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The Effect of Spatial Autocorrelation in Analyzing the Relationship between the Characteristics of Walkable Neighborhoods and Multi-Family Residential Property Values

부동산 가치의 공간자기상관성이 보행친화적인 근린 주거환경과 공동주택 가격과의 관계 분석에 미치는 영향

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Contents

Ⅰ. Introduction

Urban planners and the advocates of the Smart Growth movement have been trying to reverse a current development pattern, often referred to as sprawl, which is characterized by auto-oriented, decentralized and incoherent patterns of development. They propose to change the perceived undesirable features of sprawl such as low density developments rigidly separated homes, shops, and workplaces; and a network of roads marked by huge blocks, into more town-centered, transit - and pedestrian - oriented features with a greater mix of housing, commercial and business uses. They also suggest preserving open space and other environmental amenities to enhance the quality of urban life. The key element of Smart Growth, as reflected in these ideas, is the concept of walkable neighborhoods. According to Emerging Trends in Real Estate – 1999(Emerging Trends in Real Estate - 1999) by Lend Lease Real Estate Investments and Price waterhouse Coopers, the market for the type of development Smart Growth encourages will continue to expand, and real estate values will rise the fastest in communities that incorporate characteristics of walkable neighborhoods, such as a concentration of amenities, a mix of commercial and residential uses, and a pedestrian-oriented configuration.

Recently researchers have been examining the validity of these ideas. One of the quantitative research approaches frequently used in the studies is to investigate the relationship between property values, as an indicator of the economic performance or market preference, and the physical attributes reflecting the characteristics of physical development patterns promoted by advocates of the Smart Growth movement. For example, Song and Knaap(2003) analyzed the impact of mixed land use on the prices of single family houses. Plaut and Boarnet(2003) also examined the association of housing values with neighborhood design attributes supported by New Urbanists. Such studies typically used price functions based on regression analysis techniques known as the hedonic price model.

One of the methodological concerns with the hedonic price model is the potential model bias owing to the use of property value data that are spatially autocorrelated. Spatial autocorrelation refers to the pattern in which observations from neighboring locations are more likely to have similar magnitude than by chance alone(Legendre and Fortin. 1989). This means that when data are spatially autocorrelated, their arrangement is not random, which violates one of the assumptions of regression models that data are independently random. The hedonic model using such data may have spatial autocorrelation in the residuals, which indicates that the model is systematically overestimating or underestimating the observed values, and thus misleads us to believe that some independent variables are significant, when in fact they are not.

The purpose of this study is to examine the significance of the relationship between physical characteristics of walkable neighborhoods, as are supported by advocates of Smart Growth, and multi-family residential property values using hedonic price models. More specifically, it quantifies physical neighborhood characteristics that are expected to promote walkability and measures their relationships to multi-family residential property values. The reliability of the estimated hedonic model is tested by examining the effect of spatial autocorrelation on the estimation of the hedonic price model. Assessed multi-family residential property value data in King County, WA, obtained in 2002, are used in the model estimation.

II. Literature Review: Measuring the Relationships between Property Values and Physical Characteristics of Walkable Neighborhoods

The walkable neighborhoods supported by Smart Growth are characterized by medium- to high-density residential development, a mixture of land uses that are close together to reduce or eliminate the need to drive between routine activities, for example well - connected street networks, and specifically improved accessibility to retail stores, transit, and recreational areas(Katz. 1994; Crane and Crepeau. 1998; Morrow-Jones, Irwin, and Roe. 2004; Song. 2005).

The concept of compact development is one of the key elements of walkable neighborhoods emphasized in Smart Growth. In general, the findings in previous studies indicate that the residential real estate market is not supportive of compact development. For example, Poor et al.(2001) investigated residents' preference to the water quality by means of residential property values using a hedonic model. The results obtained from the model using house sales data indicated that higher housing density is negatively related to sale prices. Song and Knaap(2003) examined the relationship between urban form measures and residential property values. In the model, two density measures(single-family residential dwelling unit density and population density) were included. Negative signs of both measures were consistently found, which revealed the consumers'preference for low population density and low dwelling-unit density.

Eppli and Tu(1999) examined four of the most complete examples of new urbanist developments and compared single family home prices to surrounding developments that were not planned. Included in several different regression models were attributes such as lot size, living areas, number of bathrooms, construction quality as well as some principles of new urbanism such as inter-connected networks of streets and blocks, a clear neighborhood center, mix of land uses, compact form, and pedestrian-oriented design with an emphasis on quality civic spaces. The findings indicated that the price differential between new urbanist communities and conventional suburban developments is statistically significant and of sizable magnitude in all cases. Asabere's study(1990) estimated the effects of neighborhood street pattern on the housing values using data from Halifax, Nova Scotia. The study identified two categories of streets - cul-de-sac and grid - and measured their impacts on house value. It was reported that the cul-de-sac generated a twenty nine percent price premium over the grid street pattern, supporting the hypothesis that the cul-de-sac attracts premium values.

Some researchers in the field of urban planning and transportation assessed the market preference for availability of transit options and transit oriented development(TOD). For example, Cervero and Duncan(2002) modeled the effects of proximity to light and commuter rail stations, and freeway interchanges on commercial-retail and office properties in Santa Clara County, California. It was found that substantial capitalization benefits were produced for a typical commercial parcel near a light rail transit stop and for commercial land in a business district within 0.25 mi of a commuter rail station. Ryan's study(2005) reported that access to highways is an important factor in estimating office property rents, while access to light rail systems is less significant. She also found that industrial firms in the San Diego area were not paying rent premiums to locate near highways or light rail transit.

Irwin(2002) estimated the marginal values of different open space attributes using a hedonic price model with residential sales data from central Maryland. Results showed a premium associated with a permanently preserved open space relative to developable agricultural and forested lands, which supported the hypothesis that open space is valued more for providing an absence of development, rather than providing a particular bundle of open space amenities. Shultz and King(2001) examined the effects of amenities related to open space on the housing value using the data from the 1990 census of housing. The findings indicated that proximity to the large protected natural areas and golf courses influenced housing values positively, while proximity to undeveloped and neighborhood parks influenced housing values negatively.

III. Methods

1. Research Design

Hedonic price models have been extensively used in research to investigate the effects of various factors on an item's price. It generally takes the form of linear regression where the variation in the price of an item is explained by a bundle of characteristics that affects it. In real estate economics, for example, a house can be broken down into different characteristics, such as the number of bedrooms, size of plot, and distance to the city center. A hedonic regression equation treats these attributes separately and estimates the price of each individual characteristic. Hedonic price models have proved to be particularly useful for estimating the value of so-called non-market environmental amenities, such as parks and open space(Mc Connell and Walls. 2005).

The proposed hedonic model is designed to examine the relationship between multi-family residential property values and the physical characteristics of a neighborhood reflecting the concept of walkable neighborhoods promoted by Smart Growth. Four physical aspects of a neighborhood are quantified(land use pattern, accessibility to open space, amenities associated with walking and transit, and development density) using GIS spatial analysis techniques, and then their associations with multi-family housing unit values are estimated. In order to obtain more robust results, the model is controlled for physical attributes of a property, regional location factors, and socio-demographic factors. Table 1 shows the list of variables considered in the model. Physical attributes of a property, or parcel level attributes, are fundamental factors determining property values. Attributes such as number of bedrooms, number of bathrooms, building quality, and dwelling age are commonly used in hedonic pricing models to appraise property values. The findings from the literature(Irwin. 2002; Thilbodeau. 2003; Brasington and Hite. 2005) generally note that the size of land(parcel) and the size of building are strongly correlated to property values. Socio-demographic factors are also thought to influence real-estate market outcomes(Mc Millen and Mc Donald. 1991). In the historical summary of the evolution of retail research, DeLisle(2005) notes that the evidence from the retail research indicates that the impact of consumers' age and ethnic characteristics on the performance of retail use is significant. The study of Cervero and Duncan(2004) examining the land-value impacts of neighborhood land-use and racial composition indicates that racial diversity lower residential property values, while average household income in the neighborhood work in the opposite way. Brasington and Hite(2005) confirm that the proportion of white residents and income level are positively related to the residential property value. Ring and Boykin(1986) note that the valuation of real estate must consider the age and income distribution of the community as they describe the status of economic support in the community. Regional location is one of the key environmental factors that need to be considered in the real estate appraisal because it influences

<Table 1> Summary of Variables Used in the Models

Variable	Description	Unit of measures	Type	Data Source
Dependent Variable				
val_unt_l	Logged property value per unit (land value/unit + improvement value/unit)	Log(dollar)	Vector	Parcel record data**
Independent Variables				
1) Property physical characteristics				
Untarea_l	Logged area of a parcel per unit	Log(sqft)	Vector	Parcel record data*
untsqft_l	Logged building sqft per unit	Log(sqft)	Vector	Parcel record data**
yr_built	Year when the building construction finished	Year	Vector	Parcel record data**
2) Neighborhood socio-demographic characteristics				
hh_income_l	Average household income in a neighborhood	Log(dollar)	Raster	Census data
hh_age	Average household age in a neighborhood	age	Raster	Census data
p_nowhite_l	Percent of non-white residents in a neighborhood	Log(%)	Raster	Census data
3) Regional location characteristics				
d_dwntn_l	Distance to Seattle Downtown	Log(ft)	Raster	Urban center data
d_ubct_l	Distance to the closest urban center	Log(ft)	Raster	Urban center data
4) Neighborhood Land use pattern				
prx_mf_l	Average distance to multi-family residential use	Log(ft)	Raster	Parcel record data*
prx_retser_l	Average distance to retail-service use	Log(ft)	Raster	Parcel record data*
prx_off_l	Average distance to office use	Log(ft)	Raster	Parcel record data*
p_mf_rcl	Percent of multi-family residential parcel area	-	Raster	Parcel record data*
p_retser_rcl	Percent of retail-service parcel area	-	Raster	Parcel record data*
p_off_rcl	Percent of office parcel area	-	Raster	Parcel record data*
LU_MIX	Land Use Balance(Entropy Index)	-	Raster	Parcel record data*
5) Accessibility to open space				
d_prks_l	Distance to the closest park in a neighborhood	Log(ft)	Raster	Park data
6) Amenities associated with walking and transit				
d_bustop_l	Distance to the closest bus stop in a neighborhood	Log(ft)	Raster	Bus stop data
st_acre	Street density in a neighborhood	ft/acre	Vector	Street data
sdwk_acre_rcl	Sidewalk density in a neighborhood	ft/acre	Vector	Sidewalk data
com_qlty	Average of commercial building quality score	-	Vector	Parcel record data**
7) Development density				
avgfar_l	Average of Floor Area Ratio in a neighborhood	Log	Raster	Parcel record data**

Note: * parcel record data from Washington Geospatial Data Archive(WAGDA) in 2002
** parcel record data from King County Department of Assessments in 2002

the relative accessibility of the property in terms of time and distance to important destinations(American Institute of Real Estate Appraisers 1987). Usually, regional accessibility has been gauged by various measures of access to the CBD, representing the influence of the bid-rent curve on property price as proposed in the urban economics literature.

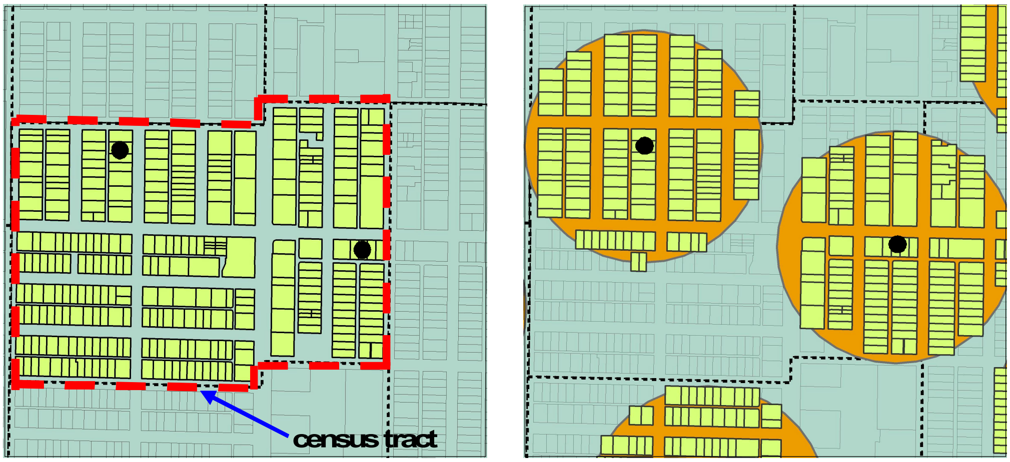
All independent variables, except for the physical attributes of a property, are neighborhood measures estimated within the boundary of a neighborhood defined as the quarter-mile(400m) radius buffer around the sample multi-family residential parcel <Figure 1>.

Employing a circular buffer around a sample point as the spatial unit of analysis allows for avoiding the data redundancy that occurs when multiple samples share the identical value of a neighborhood measure as a result of the use of a larger predefined spatial unit such as a census tract, census block-group, or transportation analysis zone(TAZ) as the boundary of the spatial analysis. <Figure 2>, for example, illustrates such a case and how the data redundancy can be reduced when the suggested neighborhood definition is used in estimating neighborhood measure. Given that two samples(points in black) are located in the same census tract(first figure of <Figure 2>, outlined in dark grey), using a census tract as the boundary of a neighborhood would produce the same neighborhood measure(e.g. population density) for the two observations(dots in black), while defining neighborhood as the buffer area around each sample(second figure of <Figure 2>, circles in dark grey) would produce different values for each sample.

<Figure 1> Illustration of Neighborhood Measure Estimation

This unit of analysis also allows capturing the characteristics of a neighborhood at a scale sensitive to the particular phenomenon of interest, by defining the appropriate extent of a neighborhood. Since the objective of this research is to assess the effects of physical characteristics of a neighborhood associated with the concept of walkable neighborhoods, the boundary of a neighborhood was established corresponding to the spatial range of people's walking behavior. Several studies provide useful information for determining the spatial boundary of a neighborhood affecting people's walking

<Figure 2> Illustration of Proposed Neighborhood Analysis



behavior. Ewing(1995) reports that people walk an average of 0.3 miles for shopping trips, 0.28 miles for accessing transit stops and family businesses, and 0.54 miles for social or recreational purposes, based on the 1990 National Personal Transportation Survey(NPTS) data and a walking speed of 3.16 mph. A case study conducted by the Federal Highway Administration(FHWA) to build transit catchment areas for determining walking accessibility to transit stops used one-quarter mile as the maximum distance that riders feel convenient to walk. Other studies examining pedestrian travel patterns also used one-quarter mile or 5 to 10 minutes of walking distance in defining the extent of a neighborhood(Rood. 2000; Dill. 2003). Based on the information from the existing literature, the current study used a one-quarter mile radius buffer around the sample multi-family residential parcels as a neighborhood boundary.

2. Methods to Deal with Spatially Autocorrelated Data

Property values may be spatially correlated for several reasons. First of all, property value is affected by its location because the location determines which factors come in to play, and to what extent the factors affect the price. This is referred to as spatial heterogeneity or proximity externality in the literature(Irwin. 2002; Thilbodeau. 2003). Second, the properties located in the same jurisdiction or neighborhood may have the same level of effects from certain factors. Factors such as access to public services, and distances from a city center or other important locations can be included in this category. This type of relative spatial effect is referred to as neighborhood effects in the literature(Sun, Tu, and Yu. 2005; Haurin, Dietz, and Weinberg. 2003). Third, although there is no causality, it is also possible that many properties with a similar price range and similar structural characteristics are concentrated in a small area; in this case, property values may change simply because values of other neighboring properties have changed.

Several methods have been suggested in order to deal with spatially autocorrelated data in a regression model. One is to design a statistical model that can either incorporate spatially dependent error functions(e.g. maximum likelihood(ML) model) or condition the parameters of the model on the coordinates of the observations(e.g. geographically weighted regression). Although such methods are known to improve the quality of predictions(Gress. 2005), they are computationally intensive. Another shortcoming of this approach is that it does not have the capacity to identify the causes of spatial autocorrelation(i.e. variables associated with neighborhood effects) owing to their methodological limitation.

On the other hand, researchers who are more interested in investigating the factors related to the neighborhood effects have been trying to find additional predictor variables that explain spatial autocorrelation. This method has come from the idea that, to quote Odlund(1988), “the ‘problem’ is not the presence of autocorrelation in the residuals but the absence of an explanation for autocorrelation in the model. The ‘solution’ is to develop a model that does account for autocorrelation.” To date, hundreds of articles have been published using price models that apply the estimation of a variety of neighborhood effects such as natural amenities(Weicher and Zerbst. 1973; Shultz and King. 2001), neighborhood design(Plaut and Boarnet. 2003), and land use characteristics(Song and Knaap. 2004). Empirical evidence, however, shows that it may be difficult to fully explain the spatial variation by adding locational variables or neighborhood attributes(Paez, Uchida, and Miyamoto. 2001).

Alternatively, ecologists and spatial statisticians have been trying to develop spatial sampling schemes to overcome the limitations of statistical models in correcting spatial autocorrelation errors. This approach aims at reducing spatial autocorrelation errors by using a noncontiguous subset of observations and by omitting observations that are spatially dependent. The advantage of this approach is that a standard probability model can be applied since the resulting error structure is presumed to be independent. Various spatial sampling schemes have been suggested to account for spatial autocorrelation such as Markov chain designs(Breidt. 1995) and simple Latin square sampling(Munholland and Borkowski. 1996).

Although the first method-designing a statistical model that can either incorporate spatially dependent error functions or condition the parameters of the model on the coordinates of the observations- resolves the problem of spatial autocorrelation in a regression model, it is computationally intensive, and does not provide information on the relationship between the features of a neighborhood and property values because of its methodological limitation. Since the primary interest of this research is to investigate the effects of physical characteristics of a neighborhood on multi-family residential property values, this research utilizes the other two approaches - i.e. by adding predictor variables, and by designing an appropriate spatial sampling scheme - to deal with the issue of spatial autocorrelation.

3. Examining the Effect of Spatial Autocorrelation on Hedonic Price Model

Two sets of hedonic model were estimated and their results were compared to examine the effects of spatial autocorrelation on the hedonic price model. The two estimated models were identical in terms of the model structure, but the samples used for each model were selected using different sampling schemes. In the first hedonic model, randomly selected multi-family residential samples were used. The second model employed a probability sampling method introduced by Haining(1993) and Irwin(2002) for selecting samples in order to reduce the spatial autocorrelation in the residuals. This sampling method draws a randomly selected subset of the data in which observations standing closer than specified distance are dropped out from the dataset(see Figure 3). This method has the advantage of creating better coverage of the area with lower information redundancy than simple random sampling. It also allows for using standard probability models such as linear regression because randomization is implemented in the sample data selection process. The sample selection was conducted in the GIS program using an ArcView extension called “Random Point Generator” developed by Jenness enterprises.

After estimating the two models, Moran’s index is measured for the residuals of each model to check the existence of spatial autocorrelation in the residuals. Moran’s index, generally referred to as Moran’s I, is commonly used to test statistics for spatial autocorrelation in univariate map patterns or in regression residuals(Tiefelsdorf. 2002). Given a set of features and an associated attribute, Moran's I evaluates whether the pattern expressed is positively correlated, negatively correlated, or random. Roran’s I values are in the range from approximately -1 to 1. The value near

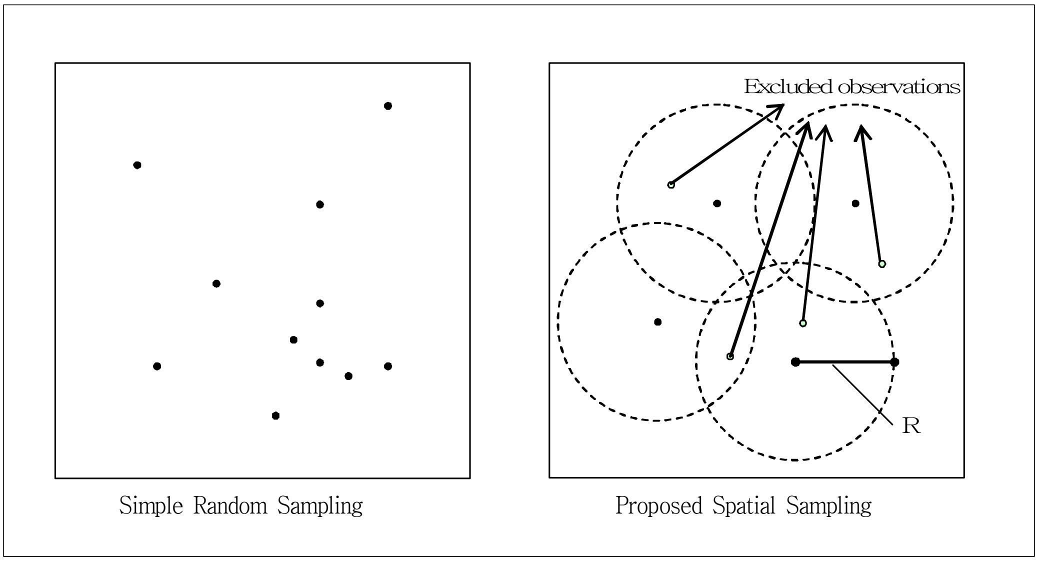
+1.0 indicates positive spatial autocorrelation and a value near −1.0 indicates negative spatial autocorrelation; with a zero result representing no spatial autocorrelation. The Moran's I function also calculate a z score value that indicates whether the spatial autocorrelation could be the result of random chance or is statistically significant. To determine if the z score is statistically significant, compare it to the range of values for a particular confidence level. For example, at a significance level of 0.05, a z score would have to be less than −1.96 or greater than 1.96 to be statistically significant. The computation of Moran's I is conducted using a standard ArcGIS tool called "Spatial Statistics".

4. Data

The study area is the urban growth area(UGA) of King County, WA. First established in 1985, the urban growth area has been used to limit growth to areas with an existing infrastructure for facilities and services. The City of Seattle and major suburban cities of the region such as cities of Bellevue, Kirkland, and Redmond are located in this area. Based on building permits issued by the cities and King County, more than 93 percent of new housing in the region has been built in urban growth area from 1994 through 2001(Ron Sjms. 2003, "Smart Growth, King County's Growth Management Initiative", http://www.metrokc.gov/smartgrowth).

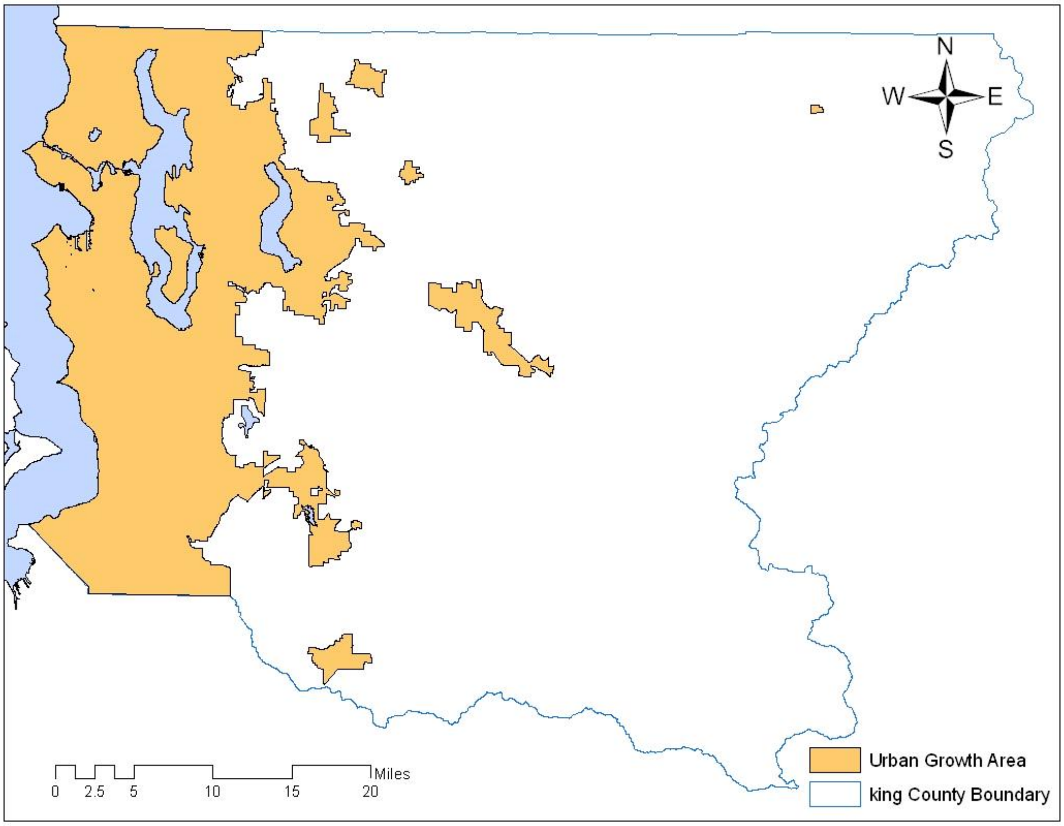
The primary data for this research are parcel

<Figure 3> Proposed Spatial Sampling Method



Note: R : Distance from the selected observation
Observations standing closer than the specified distance (R) to the selected onces are eliminated

<Figure 4> Study Area: Urban Growth Area in King County, WA



record data obtained from Washington Geospatial Data Archive(WAGDA) and King County Department of Assessments. The parcel record data contain basic attributes of individual parcels such as parcel boundary and size, as well as detailed information on parcels and their development status including land use types, physical attributes of buildings(e.g. number of bedrooms, number of bathrooms, fireplace, Floor Area Ratio, building square-footage, building quality, etc) and other miscellaneous information on individual parcels in addition to the assessed value data of land and building. A total number of 480,646 parcel records were available within the urban growth area.

In addition to the parcel record data, several GIS data sets providing information on public parks, bus stops, urban centers, street networks, and socio-demographic attributes are collected in order to measure neighborhood characteristics, which are then used as independent variables.

Ⅳ. Model Estimation

As discussed above, two sets of hedonic models were estimated in order to examine the effects of spatial autocorrelation on the results of hedonic model estimation. Both models used logged property value per multi-family housing unit as the dependent variable.

The first model was estimated using 508 randomly selected multi-family residential parcel samples. The results of Moran's I test for this model indicated that statistically significant positive spatial autocorrelation (Moran's Index = 0.26, Z Score = 24.964) existed in the residuals, confirming that the spatial autocorrelation in property value data was not sufficiently explained in the model. In the second hedonic model, a different sample data set was drawn using the spatial data sampling scheme, discussed above, in order to reduce the spatial autocorrelation in the dependent variable. This sample data set included 524 randomly selected multi-family residential parcels that were separated from one another by at least a quarter-mile(400m). The figures 5-4 A and B show the distribution of the locations of sampled multi-family residential parcels for the first and second hedonic models respectively. The

<Figure 5> Distribution of The Locations of Sampled Multi-Family Residential Parcels

(Sample A: Randomly selected samples) (Sample B: Randomly selected samples separated to each other by more than one-quarter mile) locations of sampled parcels in the second model were more evenly distributed and their clustering in the Seattle and Bellevue areas was weakened. The comparison of Moran's Index test results between the first and second models showed that the Moran's I scores changed from 0.25 to 0.002 with the Z score decreasing from 24.964 to 0.044, confirming that the spatial autocorrelation in the residuals of the model was sufficiently eliminated in the second model. These results confirmed that the hedonic price model using randomly selected multi-family residential parcel samples had statistically significant spatial autocorrelation in the residuals, indicating that the model failed to explain the spatial autocorrelation in the dependent variable appropriately, whereas the other model with the samples that were selected using the spatial sampling scheme successfully explained it. The result also demonstrated that the spatial sampling scheme in which the locations of the sampled parcels are spatially controlled is effective in reducing spatial autocorrelation in property value data.

The results of the two hedonic models are reported in <Table 2>. The explanatory power of the first model was slightly higher than that of the second model, but the difference was marginal.

In the first model, four physical neighborhood attributes(the average distance to retail-service use in a neighborhood, the average distance to office use in a neighborhood, the proportion of multi-family residential area in a neighborhood, and sidewalk density in a neighborhood) were found to be statistically significant. The increase of the average distance to retail-service use in a neighborhood(prx_retser_l) supported the increase of multi-family residential property values, while the average distance to office use(prx_off_l) influenced the multi-family residential valuesin a negative way. The multi-family residential property values were higher in a neighborhood where the proportion of multi-family residential parcel area was lower, showing the negative effect of the multi-family housing concentration. Better sidewalk coverage in a neighborhood increased the multi-family residential property values. None of the physical neighborhood attributes related to compact development(the average FAR in a neighborhood) and accessibility to open space(the distance to the closest public park) showed significant relationships to the dependent variable.

Among the three parcel attribute measures, the building square footage per unit and the year built were significant at the 0.01 level and were of the expected sign. The average household income in a neighborhood, the proportion of non-white residents in a neighborhood and the distance to Seattle downtown were also significantly related to the dependent variable.

Results from the second model showed that

<Table 2> Model Results for Multi-Family Residential Parcels

Variable	Model A				Model B			
	Beta	(Sig)	Standard Error	t	Beta	(Sig)	Standard Error	t
(Constant)	−2.178	−	1.472	−1.480	−5.037	***	1.823	−2.763
untarea_l	0.014	−	0.024	0.564	0.146	***	0.025	5.902
untsqft_l	1.107	***	0.042	26.354	0.846	***	0.045	18.833
yrbuilt	0.005	***	0.001	6.488	0.006	***	0.001	7.185
hh_income_l	0.114	**	0.045	2.539	0.058	−	0.047	1.227
hh_age	0.003	−	0.003	0.963	0.005	−	0.003	1.544
p_nowhite_l	−0.189	***	0.024	−7.981	−0.159	***	0.023	−6.892
d_dwntn_l	−0.292	***	0.031	−9.368	−0.378	***	0.031	−12.389
d_ubct_l	0.007	−	0.022	0.344	0.002	−	0.020	0.093
d_ramp_l	0.012	−	0.013	0.960	0.065	−	0.043	1.533
prx_mf_l	−0.039	−	0.039	−1.016	−0.007	−	0.037	−0.178
prx_retser_l	0.069	*	0.036	1.907	0.008	−	0.028	0.303
prx_off_l	−0.083	***	0.027	−3.056	0.030	−	0.034	0.877
p_mf_rcl	−0.069	**	0.032	−2.146	−0.002	−	0.030	−0.066
p_retser_rcl	0.005	−	0.029	0.181	0.025	−	0.033	0.753
_off_rcl	−0.004	−	0.031	−0.138	0.000	−	0.000	0.716
LU_MIX	0.000	−	0.000	−0.757	0.001	−	0.014	0.059
d_prks_l	−0.015	−	0.015	−0.989	0.003	−	0.014	0.252
d_bustop_l	0.011	−	0.018	0.619	0.000	−	0.000	0.972
st_acre	0.000	−	0.000	0.088	0.001	−	0.023	0.061
dwk_acre_rcl	0.042	*	0.022	1.872	0.063	***	0.020	3.138
res_grade	0.011	−	0.011	1.075	0.050	−	0.039	1.281
N				508				524
R Square				0.796				0.753
Adjusted R Square				0.786				0.743

Notes: Dependent Variable: Logged property value per unit(land value per unit + improvement value per unit)
* : significant at 0.1 level
** : significant at 0.05 level
*** : significant at 0.01 level

fewer independent variables were significant. Of the four physical neighborhood attribute significant in the first model, only sidewalk density was statistically significant at the 0.01 level. On the other hand, the significance level of parcel area per unit increased and became significant at the 0.01 level. Among the three control variables that were significant in the first model, the proportion of non-white residents in a neighborhood and the distance to Seattle downtown remained significant, but the average household income in a neighborhood lost its significance.

V. Discussion

For decades, advocates of new planning movement such as Smart Growth and New Urbanism have been trying to promote walkable neighborhoods as an alternative to auto-oriented development patterns. They claimed that creating walkable neighborhoods would enhance quality of life and stimulate the economic viability of communities, but little research has been examined the validity of such claims.

This research presented a quantitative research method to assess the market performance of the concept of walkable neighborhoods proposed by Smart Growth advocates. The hedonic model used in the research was designed to examine the relationships between multi-family residential property values and physical characteristics of a walkable neighborhood promoted by Smart Growth. The primary concern in the analysis was to examine the effect of spatial autocorrelation on the estimation of hedonic price model.

The findings indicated that better sidewalk coverage in a neighborhood was preferred in a multi-family residential property market. But the effects of other physical factors such as denser development density, mixed land uses, and provision of open space on multi-family residential property values were not significant. Moreover, the results presented that the effects of physical characteristics of a neighborhood on the property values were not as strong as those of other factors such as property attributes, regional location and socio-demographic factors. Although some studies reported that the urban environment promoted by Smart Growth policies became popular in the market, most of the findings from this research did not support such argument. Comprehensive case studies with sound research methods are needed in order to assess the effects of Smart Growth policies more clearly.

The comparison of the two hedonic models illustrated the effects of spatial autocorrelation on the hedonic price model were not negligible. Although its effect on the explanatory power of the model was fairly marginal and the directions of the relationships between the dependent variable and all independent variables that were statistically significant in both models were fairly robust, the significance levels for several independent variables were substantially over- or underestimated in the model that did not appropriately explain the spatial autocorrelation in the dependent variable. Such results give a clear warning that there is a possibility that, if the spatial autocorrelation in the property value data is not controlled, the analysis of the hedonic price model can be substantially biased and thus a defective translation of the statistical model may be produced. Therefore studies dealing with property value data should take the potential error from the effect of spatial autocorrelation into account and need to construct research design that can address this problem.

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ABSTRACT

부동산 가치의 공간자기상관성이 보행친화적인 근린 주거환경과 공동주택 가격과의 관계 분석에 미치는 영향

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※ 주요단어: 분산, 제조업의 지방분산, 지역화경제, 도시화경제, 고정효과(Fixed Effect) 모형

최근 국내외적으로 기존 도시성장 패턴의 폐해를 막고 자연환경을 보존하기 위한 대안으로 스마트성장에 대한 관심이 높아지고 있다. 스마트성장에서는 개발의 고밀화, 토지 이용의 혼합, 오픈스페이스의 보존, 보행 및 대중교통 위주의 도시 환경 조성 등의 원칙을 제시하고 있다. 그러나 이러한 스마트성장의 원칙에 대한 검증은 이론적으로나 경험적으로 아직 충분히 이루어지지 않고 있으며, 특히 미국의 도시계획분야 전문가들 사이에서는 기존의 도시개발 패턴에 익숙한 부동산시장이 스마트성장에서 제시하고 있는 새로운 계획원칙에 의한 도시환경의 변화를 긍정적으로 수용할 수 있을 것인지에 대한 의구심이 제기되고 있다.

시장 선호도 측면에서 특정 요인의 영향을 분석하는 일반적인 기법으로서 가격 데이터를 활용한 헤도닉 모형이 많이 사용되고 있다. 본 논문에서는 미국 워싱턴주의 킹카운티지역 공동주택 가격데이터를 이용한 헤도닉 모형을 측정하여 스마트성장의 계획 원칙들에 의해 형성되는 도시의 물리적 환경요인과 공동주택 가격과의 상관성을 분석하였다. 이는 스마트성장의 계획원칙에 대한 부동산 시장 측면에서의 효과를 검증하기 위한 시도다. 방법론적인 측면에서 본 논문은 헤도닉 기법을 사용할 때 문제의 하나로 지적되고 있는 공간자기상관성으로 인한 통계모델의 불안정성 문제를 해결하기 위한 새로운 공간 샘플링 및 공간분석 기법을 제시하며, 이러한 방법을 통해 실제 공간자기상관성이 헤도닉 가격 모형에 미치는 영향을 분석하였다.

연구결과 일반적인 무작위추출 샘플링 기법을 이용한 샘플 선택방법은 부동산 가격 데이터에 기본적으로 내재된 공간자기상관성을 효과적으로 제거하지 못하여 헤도닉 모형과 같은 선형회귀모델의 통계적 안정성을 상당히 저해하는 결과를 초래함을 확인하였다. 반면에 본 논문에서 제시한 새로운 공간 샘플링 및 공간분석 기법은 공간자기상관성에 효과적으로 대응하여 헤도닉 모델의 안정성을 개선하였다. 또한 본 논문은 공간자기상관성이 헤도닉 모델에 의해 측정되는 각 독립변수의 상관계수와 통계적 유의도를 왜곡시켜 잘못된 결론에 이르게 함을 확인하였다.