Impacts of the Boom-Bust Cycle on the Effectiveness of Policies for Moderating the Consequences of Sprawl on Residential Development

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1. Introduction

Ever since World War II, urban sprawl (i.e., the leapfrogging of development beyond the city's outer boundary into smaller rural settlements) has become a widespread phenomenon in the United States (Jackson 1985). Urban sprawl has been driven by household preferences for bigger houses, larger lots, lower land prices, lower noise and pollution, lower crime, and higher-quality schools (Hanham and Spiker 2005). This dominant pattern of development over 50 years in the United States has been interrupted by the housing –market collapse and high gasoline prices during the first decade of the twenty-first century (Gillham and MacLean 2002). Some economists believe there exists significant evidence that sprawl has been waning since the mid-2007, when the US housing market began experiencing a sub-prime mortgage market "meltdown" (Bowen 2009). The slowdown of sprawl is not surprising because the housing slump and financial crisis have taken their toll on real estate markets almost everywhere in the United States, including suburban housing markets that were characterized by suburban sprawl before the housing market collapse.

While the housing slump and financial crisis that started in mid-2007 may have been a factor in the recent slowdown of sprawl, the unanswered question is whether this slowdown is a cyclical or long-term shift. Some researchers argue that economic recession could lead to eradication of sprawling development in the long run. The underlying premises behind the argument for the long-term slowdown of sprawl are, in part, anticipation of continuous high-gasoline price and gradually diminishing preferences for larger-lot houses.

The gasoline price rose from under $2 per a gallon for regular unleaded in the boom years to over $4 per gallon by 2008 (U.S. Energy Information Administration 2010). It has stayed over $2 per gallon since 2008 and is projected to reach $4 per gallon again in by mid-2011, mainly due to recent turmoil in the Middle East (U.S. Energy Information Administration 2010). High gasoline prices increase the burden of transportation costs on household expenses. By one estimate, Americans spend $1.25 billion less on consumer goods for each one-cent increase in the price of gasoline (La Monica 2009). National average vehicle miles traveled decreased 3.6 percent between 2007 and 2008 (American Public Transportation Association 2009). Increased transportation costs are a greater burden on outer suburban residents than city dwellers because of the greater average transportation expense for the outer suburban residents (Center for Neighborhood Technology 2010). The extra burden on household budgets has forced home foreclosures in exurban areas and encouraged outer suburban residents to move into city centers (Karlenzig 2010). Thus, high gasoline prices now and in the future may reduce sprawling development in the long run.

Another potential explanation for the long-term slowdown in sprawl is diminishing preferences for bigger houses among younger-generation, later-marrying, baby-boomer children, and empty nesters. Trends indicate that these groups continue to migrate into urban core areas, because they lack preferences for bigger houses on larger lots in suburban areas (Urban Land Institute and PricewaterhouseCoopers 2010), and prefer living in urban infill housing, such as apartments or townhouses, which are closer to cultural and entertainment attractions, require less upkeep, and have less road congestion and lower energy costs. Also, young households without children have less concern for better educational environments that may exist in suburban areas, reducing the demand for suburban living that drives urban sprawl (Urban Land Institute and PricewaterhouseCoopers 2010).

While arguments for a long-term slowdown in sprawl may seem convincing, contrasting arguments suggest that the current slowdown is a temporary phenomenon. It is difficult to predict when the real estate market will rebound; however, the overwhelming consensus is that the market will rebound as it did after previous recessions (e.g., rebounds after 1982, 1991, and 2001 recessions), because of the cyclical nature of the real estate market (National Bureau of Economic Research 2010). Assuming the real estate market eventually recovers, the question is whether the recovery will lead to a rebound in urban sprawl.

Evidence suggests that recovery in the real estate market will lead to the return of urban sprawl to some extent. One indicator is the stability of most households' preferences for housing features that drive sprawl (e.g., bigger houses, larger lots, lower land prices, lower noise and pollution, lower crime, and higher-quality schools). Much hedonic literature has shown that more finished area, larger lots, lower noise and pollution, and higher-quality schools add value to houses regardless of the study area or study period (e.g., (Anderson and West 2006; Cho, Bowker et al. 2006; Cho, Poudyal et al. 2008; Anselin and Lozano-Gracia 2009; Cavailhès, Brossard et al. 2009; Cho, Kim et al. 2009; Páez 2009). These consistent preferences were found even during the 2008 recession (e.g., Cho et al. 2011). These household preferences are unlikely to change appreciably even with the gradually diminishing preferences for bigger houses and larger lots among the aforementioned demographic groups. Thus, the decrease in sprawl of recent years may not have come from changes in household preferences but rather from external factors such as the recession and collapse in the real estate market.

Regardless of the future of urban sprawl, the present (2011) is a good time to evaluate potential policy tools that aim to contain sprawl, because in the last four years the U.S. economy has experienced the largest real estate boom and housing slump in the five decades (National Bureau of Economic Research 2010). Thus, the objective of this research is to evaluate the effectiveness of alternative land-use policy tools for controlling sprawl development in a sprawling metropolitan area during two extreme market conditions, namely a real estate boom and a recession. Specifically, two hypotheses are tested: (1) the alternative sprawl-management policies promote more compact and less leapfrogging development, and (2) the effectiveness of the policies in controlling sprawl varies between periods of real estate boom and recession.

The key contribution of this research is to provide the first empirical evaluation of land-use policies for containing urban sprawl under different market conditions. An implicit assumption typically made in previous literature is that the effectiveness of the policy tools is evaluated under normal economic conditions, i.e., neither a recession nor a boom (e.g., Brueckner and Kim 2003). Our research tests three types of land use policies to promote compact development and discourage leapfrogging development while acknowledging two extreme market periods. Two models, one for a boom and another for a recession, and their simulation results will reveal different effects of three land-use policies on individual development decision-making for two extreme market conditions. These results will provide researchers, policy makers, and those who advise them a way to inform public policymaking in an important, useful, and easily understandable way.

2. Empirical Model

Extending Carrión-Flores and Irwin (2004), a two-step approach is used that combines step (1) a parcel-level, spatial discrete-choice model (Klier and McMillen 2008) to explain individual land conversion decisions, and step (2) *ex ante* simulations of the spatial discrete-choice model with and without the three land-use policies, assuming either a real estate boom or a recession, to estimate the policy impacts on sprawl using spatial landscape-pattern metrics.

2.1. Step (1): Spatial lag probit model for parcel-level land conversion decisions

Land conversion decisions may be co-determined through neighborhood spillover effects, because neighbors share common characteristics, and hence their decisions exhibit high dependence among the error terms in a land conversion model (Irwin and Bockstael 2001; Carrión-Flores and Irwin 2004; Cho, Newman et al. 2005; Irwin, Bell et al. 2006). Spatial dependence can occur due to spatial correlated land-use decisions or as a consequence of residual correlation caused by unobserved factors that are spatially dependent.

The simple characterization of the development decision for a parcel of land is that the decision depends on differences between the rent R from development d and no development u at parcel location i. A parcel of land is developed if:

[1] $$R_{id} > R_{iu}.$$

The probability that land parcel i is developed is a function of observable variables X and a random error ε:

[2] $$\Pr\left(X_{id} + \varepsilon_{id} > X_{iu} + \varepsilon_{iu}\right).$$

The observation variables are location and neighborhood-specific factors determining the rent, and the ε's are random disturbances reflecting an imperfect relationship between the local attributes and rents. It is likely that the rents from development and no development are codetermined as functions of rents occurring at other locations. Thus the probability function [2] can be revised as follows:

$$[3] \qquad \Pr\left(\rho^{d} R_{-id} + X_{id} + \varepsilon_{id} > \rho^{u} R_{-iu} + X_{iu} + \varepsilon_{iu}\right)$$

with ρ^{d} and ρ^{u} determine the degree of correlation between rents from development and no development at other locations *-i* (i.e., locations other than *i*), respectively. Thus, the probability that parcel *i* is developed is given by:

$$[4] \qquad \Pr(develop) = \Pr\left[(\rho^{d} R_{-id} - \rho^{u} R_{-iu}) + (X_{id} - X_{iu}) > (\varepsilon_{id} - \varepsilon_{iu})\right].$$

Klier and McMillen (2008) provide the details for estimation of equation [4] based on a spatial lag probit model. Using Klier and McMillen's (2008) notation, the covariance of the spatial lag land-development model for limited dependent response variables:

$$[5] \qquad Y = \rho \mathbf{W} Y + X\beta + \varepsilon,$$

is $\sigma_{\varepsilon}^{2}[(I-\rho\mathbf{W})'(I-\rho\mathbf{W})]^{-1}$, where $\mathbf{W}$ is a matrix representing the neighborhood structure and ρ is the coefficient of spatial lag to be estimated. Because the scale of Y cannot be identified in discrete choice models, σ_{ε}^{2} is restricted to be a constant. For simplicity, notation for the two time periods is suppressed as the same model is applied to each time period (recession and boom periods). In the case of the probit specification, $\sigma_{\varepsilon}^{2} = 1$, with the variance ($\sigma^{2}$) specified as the diagonal elements of the term. Define *S* to be an *n* by *n* matrix with σ_{i}^{-2} on the diagonals and let ω_{ij} be an element in the *n* by *n* matrix $S(I - \rho\mathbf{W})^{-1}$. Then the error terms for the first stage latent variable model are:

$$[6] \qquad \varepsilon_{i}^{*} = \sum_{j=1}^{n} \omega_{ij} \varepsilon_{ij}.$$

The marginal probabilities of the spatial-probit model are calculated as:

[7] $\partial E(\mathrm{Y} \mid \mathrm{X}r) / \partial \mathrm{X}r = \phi[(\mathrm{I}-\rho\mathbf{W})^{-1}\mathrm{I}\bar{\mathrm{X}}r\beta r] \odot (\mathrm{I}-\rho\mathbf{W})^{-1}\mathrm{I}\beta r$,

where Xr is *r*th explanatory variable, $\bar{\mathrm{X}}r$ is the mean value of Xr, $\phi(\cdot)$ denotes the standard normal density, and $\odot$ represents Hadamard or element-by-element multiplication. The diagonal elements represent the direct impacts, the average of the row sums is the total impact, and the difference between these two measures is the indirect impacts (LeSage and Pace 2009).

The likelihoods of a given parcel being developed during the 2004–2006 and 2008–2009 periods were estimated using separate discrete-choice models. The development model for the 2004 –2006 period was used to represent a real estate boom (hereafter referred to as “the boom model”) and the model during the 2008–2009 was used to represent a recession (hereafter referred to as “the recession model”).

2.1.1. Specification of neighborhood structure

The spatial weight matrix **(W)** is based on Tobler’s First Law of Geography, where near things are more related than distant things (Tobler 1970, p. 236). In general, there is no consensus which weights are most appropriate for any econometric study (Anselin 1988), and the selection of appropriate weight matrices **W** in the equation [5] remains a challenge. Florax and Rey (1995) discuss some problems that may arise if spatial weight matrices are poorly selected. We test several types of weighting matrices, show how they influence model estimates, and select a weight matrix with the best goodness of fit for both the recession and boom models.

We consider a variety of neighborhood specifications, including K-nearest neighbor (KNN), Thiessen polygon (“queen” contiguity) arrangements, and inverse distance matrices with the distance cut-off specified by the KNN or Thiessen polygon neighborhoods.[1] The KNN weight matrix was constructed so that the number (*k*) of nearest neighbor parcels was identified based on the Euclidean distances between any two possible centroids of parcels. Given the identified KNN, **W** was structured the same way as the Thiessen polygon weight matrix. The KNN weight matrix is based on the assumption that observations outside the KNN of any given observation have no influence on the given observation. Several numbers of neighbors (i.e., 1, 2, 3, 4, 5, 7, 11, 26, and 131 nearest neighbors) were used to construct the KNN weights for use in estimation.

The Thiessen polygon weight matrix was constructed in two steps. In the first step, Thiessen polygons were constructed so that the centroid of each parcel was assigned to an area whose boundaries are defined by the median distance between the centroid of a parcel and its nearest centroids of parcels. In the second step, the first-order contiguous Thiessen polygons were identified as observations that share a common border or vortex. **W** was structured so that, if parcels *i* and *j* were identified as neighbors, the off-diagonal elements of the spatial weight matrix $\mathbf{W}_{ij}$ took the value of 1, and 0 otherwise. The diagonal elements took the value of 0. A Thiessen polygon weight matrix effectively turns the spatial representation of a sample from points into area (Anselin 1988).

Each KNN or Thiessen polygon neighborhoods was interacted with an inverse distance matrix to include decay effects between neighbors. The inverse distance weight matrix was constructed so that Euclidean distances between any two possible centroids of parcels were measured and their inversed values within the distance cut-off specified by the KNN or Thiessen polygon neighborhoods were taken as the off-diagonal elements of the spatial weight matrix $\mathbf{W}_{ij}$. Again, the diagonal elements took the value of 0. All matrices were row standardized such that

[1] A polygon is a plane figure that is bounded by a closed path. Thiessen polygons are polygons whose boundaries define the area that is closest to each point relative to all other points (GeoDa Center 2010).

the column sum of each row was one. Weight selection was based on overall model fit including the log likelihood and McFadden R^2.

2.1.2. Specification of parcel-level development model

A common way to define residential development of land parcel *i* is to identify whether or not a structure for residential purposes has been built during a given period of time (e.g., Cho et al. 2010; Cho and Newman 2005; Cunningham 2006). Identifying the development status of a parcel based only on the placement of a structure on the parcel, regardless of the parcel's fragmentation status, presents problems in using the land conversion model to identify spatial patterns of land-use changes. Specifically, building a structure on a parcel within an developed subdivision does not represent new development and is not associated with the spatial pattern of land-use changes, i.e., for our purposes, a parcel with such construction should not be counted as a "developed" parcel in the land conversion model in equation [5]. Another problem with the typical land conversion modeling approach is that structures built on parcels within a subdivision are counted as individual land-development decisions, when in fact development of the subdivision represents only one land-development decision by a landowner or a group of landowners.

The aforementioned issues can be mitigated by treating large parcels prior to subdivision fragmentation as development units that are in either a developed or an undeveloped state. Using this notion and following Irwin and Bockstael (2004), we define Y in equation [5] as undeveloped parcels at the beginning of the study period that could have been developed for residential uses (i.e., minimum size of subdivision development in 2004–2009). Some parcels in the data were entirely vacant while others had at least one structure. All such parcels developed as residential uses by the end of the study period are considered as developed parcels.

2.2. Step (2): Spatial landscape pattern metrics with and without the policy variables

The hypotheses that each policy tool reduces the leapfrogging pattern of development and decreases fragmented development at the county level are tested by comparing three landscape pattern metrics: the number of patches, the mean patch size, and the total edge length (i.e., the sum of the perimeters for all patches belonging to a particular land use) with and without the three land use policies. The hypotheses that each policy tool increases the compact pattern of development at the county level are tested by comparing two landscape pattern metrics: mean nearest neighbor and mean perimeter-are ratio with and without the three land use policies.

Number of patches measures total number of contiguous residential developments. Mean patch size measures average size of contiguously developed residential patches. Total edge length measures the total perimeter of contiguously developed residential patches. Mean perimeter/area ratio is calculated as the sum of the perimeters of each residential patch divided by the number of residential patches. Mean nearest neighbor measures the average of the nearest neighbor distance from individual residential patches to their shortest edge-to-edge distance to another patch of the same land use. The landscape pattern metrics were created using the GIS shape files of individual parcel data and Patch Analyst tool in ArcGIS 9.3 (Rempel 2011).

Combinations of the landscape pattern metrics provide an indication of the size and degree of fragmentation of the landscape. The hypothesis that each policy tool promotes a compact development pattern differently during a real estate boom and a recession is tested in the model by comparing mean nearest-neighbor and mean perimeter/area ratio metrics for developed land uses with and without the policy, providing an indication of the dispersion of developed patches. The hypothesis about differences in the effectiveness of land-use policies during the real estate boom and recession is tested by comparing the significance and signs of the land-use policy variables in the spatial discrete-choice models for the two extreme market conditions.

3. Study Area and Data

The study area is Knox County, Tennessee, which covers 526 square miles in East Tennessee, and has a population of approximately 436,000 in 2009 (U.S. Census Bureau 2010). Sprawl-management policies that could be used in the area are urban growth boundaries to represent development guidelines, agricultural zoning representing zoning ordinances, and property tax on land value representing incentive-based policies. Knox County, Tennessee adopted an urban growth boundary in 2001. The urban growth boundary covers about 42 square miles locates mostly around the outside boundary of the City of Knoxville. The land within the urban growth boundary is reasonably compact but adequate to accommodate the city's expected growth over the next 20 years (Metropolitan Planning Commission 2001). Agricultural zoning covers about 300 square miles, mostly outside the City of Knoxville. It separates farming activities from conflicting non-farm land uses to protect a critical mass of farms and farmland (Cordes 2001). Knox County uses the same property tax rate (i.e., 2.96% for the 2004–2006 period and 2.69% for the 2008–2009 period) on the values of land and structure when levying property taxes on residential property. A shift in the burden of property taxation towards land value and away from land improvements is tested as a sprawl policy to promote greater economic incentive to develop land around existing infrastructure and related amenities where land values are higher, and simultaneously discourage development in areas distant from infrastructure (Brueckner and Kim 2003).

Three major GIS data sets were used for this study: individual parcel data, census-block group data, and environmental feature data. Detailed descriptions and detailed statistics of the individual variables used in the regressions are reported in Table 1. Individual parcel data as polygon shape files were obtained from the Knoxville, Knox County, Knoxville Utilities Board Geographic Information System (KGIS) and the Knox County Tax Assessor's Office. Individual parcel data include attribute tables showing information about development status, location information of parcels (i.e., urban growth boundaries, agricultural zoning, City of Knoxville, Town of Farragut, high school district), assessed land value, and parcel size. The development data were collected for the 2004–2006 period and 2008–2009 period for the boom model and the recession model, respectively. At the beginning of 2004 and 2008, the numbers of undeveloped parcels that could have been developed into at least 0.5-acre residential uses (i.e., minimum size of subdivision development in 2004–2009) in Knox County were 17,288 and 17,188, respectively. Only residential developments were considered as developed parcels in both boom and recession models. Of those undeveloped parcels at the beginning of 2004 and 2008, 105 and 39 were fragmented for residential development or developed by building a structure on a parcel outside of developed subdivision during the 2004–2006 and 2008–2009 periods, respectively. Since any parcel was not developed inside City of Knoxville during the recession period, dummy variable for City of Knoxville was excluded in the recession model to obviate the complete separation, which cause serious problem of the model validity.

Environmental feature data (i.e., park, golf course, greenway, railroad, highway, water body, and sidewalk) and location of central business district (CBD) were obtained from KGIS

(2006) and Environmental Systems Research Institute Data and Maps 2008 (ESRI 2008) to create distance variables. The elevation data were obtained from the US Geological Survey (USGS 2004) and were calculated at a resolution of 1/3 arc-second (approximately 100 square meters); a scale sufficiently small to account for the smallest parcels (about 2,000 square meters). The slope was derived from a digital elevation model using the elevation data (USGS Digital Elevation Model Information, 2001).

American College Testing (ACT) scores for the twelve high schools were obtained from the Tennessee Department of Education (TDE 2009), which was used as a proxy for school quality. The ACT scores at the beginning of each study period (2004 for the boom and 2008 for the recession) were assigned to parcels in each high school district. The census-block group data from the 2000 Census, including median household income, housing density, travel time to work, unemployment rate and vacancy rate, were assigned to parcels within their census-block groups. The periodic nature of census taking means that the census and parcel records are not perfect matches; however, the census data were treated as lagged variables.

Since the unstable estimates and high standard error are expected in the regression results when multicollinearity exists in the model, the condition indices and the variance inflation factors are used to find out which variables are nearly collinear with which other variables. The condition indices are the square roots of the ratio of the largest eigenvalue to each individual eigenvalue. Belsey, Kuh, and Welsch (1980) suggested that the estimates might have a fair amount of numerical error if the number is larger than 100. The condition indices for the variables of urban growth boundary, agricultural zoning, property tax on land value and Farragut were greater than 100 in both regression models while the condition indices for the variables of Knoxville and ACT score are greater than 100 in the boom model and in the recession model, respectively. However, all variables were used in the regression because the inflation in the variances of the parameter estimates due to multicollinearities measured by variance inflation factor was not serious (the highest was 2.9 and 3.6 among all variables in the boom and recession models, respectively).

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Table 1. Variables and definition

Variables (Unit)	Definition	Boom	Recession
Dependent variable			
Development	Dummy variable of subdivision development in 2004-2006 for boom in 2008-2009 for economic recession (1 if developed, 0 otherwise)	0.006 (0.078)	0.002 (0.048)
Policy variables			
Urban growth boundary (UGB)	Dummy variable for urban growth boundary (1 if in urban growth boundary, 0 otherwise	0.097 (0.296)	0.096 (0.295)
Agricultural zoning	Dummy variable for the agricultural zoning (1 if in agricultural zoning, 0 otherwise)	0.988 (0.108)	0.992 (0.087)
Property tax on land value ($)	Property tax on land value	750.735 (760.709)	682.496 (695.038)
Socioeconomic variables			
Median household income ($)	Median household income for census-block group	20,566.552 (7,198.918)	20,521.296 (7,176.327)
Housing density (houses/acre)	Housing density for census-block group	0.308 (0.330)	0.304 (0.321)
Travel time to work (Minute)	Average travel time to work for census-block group in 2000	25.980 (3.965)	26.003 (3.962)
Unemployment rate	Unemployment rate for census-block group in 2000 (ratio of unemployed to the labor force, age 16 or older)	0.037 (0.021)	0.037 (0.021)
Vacancy rate	Vacancy rate for census-block group in 2000 (ratio of vacant housing units to total housing units of any type)	0.067 (0.021)	0.067 (0.021)
Distance and physical variables			
Distance to park (feet)	Euclidean distance from the centroid of a parcel to the centrioid of the nearest park among 42 municipal parks	29,468.632 (14,164.907)	29,587.551 (14,149.714)
Distance to golf course (feet)	Euclidean distance from the centroid of a parcel to the nearest golf course	17,874.082 (8,120.861)	17,929.983 8,128.046)
Distance to greenway (feet)	Euclidean distance from the centroid of a parcel to the nearest greenway (a mostly contiguous vegetated pathway developed for recreation, pedestrian, and bicycle uses)	18,559.659 (9,555.118)	18,648.959 (9,538.317)

Distance to railroad (feet)	Euclidean distance from the centroid of a parcel to the nearest railroad	12,635.939 (8,791.858)	12,683.234 (8,798.126)
Distance to highway (feet)	Euclidean distance from the centroid of a parcel to the nearest interstate highway	20,052.652 (12,980.273)	20,127.714 (12,995.385)
Distance to water body (feet)	Euclidean distance from the centroid of a parcel to the nearest water body	11,361.189 (8,208.319)	11,378.740 (8,222.779)
Distance to sidewalk (feet)	Euclidean distance from the centroid of a parcel to the nearest interstate highway	12,167.181 (9,618.737)	12,237.390 (9,623.790)
Distance to CBD	Euclidean distance from the centroid of a parcel to the centroid of the central business district	53,534.129 (16,969.032)	53,534.978 (16,941.097)
Elevation	Average elevation of parcel	3,400.825 (386.741)	3,400.960 (387.529)
Slope (°)	Degree of slope at the parcel location	7.741 (4.434)	7.759 (4.442)
Lot Size (Acre)	Size of developable parcel or developed subdivision	5.434 (13.044)	5.239 (12.401)
Spatial fixed effect Variables			
ACT score	Average composite score of American College Test by high school district in 2004 for economic boom and in 2008 for economic recession	20.542 (0.717)	21.160 (1.015)
Knoxville	Dummy variable for City of Knoxville (1 if in City of Knoxville, 0 otherwise)	0.026 (0.160)	
Farragut	Dummy variable for Town of Farragut (1 if in Town of Farragut, 0 otherwise)	0.004 (0.059)	0.003 (0.051)

Table 2. Model selection criteria

Weighting Matrix	Boom		Recession	
	Log likelihood	McFadden R^2	Log likelihood	McFadden R^2
K nearest neighbors of order q [KNN(q)]				
KNN(1)	-391.940	0.388	-190.568	0.310
KNN(2)	-380.595	0.410	-188.957	0.316
KNN(3)	-383.965	0.401	-201.318	0.271
KNN(4)	-404.166	0.369	-225.055	0.185
KNN(5)	-399.370	0.377	-195.878	0.291
KNN($7=n^{1/5}$)	-387.362	0.395	-192.261	0.304
KNN($11=n^{1/4}$)	-383.102	0.402	-190.802	0.309
KNN($26=n^{1/3}$)	-383.788	0.401	-190.647	0.310
KNN($131=n^{1/2}$)	-383.788	0.401	-190.647	0.310
Queen Contiguity	-384.239	0.400	-189.349	0.315
Hybrid with inverse distance (ID)				
KNN(1) × ID	-391.940	0.388	-190.568	0.310
KNN(2) × ID	-396.106	0.382	-199.495	0.278
KNN(3) × ID	-391.315	0.389	-204.019	0.261
KNN(4) × ID	-397.006	0.380	-209.562	0.241
KNN(5) × ID	-399.370	0.377	-206.112	0.254
KNN($7=n^{1/5}$) × ID	-423.095	0.340	-209.291	0.242
KNN($11=n^{1/4}$) × ID	-451.135	0.296	-195.839	0.291
KNN($26=n^{1/3}$) × ID	-415.882	0.351	-190.313	0.311
KNN($131=n^{1/2}$) × ID	-383.921	0.401	-189.743	0.313
Queen Contiguity × ID	-384.239	0.400	-189.349	0.315

Note: Aspatial probit log likelihood = -640.580 (boom) and -276.242 (recession)

Table 3. Regression result

Variables (Unit)	Boom		Recession	
	Coefficient	Std. Error	Coefficient	Std. Error
Constant	-1.791	8.165	-12.409	8.776
Policy variables				
Urban growth boundary	0.316	0.182	0.118	0.248
Agricultural zoning	-1.403*	0.152	-1.516*	0.243
ln(Property tax on land value)	0.173*	0.059	0.111	0.085
Socioeconomic variables				
ln(Median household income)	-0.488	0.270	0.632*	0.281
Housing density	0.049	0.109	0.304*	0.148
Travel time to work	0.049	0.026	0.091*	0.027
Unemployment rate	-4.473	3.828	-22.110*	7.029
Vacancy rate	-1.772	1.919	-7.263*	3.471
Distance and physical variables				
ln(Distance to park)	-0.001	0.159	-0.011	0.164
ln(Distance to golf course)	-0.314*	0.124	-0.674*	0.155
ln(Distance to greenway)	-0.340*	0.077	-0.619*	0.093
ln(Distance to railroad)	-0.030	0.057	-0.193	0.108
ln(Distance to highway)	0.183	0.105	0.125	0.093
ln(Distance to water body)	0.004	0.112	0.267*	0.115
ln(Distance to sidewalk)	0.039	0.095	0.528*	0.139
ln(Distance to CBD)	0.121	0.219	-1.066*	0.312
ln(Elevation)	-0.070	0.811	0.305	1.004
ln(Slope)	-0.140*	0.031	-0.097	0.053
ln(lot size)	0.602*	0.093	0.689*	0.100
Spatial fixed effect Variables				
ACT score	0.327*	0.127	0.716*	0.132
Knoxville	0.299	0.263		
Farragut	-1.131*	0.458	-0.254	0.436
Spatial lag				
ρ	0.229*	0.097	-0.274	0.153

* significant at the 5% (p<0.05)

Table 4. Spatial configuration of residential land uses based on subdivision development with policy variables (status quo) and without policy variable during boom and recession.

Landscape Metric		Boom	Recession
Number of patch [1]	Baseline	2,105	2,085
	Without agricultural zoning	1,960	2,069
	Without property tax on land value	2,121	
Mean patch size [2] (acre)	Baseline	2,983,048	3,024,539
	Without agricultural zoning	3,428,084	3,061,623
	Without property tax on land value	2,943,237	
Total edge length [3] (mile)	Baseline	3,190	3,184
	Without agricultural zoning	3,262	3,187
	Without property tax on land value	3,198	
Mean Nearest Neighbor [4]	Baseline	2,194	2,195
(feet)	Without agricultural zoning	2,147	2,197
	Without property tax on land value	2,192	
Mean Perimeter-Area Ratio [5]	Baseline	0.010933	0.010823
	Without agricultural zoning	0.010919	0.010838
	Without property tax on land value	0.011026	

[1] Total number of contiguously developed residential land uses

[2] Average size of contiguously developed residential land uses

[3] Total perimeter of contiguously developed residential land

[4] Average of the nearest neighbor distance from each individual patch of residential land uses to its shortest distance to another patch of same land uses (edge to edge)

[5] Sum of each patches perimeter/area ratio divided by number of patches