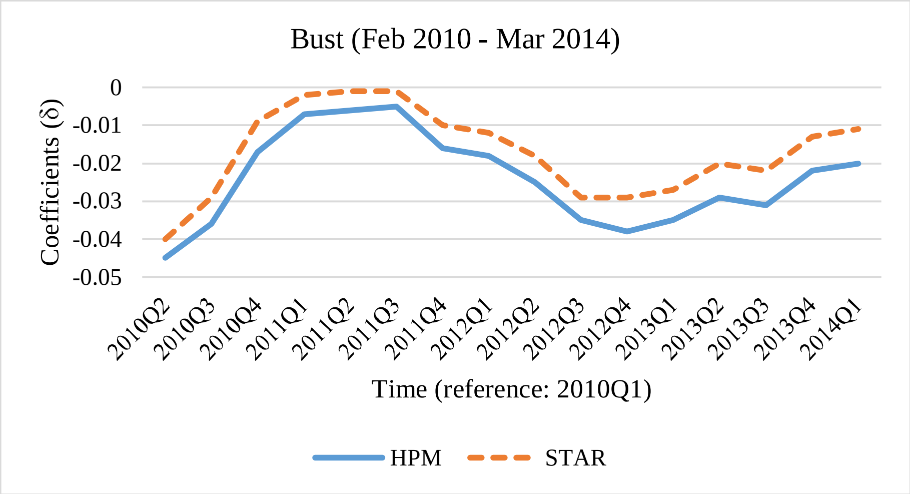
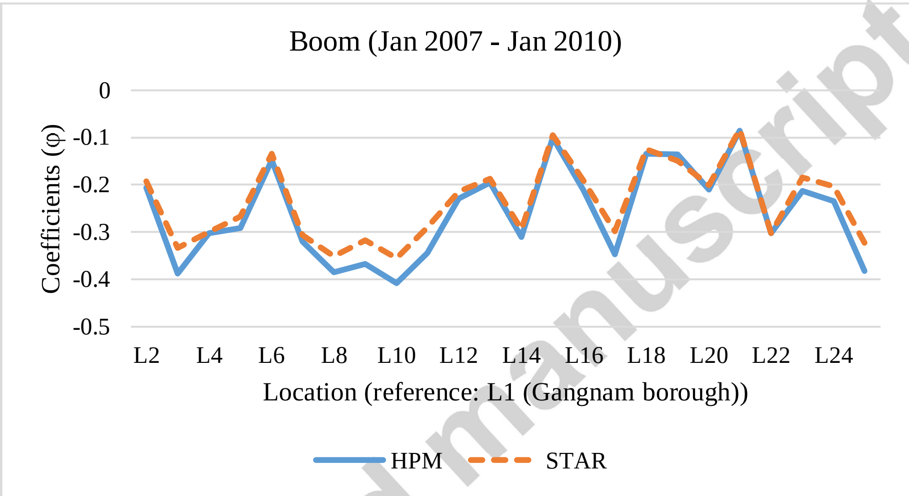


Fig. 6. Time fixed effect for the boom and bust.



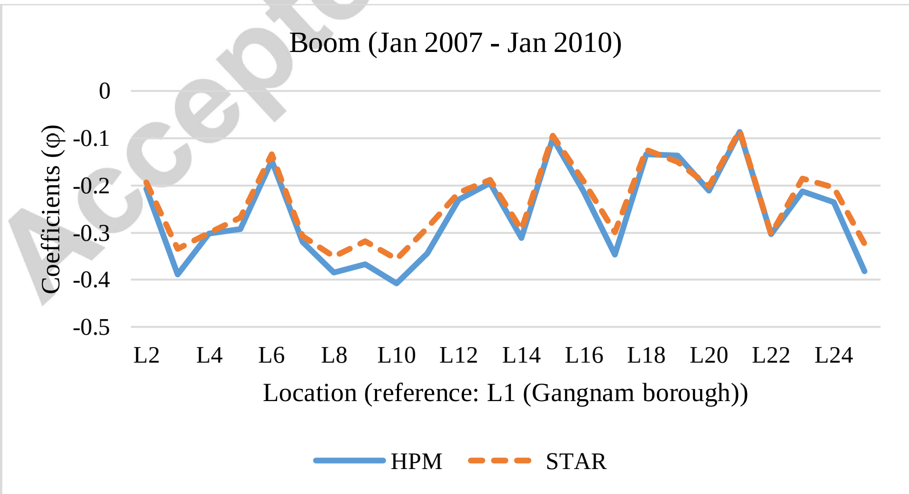


Fig. 7. Location fixed effect for the boom and bust.

6. Conclusion

This study examines the spatial dependence across a large number of house price transactions during a boom and a bust. We argue that spatial dependence in house prices can vary across the housing cycle controlling for property and neighbourhood level characteristics. The reasons for asymmetric spatial coefficients can be attributed to behavioural biases. If neighbouring house prices are used as a benchmark, they may do a good job in a booming housing market which is a 'seller's market'. Prices are driven by the sellers rather than the buyers, market liquidity is higher and asking prices are closer to sale prices. On the contrary, surrounding house prices may do a poor job as a benchmark in a falling market which is a 'buyer's market'. Prices are driven by buyers and sellers may decide to sit on their houses rather than sell them at a discount. The latter behaviour has been explained with the prospect theory and seller's loss aversion tendency. It would lead sellers to behave differently in the housing market cycle.

We incorporate a spatio-temporally lagged dependent variable into a hedonic price model using a rich data set of apartment transaction prices in Seoul for a full housing cycle between 2007 and 2014. The empirical results strongly support the arguments. Approximately eight times higher spatial dependence is found in a boom period than in a bust period. In particular, the value of the spatial coefficient during the market downturn is nearly zero, implying that sellers tend to sell their properties at prices which are unrelated to neighbouring property prices controlling for apartment, building and neighbourhood attributes. The results can have behavioural explanations following the prospect theory. The loss aversion tendency of sellers may have a crucial role in house price determination, and neighbouring house prices may not be indicative of future house prices in the same area during downturns. Furthermore, we stress the importance of considering a unidirectional temporal dimension in the spatial relations by estimating a STAR and a SAR model. Ignoring time causality leads to overestimate the spatial dependence and weaker hedonic coefficients in the SAR model.

The implications of our findings are that one needs to be careful in overstating the spatial effect in house prices. We need to account for behavioural biases when benchmarking transaction prices in highly cyclical housing markets as conventional benchmarks such as neighbourhood prices fail to show a significant impact. One may think of momentum benchmarks similarly to those used in the financial markets. There remain avenues for further research. First, we show that there is a significant difference in the spatial relationship during booms and busts, however we do not identify the channel of transmission as this goes beyond the scope of this research. A follow-up paper could look at the spatial linkages between the asking price and the sale prices of surrounding transactions. Second, given that the spatio-temporal matrix captures both the spatial and the temporal linkages across house prices, the spatial coefficient can rather reflect the temporal dependence and less so the spatial dependence. Further research should aim to disentangle those effects in the peruse of a precise spatial identification.

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Highlights

- Neighbouring apartment prices are eight times more likely to spill over onto future transactions in a rising housing market as opposed to a falling one.
- Accounting for unidirectional temporal relations improves the application of spatial econometrics in a hedonic house price model.
- Ignoring the time dimension results not only in overestimating the spatial spillover effect but also in underestimating the impacts of the hedonic variables.