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Spatial Autocorrelation in a Retail Context

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This paper describes and applies the weighted least squares (WLS) technique that corrects for spatial autocorrelation in the residuals of hedonic regressions. Most empirical studies to date have focused on spatial autocorrelation in the housing market, i.e., single family home valuation. This study focuses on mall stores within shopping centers, with an emphasis on retail site selection within the mall.

Keywords

Spatial autocorrelation, hedonic modeling, bid rent, retail rents

Introduction

Spatial autocorrelation in real estate data has recently become an important topic for researchers interested in features associated with property location. Pace and Gilley (1997, 1998), in particular, have done a great deal to develop this important concept in the area of real estate. Wiltshaw (1996) also recognized the great importance of detecting and remedying spatial autocorrelation in the econometric analysis of valuation. As a result, some significant findings have been made on real estate issues that have been the subject of inquiry for some time.[1] Until recently, spatial autocorrelation was a topic that only geographers seemed to worry about. Griffith (1987). For geographers, spatial autocorrelation measures show definable patterns of

[1] For instance, no one had really explained in a statistically meaningful way the role of grid estimators as used by appraisers. Pace and Gilley (1998) concluded at 344:

> *Effectively, the grid estimator is the "poor man's" spatial autoregression. For very little effort one obtains in this case about half the gain of adopting the more efficient spatial autoregression. Given the technology present when appraisal evolved, coupled with the necessity of communicating their results, the grid estimator has and continues to suit the needs of the appraisal community.*

location characteristics on two-dimensional surfaces. For researchers in real estate, spatial autocorrelation is studied for the statistical improvements that can be gained in hedonic modeling.

Spatial autocorrelation is defined as the patterning of mapped residuals (across space) that may result from a hedonic regression. For instance, in the case of a hedonic model of housing prices containing independent variables of characteristics of the lots and houses, large positive residuals show up in one area (neighborhood) while large negative residuals show up in another area (neighborhood). When this happens, the ordinary least squares (OLS) assumption of independently and identically distributed residuals is violated.

Empirical studies so far have been in housing, because of the availability of data and because of familiarity with the kinds of hedonic models used. Dubin, Pace and Thibodeau (1999) in a recent article state that retail store location would be a prime problem for focusing on spatial autocorrelation. Just as in housing, stores in a shopping mall share location characteristics, and so statistical techniques designed to correct for spatial autocorrelation should be helpful. Carter (1999) has shown that store size (square footage), total rents and gross sales all vary based on stores' location within a shopping mall. [2] Accordingly, the assumption underlying hedonic models of independent error terms cannot be met.[3] Characteristics of mall stores will almost certainly be spatially dependent.[4]

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[2] The study used a modified bid-rent model fashioned after Alonso's (1964) bid-rent theory of the urban firm to demonstrate how store size and rents vary by location within shopping centers. Rents per square foot were found to increase while square footage was found to decrease with distance from a centroid point, consistent with a negative exponential density function.

[3] Model assumptions are:

1) *The mean of the probability distribution of e is 0. That is, the average of the errors over an infinitely long series of experiments is 0 for each setting of the independent variable x. This assumption implies that the mean value of y, E(y), for a given x is* $E(y) = B_0 + B_1x$.
2) *The variance of the probability distribution of e is constant for all settings of the independent variable x. For the straight-line model, this assumption means that the variance of e is equal to a constant for all values of x.*
3) *The probability distribution of e is normal.*
4) *The errors associated with any two different observations are independent. That is, the error associated with one value of y has no effect on the errors associated with other y values.*

Mendenhall and Sincich (1993): 105

[4] Heteroscedasticity is another problem that often arises with the use of location variables. It arises in the context of hedonic pricing models for housing when separate models are not used for neighborhoods. A wider variance for the error term results for

Following is a brief literature review on spatial autocorrelation, section two, while section three briefly describes the theoretical model explaining patterns of shopping center store location. Section four describes the data collected for this study. Section five reports the results of hedonic models regressing store rents on tenant, lease and location variables before and after corrections for spatial autocorrelation and section six gives concluding remarks.

Literature Review

Emphasis on location in the econometric analysis of the value-price question dates from the 1990s. A related advance in real estate valuation, the selection and weighting of comparables, was made by Vandell (1991). Before then, as pointed out by Wiltshaw (1996), emphasis was on "the usual topics: estimation techniques, multicollinearity, serial correlation, … ." In the past, simple hedonic pricing models for housing frequently left out variables having to do with features associated with the property's location. Problems arose regarding fulfillment of the assumptions underlying the multiple regression statistic and it was easier to omit location variables. Dubin (1988). Pace (1996) has chronicled attempts at using nonparametric means to get around dimensionality problems associated with hedonic pricing and mass assessment.

The notion of incorporating elements of spatial statistics into this area constitutes a relative breakthrough. Recent literature confirms that what might otherwise seem to be an accurate exercise in hedonic valuation using housing prices can be seriously flawed by spatial autocorrelation. Wiltshaw (1996): 280-283. Likewise, a study showing little or moderate value accuracy using hedonic pricing could in fact be very accurate after successful measures are taken to correct for spatial autocorrelation. Egregious econometric effects of the presence of spatial autocorrelation are the same whether in a spatial or serial context.[5]

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higher-priced properties, showing that higher-priced properties tend to sell over a broader range of variables (square footage, number of bedrooms, etc.) than lower-priced properties. WLS corrects for heteroscedasticity.

The same would apply to an hedonic model of shopping centers located in different areas of the country. Tenants with high rents and sales exist over a broader range of independent variable characteristics than tenants with low rents and sales. A shopping center in San Francisco is the equivalent of a house in a upper-class neighborhood, while a shopping center in Memphis is the equivalent of a house in a lower-class neighborhood.

Techniques that correct for spatial autocorrelation can use information contained in spatial residuals to improve the accuracy of predictions made from OLS equations. The techniques make improvements in predictive accuracy, change parameter estimates and their interpretation by controlling for omitted variables correlated with location, and improve inference. Dubin, Pace, and Thibodeau (1999): The same statistical improvements made in hedonic pricing models for housing should be expected from data in a retail setting.

A simple illustration derived from the geographic literature of spatial statistics may serve to demonstrate how corrections for spatially dependent error terms could be done. Griffith (1987), in his primer on spatial autocorrelation, sets out three different map patterns described by the letters (a), (b) and (c) (Figure 1). Let the spatial patterns for error terms be represented by the three boxes, with positive error terms represented by higher numbers (4, 5) and low negative error terms represented by lower numbers (1, 2). 5 represents a more positive error than 4, 2 represents a more negative error than 1, and 3 represents where the prediction of the hedonic pricing model falls near the actual sales price of the house.[6]

Figure 1 Patterns of retail location clustering

(a) similar values clustering

1	2	3
2	3	4
3	4	5

(b) random pattern

3	4	3
4	3	2
1	2	5

(c) dissimilar values clustering

4	1	4
2	5	2
3	3	3

It is intuitive that box (a) represents similar values clustering, (b) represents a random pattern, and box (c) represents dissimilar values clustering. The object in correcting for spatial autocorrelation is to weight observations in the data set so that the error terms of an hedonic model show a random pattern, like that of box (b). Once discovered, finding weighting schemes to ameliorate the problem becomes the task.

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[5] What is described here is first-order spatial autocorrelation.

[6] The patterns are diagrammatic only, emphasizing the relative locations of the errors.

Much of the most recent literature in this area undertakes development of correlation functions or algorithms for modeling spatial relationships existent in housing data. Only when a correlation function is found that models the spatial relationships can a weighting scheme be administered to the data to substantially reduce spatial autocorrelation. These studies are not directly relevant and no serious attempts are made here to completely eliminate spatial autocorrelation existent in the retail sample data. Our purpose is merely to show how the same principles apply in a retail context.

Model of Shopping Center Store Location Variables

Spatial autocorrelation in a residential context is concerned with neighborhood properties sharing location characteristics. Neighborhood influences on property values include similar-sized lots, similar housing vintage and other structural characteristics, similar socioeconomic status of residents and similar quality of public services. The theory on which the location variables of the empirical model used here is based is a modified Alonso (1964) bid rent model. To begin to correct for spatial autocorrelation in shopping centers we need an idea of how stores are located. We found that like land use in a monocentric city, stores' rent and size determine their location with respect to the center of the shopping center. Store rent and store size in a regional or super-regional mall are similar to land rent and lot size in an urban area, although they are driven by customer density instead of by transportation costs. Customer traffic is highest at the mall center, tapering off towards its periphery.

In the theory we assume a shopping mall as a bounded linear region one unit in length with anchor stores at each end. The mall is symmetric about its center at distance $t = 0$.[7] There are *n* types of mall tenants and each mall tenant *i* has the following profit function:

$$P_i = p_i \alpha_i u_i(A_i)d(t)A_i - C_{Fi}A_i - C_{Li} \alpha_i u_i(A_i)d(t)A_i - C_{oi}\alpha_i u_i(A_i)d(t)A_i - rA_I \quad (1)$$

where

P_i = total profit

p_i = price per unit of good sold

α_i = quantity of goods sold per purchasing customer visit

A_i = store area

$u_i(A_i)$ = proportion of customer traffic per unit store area that purchases

$d(t)$ = density of customer traffic as a function of distance t from the center

[7] See Carter (1999) for the full mathematical treatment of the model.

C_{Fi} = fixed costs unrelated to store area or sales volume (such as overhead)
C_{Mi} = quasi-fixed costs
C_{Li} = labor and operating costs dependent both upon sales volume per unit area and store area
C_{oi} = cost of goods sold, dependent both upon sales volume per unit area and store area
r = rent

The total number of purchases for a store of area A_i and a given level of customer traffic density, represented by the relationship $u_i(A_i)A_i$, exhibits decreasing returns to scale (i.e., $\partial u_i(A_i)A_i / \partial A_i > 0$ but $\partial^2 = u_i (A_i) A_i^2 < 0$). Thus stores have an incentive to limit size to a level where marginal revenue from an additional square foot of space is just offset by the marginal cost.

In terms of the profit function, optimizing profits for store area (A*) and rents (r*)[8] (suppressing subscripts i and assuming $u(A)A = k_1 A^{k2}$ where $0 < k_2 < 1$ represents decreasing returns to scale) yields

$$A^* = [C_F / \alpha\, d(t)\, k_1 (p - C_L - C_o)(1 - k_2)]^{1/k2} \quad (2)$$

$$\begin{aligned} r^* &= C_F [k_2/(1 - k_2)][\alpha k_1 (1 - k_1)\, d(t)\, (p - C_L - C_o) / C_F]^{1/k2} - C_M \\ &= C_F [k_2 / (1 - k_2)] / A^* - C_M \end{aligned} \quad (3)$$

The comparative statics of (2) include the optimal store area A* decreasing with increases in density of customer traffic d(t). Hence stores decrease in size as they are located closer to the mall center. A* increases with increases in fixed costs. Comparative statics of (3) include optimal rent r* increasing with density of customer traffic d(t). Hence store rent is highest at the center and drops at a rate $1/k_2$ with customer density. Optimal rent r* increases with an increase in price per unit of good sold p, but decreases with increases in fixed costs.

The model depends on the fact that d(t) is downward sloping with distance t from the center. Evidence of this is found in circulation studies of customer shopping in malls (Brown (1991) and Sim and Way (1989)), suggestions in the literature (Fisher and Yezer (1993) and Brown (1994)) and a simulation of customer traffic under reasonable assumptions by Carter (1999): 53-55.

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[8] Following Alonso (1964), normal profits are assumed and the mall developer extracts all excess rents from the mall stores. This fits with the notion of Pashigan and Gould (1998) that shopping centers internalize externalities.

The Shopping Center Data

Tenant, lease, and location data on non-anchor, mall stores from regional and super-regional shopping centers were supplied by two large American real estate investors that required confidentiality. The stores' names and specific

shopping center data were not to be revealed. The original database consisted of 1012 non-anchor tenants doing business during 1991 and 1992 from nine shopping centers located throughout the United States. Geographic diversity of the centers is as follows: Pacific 2; West North Central 1; East North Central 1; Southeast 2; Northeast 3.[9]

The centers are enclosed, of contemporary design, comparable in amenities and occupancy (near 100%), and competitive within the markets they serve. The shopping centers differed somewhat in size: from 503,000 square feet to 1,004,000 square feet with an average size of 828,600 square feet. Six of the malls were single level, two had two levels, and one had three levels.

Descriptive statistics for this sample are displayed in Tables 1 and 2. Table 1 shows non-anchor tenant information on sales per square foot (SALES), total rent per square foot (TRNT), and size in square feet (SF). Table 2 gives descriptive statistics on non-anchor stores by selected store type.[10] The tables show there is a good deal of variability among different store types in mean sales per square foot, mean total rent per square foot, and the proportion of stores of each store type present in the malls.

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[9] Geographic sub-regions are as follows: 1) Pacific: Washington, Oregon and California; 2) West North Central: N. Dakota, S. Dakota, Minnesota, Iowa, Missouri, Nebraska, and Kansas; 3) East North Central: Illinois, Wisconsin, Indiana, and Ohio; 4) Southeast: Texas, Oklahoma, Arkansas, and Louisiana; 5) Northeast: Maine, Vermont, N. Hampshire, N. York, Mass., Conn., R.I., and Penn.

[10] All stores were divided into eleven store types. The store types in Table 2 represent a good cross-section of the store types by average size and the proportion of stores of each store type present in the malls. The eleven store type categories are similar to those used by the Urban Land Institute (1993) and Eppli and Shilling (1995): jewelry, cards & gifts, women's apparel (including women's accessories), fast food, family apparel, men's apparel, leisure & entertainment, houseware, men's and boys' shoes, and specialty food.

Table 1: Store Characteristics

Variable	Mean	Stnd. Dev.	Minimum	Maximum
Square Feet (SF)	2,395	2,233	120	27,000
Sales per Square Foot ($/SF)	361	217	33	1,632
Total Rent per Sq. Ft. ($/SF)	36.64	25.71	5.83	277

Table 2: Characteristics by Selected Store Type

Variable/Store Type (Observation Frequency)	Mean	Stnd. Dev.	Minimum	Maximum
SF (Gifts) (6.5%)	2,088	1,173	665	5,475
SF (Women's Shoes) (5%)	1,750	1,003	1,000	6,437
SF (Women's Apparel) (18%)	3,907	2,475	569	13,915
SF (Jewelry) (6.2%)	1,301	648	472	4,278
SALES ($/SF)(Gifts)	299	123	136	711
SALES (Women's Shoes)	304	117	84	566
SALES (Women's Apparel)	258	113	90	751
SALES (Jewelry)	676	276	213	1,433
TRNT ($/SF)(Gifts)	31	12	16	64
TRNT (Women's Shoes)	32	10	12	51
TRNT (Women's Apparel)	28	17	6	77
TRNT (Jewelry)	60	27	17	127

The average size of non-anchor tenants for the nine malls was 2395 square feet. Overall, both sales and rents tended to decrease at a decreasing rate with amount of square footage and distance from the center of the mall. Non-anchor tenant sales ranged from $33 per square foot for a minor anchor store to $1632 per square foot for a kiosk (a freestanding booth located in a main aisle of about 300 square feet). Average annual non-anchor store sales for all nine malls was $361 per square foot. For the individual malls, average non-anchor tenant sales ranged from $266 per square foot to $435 per square foot. Differences in sales per square foot seemed to depend on income per capita in the market areas, e.g., downtown San Francisco (highest) versus metropolitan Memphis (lowest). Vacancy did not vary a great deal, averaging 3.1%, and none of the vacancies was excessively high.

The data used in the empirical model represent 689 observations from eight of the malls, the triple-level mall being excluded because of difficulties in measuring location variables. In addition to size and annual sales and rent per square foot, mall stores were differentiated by length of lease, whether stores were local or part of a national or regional chain, and location characteristics, including distance from the center of the mall. Local tenants (businesses originating from nearby) made up 37% of the database, while national chains (businesses having stores located in at least a couple of states) made up 63%.[11]

Distance measures used in the empirical model required normalization and a common definition of a mall's "center" was needed. Normalizing distance measures and the logic behind workable definitions of common reference points among the malls were from Carter (1999).

Empirical Model and Findings

The following model was fitted:[12]

$$\ln TRNT = \alpha_0 + \beta_1 CHN + \beta_2 SF + \beta_3 SF2 + B_4 TERM + \beta_5 COMP + \beta_6 SAME + \beta_7 CENTER + \beta_8 VACA + \beta_9 LOCATION + e \qquad (4)$$

where:

- TRNT: total rent (base rent plus percentage rent)
- CHN: a dummy variable = 1 if a tenant is a member of a national or regional chain, 0 otherwise
- SF: size in square feet
- SF2: square feet squared
- TERM: length of lease
- COMP: a dummy variable = 1 if a tenant is a comparison store type[13], 0 otherwise
- SAME: feet distance to the nearest same type store
- CENTER: feet distance to the mall's center (normalized)
- VACA: feet distance to the nearest vacant store
- EXIT: feet distance to the nearest mall exit
- LOCATION: location dummy variables for the eight malls

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[11] Eppli's (1991) larger database, containing 54 regional and super-regional malls scattered throughout the United States, contained 26% local tenants and 74% national chain stores.

[12] Another model, with ln SF as the dependent variable, was fitted and estimated successfully using most of the same independent variables. It was noted that the two models could be treated using application of two-stage least squares. In the simultaneous equations, the case is one of overidentification and SF and TRNT are assumed endogenous. Consequently, improvements would be obtained by using a two-stage model.

[13] Comparison store types were chosen using data provided by Stillerman, Jones and Company, an American retail consulting firm (see Carter (1999)). The data was gathered during 1992 and 1993 on comparison shopping by customers of American regional and super-regional shopping malls.

The WLS and WLS correcting for spatial autocorrelation estimations are set out in Table 3.[14]

Generally, the above results confirm some of the findings about shopping centers made by Benjamin, Boyle, and Sirmans (1992) as well as show decreasing rent (rent per square foot) and increasing size (square feet) for mall stores with distance from the mall center. For instance, in a bid-rent context, factor substitution occurs and square footage of stores (SF) increases significantly at a decreasing rate (SF2), with increases in rents. According to Benjamin, Boyle and Sirmans (1992), TERM is supposed to be negative and significant in the TRNT regression. This represents a rent discount for lower default probability of chain stores that generally hold longer leases. See also, Tse (1999).

CENTER is negative and significant in accordance with our theory. VACA is also negative and significant (at the 10% level in the first regression), which reflects the fact that vacancies are more plentiful at the periphery of the malls.[15] Dummy variables for location follows Benjamin, Boyle, and Sirmans (1992), Guidry and Sirmans (1993), and Gatzlaf, Sirmans, and Diskin (1994) to capture location characteristics of the shopping malls.[16] The use of location dummy variables can also be explained in the context of spatial autocorrelation.

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[14] The semi-log form is consistent with the negative exponential density functions used by Mills (1972) and Muth (1969) to describe how population falls, i.e., at a decreasing rate, with distance from a city center. It is simple and effective for purposes of describing the relationship between land rent and distance from a city center.

Kennedy (1981) has shown that estimation using a semi-log functional form with dummy variables causes a degree of bias in the estimated coefficients. Any adjustments suggested by Kennedy did not lead to economically meaningful results.

The hypothesis that regression errors are homoscedastic is rejected for each of the equations (i.e., p-values less than .025), indicating WLS is appropriate. Multicollinearity among independent variables of the regressions was not a problem, based on variation inflation factors, condition indices, and eigenvalue and tolerance limits procedures outlined by Belsley, Kuh and Welsh (1980). Heteroscedasticity was eliminated after application of WLS regression to the models (weighting by the reciprocal of the observations' error terms).

[15] The results of COMP and SAME may show a lack of overall clustering among stores of the same type. Comparison store types seem to gain little by the fact that their customers frequent stores of the same type more than any other store type – if higher rent can be expected for an environment conducive to comparison shopping. Likewise, lack of extra rent paid for proximity to stores of the same type suggests it is unimportant.

[16] For an explanation of how location dummies fit into the notion of spatial autocorrelation and weighting observations see Pace and Gilley (1998).

Table 3: Regression results (dependent variable: ln TRNT)

	WLS			WLS Correcting for Spatial Autocorrelation		
Independent Variables	Coeff.	t-stat.	Std. error	Coeff.	t-stat.	Std. error
Intercept	4.0187	53.322	0.0754	4.0274	54.462	0.0739
Chain Store (CHN)	0.0109	0.351	0.0310	0.0216	0.738	0.0293
Nonanchor Square Feet (SF)	-0.0001	-14.25**	0.0000	-0.0001	-13.840**	0.0000
Nonanchor Sq Ft Squared (SF2)	0.0000	6.626**	0.0000	0.0000	6.064**	0.0000
Lease Term (TERM)	-0.0010	-2.666**	0.0004	-0.0014	-3.763**	0.0004
Comparison Shopping Store (COMP)	0.0147	0.478	0.0308	-0.0286	-0.982	0.0291
Distance from Nearest Exit (EXIT)	-0.0001	-1.291	0.0001	-0.0001	-0.727	0.0001
Distance from Nearest Same Type Store (SAME)	0.0000	0.614	0.0001	0.0000	0.734	0.0001
Distance from Center (CENTER) (normalized)	-0.0004	-5.236**	0.0001	-0.0004	-4.586**	0.0001
Distance from Nearest Vacancy (VACA)	-0.0003	-1.826*	0.0001	-0.0005	-3.733**	0.0001
Mall Dummy Variables (location dummies)						
mall A	0.5881	10.104**	0.0580	0.6413	11.407**	0.5622
mall B	-0.3741	-6.545**	0.0572	-0.3926	-7.150**	0.0549
mall C	-0.0744	-1.326	0.0561	-0.0870	-1.577	0.0552
mall D	-0.5420	-8.924**	0.0607	-0.5440	-9.206**	0.0591
mall D	-0.4295	-6.659**	0.6450	-0.4608	-7.579**	0.0608
mall E	0.1762	2.923**	0.0603	0.1695	2.953**	0.0577
mall F	-0.3760	-6.124**	0.0614	-0.3901	-6.586**	0.0592
mall G	-0.2705	-4.970**	0.0544	-0.2474	-4.238**	0.0534
N		689			689	
R-Square		0.6516			0.6982	
Adj. R-Square		0.6440			0.6917	
F Value		86.674			107.250	

* Significant at the 10% level , ** Significant at the 5% level

Correcting for Spatially Autocorrelated Error Terms

A spatial view of the residuals from the regression show a non-random pattern. Clustering of residuals occurs at points along the shopping mall, with large positive residuals near the centers of the malls and large negative residuals at the peripheries.[17] The object is to make weighting adjustments to observations so as to create a more random pattern of residuals along the mall.

Visual inspection of a scatter plot of residuals against distance from the mall center show observations with relatively large positive residuals near the mall center. The vast majority of stores are located within 700 feet of the mall center. Residual clustering viewed against distance tends to fall at about a 60° angle southeast for 200 feet. At 200 feet residuals are clustered and slightly negative. Beyond 200 feet residuals looked homogeneous. Reweighting the observations to even out the spatial error terms within the first 200 feet of the mall center was a first effort at correcting for spatial autocorrelation in this instance which significantly affected regression results.[18]

Results of the use of the spatial autoregression estimator on the hedonic model show a higher R-squared and Adj. R-squared. Also, substantial reduction in sum-of-squared errors was obtained when going from WLS to WLS plus an autoregression estimator. Reductions in the sum-of-squared errors of the hedonic model is important in making predictions. For further tests showing the autoregression estimator method superior see Pace and Gilley (1998).

Reduction in Standard Error Terms for bs

The standard error (SE) of β measures the accuracy of the estimation of b (sample slope) and forms the basis for confidence intervals and tests of significance. The SE links the inherent variability of Y with the accuracy of b. Lowering the SE makes for better prediction of shopping center rents from the hedonic model based on the location and other characteristics. Simulations and exsample experiments can be performed using the model with much greater confidence. Here the drop in the sum-of-squared errors is about 4%. A systematic effort to eliminate spatial autocorrelation should drop the sum-

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[17] Mall stores are represented two-dimensionally, rather than three-dimensionally, because of the need to aggregate the data of several regional malls. The distances were normalized in such a way as to be comparable across malls.

[18] This can be done simultaneously using the WEIGHT and REWEIGHT statements from SAS.

of-squared errors further. Pace and Gilley (1997) obtain about a 40% reduction in sum-of-squared errors in their housing model when going from OLS to a simultaneous autoregression estimator (SAR).

Conclusion

The recent articles on correcting for spatial autocorrelation have revolutionized the estimation of real property market valuation by making very usable the data associated with a property's location. This has been done mostly in the area of housing. Hedonics involving any type of real estate can benefit from these techniques where location is a factor, since some sort of spatial autocorrelation will likely be present.

Shopping mall developers have long been known to discriminate rents based on characteristics of the tenant, and recently tenant location has been shown to be an important part of rent. In this paper we regressed shopping mall store rent on independent variables representing store characteristics, including location characteristics, and discussed a theory on what was expected regarding store location. Corrections in the regression model were then made for spatial autocorrelation consistent with the location theory, which improved accuracy. The following appropriate closing remarks are from Dubin, Pace and Thibodeau (1999): 90.

> *Ironically, real estate as a discipline espouses the supremacy of location while employing economic tools designed for a spaceless world. Adoption of spatial statistical techniques offers the opportunity to align theoretical considerations with empirical practice.*

References

Alonso, W. (1964), Location and Land Use, Cambridge, Mass.: Harvard University Press.

Belsley, D. A., Kuh, E. and Welsh, R. E. (1980), *Regression Diagnostics*, New York: John Wiley & Sons.

Benjamin, J. D., Boyle, G. W. and Sirmans, C. F. (1992), Price Discrimination in Shopping Center Leases, *Journal of Urban Economics* **32**, 3, 299-317.

Brown, S. (1991), Tenant Placement in Planned Shopping Centres: Implications of an Observation Survey, *Journal of Property Research*, **8**, 2, 179-181.

Brown, S. (1994), Retail Location at the Micro-scale: Inventory and Prospect, *The Service Industry Journal*, **14**, 4, 542-574.

Carter, C. C. (1999), *The Nature of Store Location in Shopping Centers*, PhD dissertation, School of Business, University of Wisconsin-Madison.

Dubin, R. A. (1988), Estimation of Regression Coefficients in the Presence of Spatially Autocorrelated Error Terms, *Review of Economics and Statistics*, **70**, 3, 466-474.

Dubin, R. A., Pace R. K. Pace and Thibodeau, T. G. (1999), Spatial Autoregression Techniques for Real Estate Data, *Journal of Real Estate Literature*, **7**, 1, 79-95.

Eppli, M. J. (1991), *Retail Leasing with Anchor Tenant Externalities*, doctoral dissertation, University of Wisconsin-Madison, School of Business

Eppli, M. J. and Shilling, J. D. (1995), Large-scale Shopping Center Development Opportunities, *Land Economics*, **71**, 2, 35-41.

Fisher, J. D. and Yezer, A. M. J. (1993), *Spatial Structure and Rents in Shopping Centers*, working paper, Indiana University.

Gatzlaf, D. H., Sirmans G. S. and Diskin, B.A. (1994), The Effect of Anchor Tenant Loss on Shopping Center Rents, *Journal of Real Estate Research*, **9**, 1, 99-110.

Griffith, D. A. (1987), *Spatial Autocorrelation: A Primer*, Washington D. C.: Association of American Geographers.

Guidry, K. A. and Sirmans, C. F. (1993), The Determinants of Shopping Center Rents, *Journal of Real Estate Research*, **8**, 1, 107-115.

Kennedy, P. E. (1981), Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations, *American Economic Review*, **71**, 4, 801.

Mendenhall, W. and Sincich, T. (1993), *A Second Course in Business Statistics: Regression Analysis*, New Jersey: Prentice Hall.

Mills, E. S. (1972), *Studies in the Structure of the Urban Economy*, Baltimore, Md.: The Johns Hopkins Press.

Muth, R. F. (1969), *Cities and Housing*, Chicago: University of Chicago Press.

Pace, R. K. (1993), Nonparametric Methods with Applications to Hedonic Models, *Journal of Real Estate Finance and Economics*, **7**, 2, 184-204.

Pace, R. K. (1996), Relative Efficiencies of the Nearest Neighbor, Grid, and OLS Estimators, *Journal of Real Estate Finance and Economics*, **13**, 2, 203-218.

Pace, R. K. and Gilley, O. W. (1998), Generalizing the OLS and the Grid Estimator, *Real Estate Economics*, **26**, 2, 331-347.

Pace, R. K., and Gilley, O. W. (1997), Using the Spatial Configuration of the Data to Improve Estimation, *Journal of Real Estate Finance and Economics*, **14**, 3, 333-340.

Pashigan, B. P. and Gould, E. D. (1998), Internalizing Externalities: The Pricing of Space in Shopping Malls, *Journal of Law and Economics*, **41**, 1, 115-142.

Sim, L.L. and Way, C.R. (1989), Tenant Placement in a Singapore Shopping Center, *International Journal of Retailing*, **4**, 1, 4-16

Tse, R. Y. C. (1999), Lag Vacancy, Effective Rents, and Optimal Lease Term, *Journal of Property Investment and Finance*, **17**, 1, 75-88.

Urban Land Institute (1993), *Dollars and Cents of Shopping Centers: 1993*, Washington, D. C.: ULI – Urban Land Institute.

Wiltshaw, D. G. (1996), Spatial Autocorrelation and Valuation Accuracy: A Neglected Methodological Problem, *Journal of Property Research*, **13**, 4, 275-286.

Vandell, K. D. (1991), Optimal Comparable Selection and Weighting in Real Property Valuation, *Real Estate Economics*, **19**, 2, 213-239.