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Rent Capitalization of Access to Rail Transit Stations: Spatial Hedonic Models of Office Rent in Bangkok

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Abstract: We examined the rent capitalization of access to rail transit station in Bangkok. Because office rents are spatially autocorrelated, OLS estimation of hedonic models yields biased and inconsistent results. Therefore, we used the spatial econometric technique to remedy this problem. We measured access to rail transit stations by street-network distances from property to station. The distances were also the basis on which spatial relations among office rents were defined, and from which spatial weights matrices were constructed. We estimated spatial hedonic regressions from a sample of 85 office properties in Bangkok, using spatial lag and spatial error model structures. The results reveal that the monthly rent premium of being located nearer to a transit station by one kilometer is approximately 19 Baht per square meter, and the elasticity of rent with respect to the distance is -0.06.

Key Words: *access to rail transit station, office rent, hedonic model, spatial econometrics*

1. INTRODUCTION

In this paper, we examined the office rent capitalization of access to rail transit station in Bangkok. It is well known that improvement of rail transit system can influence real estate markets, both residential and commercial by increasing property values, and there is a long tradition in the literature in modeling and examining this effect in the U.S. and European countries. (See, for example, Parsons Brinckerhoff (2001) and Debrezion *et al.* (2003) for extensive reviews.) The reason for such interests in the research community stems from the need to measure the beneficial impact of transit improvement on the value of real estate properties, which can be captured and used to finance the improvement program. In Thailand and many other Asian countries where a vast amount of investment is required for construction of new transit systems, this source of revenue could prove a vital alternative to general taxes, which can scarcely cover other important public services. However, the extent of the impact of rail transit improvement on property value, also known in the academic literature as the rent capitalization of access to transit, must be well understood before any effective policy tools can be properly designed and implemented. In this paper, we hope to provide for the policy prescriptions with inputs from empirical research results in Asia.

The contribution of the paper is three-fold. Firstly, although many researchers studied the capitalization of access to rail transit station into residential property prices, few examined the impact of improved transit access on office-commercial property rent. Secondly, while this strand of literature is well developed in the U.S. and Europe, a handful of researchers in Asia devoted effort to understanding the impact of rail transit improvement on the real estate property markets. (Exceptions can be found in Bae, *et al.* (2003), Chalermpong (2007), etc.) This research fills the gap in the literature by providing systematic investigation of the relationship between access to rail transit station and office-commercial real estate market in Asia. Thirdly, as pointed out by several researchers (such as Can, 1992), the hedonic modeling approach, the most commonly used methodology for this type of research, can be improved by utilizing spatial dependence structure in the geographic data. While some researchers applied this methodology for modeling residential property prices (Rodriguez and Targa, 2004; Chalermpong, 2007), very few have done so for studying commercial property market (e.g. Kim and Zhang (2005)), and none, to the authors' knowledge, office property markets. Thus, another contribution of this paper is to provide an empirical example of how spatial econometrics can be applied in the hedonic modeling of office rent.

This paper is organized into six sections. Section 1 describes background and motivations of the paper. Section 2 provides an overview of the literature, focusing on recent evidence from hedonic studies of commercial properties, particularly those from Asia. Section 3 discusses the modeling approach, specifically the application of spatial econometrics in hedonic modeling. Area of study and data are discussed in Section 4. Empirical results are reported in Section 5. Finally, conclusion and policy implications are discussed in Section 6.

2. LITERATURE REVIEW

Hedonic regression technique, introduced by Rosen (1974), has been the predominant tool, which researchers use to examine the relationship between values of real estate properties and their characteristics. The hedonic models of property values usually include structural and building characteristics, amenities, services, and location-specific characteristics of properties as explanatory variables. A large body of literature focused on the impact of public transit improvement, often measured by the distance from property to transit station, and found that the impact on property value range from marginal to substantial (Vessali, 1996). A majority of the hedonic studies were conducted in the U.S. and European property markets, and mainly residential property markets were the subject under investigation. (See Parsons Brinckerhoff, 2001, for example.) There are two obvious gaps in the literature. First, the impacts of access to public transportation in Asian countries are neither well examined nor understood. This is particularly true in the case of countries where rail transit systems are relatively new, such as Thailand. Second, while the impacts of public transportation improvement on residential property market are extensively scrutinized, those on commercial property markets are not nearly as well examined. The comparative lack of research in the commercial property markets is common in North America and Europe and even more so in Asia. As the focus of this paper is on commercial properties, its literature review deals mainly with this type of property. Readers interested in residential properties are referred to Vessali (1996) and Parsons Brinkerhoff (2001) for more extensive reviews.

Commercial Property Values

Unlike empirical results reported in the studies of the impact of access to public transportation, which generally showed significant and often substantial impacts on residential property values, the studies of commercial property markets often revealed impacts that were rather mixed and inconclusive. Bollinger *et al*. (1998) reported that office rents of buildings within one mile radius of heavy rail transit stations in Atlanta metropolitan area were lower than those farther away, after controlling for structural characteristics of the properties, lease term, and other location-specific characteristics. Ryan (2005) examined the impact of the light rail transit system on office and industrial property markets in San Diego between 1986 and 1995. Like Bollinger *et al*., she found that the light rail system exerted insignificant impact on office rents, and in certain areas, she also found that the impact on rent was negative for office properties located near the light rail corridor.

Contrarily to negative results reported by Bollinger *et al*. and Ryan, Nelson (1999) found that commercial property values in Midtown area of Atlanta were positively influenced by access to heavy rail stations. However, the positive impacts might be partly attributed to the fact that zoning regulations in the area surrounding the stations were somewhat relaxed to encourage development. Cervero and Duncan (2001) examined the impact of commuter rail and light rail station on commercial land values in Santa Clara County, California between 1998 and 1999. They found positive impacts of commuter rail, and to a lesser extent, light rail on land values, reporting that properties within ¼ mile of commuter rail station commanded a premium of U.S. $25 per square foot and those within ¼ mile of light rail station commanded a premium of U.S. $4 per square foot.

The literature on the impact of rail transit station access on commercial property values in Asia in general is quite sparse, with South Korea as an exception. Kim and Zhang (2005) reviewed the Korean literature, and found several relevant studies, which reported significant value premiums of access to transit stations in largest cities in Korea. Unfortunately, these studies were available only in local language. Kim and Zhang studied the impact of access to subway station on commercial land values in Seoul, South Korea, measuring property values by appraised land value per sq.m. available from the local government. Based on the cross-sectional data set of 731 observations across the city, they found a substantial premium in commercial land value of US$7.54 per sq.m. for each meter closer to a subway station in the Seoul CBD, but the premium was smaller and even insignificant in other subcenters within the city.

Spatial Hedonic Modeling

It has long been noted by several researchers that the use of traditional OLS method of estimation, which ignores geographic features of the data, was not appropriate for hedonic modeling of real estate property values, due to spatial autocorrelation and spatial heterogeneity, common features of real estate property data (Can, 1992). In early research, researchers attempted to control for location-specific characteristics of properties by including variables that reflect convenience of transportation access, quality of public services, public safety, quality of the environment, which were specific to the location where the property was located. More recently, realizing that even the best effort to control for location-specific characteristics might fall short because of the lack of data, several researchers utilized the fact that these unobserved characteristics were often spatially correlated and began to use the spatial econometric technique to explicitly address the issue of spatial autocorrelation and heterogeneity (Haider and Miller (2000); Rodriguez and Targa (2004)).

In recent years, a few researchers have applied spatial econometric technique to hedonic modeling of property values in Asia (Kim and Zhang (2005); Shin *et al.* (2007); Chalermpong (2007)). Among these, Shin *et al.* and Chalermpong studied residential property values, and only Kim and Zhang examined the commercial land market. In general, researchers who applied spatial econometric technique to hedonic modeling reported somewhat consistent findings. First, they found that the technique improved statistical fit of the estimated models. Second, the impacts of access to transit station were overestimated by OLS. The value premiums of transit access implied by the coefficient in spatial hedonic model were somewhat lower than those implied by the OLS-estimated model. Third, statistical significance of certain explanatory variables as inferred by OLS might disappear after controlling for spatial autocorrelation.

As discussed in the review above, the literature on the impact of access to rail transit station on real estate property markets in Asia is still in development stage. While several researchers demonstrated the usefulness of spatial econometric technique in hedonic modeling which could greatly improve empirical results in this literature, few have done so to investigate the real estate property markets, particularly commercial property markets, in Asia. In this paper, we strive to contribute to the literature by applying the spatial econometric technique to hedonic modeling of office rent in Bangkok, Thailand.

3. MODELING APPROACH

The modeling approach consists of two main stages. First, we test for spatial dependence in the hedonic regression. This can be done by testing the hypothesis of spatial dependence among the errors from OLS estimation of the hedonic regression. The hedonic regression equation is specified as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{1}$$

where
$\mathbf{y}$ = N x 1 vector of office rent,
$\mathbf{X}$ = N x (p+1) matrix of characteristics variables of office property for rent,
$\boldsymbol{\beta}$ = (p+1) x 1 vector of coefficients,
$\boldsymbol{\varepsilon}$ = N x 1 vector of random errors,
N = number of observations, and
p = number of hedonic parameters.

Based on the OLS results, we test the hypothesis of spatial dependence, using Moran's I statistic as shown below (Anselin, 1993):

$$I = \frac{\boldsymbol{\varepsilon}'\mathbf{W}\boldsymbol{\varepsilon}}{\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}} \tag{2}$$

where $\mathbf{W}$ is the spatial weights matrix specified to reflect spatial relations among observations of dependent variable, $\mathbf{y}$. The weights matrix can be specified using many different criteria (Anselin, 1993; Brenner and Bao, 1998; LeSage 1999). Four criteria for spatial weights matrix specification are shown in Table 1.

The presence of spatial dependence can be detected by the significance of Moran's I, and the magnitude of Moran's I indicates the extent of spatial dependence based on the weights matrix, $\mathbf{W}$. Therefore, we select the criterion for weights matrix specification that yield the largest value of Moran's I.

Table 1 Criteria for spatial weights matrix specification

Criteria	Definition
Adjacency criterion	$w_{ij} = 1$, if observation *i* is adjacent to observation *j*; $w_{ij} = 0$, otherwise.
Distance criterion	$w_{ij} = 1$, if observation *i* is within the distance *d* of observation *j*; $w_{ij} = 0$, otherwise.
Generalized distance criterion	$w_{ij} = d_{ij}^{-a}$, where d_{ij} is the distance between observation *i* and *j*, and *a* is a constant.
k-Nearest neighbors	$w_{ij} = 1$, if observation *i* is among the k nearest neighbors of observation *j*; $w_{ij} = 0$, otherwise.

Once spatial dependence is confirmed, we cannot rely on OLS to produce unbiased or consistent estimates of coefficients. The second stage is to select the appropriate specification of spatial hedonic regression. The most general form of spatial regression can be written as follows (LeSage, 1999):

$$\mathbf{y} = \rho\mathbf{W}_1\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$
$$\boldsymbol{\varepsilon} = \lambda\mathbf{W}_2\boldsymbol{\varepsilon} + \boldsymbol{\zeta} \tag{3}$$

where ρ and λ are the autoregressive coefficient, $\mathbf{W}_1$ and $\mathbf{W}_2$ are the spatial weights matrices as defined earlier, and $\boldsymbol{\zeta}$ is a vector of well-behaved random errors.

In this paper, we test two special cases of the spatial regression in equation (3). First, when $\mathbf{W}_2$ is zero (i.e. the error term, $\boldsymbol{\varepsilon}$, is now well-behaved white noise), equation (3) is reduced to:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{4}$$

Anselin (1993) referred to this form of spatial regression as mixed regressive-spatial-autoregressive model, which is also known as spatial lag model.

In the other case, $\mathbf{W}_1$ is set to zero, and equation (5) becomes:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$
$$\boldsymbol{\varepsilon} = \lambda\mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\zeta} \tag{5}$$

In this model structure, the error term, $\boldsymbol{\varepsilon}$, becomes autocorrelated, and therefore the model is referred to as spatial error model.

Both model structures in equations (4) and (5) can be estimated by Maximum Likelihood method. See LeSage (1999) for details on the likelihood functions and estimation procedures. To choose between the two spatial dependence structures, we need to conduct hypothesis tests about the autoregressive coefficients. To test the spatial lag dependence structure, the null hypothesis: ρ = 0, can be tested using the Lagrange Multiplier (LM) statistic below (Anselin, 1993):

$$LM(lag) = \frac{(\boldsymbol{\varepsilon}'\mathbf{W}\mathbf{y}/\sigma^2)^2}{(\mathbf{WX\beta})'\mathbf{MWX\beta}/\sigma^2 + tr[\mathbf{W}'\mathbf{W} + \mathbf{W}^2]} \tag{6}$$

where **M** is the projection matrix, $\mathbf{I} - (\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}')$, and $\sigma^2 = \boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}/N$. The statistic is χ^2 distributed with one degree of freedom.

To test the spatial error dependence structure, the null hypothesis: λ = 0, can be tested using another LM statistic below:

$$LM(error) = \frac{(\boldsymbol{\varepsilon}'\mathbf{W}\mathbf{y}/\sigma^2)^2}{tr[\mathbf{W}'\mathbf{W} + \mathbf{W}^2]} \tag{7}$$

Based on the LM statistics, *LM*(*lag*) and *LM*(*error*) the appropriate specification of spatial hedonic regression can be selected. If neither statistics are significant, we can reject spatial dependence hypothesis and can use OLS estimation of the model. If only one of the two statistics is significant, we can choose the spatial dependence structure with significant LM statistic. However, if both statistics are significant, we need to estimate robust LM statistics (Anselin *et al*, 1996). Finally, we can then compare the value of robust LM statistics, and the model specification with greater value of robust LM statistic should be selected as the preferred model (Galvis, 2007).

4. AREA OF STUDY AND DATA

In this research, we examined the impact of access to rail transit stations on office rent in Bangkok metropolitan area. Two rail transit systems were opened in the last ten years, including the Bangkok Transit System (BTS) and the Mass Rapid Transit Authority (MRT) subway. The BTS, which began operation in late 1999, consists of two elevated heavy rail lines radiating from central Bangkok with 24 stations. The MRT, which began operation in 2004, consists of one semi-circumferential line originating from central Bangkok with 20 stations. (See Figure 1 for maps of the systems.) The combined ridership of the two systems in 2007 is approximately 600,000 passengers per day (Office of Transportation and Traffic Policy and Planning, 2007).

Bangkok is Thailand's largest metropolitan area with estimated population of 5.7 million within the city's jurisdiction and approximately 10 million when neighboring provinces are included (National Statistical Office, 2005). Silom and Asok are the city's two largest business districts, and Siam Square the city's largest commercial-retail district. All of these commercial centers are well served by rail transit systems—all are interchange stations, and the majority of office buildings in our sample are located within five kilometers of these centers. There are also several smaller commercial subcenters located along the rail transit lines, including Aree-Saphan Kwai, Ratchada, Chatuchak, and Thong Lor. Office buildings in these areas tend to be newer and less densely developed than those in Silom and Sukhumvit.

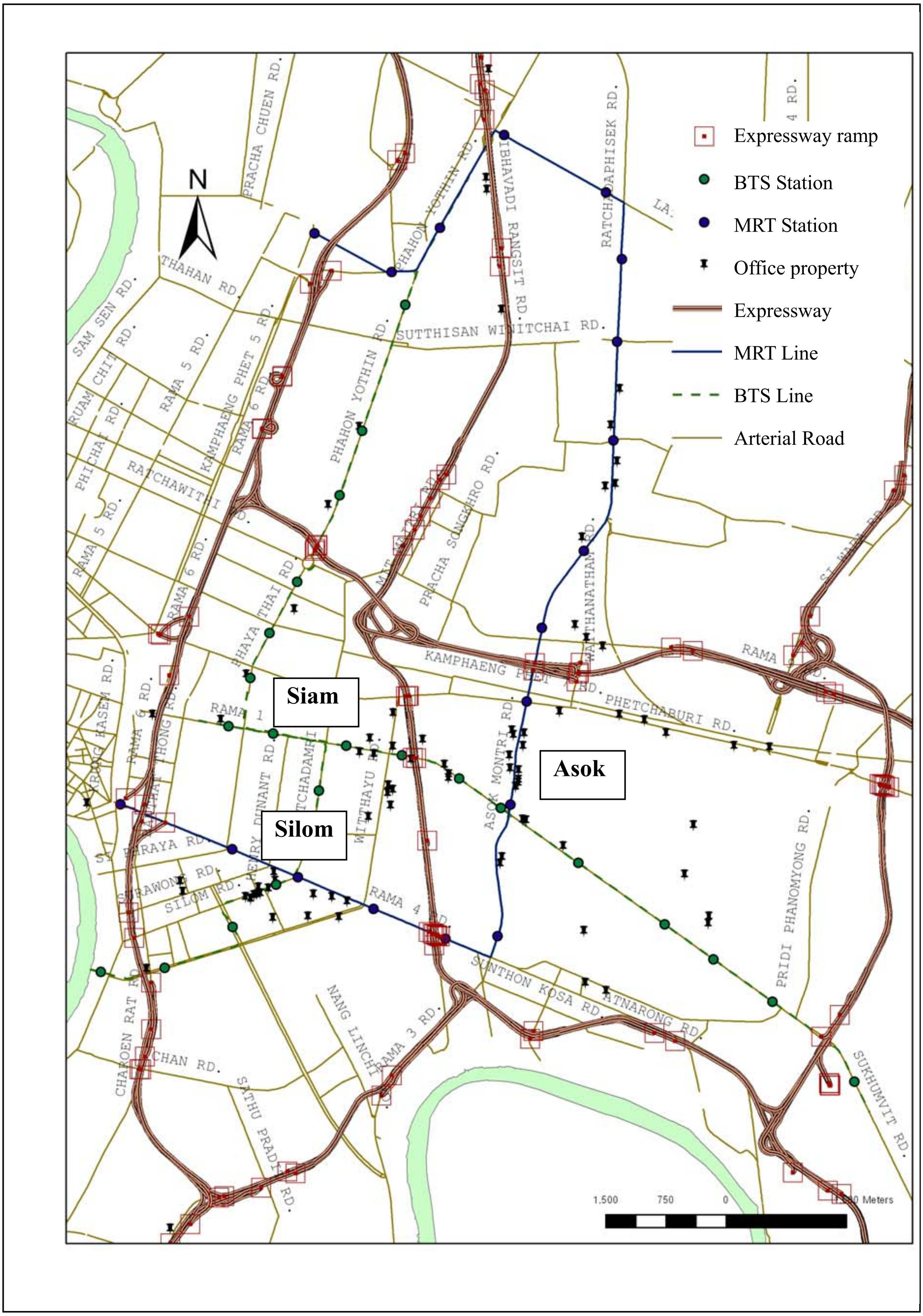

Figure 1 Map of Bangkok's rail transit systems and locations of sampled office buildings (ArcData, Bangkok, 2006)

We used the data from questionnaire interviews with managers or sales representatives of 100 high-rise office buildings in Bangkok between October 2007 and January 2008. To ensure the high quality of data, the surveys were conducted by real estate professionals, who are familiar with local market conditions. Figure 1 shows the map of Bangkok's rail transit systems and locations of sampled office buildings. As there are approximately 500 high-rise office buildings in Bangkok metropolitan area (Department of City Planning, 2005), the sample used in this study constitutes roughly 20 per cent of the population of interest. The interview consisted of questions regarding general characteristics of buildings, characteristics of office space for rent, amenities, services, rental contract terms, and office rent. After cleaning for incomplete or incorrect data, 85 records of office buildings were obtained for further analysis. Another important step of data preparation involved using ArcGIS® 9 software to generate spatial characteristics data, including distances to rail transit stations, other transportation facilities, as well as Bangkok's three main commercial districts. The software was also used to calculate the distances between office buildings, upon which spatial weights matrices discussed in the previous section were based. As Bangkok's streets are complicated and often do not follow hierarchical network structure, as those in a well-planned city, to measure spatial relations between properties and location-specific amenities like rail transit station as well as among the properties themselves, it might be necessary to use network distance to represent such spatial relations. Network distance is superior to aerial (straight-line) distance as a measure of spatial relations, as it reflects actual distance that needs to be covered in order to travel between two locations. Therefore, in this study, the distances were measured both as straight-line and network distances. Both were tested in the statistical models, and network distance was found, as expected to be a better representation of spatial relations among locations. Detailed description of data preparation can be found in Wattana (2008). Summary statistics of the data can be seen in Table 2.

Table 2 Summary statistics of the data for empirical analysis

Variables	Average	S.D.
Property characteristics		
Building age (year)	16.39	8.69
Floor	21.04	11.05
Number of elevators	5.83	5.62
Size of office space (sq.m./unit)	366.93	549.31
Monthly rent (Baht)	409.72	460.72
Electricity cost (Baht/unit)	5.64	1.96
Water cost (Baht/unit)	13.76	7.87
Distance variables		
Distance to rail transit station (meter)	1,601.13	2,276.25
Distance to arterial road (meter)	159.40	228.82
Distance to expressway ramp (meter)	1,481.07	995.85
Distance to Silom CBD (meter)	5,321.31	3,892.72
Distance to Asok (meter)	4,646.29	3,473.11
Distance to Siam (meter)	5,435.67	3,800.06

5. MODEL ESTIMATION RESULTS

Table 3 shows OLS estimation results of the linear hedonic model of office rent. After testing various combinations of variables listed in Table 2, we chose to include only five explanatory variables in the preferred hedonic specification. Among these five variables, two are measures of accessibility, namely distance to rail transit station and Silom dummy variable, defined as equal to 1 when the property is located within two km of Silom, and 0 otherwise. The estimated errors were then used for testing spatial dependence in the hedonic relationship.

Table 3 OLS Estimation results of the linear hedonic model of office rent

Variable	Coefficient	p-value
Dependent variable: monthly rent		
Constant	456.795	0.000
Building age	-2.329	0.105
Number of elevators	8.038	0.004
Air conditioning system	-90.380	0.000
(= 1, split type; = 0, centralized)		
Distance to rail transit station (meter)	-0.027	0.000
Silom dummy variable	104.111	0.000
(=1, within Silom area; =0, otherwise)		
Number of observations	85	
R^2	0.556	
Adjusted R^2	0.533	

Selection of spatial weights matrix

We used generalized distance and k-nearest neighbor criteria to construct several spatial weights matrices, which were in turn used to calculate Moran's *I* statistics as shown in equation (2). After testing several values of the parameter *a* for the distance criterion, we found that the value of Moran's *I* was maximized when *a* = 1. Then, we proceeded by calculating Moran's *I* using the weights matrices with different values of distance, *d*. Figure 2 shows the plot between Moran's *I* statistics against the distance. The calculation showed that, Moran's *I* was maximized at 0.334 when the distance, *d* = 800.

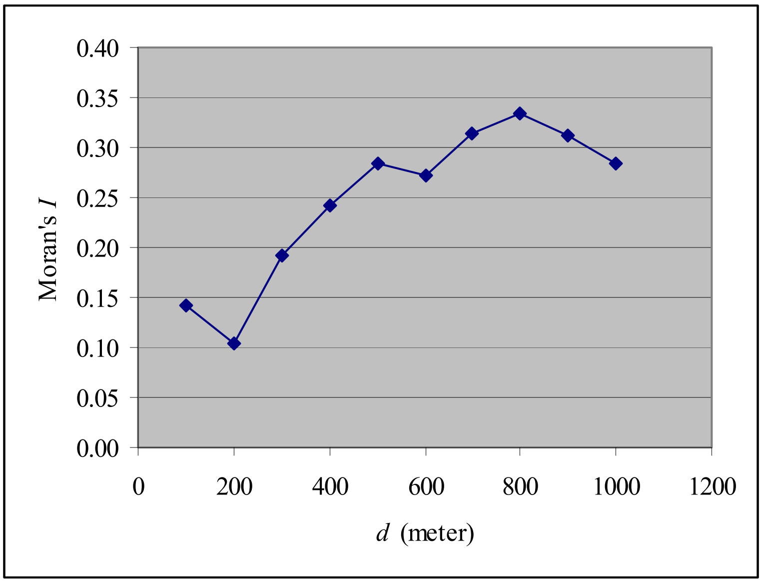

Figure 2 Moran's *I* statistics of spatial weights matrices constructed based on generalized distance criterion with constant *a* = 1

Figure 3 shows the plot between Moran's *I* against the number of nearest neighbors, k, which was the basis for constructing the spatial weights matrix. As can be seen, Moran's *I* was maximized at 0.408 when k = 5. Note also that the magnitude of Moran's *I* based on the weights matrix constructed using the 5-nearest neighbor criterion is larger than that based on the matrix constructed using the distance criterion. Therefore, we selected the former weights matrix for further analysis. Detailed discussion of spatial weights matrix specification and selection can be found in Wattana (2008).

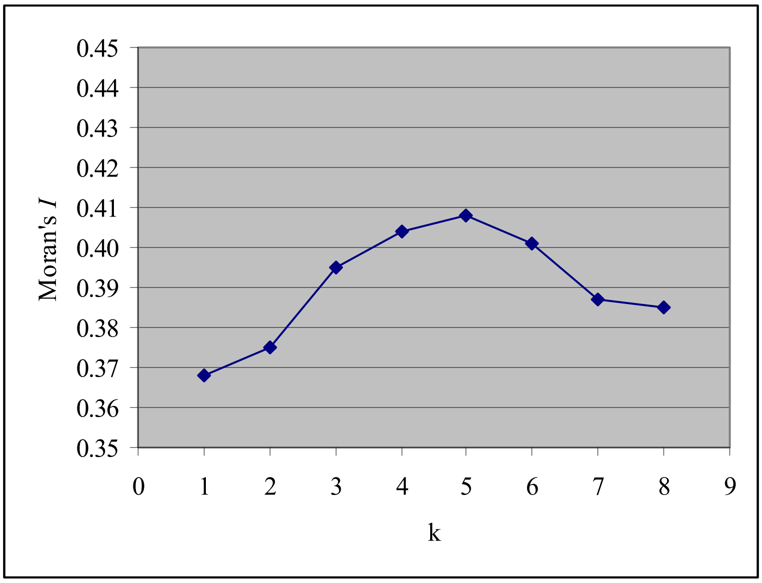

Figure 3 Moran's *I* statistics of spatial weights matrices constructed based on k-nearest neighbor criterion

Specification of spatial hedonic model

Using GeoDa™ statistical software, we estimated the two forms of spatial regressions discussed above, based on the 5-nearest neighbor spatial weights matrix. Table 4 reports spatial dependence statistics for the two spatial hedonic models.

Table 4 Spatial dependence statistics for linear hedonic specification

Statistics	Spatial Lag Model	Spatial Error Model
Lagrange Multiplier	7.595	3.851
	(0.005)	(0.050)
Robust LM	4.099	0.355
	(0.042)	(0.551)

Note: p-values are shown in the parentheses.

As can be seen in Table 4, LM statistics of both spatial lag and spatial error models are significant at the 95 percent level, indicating the presence of spatial autocorrelation in the hedonic model. This confirms that OLS estimates in Table 3 are biased and inconsistent, and thus statistical inferences, based on those results, incorrect. When we consider the robust LM statistic, however, only the statistic for the spatial lag model is significant. Therefore, we selected the spatial lag model specification for further analysis. The maximum likelihood estimation result of the spatial lag model is shown in Table 5.

As expected, the coefficient of spatial lag term is statistically significant as shown in Table 5. While the signs of coefficients in the spatial lag hedonic model are intuitively correct, their magnitudes are somewhat unexpected, particularly that of the distance to rail transit station coefficient. The result implies that for every 1000 meter closer to station, monthly rent would increase by only 19 Baht per meter. Variation in office rent can be explained in large part by the proximity to Silom CBD. Office properties in this area command the premium of 78 Baht per sq.m. per month, roughly 20 percent of average monthly rent. Table 5 also shows that the estimates of coefficients in the spatial lag model are smaller in magnitude than OLS estimates, reflecting OLS failure to capture the effect of spatial dependence, thereby overstating the effects of explanatory variables. It should also be noted that estimation of the spatial lag model provides better fit than does OLS, as shown by the value of the goodness of fit measure, R^2. Although this value is not very high, it is within the high range of values found in previous hedonic studies reviewed in Section 2. For example, the values of adjusted R-squared ranged from 0.308 (Cervero and Duncan's study of commercial land values in Santa Clara), 0.314-0.518 (Ryan's study of office rent in San Diego), to 0.44-0.59 (Sivitanidou's study of office rent in Los Angeles).

Table 5 Maximum likelihood estimation results of the spatial lag hedonic model of office rent

Variable	Coefficient	p-value
Dependent variable: monthly rent		
Constant	348.581	0.000
Building age	-2.143	0.107
Number of elevators	7.686	0.003
Air conditioning system (= 1, split type; = 0, centralized)	-89.969	0.000
Distance to rail transit station (meter)	-0.019	0.000
Silom dummy variable (=1, within Silom area; =0, otherwise)	77.647	0.001
Spatial lag, **Wy**	0.245	0.030
Number of observations	85	
R^2	0.587	
Log likelihood	-605.758	

We also estimated log-linear hedonic model, in which all variables are log-transformed. In this case, the coefficient of each variable can be interpreted as price elasticity with respect to that variable. The results of OLS estimation of the log-linear hedonic model, spatial dependence statistics, and those of ML estimation of the spatial log-linear hedonic models are reported in Table 6 through Table 8. As can be seen in Tables 6 and 8, coefficients estimates in the spatial lag model are smaller in magnitude compared to those estimated by OLS, except for Air conditional system dummy variable. The coefficient of rent variable estimated in the spatial lag model implies that rent is extremely inelastic with respect to distance to rail transit station, with the elasticity of -0.06. Other results follow similar pattern as those in the linear spatial hedonic model discussed earlier.

Table 6 OLS Estimation results of the log-linear hedonic model of office rent

Variable	Coefficient	p-value
Dependent variable: monthly rent		
Constant	6.703	0.000
Building age	-0.120	0.023
Number of elevators	0.138	0.003
Air conditioning system (= 1, split type; = 0, centralized)	-0.232	0.000
Distance to rail transit station (meter)	-0.085	0.003
Silom dummy variable (=1, within Silom area; =0, otherwise)	0.262	0.003
Number of observations	85	
R^2	0.552	
Adjusted R^2	0.528	

Table 7 Spatial dependence statistics for log-linear hedonic specification

Statistics	Spatial Lag Model	Spatial Error Model
Lagrange Multiplier	6.477 (0.011)	3.476 (0.062)
Robust LM	3.092 (0.079)	0.091 (0.132)

Note: p-values are shown in the parentheses.

Table 8 Maximum likelihood estimation results of the spatial lag log-linear hedonic model of office rent

Variable	Coefficient	p-value
Dependent variable: monthly rent		
Constant	5.153	0.000
Building age	-0.100	0.041
Number of elevators	0.132	0.000
Air conditioning system (= 1, split type; = 0, centralized)	-0.238	0.000
Distance to rail transit station (meter)	-0.060	0.042
Silom dummy variable (=1, within Silom area; =0, otherwise)	0.212	0.009
Spatial lag, $\mathbf{W}\,\boldsymbol{ln}\,\mathbf{y}$	0.226	0.042
Number of observations	85	
R^2	0.579	
Log likelihood	-10.318	

The unexpected lack of impact of access to rail transit station on office rent might stem from the nature of office property market in Bangkok. Unlike residential properties which were quickly developed following the opening of the rail transit systems, most large office buildings were already in place when BTS and MRT systems were opened in 1999 and 2004, respectively. Note that the average age of office buildings in the sample is over 16 years. Most of these office properties were already established by the time the transit systems were opened, and thus experience little change in the market as a consequence. Moreover, as noted earlier, high-rise office buildings in Bangkok are usually clustered in the three main commercial centers, which are well served by the rail transit stations. To many renters of office space in high-rise buildings, access to transit station may almost be guaranteed, and therefore does not much influence the rent.

The small rent capitalization of access to rail transit station might also be explained by some characteristics that are unique to Bangkok. The city's rail transit systems are relatively new and underdeveloped, with limited coverage of the metropolitan area. Access to transit stations is generally difficult because of the lack of amenities for pedestrians and limited and poorly coordinated transit feeder service. Hence, automobile is still very competitive with rail transit in many parts of the city, including commercial districts. To make the matter worse, Bangkok's ancient building codes require that a certain number of parking spaces be provided in commercial properties on the basis of floor area. This means that even in high-rise buildings located in the Bangkok CBD, ample parking space can be found, often free of charge. As a result, while access to rail transit station may be useful, it is not as highly valued by office property renters as some other characteristics of the property. The substantial premium of being located in Silom CBD shows that the most important determinant of office rent, as far as accessibility is concerned, remains agglomeration benefit, that is the benefit of locating close to other similar businesses.

6. CONCLUSION

In this paper, we applied spatial econometric technique to hedonic modeling of office rent, focusing on the impact of access to rail transit station on office rent in Bangkok metropolitan area. The application of this technique provided improved estimation results of the hedonic regression over those from OLS estimation, in terms of statistical fit and consistency in the coefficient estimates. The estimation results of spatial lag hedonic regression, based on 85 records of office properties, implied that access to rail transit station, as measured by street-network distance, exerts statically significant, but relatively small impact on office rent. Specifically, the monthly rent premium of being located nearer to a transit station by one kilometer is approximately 19 Baht per sq.m. In addition, the office rent is inelastic with respect to distance, with the elasticity value of -0.06. On the other hand, access to Bangkok's CBD, Silom district, is highly valued. Office properties located within the district command roughly 78 Baht per sq.m. in monthly rent higher than those outside the district.

The findings of this research add to the lack of consensus about the impact of access to rail transit station on commercial property values. In this case, although the impact on office rent is statistically significant, its magnitude is minute. This is contrary to the empirical results from hedonic studies of residential property prices, in which substantial premium of rail access transit station were consistently reported. Therefore, the evidence found in this study implies that value capture policies proposed vigorously by many researchers, based on the studies of residential properties, may not be effective in raising funds for rail transit investment from commercial property taxes.

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