Price competition in the spatial real estate market: Allies or rivals?

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Abstract

This paper examines real estate pricing featuring the price response curve, both theoretically and empirically. The Bertrand model with differentiated products suggests that the price response of real estate may differ when properties in the vicinity are priced by an affiliated firm or one's own firm. This is because the firm can maintain the collusive state if real estate prices in the neighborhood are priced by allies, whereas it loses it if prices are priced by rivals. To examine this prediction, a spatial autoregressive model with autoregressive and heteroskedastic disturbances, including a share of allies in the vicinity, is estimated using data on the residential condominium market in central Tokyo. Empirical results provide support for the model prediction.

JEL classification: C31, D21, D22, D43, L85, R31

Key words: real estate prices, strategic pricing, spatial econometrics

1 Introduction

Although real estate properties are differentiated in a spatial dimension, real estate firms are confronted with severe price competition against their neighbors. This implies that there is essentially a prisoner's dilemma at work for property prices. Real estate firms, however, may avoid price competition when properties in the vicinity are priced by an affiliated firm or one's own firm. In other words, firms can maintain a certain level of monopoly power in this case. The reason is straightforward: such conditions may be similar to those arising from the collusion or merger of oligopoly firms. The purpose of this paper is to develop a theoretical model to test the above hypothesis using spatial statistical techniques.

Analysis of the strategic interaction among decision makers in the geographical space has been a major issue in economics (Brueckner, 2001). Strategic interaction is described by the reaction function: an individual's optimal choice depends on the optimal choice of agents in close proximity. The spatial lag model is an appropriate empirical model to capture this idea. In addition, the spatial lag model has considerable merit because it can examine endogeneity within the reaction functions. Generally, it is quite difficult to estimate the reaction functions, because rivals' choice is endogenous. The spatial lag model potentially has the same problem. Kelejian and Prucha (1998), however, suggested that the spatially lagged exogenous explanatory variables, which are the product of the spatial weights matrix and the other exogenous explanatory variables, can be used as an appropriate set of instruments. That is, rivals' characteristics and attributes expect to have an influence on their decisions, but may be uncorrelated with a firm's own decision. Therefore, various studies have used a spatial lag model to capture the strategic dependence among players. Examples of this from the literature include models of tax competition among local municipalities (Brueckner and Saavedra, 2001; Gérard, Jayet, and Paty, 2010); spatial price competition in the retail gasoline market (Pinkse, Slade, and Brett, 2002; Pennerstorfer, 2009); models of price interaction among local hospitals (Mobley, 2003; Mobley, Frech, and Anselin, 2009); strategic interaction among colleges in the choice of tuition (McMillen, Singell, and Wadell, 2007); and so on.

Several studies that estimate real estate price models have also used spatial statistical techniques (Anselin, 1988; Can, 1990, 1992; Can and Megbolugbe, 1997). The spatial statistical approach applied to housing prices has also been used to measure the benefits of environmental factors (Beron, Hanson, Murdoch, and Thayer, 2004; Kim, Phipps, and Anselin, 2003). These papers have included the weighted average of selling prices for nearby properties to explain the house prices. Why have the past studies considered spatial dependence? The reason is related to the concepts of spatial dependence and housing submarkets. Because not all properties may enter the choice sets of consumers, the housing market is generally subdivided (Palm, 1978; Goodman and Thibodeau, 1998). Within housing submarkets, the selling prices of properties are similar because submarkets contain close substitutes (Bourassa, Cantoni, and Hoesli, 2007; Pryce and Evans, 2007). Housing submarkets thus have a spatial dependence on house prices within the submarket. However, unlike the studies mentioned above that consider strategic interdependence among players, the papers that use special statistical techniques have received little attention in terms of strategy in the real estate industry.

In this paper, the Bertrand model with differentiated products is applied to the real estate industry to explain strategic interaction among firms in terms of real estate pricing. In this stage, not only the price of rival firms, but also the price of affiliated companies or one's own company, assume to have an impact on the pricing decisions of the firm (Bresnahan, 1987). Theoretical results indicate that the real estate prices of affiliated firms in the neighborhood have a tendency toward avoidance of price competition. Consequently, real estate firms can charge high prices as in the case of a price cartel.[1] The converse seems to also be true. That is, local real estate markets tend to plunge into price competition when nearby properties are priced by rival firms.[2]

In the empirical section, a database of residential sales in central Tokyo from 2005 to 2009 is

[1] Real estate firms can also maintain the price by limiting the supply of properties. For example, to avoid large numbers of sales in one period, Japanese real estate companies frequently mark off a period for selling a property such as the first sale period, the second sale period, and so on. This strategy may be effective if there are groups with demand functions of different elasticity. In this paper, however, we do not examine this type of strategy.

[2] Based on a hedonic model with monopolistic competition, Chen, Clapp, and Tirtiroglu (2011) demonstrated theoretically that a monopolistic real estate firm can set a price higher than marginal cost when the elasticity of demand for housing units is decreasing with respect to size. Empirical results appear to support this hypothesis.

used. Data for 599 condominiums were used for the analysis. The database is unique because it contains the average sale price of units in each condominium, the location of the site, and also the name of the firm that sells the property. Therefore, the data appear to identify whether properties in the vicinity are provided by allies. Similar to previous studies, we attempt to test for the presence of strategic interaction using a spatial lag model. The share of allies inside submarkets is incorporated into the empirical model to capture the impact of pricing by the firm or affiliated company.

The approach used in this paper is close to that used by Mobley, Frech, and Anselin (2009) and Pennerstorfer (2009), which incorporated the degree of market competition into the spatial lag model. Mobley, Frech, and Anselin (2009) examined the effect of the Herfindal–Hirshman Index (HHI), defined over market shares of net patient revenue at the hospital's Health Facility Planning Area in California, on hospital pricing. Their empirical results suggested that the local market concentration increases net patient revenue for all hospitals. Pennerstorfer (2009) considered the impact of the share of unbranded gasoline stations on the pricing of branded stations in Lower Austria. He hypothesized that unbranded stations reduce price competition among branded stations, because a large share of unbranded stations in a local market implies little competition in the high-quality segment of the market. His empirical results supported this hypothesis.

Because our model includes the nearby affiliated firm's prices, the error terms should be positively correlated. Therefore, a spatial error term is used. In addition, because real estate prices are measured as averages, and they tend to depend on a location pattern, the error terms are also heteroskedastic. Controlling the spatial error and allowing for heteroskedasticity, the empirical results support our theoretical hypothesis: real estate firms are more likely to avoid price competition when properties in the vicinity are priced by affiliated firms, while they are more likely to compete on price when nearby properties are priced by rivals. Although the actual shares of affiliated firms are far from the monopoly outcome, our empirical results suggest that oligopolization in the spatial real estate market appears to induce a price increase.

The remainder of the paper is organized as follows. Section 2 presents starts of residential condominium development in Tokyo. Section 3 constructs a theoretical model that formalizes the intuition above. The data and empirical model used are discussed in Section 4, along with the empirical results. Section 5 conducts several tests to check the robustness of the empirical results. Section 6 summarizes the main conclusions.

2 Housing Starts in Tokyo

The Ministry of Land, Infrastructure, Transport and Tourism (MLIT) reports new housing starts every month. There are four types of housing: custom-built detached houses, ready-built houses, rental dwellings, and company-provided housing. Ready-built houses are divided into two categories: condominium units and detached houses. The asking prices of condominium units are easier to compare because condominium units are more standardized than detached houses in Japan. In the empirical section, we thus use the prices of condominiums.

According to MLIT, the number of housing starts in Japan between 2005 and 2009 was 5,469,202. Of these, approximately 34.0% (1,860,254 units) were built in the Tokyo metropolitan area, which includes Saitama, Tokyo, Chiba, and Kanagawa prefectures, and approximately one quarter of the housing starts (474,531 units) were condominium units. The ratio in Tokyo is much higher; approximately one third are condominiums, or 241,130 of the 775,729 units. In the empirical section, we examine data from 2005 to 2009 in the 10 wards of central Tokyo: Chiyoda, Chuo, Minato, Shinjuku, Shibuya, Bunkyo, Taito, Sumida, Koto, and Toshima wards. The 10 wards of central Tokyo are selected by the Tokyo Metropolitan Government. MLIT reveals that of the 198,920 housing starts, approximately 45.1% (89,797 units) are classified as condominiums.

The Japan Fair Trade Commission reports the degree of market competition using the HHI. In the report, however, there is no description in relation to sales agents of condominium buildings.[3] This suggests that the condominium market is not oligopolistic.[4] On the other

[3] According to industrial classifications, used in the 2006 Establishment and Enterprise Census (EES) issued by The Statistics Bureau and the Director-General for Policy Planning of Japan, real estate firms that sell condominiums are classified into "Sales agents of buildings and houses and land subdividers and developers". The 2006 EES reveals that the number of establishments in this group in Japan is 18,010.

[4] Beck, Scott, and Yelowitz (2012) also demonstrated the HHI is sufficiently small in medium and large

hand, the Real Estate Economic Institute (REEI) reported the market share of the top 20 firms in all of Japan. The share is calculated as the percentage of new condominiums that are built by real estate companies. According to the REEI, this figure in 2010 is 55.9%; namely, the average share of the 20 top-ranking firms is approximately 2.8%. The REEI also reports that oligopolization in the Japanese condominium market has been increasing. To our knowledge, there is no report on the degree of market competition in the Tokyo condominium market.

3 The Bertrand Price-Setting Model

Real estate properties are generally differentiated in a spatial dimension. At the same time, real estate firms compete on price within spatial submarkets, because properties are close substitutes. In this sense, the Bertrand model with differentiated products is relevant to the real estate market.

Assume there are two properties i and j ($i, j = 1, 2$, and $i \neq j$) in a local housing market. Let us denote demand for a property i, h_i. The demand function depends on the own-price p_i, a vector of housing traits $\mathbf{X}_i$, and the rival's price p_j, which is weighted by a given W: $h_i = h_i(p_i, Wp_j, \mathbf{X}_i)$. The weight, W, represents the degree of similarity between properties and takes a large value when the rival property is similar to the own property. In our context, W captures the spatial dimension in the local housing market. For example, within spatial submarkets, properties that are relatively close to the own dwelling are more likely to have an impact on the own-price. In this case, W is large. Assume that the demand for property follows the law of demand: the demand h_i falls when the own-price p_i rises. Assume also that properties are gross substitutes. These assumptions imply that $\partial h_i/\partial p_i < 0$ and $\partial h_i/\partial p_j = W(\partial h_i/\partial P_j) > 0$, where $P_j = Wp_j$. Both properties have identical average and marginal construction costs; namely, the cost of producing output h_i is assumed to be a linear function ch_i, where c is a positive constant. The profit from the property i then becomes:

$$\Pi_i = p_i h_i(p_i, Wp_j, \mathbf{X}_i) - ch_i(p_i, Wp_j, \mathbf{X}_i) + \theta_i \left[p_j h_j(p_i, Wp_j, \mathbf{X}_j) - ch_j(p_i, Wp_j, \mathbf{X}_j) \right],$$

residential real estate brokerage markets in the US.

where θ_i is a parameter registering the strength of the alliance. If a firm that supplies property i considers a firm that supplies property j as the rival, then $\theta_i = 0$, whereas if property i's firm considers property j's firm as an ally, then $\theta_i = 1$. The former case is a general case in the Bertrand model: property i's supplier only pursues its own self-interest when deciding the property price. On the other hand, in the latter case, property i's supplier takes into account the level of interest in property j, because property j's supplier is the ally. We treat θ_i as the continuous variable, which ranges from zero to one, because it allows us to differentiate the profit function. Actually, the share of the ally's properties is a proxy for the strength of the alliance in the empirical section.

Both suppliers of properties have pure strategies in price. That is, given p_j, θ_i, $\mathbf{X}_i$, and $\mathbf{X}_j$, property i's supplier chooses the own-price to maximize the profit from the property i. Suppose that the demand function is linear (Mobley, 2003). Under this assumption, $\partial^2 h_i/\partial p_i^2$, $\partial^2 h_i/\partial p_i \partial p_j = W(\partial^2 h_i/\partial p_i \partial P_j)$, $\partial^2 h_i/\partial p_i \partial x_i$ are equal to zero, where x_i is one of the elements in $\mathbf{X}_i$. The reaction function for property i is then defined by:

$$p_i = p_i(Wp_j, \theta_i, \mathbf{X}_i), \tag{1}$$

where

$$\frac{\partial p_i}{\partial p_j} = -\frac{\partial^2 \Pi_i/\partial p_i \partial p_j}{\partial^2 \Pi_i/\partial p_i^2} = -\frac{\partial h_i/\partial p_j + \theta_i(\partial h_j/\partial p_i)}{2(\partial h_i/\partial p_i)} > 0 \tag{2}$$

$$\frac{\partial p_i}{\partial \theta_i} = -\frac{\partial^2 \Pi_i/\partial p_i \partial \theta_i}{\partial^2 \Pi_i/\partial p_i^2} = -(p_j - c)\frac{\partial h_j/\partial p_i}{2(\partial h_i/\partial p_i)} > 0 \tag{3}$$

$$\frac{\partial p_i}{\partial x_i} = -\frac{\partial^2 \Pi_i/\partial p_i \partial x_i}{\partial^2 \Pi_i/\partial p_i^2} = -\frac{\partial h_i/\partial x_i}{2(\partial h_i/\partial p_i)}. \tag{4}$$

Note that all denominators on the right-hand side in Eqs (2), (3), and (4) are negative, because the demand function follows the law of demand.

First, Eq. (2) attempts to calculate the slope of property i's reaction function with respect to the given rival's price: the impact of exogenous changes in the rival's price, all else being equal, on the own-price. Because products are assumed substitutes, the reaction function is positively sloped.

Second, Eq. (3) focuses of the main relationship examined in this paper. Bertrand firms can charge prices above marginal cost when their products are differentiated; thus, p_j in Eq. (3) is larger than c. When property j is a rival of property i, and only property i's supplier raises the selling price of their property, property i's supplier loses some profits, because properties are substitutes. Eq. (3), however, suggests that property i's supplier can internalize the profit $(p_j - c)$, when property j is priced by the ally. Consequently, the sign of $\partial p_i / \partial \theta_i$ becomes positive. Property i's firm aggressively raises its own-price in the case where it considers property j as an ally.

Last, Eq. (4) suggests that the sign of $\partial p_i / \partial x_i$ depends on the sign of $\partial h_i / \partial x_i$. For example, consider the case where the sign of $\partial h_i / \partial x_i$ is positive. This case implies that property i attracts demand by providing a high-quality attribute; thereby, the firm raises the own-price.

A Bertrand equilibrium with differentiated products in the real estate market is described by the intersection of the reaction functions. We denote the equilibrium price as:

$$p_i^* = p_i^*(\theta_i, \mathbf{X}_i, \theta_j, \mathbf{X}_j).$$

One of objectives of this paper is to examine the effect of θ_i on the property price. We can calculate this effect as follows:

$$\underbrace{\frac{\partial p_i^*}{\partial \theta_i}}_{\text{indirect}} = \underbrace{\frac{1}{(1-\Phi)}}_{\text{multiplier}} \underbrace{\frac{\partial p_i}{\partial \theta_i}}_{\text{direct}} > 0, \tag{5}$$

where

$$\Phi = \left(- \frac{\partial^2 \Pi_i / \partial p_i \partial p_j}{\partial^2 \Pi_i / \partial p_i^2} \right) \left(- \frac{\partial^2 \Pi_j / \partial p_j \partial p_i}{\partial^2 \Pi_j / \partial p_j^2} \right) \in (0, 1).$$

Note that the formula in the first set of parentheses on the right-hand side is the slope of property i's reaction function (see Eq. (2)), while that in the second set of parentheses is the slope of property j's reaction function.

The direct effect, as it was labeled by Small and Steimetz (2007), in Eq. (5) corresponds to Eq. (3). That is, when property i's supplier assumes that property j is priced by the ally, property i's supplier raises its own property's price, given price p_j. However, property j's supplier raises p_j in reaction to this increase, because property j's reaction function is also positively sloped. Then property i's supplier again raises its own property's price; namely, p_i increases more than the direct effect in the equilibrium. This additional impact is described by a multiplier effect in Eq. (5). The direct effect multiplied by the multiplier effect is called the indirect effect (Small and Steimetz, 2007). In the final analysis, property i's supplier can avoid price competition in equilibrium when property j is priced by the ally.

Conversely, local real estate markets tend to fall into price competition when property i's supplier knows that property j is priced by its rival ($\theta_i \to 0$). That is, there is essentially a prisoner's dilemma at work in the pricing of properties.

4 The Econometric Spatial Lag Model of Real Estate Pricing

4.1 The empirical model

In this empirical section, the reaction function can be represented in matrix notation. A spatially lagged dependent variable is incorporated into the empirical model to estimate the sale price of property. On the one hand, the spatial lag model is used to explain house prices, because the variation in the sales price of property has a spatial component: the price of a property is related to the prices of adjacent properties. The spatial lag model is one of the methods used to take into account the influence of spatial submarkets. On the other hand, the spatial lag model is appropriate for capturing the characteristics of reaction functions used in our theoretical model, because the selling price of property depends on the prices of other properties in a local real estate market.

The spatially lagged dependent variable is represented as $\mathbf{Wp}$, where $\mathbf{W}$ is a $N \times N$ spatial weights matrix, N is the number of observations, and $\mathbf{p} = (p_1, p_2, \cdots, p_K)'$ is a vector of the prices of property i to be estimated. By convention, the diagonal elements of the spatial weights matrix are set to zero and row elements are standardized such that they sum to one for all types. The structure of spatial weights matrixes depends on how we define the spatial submarkets, which is discussed below. To apply the reaction function in equation (1) to the data, the following linear estimable form of a spatial lag model is specified:

$$\mathbf{p} = \rho \mathbf{W} \mathbf{p} + \gamma \boldsymbol{\theta} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}, \tag{6}$$

where ρ is the parameter for the spatial lag that captures spatial interaction, $\mathbf{X}$ is the matrix of housing attributes that has a parameter vector $\boldsymbol{\beta}$, and the error term vector $\boldsymbol{\epsilon}$ is assumed to be homoskedastic, independent, and identical across observations. The estimate of the spatial lag parameter reflects the slope of the reaction function. The Bertrand model suggests that the sign of ρ is positive. On the other hand, the estimated parameters of housing attributes, which are included in the vector $\mathbf{X}$, are variables that can shift the reaction function. The vector $\boldsymbol{\theta} = (\theta_1, \theta_2, \cdots, \theta_N)'$ reflects the strength of allies within spatial submarkets, which links to the spatial weights matrix. The parameter γ appears to capture our main hypotheses. It suggests that the sign of γ is positive. The variable $\boldsymbol{\theta}$ is discussed later.

Equation (6) has an endogeneity issue: the prices of rivals, $\mathbf{Wp}$, are jointly determined. As in Mobley (2003), Mobley, Frech, and Anselin (2009), and Pennerstorfer (2009), we can obtain the reduced form of Eq. (6). Instrumental variables techniques are used to estimate Eq. (6), using the matrix of instruments that is formed as a subset of linearly independent columns of ($\mathbf{Z}$, $\mathbf{WZ}$, $\mathbf{W}^2\mathbf{Z}$), where $\mathbf{Z} = (\boldsymbol{\theta}, \mathbf{X})$. These instruments are proposed by previous studies such as Kelejian and Prucha (1998, 2010).[5]

So far, $\boldsymbol{\epsilon}$ is assumed to be homoskedastic, independent, and identical across observations. There are, however, two potentially problematic assumptions for the error term. First, if there are any spatially dependent omitted variables, the assumption of independence tends to be violated. This is likely to occur because our model includes the nearby ally's prices. Second, because we only obtain an average selling price of apartments in a building, the error term is more likely to be heteroskedastic. To consider these two issues, we specify the error term as following a first-order spatial autoregressive error process: $\boldsymbol{\epsilon} = \lambda \mathbf{W} \boldsymbol{\epsilon} + \mathbf{u}$, where λ is the spatial autoregressive error parameter, and $\mathbf{u}$ is an uncorrected but heteroskedastic error term. Because our data are averages, the variance of $\mathbf{u}$ is assumed to depend on the number of units in the apartment building (n_i). In addition to this, $\mathbf{u}$ tends to become heteroskedastic because of the unobserved spatial heterogeneity (Anselin, 1988). Because the variance of $\mathbf{u}$ is determined by several factors, the unknown skedastic function of $\mathbf{u}$ is assumed. When both the spatial lag

[5] When the demand function is linear, as assumed in the previous section, property prices do not depend on rivals' characteristics.

and error terms must be considered, a generalized spatial two-stage least squares (GS2SLS) procedure is used to estimate the spatial lag model with the spatial error term, while allowing for unknown heteroskedasticity in the disturbance term (Kelejian and Prucha, 2010).

4.2 The data

The data for this paper were collected by Marketing Research Center (MRC). MRC is a limited liability company, with the head office in Tokyo, Japan. MRC conducts research, collects and analyzes real estate data, and prepares articles and reports its findings.[6] The database contains the average (asking) price of newly constructed condominiums in the Tokyo metropolitan area. That is, we can observe the average price data of properties for each condominium. The database also includes housing attributes and the name of the company that constructs the condominium. In addition, this database includes not only the address of the apartment, but also the exact location, defined by longitude and latitude using the world geodetic system. Therefore, the database is appropriate for examining our theoretical hypothesis using a spatial econometric model. To repeat, we use data from 2005 to 2009 in the 10 wards of central Tokyo.

The sample used in the analysis has the following characteristics. The number of observations in Tokyo in the full period is 3,102. Of these, 23.6% (731 observations) are built in the 10 wards of central Tokyo, which is 13.7% lower than the value from MLIT. Restricting the sample to those for which all necessary information was available reduced the number of observations to 709. Of these 709, 15.5% (110 observations) were produced by joint ventures (JV), which is when a group of firms build one condominium. In Sections 4.2 and 4.3, the observations related to JV are removed from the sample, and so the sample is reduced to 599 observations. In Section 5.2, however, the observations related to JV are added.

Table 1 presents the variable definitions for both the dependent and explanatory variables, followed by Table 2 with sample statistics.

To construct the variable lag price ($\mathbf{Wp}$) in Table 1, we draw a circle with a y-kilometer radius, and define this space as the spatial submarket of dwellings. All condominiums that are

[6] Details about MRC are available at http://www.mrc1969.com/ (accessed on April 27, 2011).

observed within a y-kilometer radius are assumed to obtain the i-th row of $\mathbf{W}$. To check robustness, circles with a 2-kilometer (approximately 1.2 mile) radius, 4-kilometer (approximately 2.5 mile) radius, and 8-kilometer (approximately 12.9 mile) radius are reported. Generally, the further the properties are from the center, the less intense is the competition among them. Taking into account this matter, the spatial weights matrix is based on the inverse of the distances between properties. As mentioned, the database provides information on the firm's name. There are 122 firms. When a property is produced by one's own firm or an affiliated company, we define it as an ally. We calculate the market share and the average share of the 20 top-ranked firms in the central Tokyo area over the full sample period, which is the same as the definition by the REEI in Section 2. These values are respectively 72.0% and 3.6%, which are respectively 16.1 and 0.8 points higher than that of the REEI.

In this paper, we create the following two types of alliance strength to examine our hypothesis. The first type is a share that is based on the number of observations in the submarkets. If there are N_i properties in the submarkets of property i, and a_i of them are priced by the ally, then the share (Ally 1) will be:

$$\theta_i^1 = \frac{a_i}{N_i}.$$

When there are no allies in the vicinity, θ_i^1 takes the value zero (0%), while when all neighbor dwellings are provided by allies, θ_i^1 takes the value 1 (100%). Table 2 and Fig. 1 demonstrate that the narrower the market is defined, the more likely that a firm has market power.

The second type is a share that is based on (expected) revenue. Let p_j^A (p_j^R) be the average price of property j ($j \neq i$) that is priced by allies (rivals) in the submarkets, and n_j^A (n_j^R) be the number of units in the condominium building. Then the revenue share (Ally 2) will be:

$$\theta_i^2 = \frac{\sum n_j^A p_j^A}{\sum n_j^A p_j^A + \sum n_j^R p_j^R}.$$

Table 2 demonstrates that the values of Ally 2 are quite similar to Ally 1.

The following structural attributes of the condominium units are controlled for in the estimation; namely, average living area, the number of rooms, the condominium density, the number of elevators divided by the total floor space of the condominium, the construction material, the height of the condominium, and the number of units in the condominium.

To control for the neighborhood of the condominiums, distance to the nearest railway station is included. Although not reported in Table 2, we also add 13 train line dummies including four Japan Railway lines and nine Tokyo Metro subway lines, 10 geographical dummies comprising 10 Tokyo wards, and seven zoning code dummies. Unobservable neighborhood characteristics apart from these variables are controlled for using the spatial autoregressive error terms.

In addition to geographical categories, four year dummies for 2006 to 2009 are included, but are not reported in Table 2.

In the estimation stage, we take the logarithm of the variables price, lag price, and living area.

4.3 Estimation results

Table 3 presents the estimated results, which use the first type of share index (Ally 1). Table 3 also reports diagnostic tests based on the residuals obtained from the OLS model without lag price. The results of Moran's I indicate that spatial autocorrelation is present, regardless of the weight specifications. Therefore, both the Lagrange multiplier (LM) test statistic and its robust version are calculated to specify the estimated model (Florax, Folmer, and Rey, 2003). First, the LM lag and the LM error indicate that both the spatial lag and the spatial error coefficients are significantly different from zero in all cases. Therefore, we next carry out robust Lagrange multiplier tests to distinguish between the spatial lag and the spatial error models. However, both the robust LM lag and its error remain highly significant. This implies that a spatial model containing both a spatial lag of the dependent variable and spatially autoregressive disturbances must be considered. Thus, Table 3 demonstrates the empirical results of the reaction function by means of GS2SLS.

Moreover, heteroskedasticity tests for the OLS residuals are conducted, such as the modified Glejser (MS) tests, which are proposed by Machado and Santos Silva (2000), and Im tests, which are proposed by Im (2000). Both of these tests are robust under weak assumptions of the disturbances. As mentioned in Section 4.1, to conduct these tests, we use the variables that tend to be related to the heteroskedasticity, such as the number of units in the apartment building and the location of the building. The number of units is used because the error term appears to be heteroskedastic from averaging the dependent variable. The latitude and longitude, which indicate the location of the apartment building, are used to capture heteroskedasticity caused by spatial heterogeneity. Therefore, these statistics follow a chi-squared distribution with three degrees of freedom under the null hypothesis of homoskedasticity. As shown in Table 3, they are all significant and the null hypothesis of homoskedasticity is rejected. Normality tests are also conducted, such as JB tests, which are proposed by Jarque and Bera (1987), and adjusted JB tests, proposed by Urzúa (1996). These statistics follow chi-squared distributions with two degrees of freedom. They are significant, as indicated in Table 3, and the null hypothesis of normality is also rejected. Both the heteroskedasticity and normality tests indicate that disturbances follow nonnormal distributions and their variances are heteroskedastic; consequently, we must also consider these issues.

To estimate the model under nonnormality, Kelejian and Prucha (1998) proposed the IV estimation approach. If, however, the disturbances are heteroskedastic, the asymptotic distribution of the Kelejian and Prucha estimator is not appropriate. Kelejian and Prucha (2010) developed an estimator that allows for heteroskedastic disturbances. They proposed a robust variance and covariance matrix estimator under the assumption of heteroskedastic disturbances.

Considering the spatial autocorrelation and heteroskedasticity in the disturbances, we estimate the model using the Kelejian and Prucha (2010) method. From the estimation results of this method, shown in Table 3, where the signs of the coefficients are the same across the three specifications of the spatial weights matrix although they are of different size, the hypothesis that a spatial error is not present is rejected at the 1% significance level. After considering the spatial error, the coefficient for the pricing of properties in the closest-neighbors area has a statistically significant positive impact on the real estate price. As suggested in the theoretical section, the reaction function has a positive slope.

Furthermore, a higher share of allies leads to higher selling prices of real estate property, indicated by the significantly positive sign of the variable Ally 1. These results suggest that real estate firms tend to avoid price competition in equilibrium when their submarkets share is high. Our hypothesis is supported by the empirical results. At the same time, the empirical results imply that a prisoner's dilemma is likely to exist in equilibrium. When rivals decrease the selling prices of properties, but a real estate firm does not, the real estate firm loses customers; thereby, the real estate firms also have a tendency to decrease selling prices.

We can calculate how an increase in the share in the spatial submarkets raises the selling price of property in the equilibrium, using the estimation results. Let us measure the elasticity of properties' price to θ_i^1. Following Kim, Phipps, and Anselin (2003), this can be written as:

$$\underbrace{\frac{\partial \widehat{\ln p_i^*}}{\partial \theta_i^1}}_{\text{indirect}} = \underbrace{\frac{1}{(1-\hat{\rho})}}_{\text{spatial multiplier}} \underbrace{\hat{\gamma}}_{\text{direct}},$$

where $\widehat{\ln p_i^*}$ is the equilibrium fitted value of a property i, and $\hat{\gamma}$ and $\hat{\rho}$ are the estimated value.[7] Kim, Phipps, and Anselin (2003) called $(1-\hat{\rho})^{-1}$ a spatial multiplier. In case the of the 2-kilometer radius, for example, a 1% increase in the share increases property prices by 0.29%. The indirect effect tends to be inelastic, because the value of the direct effect is quite small. Why is the direct effect so small? To understand this, let us rewrite the direct effect of Eq. (3) so that it depends on the ratio of the price elasticity, as follows:

$$\frac{\partial p_i}{\partial \theta_i} = -\frac{(p_j - c)h_j}{2h_i}\left(\frac{\eta_{ji}}{\eta_{ii}}\right),$$

where η_{ii} is the own-price elasticity of demand for property i, and η_{ji} is the cross-price elasticity of demand for property j with respect to p_i. On the one hand, η_{ii} may be elastic for the following two reasons. First, because the share is substantially low, when the supplier of property i increases the price, buyers can choose substitute properties provided by rival firms within the housing submarkets. Second, buyers also search for properties outside spatial housing submarkets when we consider a short radius. On the other hand, η_{ji} tends to be relatively smaller than η_{ii}. Similar to the above, we can interpret this in two ways. First, when the

[7] This corresponds to the average total impact suggested in LeSage and Pace (2009, p. 37).

supplier of property i increases the price, rival properties inside the housing submarkets may capture buyers who no longer wish to purchase property i. To repeat, however, because each property accounts for only a small share, attracting customers away from property i might be rather difficult. Second, rival properties inside the housing submarkets may further fail to attract customers away from property i when buyers also search for properties outside spatial housing submarkets. These two reasons have a tendency to produce a relatively small elasticity. To sum up, the ratio of the price elasticity (η_{ji}/η_{ii}) becomes small. The share of allies thus has a smaller impact on the selling prices of properties in the case of the 2-kilometer radius.

Expanding the size of the circle of submarkets, however, results in larger values of the indirect effect, because the direct effects are larger than in the previous case. The values of the indirect effect are, respectively, 1.11% in the case of the 4-kilometer radius and 1.70% in the case of the 8-kilometer radius. In sum, the larger the spatial submarkets are defined, the greater the elasticity of price. Why do the direct effects become larger as the radius increases? Let us again consider the ratio of the price elasticity (η_{ji}/η_{ii}). Interestingly, Table 2 suggests that the wider the market is defined, the smaller the average shares of allies. For this first reason, buyers can readily find substitute properties within the housing submarkets. The first reason increases η_{ii}, yet decreases η_{ji}. However, a second reason suggests that buyers face difficulty in searching for dwellings outside spatial housing submarkets (e.g., because of workplace access) when we consider a larger radius. That is, the impact of the second reason may be weaker, resulting in a lower η_{ii}, and a larger η_{ji}. If this weakened second reason outweighs the first reason, η_{ii} eventually decreases, whereas η_{ji} increases. As a result, real estate firms effectively raise the selling price of properties. This might be the reason for the elastic impact of the ally's share.

Table 4 presents the estimation results, which use the second type of share index (Ally 2). It indicates that the results are similar to those in Table 3.

5 Robustness Checks

The empirical results provide support for the model predictions. In this section, we conduct several tests to see whether these results are robust.

5.1 Changing the definition of the spatial weights matrix

In the empirical model, we assume that real estate firms only consider properties that are built in close proximity to their rivals. Therefore, all properties that are observed within a y-kilometer radius are included in the spatial weights matrix. One concern is that real estate firms may not consider properties that are built in different years to that of rivals' properties. To deal with this issue, the elements of the spatial weights matrix are set equal to 0 if properties are priced in different years.

Only the main variables are reported in Table 5, because the signs of the coefficients are the same as those in Tables 3 and 4. The first column (the 2-kilometer radius case) indicates that the coefficient of the lag price is statistically insignificant. This may reflect the fact that the average number of properties in the spatial submarkets is quite small, when we only consider the specific year. The second and third columns, however, indicate that the property prices have a statistically significant positive impact on the real estate price, suggesting a positive slope of the reaction function in the 4- and 8-kilometer radius cases. Ally 1 in the first and second columns tends to have high standard errors; however, the shares of both types of allies are positive and significant. These results are consistent with the prediction of the model.

5.2 Sample addition

Now the observation supplied by JV is added to the sample. However, we only consider the names of firms listed first, because generally the first firm in the list contributes the largest amount to an investment to build a condominium. For example, suppose that JV comprise three real estate firms that are listed as C Buildings, A Real Estate Development, and B Estate. Then we assume that a condominium is built by C Buildings.

Although Ally 1 in column 1 is insignificant in Table 6, our hypothesis seems to be valid even though we include the observation supplied by JV.

We also regard JV as independent suppliers. For example, suppose there were JV where C Buildings is listed first. Then we assume that a condominium is built by C Buildings JV. The results are reported in Table 7, indicating that the coefficients of interest were similar.

There are, however, two other items of note in relation to JV. First, we only consider two definitions of JV. Second, JV are a strategy of real estate firms. If real estate firms may avoid price competition through establishing JV, they tend to do so. Therefore, JV must be an endogenous variable. These two issues are deferred to future research.

6 Conclusion

The strategic pricing of real estate properties has not been researched extensively. As a result, little is known about the impact of market concentration on property prices in localized housing markets. This paper examined whether real estate firms can avoid price competition when nearby properties are priced by an affiliated firm or one's own firm. In the theoretical section, a Bertrand model with differentiated products was applied to real estate markets. A price response function that depends on the rival's price and the strength (share) of allies was obtained from this model. Comparative statics suggest that real estate firms can sustain the collusive state if real estate prices in the neighborhood are priced by allies. The collusive state and the competitive state were empirically distinguished, adding the share of allies into the spatial lag model. The spatial weight matrix was linked to spatial housing submarkets. That is, we constructed a circle around each property, and defined this space as the spatial submarkets of dwelling. In the estimation stage, we considered cases of 2-, 4-, and 8-kilometer radiuses in the 10 wards of central Tokyo. After controlling the spatial and heteroskedastic error terms, our empirical results indicated that real estate firms can raise the selling price of properties when their shares in the local market increase. Specifically, the elasticity of selling prices to the share are greater than 1 in the cases of 4- and 8-kilometer radiuses.

Our empirical results may suggest that customers face a serious problem. Because an expenditure to acquire a house is frequently high, even a small percent increase in price hits buyers' pockets. Accordingly, policy makers may monitor the share of the real estate company in spatial submarkets to maintain price competition.

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Table 1. Definition of the variables.

Variable	Definition
Price	The average selling price of a property, ten thousand yen
Lag price	The average selling price of a neighbor's property weighted by the spatial weight matrix
Ally 1	The ratio of properties sold by ally within submarkets, percentage
Ally 2	The ratio of total revenue sold by ally within submarkets, percentage
Living area	Average floor space of living room, square meters
One room	A binary variable indicating the mode number of unit rooms in a condominium is one bedroom and a living room
Two rooms	A binary variable indicating the mode number of unit rooms in a condominium is two bedrooms and a living room
Three rooms	A binary variable indicating the mode number of unit rooms in a condominium is three bedrooms and a living room
FAR	Floor area ratio, percentage
Elevator	The number of elevators divided by floor area, percentage
SRC	A binary variable indicating a building whose main frames are made of steel-reinforced concrete
Skyscraper	A binary variable indicating a condominium is high-rise (20-story or more building)
Large scale	A binary variable indicating a condominium is large scale (200 or more units)
Distance	Distance to the nearest station, minutes
Train line	Thirteen binary variables indicating a condominium is located on one of the train lines
Ward	Ten binary variables indicating a condominium is located in one of the wards
Zoning	Seven binary variables indicating a condominium is located in the zoning code
Year	Four binary variables indicating a condominium was sold between 2006 and 2009

Table 2. Descriptive statistics of variables.

Variable	Mean	Median	Std. Dev.	Max.	Min.
Price (ten thousand yen)	5932.76	4417.60	5420.48	43250.00	1851.80
Ally 1 (2km, percent)	5.31	3.33	5.95	30.43	0.00
Ally 1 (4km, percent)	3.24	2.30	3.38	17.42	0.00
Ally 1 (8km, percent)	2.37	1.94	2.24	10.85	0.00
Ally 2 (2km, percent)	7.22	4.09	8.10	49.78	0.22
Ally 2 (4km, percent)	4.14	2.35	4.87	26.70	0.08
Ally 2 (8km, percent)	2.90	1.65	3.26	15.11	0.03
Living area (m^2)	59.17	58.39	25.21	196.69	20.12
One room (dummy)	0.37		0.48	1.00	0.00
Two rooms (dummy)	0.30		0.46	1.00	0.00
Three rooms (dummy)	0.33		0.47	1.00	0.00
FAR (percent)	438.12	400.00	162.27	960.00	143.87
Elevator (number/total floor area)	0.04	0.03	0.03	0.33	0.00
SRC (dummy)	0.12		0.32	1.00	0.00
Other frame (dummy)	0.88		0.32	1.00	0.00
Skyscraper (dummy)	0.07		0.25	1.00	0.00
Large-scale (dummy)	0.06		0.24	1.00	0.00
Distance (minutes)	5.65	5.00	3.44	17.00	1.00
Observations			599		

Table 3. Estimation results based on the share of allies (Ally 1).

Dependent variable = log of Price

	2km			4km			8km		
Variables	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Lag price	0.269	***	0.045	0.314	***	0.050	0.279	***	0.066
Ally 1	0.002	***	0.001	0.008	***	0.002	0.012	***	0.003
Living area	1.001	***	0.032	1.019	***	0.033	1.044	***	0.035
One room	0.058	**	0.024	0.073	***	0.024	0.079	***	0.026
Two rooms	0.015		0.019	0.029		0.019	0.035	*	0.020
Three rooms	(reference)			(reference)			(reference)		
FAR (×1000)	0.012		0.085	0.026		0.085	0.003		0.089
Elevator	0.661	**	0.324	0.664	**	0.310	0.703	**	0.339
SRC	−0.009		0.021	−0.012		0.022	−0.009		0.024
Skyscraper	0.068		0.045	0.067		0.045	0.062		0.046
Large-scale	−0.005		0.045	−0.009		0.045	−0.014		0.047
Distance	−0.010	***	0.003	−0.010	***	0.003	−0.010	***	0.003
Constant	2.377	***	0.455	1.870	***	0.487	2.084	***	0.614
Lag error	0.369	***	0.095	0.381	***	0.107	0.451	***	0.116
Ward	Yes			Yes			Yes		
Train line	Yes			Yes			Yes		
Zoning	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
Observations	599			599			599		

Note: ***, **, * indicate significant at 1%, 5%, and 10%, respectively.
Average number of the condominiums in the submarket: 56.7 in 2km; 176.9 in 4km; 437.8 in 8km.

Misspecification tests based on the OLS regression without Lag price

Spatial dependence tests	Statistics	*P*-value	Statistics	*P*-value	Statistics	*P*-value
LM lag	164.28	0.000	140.90	0.000	92.31	0.000
LM error	55.95	0.000	50.49	0.000	29.02	0.000
Robust LM lag	146.06	0.000	115.31	0.000	87.91	0.000
Robust LM error	37.74	0.000	24.90	0.000	24.62	0.000
Moran's *I*	9.20	0.000	8.61	0.000	7.87	0.000

Heteroskedastticity tests	Statistics	*P*-value	Statistics	*P*-value	Statistics	*P*-value
MS	24.38	0.000	24.34	0.000	24.61	0.000
Im	20.27	0.000	22.15	0.000	24.32	0.000

Normality tests	Statistics	*P*-value	Statistics	*P*-value	Statistics	*P*-value
Skewness	0.43		0.48		0.47	
Kurtosis	3.65		3.54		3.54	
JB	29.13	0.000	30.43	0.000	29.47	0.000
Adj JB	29.92	0.000	31.13	0.000	30.16	0.000

Table 4. Estimation results based on the revenue share (Ally 2).

Dependent variable = log of Price

	2km			4km			8km		
Variables	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Lag price	0.268	***	0.045	0.314	***	0.050	0.276	***	0.064
Ally 2	0.003	***	0.001	0.008	***	0.002	0.012	***	0.003
Living area	0.999	***	0.032	1.019	***	0.033	1.033	***	0.035
One room	0.059	**	0.024	0.073	***	0.024	0.083	***	0.026
Two rooms	0.016		0.019	0.029		0.019	0.039	**	0.020
Three rooms	(reference)			(reference)			(reference)		
FAR (×1000)	0.010		0.085	0.028		0.086	0.004		0.088
Elevator	0.723	**	0.326	0.664	**	0.310	0.727	**	0.341
SRC	−0.009		0.021	−0.012		0.022	−0.003		0.024
Skyscraper	0.072		0.045	0.067		0.045	0.057		0.044
Large-scale	−0.033		0.043	−0.009		0.045	−0.018		0.045
Distance	−0.010	***	0.003	−0.010	***	0.003	−0.010	***	0.003
Constant	2.392	***	0.451	1.870	***	0.487	2.152	***	0.595
Lag error	0.374	***	0.090	0.381	***	0.107	0.440	***	0.111
Ward	Yes			Yes			Yes		
Train line	Yes			Yes			Yes		
Zoning	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
Observations	599			599			599		

Note: ***, ** indicate significant at 1%, and 5%, respectively.
Average number of the condominiums in the submarket: 56.7 in 2km; 176.9 in 4km; 437.8 in 8km.

Misspecification tests based on the OLS regression without Lag price

Spatial dependence tests	Statistics	*P*-value	Statistics	*P*-value	Statistics	*P*-value
LM lag	163.25	0.000	140.90	0.000	98.31	0.000
LM error	55.31	0.000	50.49	0.000	31.24	0.000
Robust LM lag	148.72	0.000	115.31	0.000	93.75	0.000
Robust LM error	40.78	0.000	24.90	0.000	26.68	0.000
Moran's *I*	9.28	0.000	8.61	0.000	8.10	0.000

Heteroskedastticity tests	Statistics	*P*-value	Statistics	*P*-value	Statistics	*P*-value
MS	20.87	0.000	24.34	0.000	20.21	0.000
Im	19.64	0.000	22.15	0.000	20.11	0.000

Normality tests	Statistics	*P*-value	Statistics	*P*-value	Statistics	*P*-value
Skewness	0.41		0.48		0.45	
Kurtosis	3.70		3.54		3.51	
JB	29.21	0.000	30.43	0.000	26.27	0.000
Adj JB	30.06	0.000	31.13	0.000	26.90	0.000

Table 5. Estimation results based on the spatial weight matrix defined 0 if properties are built in different years.

Dependent variable = log of Price

	2km		4km		8km	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
(a)						
Lag price	−0.008	0.014	0.185 ***	0.059	0.231 ***	0.076
Ally 1	0.001	0.001	0.002	0.002	0.007 ***	0.003
(b)						
Lag price	0.006	0.015	0.190 ***	0.058	0.231 ***	0.072
Ally 2	0.002 ***	0.001	0.003 **	0.001	0.007 ***	0.002

Notes: *** indicates significant at 1% and ** indicates significant at 5%. Number of observation is 599.
Average number of the condominiums in the submarket: 14.3 in 2km; 43.6 in 4km; 106.4 in 8km.

Table 6. Estimation results: Including JV sample.

Dependent variable = log of Price

	2 km		4 km		8 km	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
(a)						
Lag price	0.274 ***	0.043	0.325 ***	0.046	0.297 ***	0.057
Ally 1	0.001	0.001	0.004 **	0.002	0.006 **	0.003
(b)						
Lag price	0.273 ***	0.043	0.316 ***	0.045	0.292 ***	0.056
Ally 2	0.002 ***	0.001	0.005 ***	0.001	0.007 ***	0.002

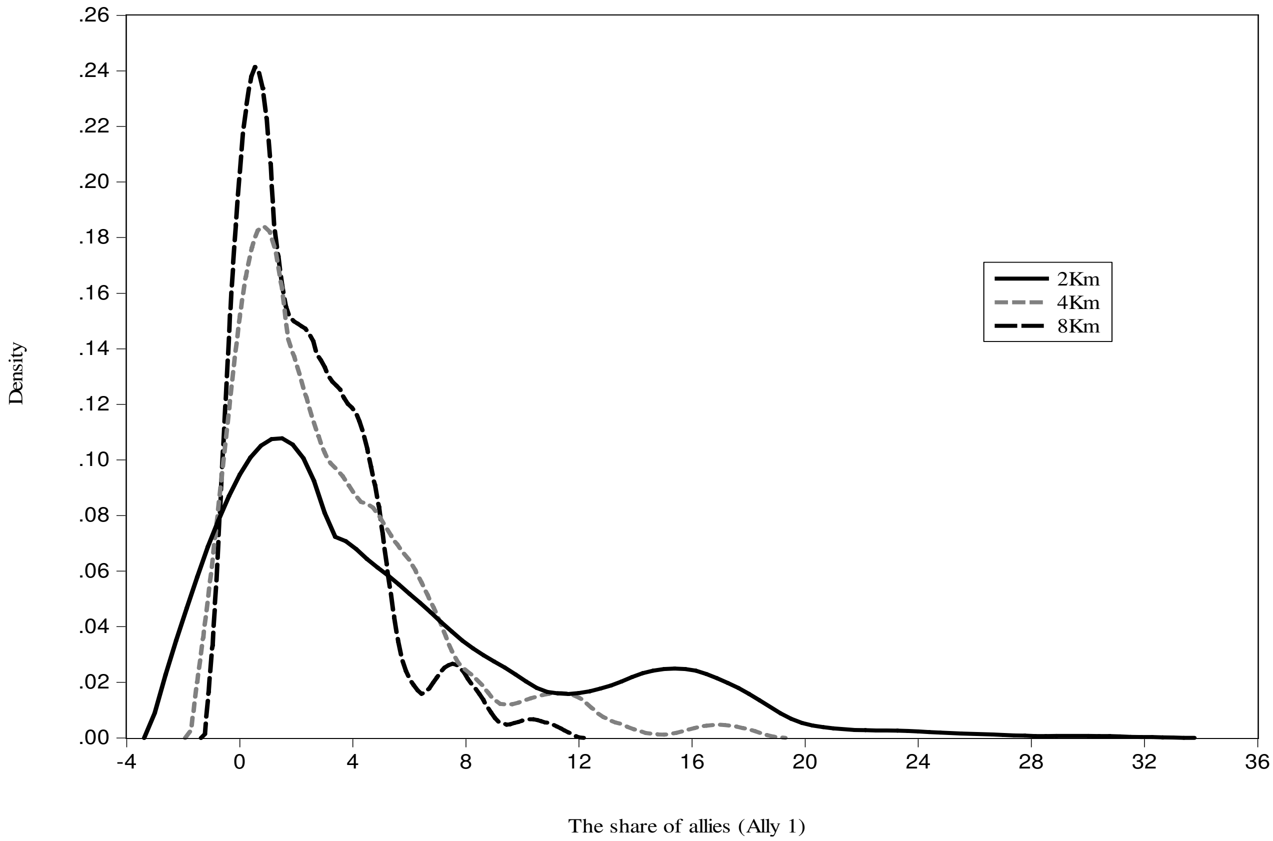
Note: *** indicates significant at 1% and ** indicates significant at 5%. Number of observations is 709.
Average number of the condominiums in the submarket: 60.8 in 2km; 193.4 in 4km; 500.0 in 8km.

Table 7. Estimation results: Including JV sample as an independent developer.

Dependent variable = log of Price

	2km		4km		8km	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
(a)						
Lag price	0.274 ***	0.044	0.318 ***	0.047	0.284 ***	0.058
Ally 1	0.001	0.001	0.007 ***	0.002	0.013 ***	0.004
(b)						
Lag price	0.270 ***	0.044	0.314 ***	0.046	0.279 ***	0.057
Ally 2	0.002 ***	0.001	0.007 ***	0.002	0.012 ***	0.003

Notes: *** indicates significant at 1%. Number of observation is 709.
Average number of the condominiums in the submarket: 60.8 in 2km; 193.4 in 4km; 500.0 in 8km.



Note: Lines refer to the densities of the ally's share calculated using Epanechnikov kernel with bandwidth is equal to 4.57 for 2-kilometer radius, 2.61 for 4-kilometer radius, and 1.63 for 8-kilometer radius, respectively.

Figure 1. The densities of the ally's share (Ally 1).