Determining Transit's Impact on Seoul Commercial Land Values: An Application of Spatial Econometrics

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Literature regarding transit's impact on land values reports mixed results concerning the economic benefits of accessibility to subway stations, specifically regarding commercial properties. After examining 731 commercial land values in Seoul, Korea, this study suggests a possible explanation for the mixed results: transit's discrimination impact on land values by location in a built-up urban area. The regression coefficient for distance to station in the central business district is the highest, the subcenters are next, and other areas are lowest – apparently a strong correlation with higher centrality and development densities of submarkets. Also, the inclusion of spatial lag and error term variables greatly improves the goodness of fit of the regression equations lowering the spatial autocorrelation in the ordinary least squares residuals as well as reduces overestimation of value premiums in association with rail transit stations, which enables a regression model to produce a more accurate and efficient estimator for transit's impact on commercial land values.

Keywords

transit impact; transit-oriented development (TOD); land value, spatial autocorrelation; geographic information systems (GIS); spline regression

Introduction

Transit's impact on land values has been a challenging research issue for studies in real estate as well as in transportation and urban economics. Since public investment in a transit system is expected to decrease travel costs to activity centers, e.g. the central business district (CBD), the primary question is whether better accessibility to a transit station is correlated with higher land value premiums.[1] With a focus on single-family housing, most empirical studies have revealed significant price premiums for station proximity (Vessali, 1996), specifically in a geographical area close to and influenced by a station, the so-called 'station area.' However, zero or weak impact by station proximity was also reported. These mixed results look more striking in studies on commercial property. At one extreme, substantial capitalization effects on retail and office rent are found (Cervero et al., 2002), and at the other extreme, transit's impact on values looks insignificant (Bollinger et al., 1998). The mixed reports are theoretically problematic. In Alonso's model, commercial land values should be more sensitive to a change in travel cost than residential values, which makes the price elasticity to accessibility to a station for commercial use higher than that for residential one. Cervero et al. (1993) doubts that a transit system is now as dominant as one hundred years ago.

Possible explanations have been posited for the mixed reports on transit's impact on land values: a negative effect for residential properties close to station, e.g. dust and noise (TRB, 2002, p. 37). In commercial properties, the premiums are correlated with land use policies encouraging intensive development within station areas (Nelson, 1999). Also, the transit quality or service a station provides can make these differences (Landis et al., 1995). However, these explanations still leave an information gap regarding the role of station's location in the city.

Location not only makes amenity features of each property different from those of others, so-called 'heterogeneity,' but also affects the price for an equal amenity from one neighborhood to another, i.e. the 'submarket effect.'[2] The two spatial phenomena occur simultaneously in all categories of property amenities. One thing to note is that accessibility to transit stations is also an amenity that may be determined by location in the city.

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[1] In the literature, the market proxies frequently used to measure the benefits of station proximity are land values or commercial rent premiums based on the location theory in which the savings in travel costs are capitalized into higher land values or rents, i.e. the station's 'value-added' impact.

[2] A submarket can be defined as a geographic area where the market price per unit of an attribute is internally constant or homogeneous but differs substantially from others (Goodman et al. (1998)).

This paper asks whether station benefits are all the same across a metropolitan real estate market. If not, are they influenced by the urban spatial structure or the development densities of station areas as suggested by Nelson (1999) - will benefits increase more in dense station areas located in centers with higher centrality than in less developed areas? In that case, there is a systematic bias in measuring value premiums for station proximity by the location in the city. This may lead research sampled from the suburbs to conclude that transit's impact on land values in the city is insignificant where this economic benefit actually exists. The question is not whether a transit station influences nearby land values, but how and where location determines the impact.

Examining 731 commercial land values in Seoul, Korea, this study tests to see if accessibility to a transit station is discriminately capitalized by the urban spatial structure causing value premiums for station proximity to be highest in the CBD, moderate in the subcenters are next and low in other areas. This capitalization tendency is congruent with implications of the bid rent model but only in a built up urban area, i.e. the endogenous impact.[3]

An affirmative study provides the theoretical background to the conclusion by Nelson (1999), suggesting a possible explanation for the conflicting reports on transit's impact on land values and shedding light on a research risk with the hedonic model specification. Also, it implies that the potential for change in land use leading to more compact and denser development in station areas -- 'transit-oriented development (TOD)' -- seems higher in dense inner cities.[4] It's a piece of good news for an outstanding urban paradigm, 'compact city.'[5] The result also suggests that 'value capture,' a

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[3] The transit's impact on land values can be cautiously classified as 'endogenous impact' in a built up urban area and 'exogenous impact' in a non-urban area. Research in the former concerns a cross-sectional analysis of the city, usually using a hedonic price model which regresses the station proximity on property price or by comparing the real estate performance, e.g. rental levels, vacancy rates, and absorption rates, of properties within station areas with those of comparables away from stations (Cervero (1997)). Studies on the latter trace changes in land values before and after a transit investment, in which case accuracy depends on selecting truly ex-ante control cases (Cervero et al. (1993)).

[4] TOD has a variety of definitions but in general is regarded as compact and mixed use development close to transit stations which is conducive to transit ridership and eliminating auto trips. It is also legitimated to preserve open space and promote 'livable communities' and 'smart growth' (TRB (2002), pp. 2-7).

[5] 'Compact city,' a sustainable model for built up cities, is intended to induce higher density and mixed use development in the inner city with the support of efficient public transportation, e.g. transit systems, and by facilitating environment-friendly access modes such as walking and cycling. The claimed benefits sound dazzling: conservation of open space and natural environment, reduced auto travel and fuel emission, better access to services and development of more efficient infrastructure (Burton (2000), pp. 1969-1970).

financing method for transit joint development, may not be successful in a built-up suburb that already has some accessibility to employment centers.[6]

Another research question presented in this paper is the problem of spatial autocorrelation in the ordinary least square (OLS) residuals. Discriminately and unidentically distributed location attributes cause property value to be dependent upon nearby property values and the regression errors to be autocorrelated by the location in the city: that is, 'spatial autocorrelation.' If any form of autocorrelation exists in the OLS errors, it makes the estimation inefficient and the conclusion based on it problematic (Wiltshaw (1996)). Most literature describing spatial autocorrelation with an emphasis on housing prices reports that the inclusion of nearby property values or a spatially lagged dependent variable in the spatial autoregressive (SAR) model can reduce the spatial dependency of OLS errors.

This study questions whether an autocorrelation remains in the SAR residuals when important variables are unintentionally omitted. The general spatial autocorrelation (SAC) model that extends the traditional hedonic model to include the spatial lag and error term enables a regression model to produce a more accurate and efficient estimator for transit's impact on commercial land values.[7]

After the introduction of the literature in the following chapter, this study suggests a theoretical background that assumes that value premiums in a dense station area are higher than in a less developed one. After detailing model specifications, it explains the rationales for selecting Seoul and describes the research data. Testing hypotheses are discussed in Section "Empirical Result" which also shows the comparison of estimation performance. The test statistics are referenced to show a strong spatial autocorrelation in the OLS ones.

Literature Review of Transit's Impact on Land Values

Literature on transit's impact has three classifications: land use, land value, and urban form. Studies on land use impact concern the savings in total travel costs and land use change in suburban areas. Research on land value impact studies the capitalization of economic benefits resulting from better accessibility to stations, 'value-added effect.' Literature concerning urban

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[6] 'Value capture' is one of the most important rationales for transit joint development. It suggests that a transit development with expropriated properties near stations can finance project costs with increased land values and real estate taxes.

[7] However, it is not clear whether the use of the spatial autocorrelation technique can control for spatial elements of appraiser bias. This is an issue we recommend for future studies.

form can trace its origin to the earliest studies of the Chicago School sociologists who focused on transit investment and consequent urban form changes (Goldberg et al. (1984), pp 521-523).

Research on land value attempts to correlate the economic benefits of station location with cross-sectional data analysis using one of the following methods: 1) a quasi-experimental study using similar comparables from different locations, 2) the hedonic model regressing the property price or rent to accessibility to station, or 3) a hybrid of these two methods (Cervero, 1997). With a quasi-experimental approach it is difficult to discern various confounding variables of station proximity and to find the exact comparables without factoring in accessibility to a station (Cervero et al., 1993).

Some housing studies that have reviewed the economic benefits of station proximity report successful results. A study by McMillen et al. (2004) on Chicago's Midway Rapid Transit Line concluded that after opening the new line in 1993 the increase in value of single-family homes within station areas was greater than that in comparable areas farther from transit stations. Armstrong (1994) reports an approximate 6.7% market value premium on a single-family residence neighboring a rail transit in Boston. In a study by Benjamin et al. (1996) residential rents decreased by 2.4% to 2.6% for each one-tenth mile in distance from a Metro station in Washington D.C. Single family homes in Voith's study (1993) in Philadelphia showed a 7.5% to 8.0% value premium for accessibility to transit. Haider et al. (2000) also showed the effect of light rail transit (LRT) on housing prices in the Greater Toronto Area. In contrast, little or no impact by accessibility to station was also reported. A study by Gatzlaff et al. (1993) on the Miami Metrorail reported no effect with repeat sales data and weak distance impact with the hedonic model.

Unlike the housing studies, however, there have been very few studies of the capitalization benefits of proximity of rail transit to office or retail properties; results have been mixed. A study by Damm et al. (1980) on the Washington D.C. Metrorail found a significant price elasticity of –0.69 within 2,500 feet from a station. Studying retail and office properties in Santa Clara County, CA, Cervero et al. (2002) reported the premium was as much as 23% for a typical commercial parcel near an LRT stop and more than 120% for commercial land in a business district within a quarter mile of a commuter rail station. On the contrary, Cervero et al. (1993) in a study of Atlanta and Washington D.C. and Landis et al. (1995) in the San Francisco Bay Area reported small or no economic impact on commercial properties. Bollinger et al. (1998) concluded that the proximity to a highway interchange has a positive effect on office rents while being within walking distance of a MARTA train station reduces rents.

A possible reason for conflicting results in residential values may be the negative effect for properties close to a station, e.g., dust or noise. However, Dueker et al. (1998) researching Portland housing values concluded that the positive effect soon dominates the negative effect and creates the largest price differential ($2,300) between the station and areas 200 feet away. Another explanation can be inferred from Landis et al. (1995) who concluded that a heavy rail system is more likely to impact property values than a light rail system. What distinguishes stations with transit impact from stations without it may depend upon the quality of service. A finding by Nelson (1999) is most relevant to the mixed results on commercial properties and the focus of the study. It shows that commercial property values in midtown Atlanta are influenced positively by both accessibility to stations and policies that encourage more intensive development around those stations.

Studies in Seoul verified significant office rent premiums for accessibility to transit stations (Yang et al., 2001; Son et al., 2002; Lee et al., 2002). Some housing studies found that about 500 meters is a significant distance in setting a station area (Kim et al., 2002) and a turning point of modal alternative to autos (Kim et al., 2001). Using land price data, Kwon et al. (2001) found that distance impacts property values more significantly within station areas than in out-of-station areas. Seo et al. (2001) examined the market segmentation effects on land values in Pusan, the second largest city in Korea, and found that the value premiums for accessibility to transit stations are significant and important though less than the premiums for accessibility to the CBD. Studies on Seoul commercial rents dealt with three submarkets – however, none of them used the dataset across the city that limits results applied to the whole city. Still, no research has tried to measure the rent differentials and value premiums for station proximity created by different location factors.

Spatial Autocorrelation in Property Research

In the presence of spatial autocorrelation, the estimation and prediction with spatial models that extend the hedonic model to include the lag variable and/or the error term are more accurate and more robust than those with the OLS (Dubin, 2003). Since a major cause of positively autocorrelated error terms in research is the omission of key variables from the model (Dubin, 1998), earlier literature has asked if spatial dependency can be reduced by adding meaningful location or neighborhood variables. Dubin (1988) compared the OLS method and the ML method in the presence of spatial autocorrelation and discovered that the OLS under the spatial dependency is

biased but this bias can be alleviated by adding meaningful location or neighborhood variables. In her 1992 research, Dubin also eliminated all the locational attributes. Deriving housing prices from the nearby homes, he created a price contour map for Baltimore, MD. Basu et al. (1998), however, pointed out that derived housing prices could bring statistical noises when OLS was used.

Several studies have shown that the SAR model outperformed the OLS in the presence of spatial autocorrelation. According to Can (1992), the spatial lag variable can relieve the neighborhood quality effect and more efficiently trace the geographically disaggregated markets. A study by Carter et al. (2000) used the spatial lag variable to estimate retail shops rentals in shopping malls. By adjusting the spatial autocorrelation they found significantly improved regression results that confirmed the fitness of the regression equation.

Theoretical Background for Discrimination by Development Density

In the bid rent model, travel cost is more rapidly capitalized by a shorter distance to the CBD due to decreasing housing consumption, 'substitution effect.' Land rent can be defined as the price of rights to use a landowner's land per unit at a specific location in a city during a specific time period (O'Sullivan, 1996, p. 167). To construct a theoretical model for the capitalization of travel costs into land rent, assume a mono-centric city: a fixed and even density in the city and a single employment center to which commuting costs t dollars annually per mile. Travel cost of a household located at u miles from the CBD is equal to tu dollars annually. Households are identical: the number of workers per household and household income (Y) are the same for all households (DiPasquale et al. (1996), pp. 36-37).

Y can be spent only on non-housing (N), housing (H), and commuting (t). Housing consumption depends on land rent per unit ($R(u)$) at u miles from the CBD, i.e. the demand square foot (H) increases as $R(u)$ decreases, 'housing substitution.' Land is occupied by households that offer the highest rent. Then, the consumption of a household at u miles from the CBD can be written as follows:

$$Y = PN(u) + R(u)H(u) + tu \tag{1}$$

while P is the price of non-housing consumption per unit. [8] Partially differentiating Formula (1) regarding u produces the rent gradient at location u , as follows:

$$\frac{\partial R(u)}{\partial u} = -\frac{t}{H(u)} \tag{2}$$

At a given location (u), rent gradient ($\partial R(u)/\partial u$) is determined as travel cost divided by housing consumption ($H(u)$). Variations in housing consumption among different households make the rent function non-linearly related to u. With a shorter distance to the CBD, $R(u)$ increases faster than linearly as u decreases. The more elastic the change in housing consumption, the steeper the rent gradient is expected.[9] Since accessibility to a transit station is also a kind of travel cost, station proximity is assumed to be capitalized more than linearly with decreasing distance from a station to the CBD, i.e. the line-haul distance.[10]

The same model shows that travel costs are more easily capitalized in a denser city. With the land rent model, which assumes an even density distribution, only a brief illustration is possible concerning the influence of development density on the capitalization of travel cost. By transforming land rent in Formula (1) into a rental ($R(u)$) comprising land rent (L) and structure rent (S) with development density of D , then, $R(u)$ can be rewritten as

$$R(u) = L(u)\big/D + S \tag{3}$$

Suppose other assumptions still hold, then a new land rent gradient can be defined as

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[8] When a consumer's utility with the consumption of $N(u)$ and $H(u)$ is on the indifference curve, Formula (1) is in the equilibrium with the following requirement:

$$P \times \frac{\partial N(u)}{\partial u} + R(u) \times \frac{\partial H(u)}{\partial u} = 0 \,.$$

[9] The convexity of rent curve is also verified by differentiating Formula (2) regarding u , as follows:

$$\frac{\partial}{\partial u}\left[\frac{\partial R(u)}{\partial u}\right] = \frac{\partial^2 R(u)}{\partial u^2} = \left[\frac{t}{\{H(u)\}^2}\right]\left[\frac{\partial H(u)}{\partial u}\right] > 0 \,.$$

[10] More detailed approach with formulas is illustrated in the Referee's Notes and will be gladly provided upon request.

$$\frac{\partial L}{\partial u} = -\frac{tD}{H(u)} \qquad (4)$$

As development density increases evenly across the city, land rent gradient increases D times. However, this approach is applicable only when D represents an average density of a city, e.g. in a comparative study. All Formula (4) indicates is that transit's impact on land value is more easily capitalized in a denser city.

Nonetheless, if a station area is assumed to be an independent unit like a city, the capitalization of station proximity becomes steeper in a denser station area than in a less developed one due to the multiplier effect of density with travel cost of accessibility to station. If the land gradient is heightened by development density, the economic benefit of station proximity increases in centers with higher density.

Modeling Discriminant Transit's Impact by the Urban Structure

Literature on transit's impact on land values assumes that only one single regression coefficient ($\beta_{Station}$) exists across a city, as seen in Figure 1. This makes the equation look simple but ignores discriminant transportation demands from other locations in the city. In a city where the substitution exists as in Formula (4), the $\beta_{Station}$ should be conceptualized to capitalize the travel cost discriminately by the urban structure as seen in Figure 2. Then, there exist various $\beta_{Station}$ s regarding travel cost by location in the city: that is, the existence of submarkets with accessibility to stations.

Typical submarket models have focused on differential hedonic prices across metropolitan areas. The existence of submarkets is believed to contribute to spatial differences in structure/site characteristics, location features, and neighborhood amenities. In housing studies, segregation by race or income may also be an important factor for market segmentation (Vandell (1995)). Various structure and site characteristics may not be substitutes because the cost of transforming one into another is not negligible and location and neighborhood amenities are not easily replicated (Goodman et al. (1998)).

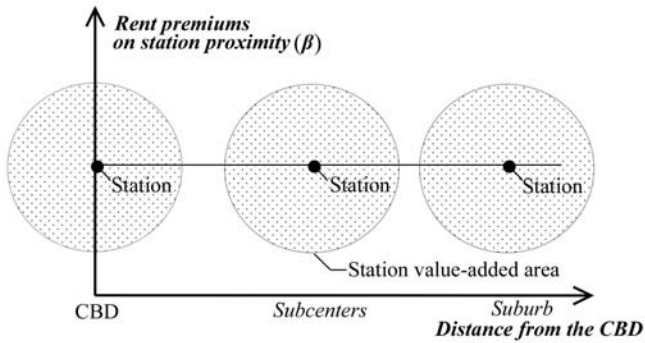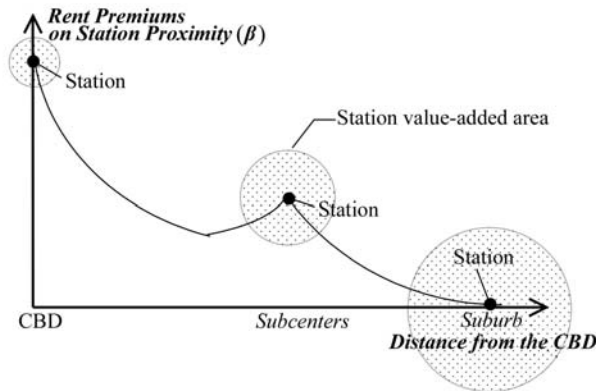**Figure 1: Single regression β on station proximity across the city**

Rent premiums
on station proximity (β)

Station   Station   Station

Station value-added area

CBD   Subcenters   Suburb
                            Distance from the CBD

Figure 2: Discriminant regression β s on station proximity in a polycentric city

Rent Premiums
on Station Proximity (β)

Station

Station value-added area

Station

Station

CBD   Subcenters   Suburb
                            Distance from the CBD

This study applies Can's (1992) methodological concept to submarkets within station proximity. Her spatial autoregressive study in segmented housing market extended the hedonic model to include the interaction between structure attributes and neighborhood quality scores in the model as follows (p. 459):

$$P = \alpha + \rho WP + \sum (\beta_{k0} + \beta_{k1} \text{NQ}) S_k + \varepsilon \qquad (5)$$

where P, NQ, and S_k denote the single-family housing prices, the neighborhood quality score and the vector of structural characteristics, respectively. In her study, W is the weight matrix for nearby dependent values and ρ is the coefficient estimate for the first-order spatial

autoregressive term.

This study compares the β_{Station} in a submarket i with other β_{Station} s in other submarkets using the interactions between β_{Station} and location dummies ($X_{\text{L}i}$), which takes a spline function form as

$$V = \beta_0 + \cdots\cdots + \beta_{\text{L}i} X_{\text{L}i} + \beta_{\text{DSTA}\times\text{L}i} X_{\text{DSTA}\times\text{L}i} + \cdots\cdots + \varepsilon \qquad (6)$$

$$\beta_{\text{Station}} = \beta_{\text{DSTA}\times\text{L}i} \qquad (7)$$

where V is land value, X_{DSTA} denotes distance from station and $X_{\text{L}i}$ is a dummy variable denoting the location i. This paper assumes a hierarchy of distribution of β_{Station} s by the urban structure: the absolute value of β_{Station} in the CBD is the highest; subcenters are the second highest and the suburbs are the lowest. This can be rewritten as

$$\left|\beta_{\text{StationInCBD}}\right| > \left|\beta_{\text{StationInSubcenter}}\right| > \left|\beta_{\text{StationSuburb}}\right| \qquad (8)$$

where $\beta_{\text{StationInCBD}}$, $\beta_{\text{StationInSubcenter}}$, and $\beta_{\text{StationInSuburb}}$ denote value or rent premium over accessibility to subway stations in the CBD, subcenter, and suburbs, respectively.

Estimation Model in the Presence of Spatial Autocorrelation

The literature has considered three main categories of attributes influencing property values: structure, location, and neighborhood attributes. The hedonic model can be denoted as

$$V = f(S, L, N) \qquad (9)$$

where S, L, and N are structure, location, and neighborhood attributes, respectively. Since this paper deals with the appraised land values, the structure category is not easily defined. In this estimation, only two categories will be considered: location and neighborhood attributes. The basic estimation model can be specified as

$$\text{Model 1:} \quad V = \alpha + \sum \gamma_k L_k + \sum \vartheta_k N_k + \varepsilon \qquad (10)$$

To test the hypothesis, the study divides location attributes by an equal number of submarkets, which revises Formula (10) as [11]

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[11] It is possible to extend all the variables to contain location dummies denoting submarkets.

Model 2: $V = \alpha + \sum (\gamma_0 + \gamma_{ki})L_k + \sum \vartheta_k N_k + \varepsilon$ (11)

while γ_{ki} is an additional value premium for location attributes only in a submarket i.

This paper extends the two hedonic estimation models to contain a spatially lagged variable (SAR) or a spatial error term (SEM) or both (SAC). Using a spatial lag variable produces a different economic meaning from using a spatial error term. The SAR implicitly assumes that the collective impact of the dependent variable in nearby properties, as well as the explanatory variables, affects each property's value. In contrast, the SEM implies that the omission of one or more key variables makes the errors spatially autocorrelated. Its focus is to correct error term autocorrelation, which enables an equation to produce more efficient estimates and ensures that the inference is correct (Kim et al., 2003, pp. 28-29).

The SAC is a mixed model of SAR and SEM which attempts to measure the weighted average of the dependent variable in neighborhood properties and to correct the autocorrelated error structure simultaneously. The study predicts that it outperforms the other two spatial models where important key variables are omitted. It takes an equation form as follows:

$$\begin{cases} y = & \rho W_1 y + X\beta \quad +\mu \\ \mu = & \lambda W_2 \mu + \varepsilon \\ \varepsilon \sim & N(0, \sigma^2 I_n) \end{cases} \quad (12)$$

where W_1 and W_2 are spatial weight matrices for the spatial lag variable and error terms, respectively. Also, ρ and λ are coefficient estimates for the spatial lag and the error terms, respectively. In Formula (12), in case W_1 is equal to W_2, there may be an identification problem. This study contrives W_2 as a second-order of disturbance structure, i.e. $W_1 ' \times W_1$, following LeSage's text (1998, p. 61). When the SAC reflects the existence of submarkets, the research model can be specified as

$V = \alpha + \rho W_1 V + \sum (\gamma_0 + \gamma_{ki})L_k + \sum \vartheta_k N_k + \lambda W_2 \mu + \varepsilon$ (13)
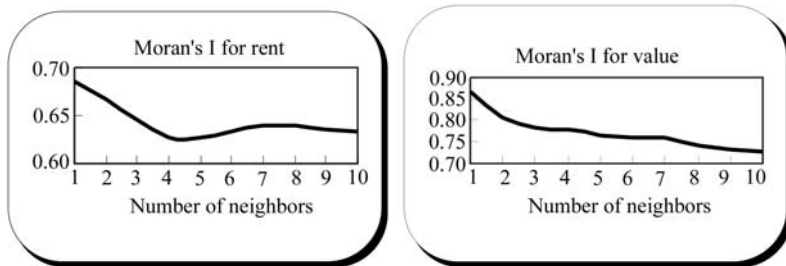

However, for two reasons the study considers only location attributes: first, main research focus is station proximity, a location attribute; second, since there exists a submarket with a small sample size, too many variables accrued by dividing every variable by the number of submarkets make the parameter estimates lose so many degrees of freedom that the significance of coefficients may be threatened.

Detection of Spatial Autocorrelation and Weight Scheme

Four asymptotic statistics are used to test spatial autocorrelation in the OLS errors ($H_0 : \lambda = 0$ or no spatial autocorrelation): Moran's I, likelihood ratio (LR), Lagrange multiplier (LM), and Wald test. Moran's I and LM statistics use the spatial weight matrix W_1 applied to the SAR, while the Wald statistic is calculated with the W_2 used in the SEM and λ, an estimate for error term autocorrelation from the SEM. The LR test uses the difference between the log-likelihoods of the SEM and the OLS, which is distributed as χ^2 (Cliff et al. (1973), Anselin (1988), and LeSage (1998)).

This study uses the k-nearest neighbor weight scheme,[12] which includes only *k* number of nearest neighbor's lag values or errors. It chooses one nearest neighbor scheme among the possible number of neighbors with the highest uni-variate Moran's I statistics for rent (0.6851) and value (0.8682) (see Figure 3).

Figure 3: Uni-variate Moran's I statistics for the *k*-nearest neighbor scheme

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Variables and Data Source

In Table 1, the dependent variable is the appraised land value per unit ($\$/\mathrm{m}^2$) announced annually by the Seoul Metropolitan Government (SMG), also available online. Since commercial properties are often large and rarely transacted, there is less market data than residential data, specifically in Seoul. Using the appraised value seems the only way to estimate transit's impact on commercial property values. There is a research risk in using the appraised value for the estimation since it may reflect the appraisers' valuation formula instead of the market values. Thus, recent studies tend to use transaction-based data in preference to the appraised data.

The location category in Model 1 includes the distance from the CBD (DCBD), from the nearest subcenter (DSUB), and from the nearest transit station (DSTA). All the expected coefficient signs are negative and distance decayed. In Model 2, location dummy variables denoting submarkets, the CBD (CBD), Kangnam (KNM), Samsung (SAM), and Yoido (YDO) replace DCBD and DSUB to avoid a multi-collinearity problem. Also, DSTA in each submarket is included to test the primary research hypothesis, i.e. DSTC for the CBD, DSTK for the KNM, DSTS for the SAM, DSTY for the YDO, and DSTO for other areas.

Two neighborhood variables are included in the model: 1) the location quotient of financial institutions (LQFI) in the local administrative district and 2) the zoning ordinance for each property (ZONE). The LQFI is based on business entity indices and the ZONE variable is a dummy indicating whether or not a property belongs to a commercial land-use.[13]

Address information geocoded with ARC-View GIS (geographic information system) is used for location category variables. The variables in the neighborhood category are primarily derived from annual public statistics. The LQFI is based on the 2003 Yearly Statistics of 25 Wards in Seoul. The ZONE comes from public land use confirmation by the SMG.

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[13] In advance, this study tested the impact of all types of zones on rent and land value. Specific zoning categorization was insignificant; only the dummy denoting if a property belongs to a commercial area showed significant signs.

Table 1: Variable description and data Source

Category	Variable		Sign	Unit	Description	Data source
	Common	Value				
Dependent	Common		NA	$/	Appraised land value of property	Public Appraised Land Value by the SMG*
Location	Model 1	DCBD	-	m	Distance to the CBD	Coordinates from ARC-View GIS
		DSUB	-	m	Distance to the nearest subcenter	Coordinates from ARC-View GIS
		DSTA	-	m	Distance to the nearest transit station	Direct distance measure using ARC-View GIS
		CBD	+	0 or 1	1 if property belongs to CBD submarket.	Coordinates from ARC-View GIS
		KNM	+	0 or 1	1 if property belongs to Kangnam submarket.	Coordinates from ARC-View GIS
		SAM	+	0 or 1	1 if property belongs to Samsung submarket.	Coordinates from ARC-View GIS
		YDO	+	0 or 1	1 if property belongs to Yoido submarket.	Coordinates from ARC-View GIS
	Model 2	DSTC	-	m	DSTA in CBD submarket	DSTA*CBD
		DSTK	-	m	DSTA in Kangnam submarket	DSTA*KNM
		DSTS	-	m	DSTA in Samsung submarket	DSTA*SAM
		DSTY	-	m	DSTA in Yoido submarket	DSTA*YDO
		DSTO	-	m	DSTA in Other Areas	DSTA*Other
Neighborhood	Common	LQFI	+	Index	Locational quotient of financial institutions in local administrative district	2003 Yearly Statistics of 25 Wards in Seoul
		PSRS	+	Persons	Daily passenger ridership of the nearest station (Leaving+Arriving)	Seoul Metro. Subway Co., Seoul Metro. Rapid Transit Co. and Korea National Railroad (2003)

*SMG is the abbreviation of the Seoul Metropolitan Government.

Site Description and Descriptive Statistic of Research Data

There are several reasons why the study selected Seoul: first, a denser city is more beneficial for measuring the capitalization of station proximity, as seen in Formula (4). Second, a city with a well-distributed subway system is more desirable for a cross-sectional analysis. Third, the subway system should play a meaningful role in total transportation costs in the city - that is, its share to total passenger trips should be significant.

The population of Seoul was more than 10 million (10,321,449) at the end of 1999. Since its area is approximately 635 km^2, its gross population density exceeds 163 persons per hectare. Considering only the developed area, Seoul's net population density is more than 300 persons per hectare. Currently, the Seoul subway system has eight operating lines and four lines under construction. The system serves all areas equally except for development-restricted areas as seen in Figure 4. According to actual traffic transportation shares per day in 2002, the subway shared 34.6% of total trips and conveyed more than 10 million passengers daily (Seoul Metropolitan Government, 2002, http://www.seoul.go.kr).

Figure 4: Seoul subway system along the street system

Allowing for land use changes to commercial uses and higher floor coverage ratios, the SMG encourages more compact and denser redevelopment in a station area. A detailed planning ordinance would cover an area within a 500-meter radius from a station, specifically stations with high passenger ridership or which are designed for passengers to transfer from one subway line to another.

This study disaggregates the site into four business centers, i.e. the CBD, Kangnam (KNM), Samsung (SAM), and Yoido (YDO). The CBD submarket, located at the center of Seoul, has a history of over six hundred years since Seoul became the capital of Korea in 1392. The other three submarkets, seven to nine kilometers (about 4.5 to 5.5 miles) from the CBD, have grown as the result of economic development of Korea and the policies of the SMG to disperse urban functions during the 1970s and 1980s. The SMG guided southward development after the Korean War to defend the capital's critical facilities against missiles in case of an unexpected attack from North Korea.

As shown in Figure 5, this study sets the radius of a business center as 2.0 kilometers for every submarket in which each nuclei is the property with the highest appraised land value. 119 properties belong to the CBD submarket, 67 properties to the KNM, 33 properties to the SAM, and 47 properties to the YDO, respectively. Dispersed widely across the city, 465 properties do not belong to the above submarkets. The surveyed properties above the Han River and in the southwestern part of Seoul are located along main artery roads which extend outward from the CBD. Offices in the southeastern part are widely distributed along the grid street system which makes it difficult to find the central point.

Figure 5: Geographic distribution of research data

The surveyed properties tend to be located near the stations, particularly in the CBD, KNM, and SAM submarkets, as seen in Figure 6. However, since the subway lines in Seoul are to be built on the main artery roads, it can not be determined whether this pattern is attributed to transit accessibility or not. It is notable that the distance to stations seems to increase the farther away a

property is from the CBD.

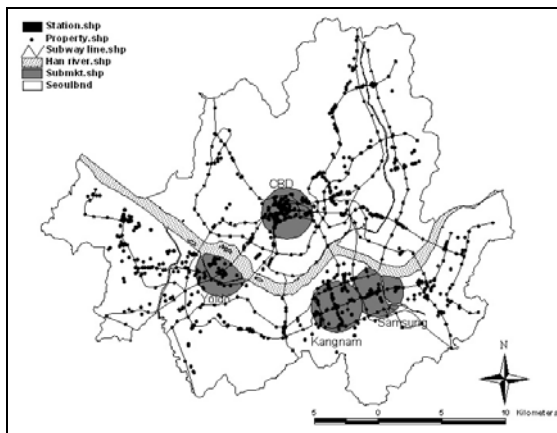**Figure 6: Distribution of research data along the subway system**

Table 2 shows the descriptives of the research data. The average appraised value in the CBD is the highest among the submarkets and values in the subcenters are next. Properties in the CBD have the best transit accessibility, while those in the YDO with only two stations have the poorest. The offices in the KNM and the SAM submarkets seem to be located within station areas. The location quotient of financial institutions, a proxy for the business service level, shows that these institutions are concentrated in the CBD and the YDO submarkets.

Table 2: Descriptive statistics of research data

Variable	Submarket	Total	CBD	KNM	SAM	YDO	Other
	Sample size	731	119	67	33	47	465
Land value	Mean	4833	9773	6904	6766	3744	3243
	St Dev	3708	5130	2723	3747	1682	1686
Dist. to CBD	Mean	7679	947	8102	9332	7197	9273
	St Dev	4095	484	990	837	737	3415
Dist. to subcenter	Mean	5839	6848	1247	901	942	7088
	St Dev	3875	778	508	607	539	3788
Dist. to station	Mean	399	214	369	422	597	429
	St Dev	378	138	264	208	358	425
LQ of Finc. Inst.	Mean	1.81	3.03	1.67	2.60	3.23	1.32
	St Dev	1.50	1.91	0.71	1.30	1.33	1.18

Empirical Results of Discriminant Transit's Impact in Seoul

Table 3 shows the estimation result of Model 1. Distance from the CBD (DCBD), the nearest subcenter (DSUB), and the nearest station (DSTA) show statistically significant and expected signs. In the neighborhood category, the location quotient of financial institutions (LQFI) and the zoning benefits (ZONE) seem statistically significant throughout the models. Clearly, the landlords of commercial properties discriminate among zoning benefits of a high floor coverage ratio in a commercial area.

Table 3 shows that the mean square error (MSE) from the OLS (8,461,114) is significantly reduced up to 50.0% with the SAR (4,233,706), 50.2% with the SEM (4,210,691), and 68.5% with the SAC (2,668,362).[14]   Table 3 confirms that the $Adj-R^2$ statistics from the OLS are obviously inflated in the presence of spatial autocorrelation. Compared with the SE s of OLS estimates, those of SAR and SAC are significantly lower but those of SEM are not definite. All the parameter estimates for ρ and λ are positive and significant, which means there is a positive spatial dependency in the dependent variable.

The estimation result of Model 2 is shown in Table 4. Location premium in the CBD is the largest, that in the Samsung submarket (SAM) is second highest, and those in the Kangnam (KNM) and the Yoido (YDO) are next. Of note is the difference between the SAM and the KNM submarkets when it is enlarged after eliminating the spatial dependency in the SAC. This hierarchy is also seen in accessibility to station, which partially backs the primary research hypothesis. Clearly, the coefficient of station proximity in the CBD (–7.54 for SAC) is the greatest, with those in the SAM (–5.88), the KNM   (–1.69), and the YDO (–1.31) following in descending order.

Though the economic benefits of station proximity in the overall city do not seem significant, they obviously exist in centers with high centrality and development densities. Also, it is noteworthy that the station benefits in Kangnam submarket and other areas look significant in the OLS estimation (t-values are –2.15 and –2.19, respectively), but they lose their significance after reducing the spatial autocorrelation with the spatial models, specifically the SAC (t-values are –1.77 and –1.13, respectively). Therefore, in the study, the estimation with the spatial models seems more beneficial than that with the OLS to produce a more efficient and robust parameter estimate for transit's impact on commercial land values. In the neighborhood category,

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[14] This percentage is calculated as: $\% = (MSE_{OLS} - MSE_{SM})/MSE_{OLS}$, where SM represents a spatial model, i.e. SAR, SEM or SAC.

all the variables seem significant throughout the models.

Table 3: Results of Model 1 in value estimation

Variable	OLS			SAR			SEM			SAC		
	Coeff	S.E.	t-stat	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t
Constant	6729.97	433.63	15.52 **	3350.78	241.35	13.88 **	7040.48	492.07	14.31 **	3547.34	258.81	13.71 **
Dist to CBD	-0.33	0.03	-11.31 **	-0.17	0.02	-9.10 **	-0.35	0.04	-9.20 **	-0.18	0.02	-9.02 **
Dist to Subcenter	-0.08	0.03	-2.88 **	-0.04	0.02	-2.14 *	-0.09	0.04	-2.48 *	-0.05	0.02	-2.27 *
Dist to Station	-1.54	0.30	-5.15 **	-0.82	0.21	-3.96 **	-1.11	0.32	-3.47 **	-0.79	0.21	-3.75 **
LQ of Fincial Inst.	621.23	78.90	7.87 **	295.29	53.41	5.53 **	297.92	74.75	3.99 **	276.40	54.58	5.06 **
Zone (Commercial)	840.58	257.15	3.27 **	709.32	181.99	3.90 **	1199.50	220.01	5.45 **	780.83	186.35	4.19 **
ρ		NA		0.47	NA	18.91 **		NA		0.43	0.02	18.89 **
λ		NA			NA		0.48	0.02	20.25 **	0.25	0.01	33.31 **
Adj-R²	0.3847			0.3847			0.6912			0.8043		
σ^2	8461114			4233706			4210691			2668362		
log-likelihood	-7095			-6447			-6450			-5900		
WT Scheme	NA			W_1			W_1			W_1, W_2		

Significance at **1% and *5%. Dependent Variable is the land value per square meter. Number of observations is 731.
Weight scheme used in this study is the one nearest neighbor. $W_2 = W_1 * W_1$.

Table 4: Results of Model 2 in value estimation

Variable	OLS			SAR			SEM			SAC		
	Coeff	S.E	t-stat	Coeff	S.E	Asymp-t	Coeff	S.E	Asymp-t	Coeff	S.E	Asymp-t
Constant	2049.39	242.16	8.46 **	1095.21	181.39	6.04 **	2032.37	223.55	9.09 **	1155.23	178.87	6.46 **
CBD Dummy	7056.19	472.55	14.93 **	4411.64	339.84	12.98 **	7665.59	434.97	17.62 **	5037.00	330.43	15.24 **
Kangnam Dummy	4494.89	549.76	8.18 **	2702.56	416.56	6.49 **	4707.59	532.29	8.84 **	2952.67	429.86	6.87 **
Samsung Dummy	5572.03	1005.56	5.54 **	3889.21	775.85	5.01 **	5685.23	919.07	6.19 **	4566.76	758.42	6.02 **
Yoido Dummy	550.35	729.87	0.75	359.22	566.71	0.63	723.60	723.81	1.00	453.47	598.16	0.76
DSTA in CBD	-8.72	1.68	-5.20 **	-5.90	1.29	-4.56 **	-10.98	1.54	-7.11 **	-7.54	1.26	-5.96 **
DSTA in Kangnam	-2.57	1.20	-2.15 *	-1.45	0.93	-1.57	-2.97	1.16	-2.56 *	-1.69	0.96	-1.77
DSTA in Samsung	-6.19	2.13	-2.91 **	-4.90	1.65	-2.97 **	-6.21	1.87	-3.31 **	-5.88	1.55	-3.79 **
DSTA in Yoido	-2.04	1.07	-1.91	-1.25	0.83	-1.51	-2.12	1.06	-2.01 *	-1.31	0.87	-1.50
DSTA in Other	-0.60	0.28	-2.19 *	-0.34	0.21	-1.58	-0.44	0.25	-1.73	-0.24	0.21	-1.13
LQ of Financial Inst.	485.93	72.87	6.67 **	261.22	55.44	4.71 **	415.10	66.96	6.20 **	232.45	54.61	4.26 **
ZONE (Commercial)	1233.80	220.30	5.60 **	955.69	170.50	5.61 **	1236.57	205.30	6.02 **	1008.12	169.48	5.95 **
ρ	NA	NA		0.39	0.02	19.41 **		NA		0.35	0.02	18.58 **
λ	NA	NA			NA		0.26	0.00	98.41 **	0.25	0.01	38.41 **
Adj-R²	0.5523			0.5507			0.7617			0.8352		
σ²	6156749			3712871			3222705			2229314		
log-likelihood	-7201			-6372			-6322			-5810		
WT Scheme	NA			W_1			W_2			W_1, W_2		

Significance at **1% and *5%. Dependent variable is the land value per square meter. Number of observations is 731.
Weight scheme used in this study is the one nearest neighbor. $W_3 = W_1 * W_1$.

The SAC in Table 4 lowers the MSEs in value estimation by 63.8% for the OLS, 40.0% for the SAR, and 30.8% for the SEM. It is obvious that the $Adj - R^2$ statistics from the OLS are distorted and the SEs of its coefficient estimates can be reduced with the SAR and the SAC. The main reason for these results is the strong spatial autocorrelation in the OLS residuals (See Table 5).

Table 5: Test statistics for spatial autocorrelation in the OLS residuals

	Test	Model 1	Model 2
Moran's I tests	Moran I	0.76	0.69
	Moran I-statistic	16.10	14.70
	Marginal Probability	0.0000	0.0000
	mean	-0.0071	-0.0140
	standard deviation	0.0475	0.0476
LM tests	LM value	254.57	208.29
	Marginal Probability	0.0000	0.0000
	chi(1) .01 value	17.61	17.61
LR tests	LR value	380.05	257.32
	Marginal Probability	0.0000	0.0000
	chi-squared(1) value	6.64	6.64
Wald tests	Wald value	11931.53	5313.75
	Marginal Probability	0.0000	0.0000
	chi(1) .01 value	6.64	6.64

Summary and Conclusion

This study presented a case study of rail transit's impact on commercial property values in Seoul, Korea. It had two major findings. First, the economic benefits of accessibility to transit stations are discriminately capitalized in the Seoul real estate market: the hedonic price ($\beta_{Station}$) in the CBD is the highest while those in subcenters are next. Transit's impact exists on commercial land values in Seoul with a strong correlation with higher centrality and development densities. Specifically, after correcting the effect of spatial dependence of sample points, the study estimated a premium of US$7.54 per meter associated with the transit stations that were located in the CBD. The premium estimate was US$5.88 for those stations located in the Samsung subcenter. For Kangnam, another subcenter of Seoul, the premium estimate was US$1.69 with a marginal level of statistical significance. This finding suggests the importance of spatial sampling to the results of study that utilizes a conventional hedonic approach: a study heavily sampled from centers may find a significantly large premium over station proximity, whereas one concentrated in the suburbs may not find the same station benefit as in the inner city.

Second, presence of spatial autocorrelation caused statistical inefficiency as well as overestimation of location premiums in association with rail transit stations for commercial properties. In the CBD of Seoul, for example, the estimated value premium was inflated by nearly 16% ((8.72–7.54)/7.54) when the influence of spatial autocorrelation was left uncorrected. Overall, spatial models, i.e. SAR, SEM, and SAC, outperformed the OLS estimation in the presence of spatial autocorrelation. Inclusion of spatial lag and error term variables greatly improved the goodness of fit of the regression equations. Thus, based on results of this study it can be concluded that the spatial model is preferred to the conventional regression model to more accurately capture transit's impact on commercial land values.

The study findings regarding the endogenous impact on land values in a well developed urban area suggest why an additional transit investment would not be an incentive for a residential suburb to change its land use into higher density use, specifically when it has some accessibility to the CBD. In a city like Seoul, a spatially constrained city where expansion is very limited, a new transit investment may reinforce the centrality of centers and facilitate the concentration of business entities. The potential for more compact and denser developments within station areas seems higher in dense inner cities, specifically in an already built up urban area.

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