EFFECTS OF LOCAL DEVELOPMENT PRESSURE ON LAND PRICES: A SPATIAL ECONOMETRIC APPROACH

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ABSTRACT: We conduct a study to examine the effects of local development pressure and other factors on the value of urban-fringe land parcels. Multiple regression spatial models were estimated using parcel-level data from Delaware County, Ohio. The empirical results provide evidence that such factors as man-made and natural features are relevant in determining property values. The econometric findings indicate that local development pressure contributes profoundly to an increase in current land prices. These results shed light on the magnitude of the effects of recently developed land and provide insights into policies to preserve farmland and the associated environmental benefits.

Key words: Land values, development pressure, hedonic pricing theory

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1. INTRODUCTION

Loss of farmland and open space has been an issue of concern at both national and local levels in the United States. The ability to understand and predict the relationship between the value of a property and its potential for development is crucial for the effective design of regional land-use policies. For many years, the structure of agricultural land prices has been the central focus of various studies in an effort to understand potential threats to agriculture posed by land development and to identify policies to prevent or discourage what may be considered to be socially undesirable land-use changes.

Recently, the 1996 Federal Agricultural Improvement and Reform Act expanded the Federal role in agricultural land preservation by funding the purchase of farmland conservation easements. In the last decade, the United States has experienced a rapid growth in the number of private land trusts, many of which are devoted to preserving agricultural land through the purchase of development rights. Establishing the dollar value of an easement is not easy because the value of the land depends partly on the likelihood of conversion, and landowners' willingness to accept compensation in exchange for development rights typically depends on future development expectations. Therefore, the value of land may reflect not only the current use value but also the value due to local development pressure, which is defined as the rate of change of spatial indicators of land-use conversion over the recent past. Large differences in development pressure may occur even in relatively small geographical areas making it difficult to design land use policies.

Understanding the behavior and the magnitude of development pressure can help investors make better informed decisions regarding the inclusion of farmland in their portfolio. In addition, knowing the implications of development pressure on land value can be useful to local government planners, tax assessors, road builders and appraisers concerned with land use policy and land appraisal.

Previous studies have attempted to measure the effects of development pressure using such variables as distance of parcels to roads and to metropolitan areas (Elad, Clifton, and Epperson 1994; Vitaliano and Hill 1994; Chicoine 1981), changes in county population (Palmquist and Danielson 1989), and changes in county population density (Mendelsohn, Nordhaus, and Shaw 1994). In this study, operational measures of development pressure are used, in addition to the standard static measures of parcel characteristics and neighborhood variables, in measuring the determinants of land prices. Built upon Stewart and Krieger (1999), Bell and Bockstael (2000), Irwin (2001), we define a small radius around each parcel to compute proxies for development pressure. These variables include the average percent change in prices of all parcels within the buffer area that were sold in the previous one, three, and five years, and the percent of neighboring land sold one year, three years and five years prior to the sale of the surrounded parcel. This paper differs from the papers referenced above by using Bayesian estimation method which takes into account non-constant variances and spatial outliers. The results indicate that ignoring the spatial configuration of the data and the presence of outliers would produce different inferences than the Bayesian models.

The rest of the paper is organized as follows. The next section outlines the conceptual framework of the study. Then, the procedures and model specification are discussed, followed by a description of the data set. The empirical results are presented in section 5. A summary of the paper and conclusions are provided in section 6.

2. CONCEPTUAL FRAMEWORK

The theoretical basis for the empirical analysis is hedonic pricing theory. While the hedonic-pricing method deals with market outcomes, it falls under the paradigm of non-market valuation techniques. This is so because properties have qualities that are not explicitly priced and traded in markets. A piece of land is a bundle of characteristics. Location relative to urban centers is a characteristic for which relatively high willingness to pay is expressed by consumers.

The theory of hedonic pricing is based on an alternative to neoclassical consumer theory in which a class of differentiated products is completely described by an array of objectively measurable characteristics (Rosen 1974 and Lancaster 1966). It is a popular technique used to reveal how much households are willing to pay for individual characteristics of a non-market commodity. Due to their ability to capture the effects on property value of a change in individual characteristics, hedonic pricing models are widely used in measuring the willingness to pay for a change in environmental characteristics.

Within the theoretical framework as presented by Rosen, the hedonic price function is generally considered to be a market clearing function evolving from the interaction of demand and supply. A hedonic price equation is a reduced-form equation reflecting both supply and demand influences. Perceiving a piece of land as a heterogeneous commodity differentiated into a bundle of attributes A = (A_1, A_2, A_3,……,A_n), an hedonic price function establishes a functional relationship between the parcel price and a particular attribute such that

$$P(A) = f(A_1, A_2, A_3, \ldots, A_n)$$

where P is the sale price or the total value of a land parcel, A_i is the ith attribute of the parcel, and f is a specified function. The prices of the characteristics may be thought of as implicit in the price of the land parcel.

The first derivative of the function with respect to any attribute i is the equilibrium marginal implicit price of that attribute:

$$\frac{\partial P(A)}{\partial A_i} = P_A .$$

It is the additional amount that must be paid by any buyer to purchase a higher level of that characteristic, ceteris paribus.

P(A) is assumed to be concave so that the marginal implicit price is declining with higher levels of A_i. However, a hedonic price function does not have to be of concave form. It could be convex and linear. The shape depends on the good whose characteristics are being evaluated. From an environmental quality perspective, it is plausible to think of a hedonic price function as being concave. Because of diminishing marginal utility, an individual's marginal willingness to pay for an attribute is increasing at a declining rate. A linear functional form would generate constant marginal attribute prices. Some writers, including Rosen (1974), suggest that functional form be selected on the basis of statistical criteria using empirical testing to estimate and evaluate various functional forms, such as log-linear, log-log, and quadratic for best fit. Guntermann (1997) found that the log-log linear model compared to the semi-log linear model has greater explanatory power with a better significance level for many variables. On the other hand, in a simulation experiment, Cropper, Deck and McConnell (1988) found that when variables are omitted or replaced by proxies, simpler functional forms, such as linear, semi-log, double-log, and linear Box-Cox forms, perform better than more complex ones. In this study, we adopt the log-linear form for a number of beneficial properties of the logarithm transformation.

Another key issue in estimating a hedonic model is the choice of the variables. In this study we made the choice of the variables on four criteria: the purpose of the study, theoretical relevance, empirical evidence, and data availability on the characteristics of the properties in the sample. Below is discussion on the relationship between the variables included in the analysis and land value.

The approach taken in the study relies on spatial interaction theory. Spatial interaction is a general concept, which has been applied to various problems including marketing, migration, communication, and commuting. Its foundation comes from Newtonian physics, according to which gravitational attraction of physical objects is directly proportional to the product of their masses but declines with increases in the distance between them (Abler, Adams, and Gould 1971). What happens to one parcel is strongly related not only to what happens to surrounding or neighboring parcels but also to the number of nearby parcels and the distance to particular parcels. The neighboring parcels' influence may be directly related to how recently these parcels have changed in one or more characteristics.

We use two variables to control for the neighbors' influence. One is the average percent change in sale price of the surrounding parcels sold in the previous years and the other is the proportion of neighboring land sold in the previous years. To determine how recently the neighbors must have changed in order to exert an influence, three time periods are used (previous year, previous three years, and previous five years). While the direction of the relationship between land value and the percentage of neighboring land sold in the previous years is uncertain, the influence of the average percentage change in sale price of the surrounding parcels sold in the previous years is expected to be positive.

In view of the fact that a parcel is defined as a lot and all improvements on it (Bell and Bockstael 2000), the characteristics of the improvements may be considered as part of a land parcel's characteristics. As such, the characteristics of both parcels and houses on the parcels need to be controlled for in the estimation. Among the characteristics of the improvements, only the total number of rooms (except bathrooms) and age of the building are included in the estimation to avoid collinearity problems. In terms of land characteristics, based on statistical tests, only parcel size is finally used in the model.

Land value is expected to be directly related to the characteristics of any improvements on the parcel. Plot size is expected to be positively related to land value. However, there has been a heated debate in the literature as to whether this relationship is concave or convex. Studies by Brownstone and De Vany (1991), Isarkson (1997), and other authors provide theoretical as well as empirical arguments supporting a concave relationship between land values and plot size. That is, the marginal price of land per unit of area decreases with plot size. As one can imagine, the cost of subdividing a plot may result in a persistent declining marginal relationship between price and size. However, using small plot sizes, a recent paper by Lin and Evans (2000) found a convex relationship. They suggest that the relationship between total land price and plot size should be analyzed using a log-log functional form. Total price is a concave function of area if the resulting elasticity is less than one. On the other hand, the function is convex if the elasticity is greater than one.

Age of the building when the parcel was sold may be negatively related to land price if landowners value parcels with recent houses more than those with old houses. The relationship may also be positive if the very old houses have been renovated and kept as part of the local cultural heritage. The relationship is therefore uncertain.

Locational attributes or neighborhood characteristics are included to control for local amenities, which are expected to contribute to the value of a property. Those attributes matter because of the fixed position of a piece of land in space. Properties in desirable locations and neighborhoods command higher prices than properties in less desirable places. Proximity to open space may be a desirable characteristic due to the public good features of such parcels. If this is the case, one can expect a positive relationship between land values and proximity to an agricultural open space parcel. In a similar vein, the ready access of urban public services to farmland adjacent to incorporated communities is expected to be capitalized into higher values for favorably situated parcels. The same argument may hold for closeness to the central city. According to theoretical models of residential location, distance to city centers is expected to negatively influence land value. However, the direction of the impact of closeness to commercial and industrial parcels on fringe area farm land prices is uncertain, since the impact depends on the land use, current or expected, and the type of neighboring activities. Closeness to an air-polluting industry would create a disamenity. The sign on distance to the nearest industrial parcel in this case would likely be positive.

As Guntermann argues (1997), subdivision activity in an area is an obvious sign that the development of any specific parcel in the area is a possibility. He hypothesized that expectations about development are formed based on the level of subdivision activity at a critical distance around each parcel. To control for subdivision activity, Guntermann assigned the variable a value of 1 if the parcel is inside a defined subdivision and 0 otherwise.

Socio-economic variables are included to capture the effects of external factors. Population density, for example, enters the estimation as a proxy for congestion. If the locality has been growing more than expected and in an uncontrolled manner, congestion might occur as a result of urban sprawl. Since congestion is utility-reducing, a negative impact on land value is expected. Real income per capita per block boundary is anticipated to be positively related to property values. As people become wealthier, they may tend to demand more land for residential, commercial, or industrial purposes. Since the supply of land is limited, the price of land will be likely to increase as income rises.

We transformed all variables except the dummies into natural logarithms because of the beneficial properties of the logarithm transformation such as the fact that they may be interpreted directly as constant elasticity estimates. (Mukherjee *et al.* 1998). However, transforming data using the logarithmic function has a drawback when the variables to be transformed take on zero and negative values. The log of zero and the log of negative numbers are undefined. This situation is somewhat worrisome in view of the fact that ways to avoid losing observations due to non-positiveness are hard to come by in the literature. The problem seems to be more complicated for negative than zero values. However, the nature of the data can be of help. In this study, the variables which take on occasional non-positive values are the proxies for development pressure. To side-step the problem, observations corresponding to negative values are excluded from the analysis, as they would indicate nonsensical sale transactions. The remaining data are transformed by adding 1 to the values of the variables before taking the log.

3. PROCEDURES AND MODEL SPECIFICATION

The empirical results of the study are obtained using an iterative process after screening the data for outliers. First, a traditional naive hedonic model without the development pressure variables was estimated. Then, alternative models including the local development pressure variables were estimated. A Lagrange multiplier test reveals a better fit when the development pressure variables are included in the models. A normal probability-probability (P-P) plot and a normal quantile-quantile (Q-Q) plot of the residuals of a preliminary regression reveal the presence of outlying observations and non-normality of the residuals. In this case, ordinary least squares (OLS) would yield estimators that are not efficient. The naïve model and the alternative models were estimated using iteratively re-weighted least squares. This method assigns lower weight to data points that do not fit well (Lesage 1999a). The study made use of a distance-based weight matrix to carry out additional tests that led to rejection of the null hypothesis of no spatial autocorrelation. Bayesian spatial models are ultimately estimated to account for spatial autocorrelation and to “robustify” against outliers.

Specification of the naive hedonic model

In this model, the transaction price of a piece of land is assumed to be dependent on the structural characteristics of any improvement on the parcel), the characteristics of the parcel, the location of the parcel with respect to city center (Columbus center), transportation systems, subdivision limits, neighborhood characteristics such as public recreational centers, proximity to streams, current use of nearby parcels (e.g., distance to nearest agricultural, commercial, and industrial parcel), and socio-economic factors.

The model is specified as follows

$$LogP_i = \alpha + \sum k\, \beta_k\, logx_{ik} + \sum h\, \beta_h\, x_{ih} + \varepsilon_b \quad (1)$$

where P_i is the deflated parcel transaction price measured in dollars, x_{ik} represents all parcel attributes except the binary attributes, x_{ih} represents the discrete attributes, and ε_b is the disturbance vector which is presumed to have a multivariate normal distribution, $N(0, \sigma^2 I)$.

Specification of the alternative models

The alternative models include the development pressure variables:

$$LogP_i = \alpha + \sum k\, \beta_k\, logx_{ik} + \sum h\, \beta_h\, x_{ih} + \rho_1 logC_i + \rho_2 logPt_i + \varepsilon_{\text{d}} \quad (2)$$

where C_i and Pt_i are the two proxies for local development pressure. They are computed as follows based on Irwin (2001):

$$Ci = \left(\sum_j w_{ij}\, D_j\, PC_j\right) \Big/ \sum_j w_{ij} \quad \text{for } j=1, \ldots.. N \quad (3)$$

where PC_j is the annual percent change in price of parcel j:

$$PC_j = ((sale_{t+n} - sale_t)/sale_t) * (1/n) \quad (4)$$

where n is the time length in terms of year between two sales. $D_j = 1$ if the second sale of parcel j occurs at least one year prior to the second sale of parcel i and zero otherwise or if $i = j$, and $w_{ij} = 1$ if distance between parcel i and j is at most 800 meters (approximately 0.5 mile). Therefore, C_i is the average percent change in price of all parcels that fall within parcel *i's* neighborhood and whose sales occur at least one year prior to parcel i's sales. It is weighted by the number of neighbors.

From all of the parcels *j,* Pt_i is the proportion of land sold one year prior to the sale date of parcel *i*:

$$Pt_i = \left(\Sigma_j w_{ij} D^*_j A_j\right) / \Sigma_j w_{ij} A_j \quad \text{for } j = 1, \ldots, N, \tag{5}$$

where $D^*_j = 1$ if the second sale of parcel j occurs at least one year prior to the second sale of parcel i and zero otherwise or if $i = j$, A_j is the area of parcel *j*, and w_{ij} defined as above. Parcels *j,* defined as neighbors of parcel i, are those that fall within a radius of 800 meters.

Similar to equation (5), two other models are estimated depending on whether the sale of parcel *j* occurs 3 years or 5 years prior to parcel *i's* sale. Furthermore, since the results might be influenced by the size of the neighborhood, another neighborhood criterion is defined by choosing a buffer size of 1.6 km radius. We, therefore, have in total six alternatives to the model specified in equation (1). *Log Ci* enters all six models whereas there is one model for each $\log Pt_i$ depending on the buffer size and the number of years prior to which parcel *j's* sale occurs as compared to parcel *i's* sale.

Diagnostic tests

A Lagrange multiplier test and a spatial autocorrelation test are carried out in this paper. The Lagrange multiplier test asks the question as to whether including the development pressure variables in the model specification significantly improves the explanatory power of the naïve hedonic model. It tests the null hypothesis that each of the development pressure variables in each alternative model has a coefficient of zero. In implementing the test, the naive model is thought of as the restricted model and each alternative model is considered to be an unrestricted model. The test is performed by first computing the residuals ε_b of the naïve model (equation 1) and then regressing these residuals on all explanatory variables including the development pressure variables. The following regression is estimated:

$$\varepsilon_b = \lambda + \Sigma_k \theta_k \log x_k + \Sigma_h \varphi_h x_{ih} + \gamma_1 \log C_i + \gamma_2 \log Pt_i + u. \tag{6}$$

This is done for each buffer size and the number years prior to which parcel j sales occur before the sale of parcel i. The Lagrange multiplier test is based on a test of significance of the regression in Equation (6). The LM test statistic, which is given by $LM = N*R^2_{0,}$ follows a chi-square distribution with 2 degrees of freedom. N is the sample size (4286) and R^2_0 is the R^2 associated with the regression in equation (7).

The spatial autocorrelation test is used to investigate whether to allow for spatial dependence in the model specification. Based on the magnitude of the parameter estimates and the residual sum of squares, the models with the largest buffer size (1.6 km) appear to be more attractive. Two of these models (model 4 and model 6) are chosen to test for spatial autocorrelation. Diagnostic tests for spatial dependence are well documented for OLS regression models (Anselin 1988 and Cliff and Ord 1973). Because they are all built on the asymptotic properties of the maximum likelihood estimator, their performance in finite samples is unknown. The Moran I-statistic, the likelihood ratio test (LR), the Wald test, and the Lagrange Multiplier test are all based on maximum likelihood estimation of the spatial error model (SEM). If the asymptotic distributional properties of the error term fail to be satisfied, as we have established, then those tests may result in invalid estimation of spatial dependence. Indeed, as Anselin and Rey (1991) argue, tests for spatial autocorrelation in the error terms are very sensitive to the normality assumption. In the presence of non-normal data, the problem is addressed in two steps. In the first step, we use robust estimation methods to generate the residuals and then we test for spatial dependence using a first order autoregressive model (FAR) based test. The FAR-based test rests on the significance of ρ, the autoregressive parameter. In the second step, we estimate the spatial models robustly using a Bayesian estimation technique which relaxes the assumption of normality of the errors (Lesage 1997).

One key component in spatial autocorrelation analysis is the specification of a spatial weight matrix defining the presumed spatial relationship between a parcel and its neighbors. In this study, we chose an inverse distance weight matrix, which implies that closer neighbors exert larger influence:

$w_{ij} = 1/d_{ij}$ if $d_{ij} <= 1600$ meters and 0 otherwise.

Specification of the spatial hedonic models

Because land parcels located in proximity to one another are prone to have similar unobservable characteristics, spatial error correlation is often present in land-use models. As a result, we chose a spatial error specification. Also, given the evidence of spatial outliers in the dataset, we use the Bayesian estimation method to estimate the models. For comparison purposes, we also estimate the models using the maximum likelihood principles. The difference between the two methods lies in the fact that in the robust versions the normality assumption required by the maximum likelihood method is relaxed. The disturbances are assumed to exhibit non-constant variance, taking on different values for each observation. The Bayesian approach relies on a prior distribution, based on beliefs, which when combined with the data via Bayes' theorem produces a posterior distribution from which the parameter estimates are derived[1]. The posterior density is in essence a weighted average of the prior density and the likelihood. The robust spatial error model, as specified below, represents informative priors. The prior distribution for V (a diagonal matrix with v_i elements) is an independent chi-square distribution ($ID\ \chi^2(r)/r$) with a single parameter r. When r is chosen so are the v_i's. Lower r-values are associated with the prior beliefs that outliers and non-constant variance exist. Lesage (1999b) suggests that r-values be between 2 and 7. If heteroskedasticity exists, this range of r-values will allow for sufficient divergence of the v_i parameters from unity to accommodate the non-constant variance or "robustify" against outliers. The parameter λ is restricted to take values between the inverse of the minimum and maximum eigenvalues ($1/lmin$, $1/lmax$) of the weight matrix W. A normal prior is placed on the parameters β. Lesage's Econometric Toolbox provides algorithms based on MATLAB code to estimate spatial Bayesian spatial econometric models.

The spatial models are expressed as follows:

$y = XB + u,\ \ u = \lambda Wu + e$

$r/vi \sim ID\ \ \chi^2(r)/r,\ r = Gamma\ (m, k)$

$B \sim N(c, T),$

$1/\ \sigma^2 \sim Gamma\ (nu, d0),$

[1] See Lesage 1997, 1999 for further details on estimating robust Bayesian spatial models.

$\lambda \sim Uniform(1/lmin, 1/lmax)$

x is the matrix containing all the independent variables. In the case of maximum likelihood method, the error term has the following distribution: $e \sim N(0, \sigma^2 I_n)$. The error term in the Bayesian model is distributed as follows: $e \sim N(0, \sigma^2 * V)$, $V = diag(v_1, v_2, \ldots v_n)$.

4. DATA

The study uses parcel level cross-sectional data. Land values and environmental characteristics are obtained from the Delaware County (Ohio) Auditor's Office and other sources. The data were collected by Brent Sohngen *et al.* and assembled by Robert Szychowicz. A total of 4,286 parcels which were sold twice between 1988 and 1998 compose the sample. Analysis of the dataset to detect outliers and other anomalies was undertaken. For instance, observations with missing information were excluded from the sample. Similarly, irrelevant or unreliable transactions, such as non-arm length sales indicated by a considerable drop in sale price, were also discarded. We also excluded parcels whose change in price is negative, based on the assumption that landowners and developers are rational and profit maximization-oriented. Fast repeat sales, which may not reflect market fundamentals, were also eliminated. A second sale based on a rational decision requires enough time so that the reservation price conditions can be satisfied. Consequently, only observations for which time length between two sales is at least one year are included in the sample. Finally, as in Bell and Bockstael (2000), to reduce the amount of measurement error and omitted information, the sample is restricted to parcels on which houses have been built at least one year prior to the sale.

5. RESULTS AND DISCUSSIONS

Results from the naive hedonic and alternative models

The regression results for the naive and the alternative models are presented in table 1. For each model, the first column reports the coefficient estimates and the second the t-ratios. Reported in table 2, the results of the Lagrange multiplier test reveal that the role of the local development pressure variables is striking. The test rejects at the 1 percent level the null hypothesis that the naive model is valid in favor of the alternative hypothesis that the local development pressure variables should be included in the model specification. Table 3 shows that the variables included in model 4 and model 6 contribute the most to the improvement of the explanatory power of the basic model since the null hypothesis is more likely to be rejected in the case of those models.

Comparing the results from the naïve model to those from the alternative models, the later yield a higher adjusted R^2 and lower residuals sum of squares than do the former. The changes in the adjusted R^2 are small indicating that the models are robust. Because adjusted R^2 penalizes the addition of new variables in a model, an increase indicates that the variables truly contribute to the explanatory power of the model. The sign of the coefficients are the same for all variables in the naïve and the alternative models. Also all coefficients remain significant except the one on the variable subdivision, which becomes non-significant in the alternative models at the conventional significance levels.

Under the assumption of no spatial autocorrelation, the results of the alternative models have the following interpretations. Plot size (LAREA) is found to be significant at the one percent level and to have a positive sign as expected. Since the coefficient is less than one, as in Brownstone and De Vany (1991), this result indicates a concave relationship between land sale price and lot size implying that the price of land per unit of area increases with plot size, but at a decreasing rate. Colwell and Sirmans (1993) explain that kind of relationship by the costs associated with subdivision activity.

Age of buildings on the parcel when the parcel was sold (LBDG_AG) is found to be significant at the one percent level and to have a negative sign. This result indicates that more recent houses on a parcel add more value to that parcel. Also, the total number of room in a house on a parcel (LROOM_T**)** is significant at the one percent level and has a positive sign, as expected. This result implies, ceteris paribus, that the price of a land parcel will be higher if the house on it has more rooms.

Among the locational and neighborhood variables, the sign on distance to commercial and industrial parcels (LCOMM, LINDUSTR) was uncertain on conceptual grounds. LCOMM and

LINDUSTR are found to be significant at the one percent level and to have positive signs. This result indicates the presence of a disamenity associated with commercial and industrial activities.

The coefficient on AJACENTAG is negative and significant at the 1 percent level, indicating that the sale price decreases if the adjacent parcel is agricultural or an open space parcel. The variable takes on the value of one whenever the parcel is close to an agricultural or open space parcel and zero otherwise. This result indicating that closeness to open space undermines land values is at odds with the hypothesis previously posited that proximity to parcels used as open space enhances land values because of the public good features of such parcels. The negative sign can be explained by the logic that farming activity such as plowing, irrigating, fertilizing and spraying may be deemed annoying by people living nearby. These activities may cause negative externalities due to noise, dust, and pesticide use. In addition, parcels that are close to farmland or open space may be less developable because of land use restrictions and nuisance spillovers. Furthermore, the presence of parks, forest preserves, and campgrounds not only brings the benefit of open space, but also the possibility of such negative aspects as noise, congestion, trespassing and crime.

Distance of the parcel to golf courses (LGOLF), highways (LHIGHWAY), school districts (LSCHOOL), Columbus center (LCOLCENTER), and streams (LSTREAM), as theorized, is shown to be significant and to have a negative sign. These results indicate that landowners value natural and man-made features.

The socio-economic variables are strongly significant and have the expected sign. The negative sign on population density (LPOP_DEN) is indicative of congestion as anticipated. Income per capita (LINC_CAP) is significant at the one percent level and has a positive sign as hypothesized. The results imply that, everything else being equal, economic growth directly influences land prices. This is a replication of the finding of Cappozza and Helsley (1989).

Table 2 presents the parameter estimates and the t-ratios for the development pressure variables for each model according to distance cut-offs and number of years in the past that the sale of the neighboring parcel occurred. All variables are significant at the one percent level. The average-change-in-price variables (LC and LC1), as expected, are both of positive sign for all models indicating that the price of a parcel reacts positively to the change in price of its neighbors. The coefficients on the proportion variables LPT_1, LPT_3, LPT_5, LPT1_1, LPT1_3, and LPT1_5 are significant at the one percent level and have a positive sign as hypothesized in all models. The results substantiate the hypothesis that a parcel of land is likely to take a higher value when nearby parcels are being developed. Models with the larger buffer size yield higher adjusted R^2.

Results from the test for spatial autocorrelation and the spatial models

The results presented in table 4 provide evidence of spatial dependence in the data indicating that spatial models should be estimated. The substantiation of outlying sample data points would make it inappropriate to rely on the maximum likelihood estimation method which rests on the assumption of normality. Bayesian estimates may provide a better basis for inference. If the sample data contain outliers or non-constant variances, the Bayesian estimates will diverge from the maximum likelihood estimates, indicating a violation of the assumption of homoskedasticity. The results of the spatial models are shown in table 5.

Incorporating the spatial variation in the analysis improves the fit of the models, as compared to the results in table 2. However, as expected, the Bayesian estimates lead to lower R-squared statistics, suggesting that some robustification took place because robust estimates avoid attempting to fit outlying sample data observations. As to the spatial dependence coefficient (λ), the table indicates that, in terms of significance level, the Bayesian estimation method provides better estimates than maximum likelihood. These results suggest that when a handful of outliers exist in the sample, the maximum likelihood method is likely to underestimate the spatial dependence. Regarding a choice between model 4 and model 6, there is no need to worry about which one to use, since the elasticity estimates in both specifications are almost identical. The log-likelihood values reported at the bottom indicate that the maximum likelihood versions of model 4 and model 6 fit the data nearly identically. It is also shown in table 5 that the signs on all coefficients are robust and so are the indicators of significance. All p-values are much lower than 0.05, except for subdivision which has the expected sign but is not significant at the conventional level. It may be the case that the variable SUBDIVISIO is correlated with the intensity of development of nearby parcels. Another explanation is that its effect may be reduced by the spatial correction since they both vary in the same way.

The local development pressure variables remain strongly significant. The results indicate that the selling price of a parcel reacts to changes in the prices of its neighboring counterparts. Also, the proportion of land sold 1 to 5 years prior within a 1-mile radius of the centroid of a parcel strongly influences the value of that parcel.

6. CONCLUSIONS

The goal of this study was to examine the effects of development pressure on the value of urban-fringe land parcels. Development pressure, defined as the rate of change of spatial indicators of land-use conversion over the recent past, is a measure of development expectations. In addition to testing the standard hypotheses relating land value to various site characteristics, the price of a land parcel is theorized to be influenced by development expectations. Our dependent variable is the natural logarithm of the deflated full transaction price. The theoretical basis for the study is hedonic pricing theory, widely used to reveal household willingness to pay for individual characteristics of a non-market commodity. The dataset for the study contains information on prices and characteristics of over 4000 parcels that were sold twice between 1988 and 1998 in Delaware County, Ohio, located on the urban fringe of the city of Columbus.

The results of the study are obtained using an iterative process after screening the data for outliers. First, a robust naive model without the development pressure variables was estimated. Then, models that include development pressure variables were estimated. A Lagrange multiplier test reveals a better fit when the development pressure variables are included in the models. The study made use of a distance-based weight matrix to carry out an additional test that led to rejection of the null hypothesis of no spatial autocorrelation. Bayesian spatial models are ultimately estimated to account for spatial autocorrelation and to "robustify" against spatial outliers.

A number of results emerge from the study. First, evidence is found that landowners prefer parcels with more recent buildings and parcels with larger lot size. Second, proximity to industrial and commercial areas and proximity to open space are found to relate to land value negatively while proximity to golf courses, highways, central city, school property, and streams is found to increase land value. Third, the analysis supports the hypothesis that congestion measured by population density leads to a decrease in land prices. Fourth, there is also evidence that land is a normal good since its demand increases with income per capita. The last and the most interesting outcome is that being located in areas under development pressure adds a great deal to the price of a land parcel.

The study has various implications in terms of policy decision-making. The results provide insights to landowners and local officials about policies to discourage conversion of land adjacent to areas under development pressure. We found that the elasticity of land values with respect to development pressure around a parcel is more than 40% suggesting that landowners would require substantial financial compensation to forego the rights of future development for their parcels.

It would be ideal if farmers would be able to purchase farms offered by other farmers but this may not be feasible. If land remains with high potential for development, only developers or speculators will be able to offer high prices. This may preclude the continuation of farming. Many observers argue that some development rights should be available for the next generation, and so should the rights to the use of man-made and natural features. From such a perspective, appropriate actions must be undertaken. Based on observed land prices, landowners exhibit high willingness to pay for natural and man-made features such as streams, golf courses, and highways. Therefore, they could be a potential source of funding for conservation programs in selected areas on the urban fringe.

Several issues remain to be addressed by further research. A first concern is the identification of neighboring development effects. More generally, the models may not include all relevant variables. Certain variables such as zoning, property tax, change in the transportation system, and change in the number of schools built in the last 5 years were not available. Therefore, it is possible that missing variable bias may affect the results. Second, the study found evidence of the effects of local development pressure, but failed to distinguish its different sources. From a policy decision-making standpoint, it might be of interest to distinguish and measure the effects of various types of development. Finally, for the purpose of the study, only parcels that were sold twice are included in the sample. This may result in sample selection bias which could be dealt with in future research using a variety of models that correct for sample selection bias.

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Table 1: Results from the Naïve and the Alternative Models

Variables	The naïve model		The alternative models											
			Buffer=0.8 km						Buffer=1.6 km					
			[1]Model 1		[3]Model 2		[5] Model 3		[1]Model 4		[3]Model 5		[5]Model 6	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	13.48***	34.10	13.11***	33.94	13.50***	34.95	13.70***	35.64	12.89***	33.70	13.19***	34.54	13.27***	34.83
LAREA	0.11***	18.20	0.11***	19.00	0.11***	18.37	0.11***	18.39	0.11***	19.10	0.11***	18.47	0.11***	18.49
LBLDG_AG	-0.08***	-17.34	-0.09***	-19.01	-0.09***	-18.62	-0.09***	-19.02	-0.09***	-20.43	-0.09***	-20.00	-0.09***	-20.20
LROOM_T	0.92***	37.58	0.85***	35.55	0.86***	35.97	0.86***	36.08	0.85***	36.04	0.86***	36.19	0.86***	36.34
AJACENTAG	-0.06***	-4.26	-0.04***	-3.16	-0.04***	-2.93	-0.04***	-3.14	-0.05***	-3.32	-0.04***	-3.26	-0.04***	-3.27
LCOMM	0.02***	4.16	0.02***	3.83	0.02***	3.36	0.02***	3.55	0.02***	3.71	0.02***	3.72	0.02***	3.75
LINDUSTR	0.03***	5.64	0.04***	6.21	0.03***	5.79	0.03***	5.58	0.04***	6.66	0.04***	6.34	0.04***	6.24
LGOLF	-0.08***	-16.65	-0.08***	-17.45	-0.18***	-17.63	-0.08***	-17.87	-0.08***	-16.40	-0.08***	-16.65	-0.08***	-16.77
LHIGHWAY	-0.02***	-4.01	-0.03***	-5.25	-0.03***	5.61	-0.03***	-5.74	-0.03***	-5.05	-0.03***	-5.12	-0.03***	-5.20
LCOLCENTER	-0.50***	-18.98	-0.46***	-19.00	-0.48***	-18.66	-0.49***	-19.13	-0.45***	-17.61	-0.46***	-17.95	-0.46***	-18.13
LSCHOOL	-0.03***	-5.35	-0.02***	-5.23	-0.03***	-5.61	-0.03***	-5.65	-0.02***	-5.40	-0.03***	-5.47	-0.02***	-5.31
LSTREAM	-0.01***	-2.76	-0.02***	-3.67	-0.02***	-3.43	-0.02***	-3.53	-0.02***	-3.95	-0.02***	-4.00	-0.02***	-4.12
SUBDIVISIO	0.04**	2.42	0.02	1.29	0.02	1.31	0.02	1.05	-0.02	1.15	0.02	0.97	0.01	0.58
LINC_CAP	0.23***	16.36	0.23***	16.65	0.22***	16.09	0.22***	15.88	0.22***	16.05	0.22***	15.53	0.21***	15.40
LPOP_DEN	-0.04***	-10.22	-0.02***	-6.54	-0.03***	-8.14	-0.03***	-8.42	-0.02***	-4.62	-0.02***	-5.62	-0.02***	-5.73

No-stars: non-significant at conventional level *: Significant at 10 % **: Significant at 5 % ***: Significant at 1 %
1: previous year 3: previous three years 5: previous five years

Table 2: Parameter Estimates for the local Development Pressure Variables

Development pressure variables	The naive model		The alternative models											
			Buffer=0.8 km						Buffer=1.6 km					
			Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
			Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Buffer =.8 km														
LC			0.32***	14.46	0.33***	14.30	0.33***	14.84						
LPT_1			0.40***	8.74										
LPT_3					0.21***	3.66								
LPT_5							0.40***	5.74						
Buffer=1.6 km														
LC1									0.45***	15.28	0.48***	16.05	0.48***	16.65
LPT1_1									0.43***	7.07				
LPT1_3											0.24***	3.28		
LPT1_5													0.38***	4.84
Adjusted R^2	0.75		0.77		0.76		0.77		0.77		0.77		0.77	
Residual sum of squares	328.87		305.82		310.15		307.85		301.54		304.14		303.04	

No stars: non-significant at conventional level *: Significant at 10 % **: Significant at 5 % ***: Significant at 1 %

Table 3: Results from the Lagrange Multiplier (LM) Test

	Buffer=0.8 km			Buffer=1.6 km		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	LC, LPT_1	LC, LPT_3	LC, LPT_5	LC1, LPT1_1	LC1, LPT1_3	LC1, LPT1_5
LM-statistic	300.22***	240.31***	273.82***	356.00***	322.17***	336.42***
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Degree of freedom	2	2	2	2	2	2

No stars: non-significant at conventional level *: Significant at 10 %

**: Significant at 5 %

*** : Significant at 1 %

Table 4: Results from the Spatial Autocorrelation Test

Test	Model 4	Model 6
FAR	ρ=0.40 ***	ρ=0.41 ***
	P-value=0.0000	P-value=0.00

No stars: non-significant at conventional level *: Significant at 10 %

**: Significant at 5 %

*** : Significant at 1 %

Table 5: Hedonic Spatial Error Models: Maximum Likelihood and Bayesian Estimates

Variables	Model 4				Model 6			
	SEM (ML)		SEM_B (Bayesian)		SEM (ML)		SEM_B (Bayesian)	
	Coef	p-level	Coef	p-level	Coef	p-level	Coef	p-level
CONSTANT	12.97***	0.00	13.05***	0.00	13.31***	0.00	13.43***	0.00
LAREA	0.11***	0.00	0.11***	0.00	0.11***	0.00	0.11***	0.00
LBLDG_AG	-0.09***	0.00	-0.09***	0.00	-0.09***	0.00	-0.09***	0.00
LROOM_T	0.76***	0.00	0.73***	0.00	0.77***	0.00	0.74***	0.00
AJACENTAG	-0.03***	0.05	-0.02**	0.02	-0.02*	0.07	-0.02**	0.04
LCOMM	0.02***	0.00	0.02***	0.00	0.02***	0.00	0.02***	0.00
LINDUSTR	0.04***	0.00	0.04***	0.00	0.04***	0.00	0.03***	0.00
LGOLF	-0.08***	0.00	-0.08***	0.00	-0.08***	0.00	-0.09***	0.00
LHIGHWAY	-0.02***	0.00	-0.02***	0.01	-0.03***	0.00	-0.02***	0.00
LCOLCENTER	-0.46***	0.00	-0.43***	0.00	-0.47***	0.00	-0.44***	0.00
LSCHOOL	-0.02***	0.00	-0.02***	0.01	-0.02***	0.00	-0.02***	0.00
LSTREAM	-0.01**	0.05	-0.01***	0.01	-0.01**	0.04	-0.01**	0.02
SUBDIVISIO	0.00	0.97	0.01	0.17	0.00	1.00	0.00	0.37
LINC_CAP	0.24***	0.00	0.20***	0.00	0.23***	0.00	0.19***	0.00
LPOP_DEN	-0.02***	0.00	-0.01***	0.00	-0.02***	0.00	-0.02***	0.00
LC1	0.42***	0.00	0.46***	0.00	0.43***	0.00	0.49***	0.00
LPT1_1	0.40***	0.00	0.40***	0.00				
LPT1_5					0.46***	0.00	0.44***	0.00
λ	0.47***	0.00	0.59***	0.00	0.46***	0.00	0.56***	0.00
R^2	0.79		0.77		0.79		0.77	
Adjusted R^2	0.79				0.79			
Log-Likelihood	-14540		-		-14544.577		-	

No-stars: non-significant at conventional level *: Significant at 10 %

**: Significant at 5 %

***: Significant at 1 %