Moderating Urban Sprawl through Land Value Taxation

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Abstract
This research evaluates the effects of a hypothetical land value tax as a smart growth policy to curtail urban sprawl in the mid-sized metropolitan areas of the Southeastern United States. The effectiveness of a hypothetical land value tax on moderating urban sprawl is determined by changes in demand for neighborhood open space, and its relationships with lot size and proximity to the central business district (CBD). Achieving this goal will (1) provide applied researchers with an empirical foundation from which the spatial dynamics of urban sprawl in local housing markets can be measured, and (2) provide policy makers, especially in the large and mid-sized metro areas of the Southeast, with an *ex ante* instrument through which alternative incentives targeting open space preservation can be evaluated. We estimate the effects of a hypothetical land value tax on urban sprawl gauged through the three metrics of demand for neighborhood open space, lot size, and proximity to the CBD by comparing the forecasted values of the demand for these goods under alternative land value taxation schemes. The first is a "regular property tax" when the tax rates on the assessed values of land and structures are identical. The second is a hypothetical "land value tax" that places more weight on the value of land than on the value of structures, holding annual total county tax revenue constant.

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1. Introduction

Rapid population and economic growth in Tennessee has led to increasing residential demand for land and a sprawling pattern of development. Consensus does not exist on the definition of urban sprawl, but experts agree that the expansion of urban development into rural areas, conversion of farmland to residential subdivisions, and leapfrog development along city limits aptly characterize the process (Hanham and Spiker 2005). The Knoxville Metropolitan Statistical Area (MSA) in Tennessee is one of the top ten fastest growing metropolitan areas in the United States (Expansion Management 2006). This growth has raised many concerns about potential negative impacts, especially the loss of benefits provided by farmland and open space and higher costs of infrastructure and community services. Concerns about the negative consequences of urban sprawl have led local policymakers and nongovernmental activists to turn to urban and suburban open space preservation as potential mechanisms to counter urban sprawl.

One example of these mechanisms includes "smart growth" policies. Smart growth policies are development initiatives that protect open space and farmland, revitalize communities, keep housing affordable, and provide more transportation choices (International City/County Management Association 2007).[1] Compact development is a key component of most smart growth policies. The objective of compact development is to preserve open space by targeting preservation of farmland and other critical environmental areas (Environmental Protection Agency 2007). Local governments have

[1] International City/County Management Association (2007) has laid out 100 policies and guidelines for communities to realize smart growth. The mechanisms include zoning, building design, transfer of development rights (TDRs), purchase of development rights (PDRs), multimodal transportation systems, and land value tax. We do not address the mechanisms other than land value tax in this project.

incorporated smart growth principles into zoning and other ordinances to promote compact development and preserve open space (Tracy 2003).

Despite efforts, some communities with commitments to controlling sprawl through smart growth directives continue to struggle with policy implementation (Cho and Roberts 2007). Achieving compact development is challenging because 1) strong preferences for lower–density development among higher income households may exist (Gordon and Richardson 1998; Skaburskis 2000), 2) demands for open space may increase over time (Cho *et al.* 2008), and 3) clearly defined policy tools that can be implemented to monitor and evaluate compact development initiatives are few and far between. As planners place more emphasis on smart growth policies that encourage compact development and preserve open space, demand for policy tools to achieve these goals will increase. This project examines a land value tax scheme as a smart growth policy tool (Mills 2001).[2] The "two–rate" taxation mechanism examined in this study taxes land at a higher rate than buildings or structural improvements. Hereafter, this taxation scheme is referred as a "land value tax".

Most residential real estate property tax in the United States is collected as a percentage of the total assessed property value, which usually is a taxable portion of the appraised value of land and the structures on it.[3] Because the total assessed value of a property is the sum of the assessed values of land and structures, land and structure values are weighted equally, producing a single property tax rate. Hereafter, this taxation scheme is referred as a "regular property tax". The taxation of buildings, structures, or land improvements allegedly discourages site improvement by reducing the economic

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[2] A land value tax was first proposed by the American social economist Henry George in the 19th Century and received wide popular support (cited in Mills 2001).
[3] The rate is expressed in "mills", where one mill is one–tenth of a cent ($0.001).

return from such improvements (Mathis and Zech 1982). Along these lines, a number of researchers found that land is developed more compactly under a land value tax than a regular property tax schedule (e.g., Brueckner 1986; Brueckner and Kim 2003; Case and Grant 1991; Mills 1998; Nechyba 1998; Oates and Schwab 1997; Skaburskis 1995). Even with this finding, questions still remain about the metrics used to gauge the *ex ante* effects of alternative tax schemes on residential development patterns and about the spatial dynamics of these effects.

Despite the potential advantages of a land value tax in promoting compact development, only a handful of U.S. municipalities have implemented such tax schemes. Among those are Pittsburgh, and a score of towns in Pennsylvania. Pittsburgh's experience with the land value tax is inconclusive. But many small towns experienced increased construction in their centers after implementing the land value tax. The evidence on the effectiveness of the land value tax to reduce sprawl is persuasive, though not conclusive, and the relative rarity of successful implementation makes its effects on urban sprawl difficult to anticipate. Evaluation of the land value tax, therefore, remains an important practical question and policy issue.

Urban sprawl is driven by increasing preferences for a suburban lifestyle, lower density development, and larger lot size. These preferences in turn drive up the demand for neighborhood open space and larger lots. People who demand more neighborhood open space and larger lots are more likely to live farther from the central business district (CBD). We hypothesize that the demand for smaller lots will increase when a land value tax is implemented through a tax scheme that places greater weight on the value of land. Consequently, households may desire to decrease distance to the CBD because houses with smaller lots will be more abundantly available closer to the CBD, assuming that being closer is more desirable than being farther from the CBD *ceteris paribus*. A decrease in distance to CBD should decrease demand for open space. In contrast, because open space may be viewed as a substitute for large residential lots (Cho *et al*. 2008; Thorsnes 2002), households may increase demand for open space and distance to CBD to substitute for the decreased amenity value of smaller lot size. Under this premise, the land value tax will successfully moderate urban sprawl through reductions in demand for open space, lot size, and distance to CBD if households' desires to be closer to CBD are greater than their desires to substitute smaller lots for more open space farther from the CBD.

Empirical measurement of the effects of any tax scheme on neighborhood open space, and its relationship with lot size and proximity to the CBD can be used to test the aforementioned hypothesis. Estimation of these interrelationships suggests a demand system capable of: (1) fully exploiting the information embedded in these correlated preferences, (2) modeling the interactions between agents across the housing market, and (3) generating forecasts that can accurately compare hypothetical land policies to counterfactual scenarios.

This research applies the following steps to evaluate the effectiveness of land value tax policies with respect to moderating urban sprawl. First, a demand system modeling preferences for open space, lot size, and proximity to the CBD is estimated. The estimation procedure applies recent developments in the spatial econometric literature, including the heteroskedastic robust General Method of Moment (GMM) estimators and optimal forecasting procedures using a first–order Spatial Autoregressive and Error Autocorrelated (SARAR[1,1]) spatial process model. Based on these estimates, a hypothetical land value tax scheme is compared to the counterfactual tax policy that places equal weights on land and buildings. Demand forecasts for open space, lot size, and proximity to the CBD are generated under different scenarios that vary the weight of the tax attributed to land, with the regular tax scheme as the base tax structure. We hypothesized that the demand for these goods under the land value tax scheme will exhibit varying degrees of spatial heterogeneity across the housing market, depending on the weight placed on land value, holding other factors constant. *Ex ante* evidence of heterogeneous policy effects on demand for these goods suggests that a sliding land value tax scale may be useful in targeting "critical" sprawl areas.

To our knowledge, studies that have attempted *ex ante* analyses using regression results from spatial process models have done so incorrectly by ignoring the spatial correlation between the response variable and disturbances. While there are currently several approaches that attend to heteroskedasticity *ex post*, we apply a procedure (GMM) that extends the most recent treatment of heteroskedastic-robust spatial process models. Second, there are few (if any) empirical studies that use spatial process models for *ex ante* policy analysis. Our analysis closes the gap in the spatial econometrics literature.

This project evaluates the effects of a hypothetical land value tax as a smart growth policy to curtail urban sprawl in the large and mid-sized metropolitan areas of the Southeastern United States. The effectiveness of the land value tax on moderating urban sprawl is determined by changes in demand for neighborhood open space, and its relationships with lot size and proximity to the CBD. Achieving this goal will (1) provide applied researchers with an empirical foundation from which the spatial dynamics of urban sprawl in local housing markets can be measured, and (2) provide policy makers, especially in the large and mid-sized metro areas of the Southeast, with an *ex ante* instrument through which alternative incentives targeting open space preservation can be evaluated.

We estimate the effects of a hypothetical land value tax on urban sprawl gauged through the three metrics of demand for neighborhood open space, lot size, and proximity to the CBD by comparing the forecasted values of the demand for these goods under alternative land value taxation schemes. The first is a “regular property tax”. This tax scheme is the one currently used by most counties in the Southeast including the study area of Knox County in Tennessee. The second is a hypothetical “land value tax” that places more weight on the value of land than on the value of structures, holding annual county tax revenue constant.

The forecasted quantities demanded under the regular property tax and under the land value tax are used to predict the effects of the land value tax on the three metrics of urban sprawl relative to the regular property tax, and to determine the optimal balance between the tax weights on land value and structure value that can curtail urban sprawl.

Details regarding the empirical procedures and methods are outlined in Section 2 [Empirical Approach]. Details of the study areas and data sources and the education and outreach components of the proposal are highlighted in Section 3 [Study Areas and Data]. Lastly, the policy implications of expected output are outlined in Section 4 [Policy Implications].

2. Empirical Approach

The empirical methodology applies state–of–the–art spatial econometric techniques to (1) estimate the demand system capable of modeling spatial autocorrelation, spatial heterogeneity, and feed–back between demand for open space, lot size, and distance to the CBD, and (2) forecast demand for lot size, open space, and proximity to the CBD for *ex ante* comparisons by applying an unbiased spatial predictor. First, the structural equations used in this research are presented. Second, the methods used to simulate the effects of a land value tax are outlined. Third, the demand system is estimated using a first–order Spatial Autoregressive and Error Autocorrelated (SARAR[1,1]) spatial process model, and details of the estimation procedure are highlighted. The approach extends the traditional feasible three–stage least squares estimator (Kelejian and Prucha 2004) to the General Method of Moments (GMM) framework. Fourth, following the recent work of Kelejian and Prucha (2007), a novel approach for generating unbiased and efficient forecasts using the results of the SARAR(1,1) model is presented, along with derivation of the reduced–form estimates used in the forecasting procedure. Quantities demanded for open space, lot size, and proximity to the CBD are forecasted under different land value tax assumptions, and compared with a status quo, counterfactual tax scheme labeled the "regular property tax".

2.1 Demand System for Open Space, Lot Size, and Proximity to the Central Business District

We hypothesize that demand for open space, lot size, and proximity to the CBD is explained by the following system of equations:

[1]

$$\begin{pmatrix} y_i^{OS} \\ y_i^{LS} \\ y_i^{CBD} \\ y_i^{POS} \end{pmatrix} = \begin{pmatrix} & \gamma_{OS}^{LS} y_i^{LS} & +\gamma_{OS}^{CBD} y_i^{CBD} & +\gamma_{OS}^{POS} y_i^{POS} & +\boldsymbol{\delta}'_{OS}\mathbf{x}_i^A + \overline{\tau}\cdot(L_i+S_i)\delta_{OS}^{TAX} \\ \gamma_{LS}^{OS} y_i^{OS} & & +\gamma_{LS}^{CBD} y_i^{CBD} & & +\boldsymbol{\delta}'_{LS}\mathbf{x}_i^A + \overline{\tau}\cdot(L_i+S_i)\delta_{LS}^{TAX} \\ \gamma_{CBD}^{OS} y_i^{OS} & +\gamma_{OS}^{LS} y_i^{LS} & & & +\boldsymbol{\delta}'_{CBD}\mathbf{x}_i^A + \overline{\tau}\cdot(L_i+S_i)\delta_{CBD}^{TAX} \\ \gamma_{POS}^{OS} y_i^{OS} & & & & +\boldsymbol{\delta}'_{POS}\mathbf{x}_i^B \end{pmatrix} + \begin{pmatrix} e_i^{OS} \\ e_i^{LS} \\ e_i^{CBD} \\ e_i^{POS} \end{pmatrix}$$

, where *OS* is the natural log of the amount of open space in the neighborhood of house *i*, *LS* is the natural log of the parcel size of house *i*, *CBD* is natural log of the distance of house *i* to the central business district, *POS* is the implicit price of open space in the neighborhood of house *i*, and *e* is a random disturbance term for house *i*. Because the implicit price of open space is not readily available, marginal implicit prices from a hedonic housing price model are used as proxies. The marginal implicit price of increasing the amount of open space within a 1-mile radius buffer of house *i* by an additional one acre yields an estimate of the price of open space in the neighborhood surrounding house *i*. Note that open space, lot size, and distance to the CBD are considered endogenous because housing consumers who demand more neighborhood open space and larger lots are more likely to live farther from the CBD. The implicit price of open space is endogenized in the open space demand equation through cov(e_{OS}, e_{LS}, e_{CBD}, e_{POS}) = $\boldsymbol{\Sigma}$. Exogenous variables hypothesized to explain demand for open space, lot size, and proximity to the CBD are represented by $\mathbf{X}^A$. These include structural attributes of the home, the average American College Test score by school district where the house is located, distance measures to amenities (i.e. lakes, parks) or disamenities (e.g., railroads, floodplain area) (See Table 1 for the complete list). The variable, $\overline{\tau}\cdot(L_i+S_i)$, is the prevailing property tax rate (e.g., $\overline{\tau}$ = 2.69% for Knox County, Tennessee) times the assessed value of land and structures at location *i*.[4] Exogenous instruments explaining the implicit price of open space are contained in $\mathbf{X}^B$ (See Table 1 for the complete list).

Given consistent estimates of the parameters of the demand system, and an unbiased and efficient procedure to forecast the demand for open space, $\bar{\tau}$ can be varied (subject to certain conditions) to test *ex ante* hypotheses about how the quantities demanded of open space, lot size, and proximity to the CBD change in particular, and how the land value tax affects urban sprawl in general. Such information can provide insight into where a land value tax can be most successful for encouraging compact development, given significant spatial heterogeneity.

2.2 Determining tax rates based on the hypothetical land value tax

To simulate the effects of a hypothetical land value tax on demand for open space, lot size, and proximity to the CBD, we determined the tax rates on assessed land value using a simple optimization procedure. The key constraint in the problem ensures the sum of the tax revenue collected from all house locations is equal 1) when the tax rates for land and structures are different and 2) when the tax rates on assessed values of land and structures are the same as under the regular property tax. The purpose of the constraint is to determine a differential tax rate scheme for land and structures that is tax neutral when compared to the regular property tax.

[4] Typically, appraisers analyze all real estate sales and develop common units of comparison and corresponding values for structure and land jointly. They review similarities and differences between the properties to arrive at a uniform assessed value for the structure and land of a particular property.

Let $R_i = \bar{\tau}_L L_i^A + \bar{\tau}_S S_i^A$, where R is the municipal government's revenue from property taxes on the assessed (A) value of land (L) and structures (S) at house location i, and $\bar{\tau}$ is a property tax rate (percent). This is considered the "regular property tax" scheme (i.e. the counterfactual, baseline case) in this research when the tax rates on the assessed values of land and structures are identical (i.e., $\bar{\tau} = \bar{\tau}_L = \bar{\tau}_S = 2.69\%$ for Knox County). Then $R^* = \sum_{i=1}^{N} R_i$ is the annual tax revenue for the county from assessed land and associated structures. Suppose the tax scheme placed more emphasis on the assessed value of land by decreasing the tax rate on structures. The revenue collected at property i is then $\widetilde{R}_i = \bar{\tau}_L L_i^A + \alpha \bar{\tau}_S S_i^A$, where $\alpha \in [0,1]$, with lower levels of α reflect greater emphasis on taxing the assessed value of land relative to structures. When α decreases, $\bar{\tau}_L$ must increase for the tax scheme to be revenue neutral.

Consider the following optimization problem that constrains total government tax revenue under the new land value tax scheme to be identical to the original property tax schedule:

[2] $\max_{\tau_L \in [0,1]} Z = 0$, subject to $\underbrace{\sum_{i=1}^{N} \left[\tau_L L_i^A + \alpha \bar{\tau}_S S_i^A \right]}_{\substack{Hypothetical \\ Land\,tax}} = \underbrace{\bar{\tau} \sum_{i=1}^{N} \left[L_i^A + S_i^A \right]}_{\substack{Original \\ tax\,scheme}}$,

where $\bar{\tau} = 2.69\%$ in the original tax scheme for Knox County. For each level of α, this optimization problem finds the levels of $\bar{\tau}_L$ that satisfies the equality constraint that requires tax neutrality between tax schemes. The justification for requiring tax neutrality from a policy perspective is that different levels of tax revenue may not be easily applicable because of public finance balances.

We hypothesize that, with a greater tax rate on the value of land than on the value of structures, households will desire to locate in areas with smaller lot sizes closer to the CBD. Thus, we hypothesize that households' desire to locate closer to the CBD stems from their willingness to sacrifice the opportunity by more open space farther from the CBD for smaller lots with less open space closer to the CBD, thus the land value tax will successfully moderate urban sprawl.

We simulate the hypothetical land value tax scheme under four levels of α; $\alpha \in [0.95,\ 0.75,\ 0.50,\ 0.25]$. Using the model in equation 2, these levels of α generated assessed land value tax rates of $\tau_L \in [3.32\%, 5.86\%, 9.04\%, 12.21\%]$ for the case of Knox County with $\overline{\tau}_S = 2.69\%$. To simulate the effect of the land value tax scheme under these scenarios, we rescaled the tax revenue by the new tax rates on land ($\tau_L L_i^A$) and structures $(\alpha\overline{\tau}_s S_i^A)$ at the *i*th location. Given consistent estimates of the demand system parameters, we forecast demand for open space, proximity to the CBD, and lot size using the rescaled land value.

2.3 General Method of Moments (GMM) Estimation of the SARAR(1,1) Spatial Process Model

Recent years have shown an increasing number of applied studies in geography, economics, and regional science in which the spatial dimension of population and economic dynamics are incorporated in regression models (e.g., Bao *et al*. 2004; Boarnet *et al*. 2005; Cho *et al*. 2007; Cohen and Paul 2005; Lambert *et al*. 2006; Monchuk *et al*. 2007; Moreno *et al*. 2004; Wojan *et al*. 2008). This surge was fueled by recent theoretical developments in spatial econometrics along with better access to spatial data and the increased availability of easy–to–use computational tools.

Most studies use a spatial process model going back to Whittle (1954), in which an endogenous variable is specified to depend on spatial interactions between cross–sectional units plus a disturbance term. The interactions are modeled as a weighted average of nearby cross–sectional units, and the endogenous variable comprising the interactions is usually referred to as a spatially lagged variable. The weights, grouped in a matrix identifying neighborhood connections, form the distinctive core of spatial process models. The model is termed a spatial autoregressive lag model in the terminology of Anselin and Florax (1995). Whittle's spatial autoregressive lag model of the first order (SAR[1]) was popularized and extended by Cliff and Ord (1973; 1981), who distinguished models in which the disturbances follow a spatial autoregressive process.

The general model, which contains a spatially lagged endogenous variable, as well as spatially autoregressive disturbances in addition to exogenous variables, is called a spatial autoregressive model with autoregressive (AR) disturbance of order (1,1) (SARAR) (Anselin 1988; Kelejian and Prucha 2006); $\mathbf{y} = \rho\mathbf{W}_1\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$, $\mathbf{e} = \lambda\mathbf{W}_2\mathbf{e} + \mathbf{u}$, $\mathbf{u} \sim \mathrm{iid}(\mathbf{0}, \boldsymbol{\Omega})$, where $\mathbf{W}_1$ and $\mathbf{W}_2$ are (possibly identical) nonstochastic, positive definite, exogenous matrices defining interrelationships between spatial units, and $\mathrm{E}[\mathbf{uu}'] = \boldsymbol{\Omega}$. The reduced–form version is $\mathbf{y} = (\mathbf{I} - \rho\mathbf{W}_1)^{-1}\mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \rho\mathbf{W}_1)^{-1}(\mathbf{I} - \lambda\mathbf{W}_2)^{-1}\mathbf{u}$. Spatial process models are typically estimated using maximum likelihood, but more frequently researcher are turning towards generalized method of moments (GMM) or instrumental variable (IV) procedures.

An iterative GMM approach is used in this study because there is no reason to believe that the errors generated by the demand system follow a pre–determined distribution. The approach taken here modifies Kelejian and Prucha's (2004) three–stage least squares estimator to an estimator robust to unspecified forms of heteroskedasticity.

2.3.1 The Heteroskedastic–robust GMM–SARAR(1,1) Estimator

Kelejian and Prucha (2004) (from here, K&P) extended the single equation SARAR(1,1) model to a system of equations. They suggested a feasible three–stage least squares (F3SGLS) estimator to determine the AR and main effect parameters. The estimator is identical to the usual three–stage least squares estimator (Greene 2000), except that the matrix of regressors including the exogenous and endogenous variables is spatially detrended using a Cochran–Orcutt filtering mechanism (see Cliff and Ord 1973; 1981).

Below, K&P's F3SGLS estimator is modified to accommodate nonspherical errors using a linear GMM estimator. But first, the F3SGLS estimator is reviewed, followed by the methods employed to estimate the spatial error autoregressive terms for each equation. Once these pieces are in place, they are combined to develop the heteroskedastic–robust GMM–SARAR(1,1) estimator applied in this research.

2.3.2 Background: the F3SGLS–SARAR(1,1) estimator

For the *j*th equation in the system ($j = 1,\ldots, M$), let $\mathbf{Z}_j = [\mathbf{W}\mathbf{y}_j, \tilde{\mathbf{Y}}_j, \mathbf{X}]$ be the *n* by *k* set of regressors including the exogenous variables ($\mathbf{X}$) and the variables determined within the system ($\mathbf{W}\mathbf{y}_j$ and $\tilde{\mathbf{Y}}_j$; $\tilde{\mathbf{Y}}_j$ contains at least one variable determined within the system), and $\mathbf{W}$ is an *n* be *n* nonstochastic weighting matrix identifying neighborhoods of observations (for exposition, we assume $\mathbf{W}_1 = \mathbf{W}_2$ as is commonly practiced in the literature). Let $\mathbf{Q} = [\mathbf{X}, \mathbf{WX}, \mathbf{W}^2\mathbf{X}]$ be the n by g matrix of instruments. Finally, let $\mathbf{P}$ be a symmetric, positive definite matrix, $\mathbf{P} = \mathbf{Q}(\mathbf{Q}'\mathbf{Q})^{-1}\mathbf{Q}'$, and $\hat{\mathbf{Z}} = diag(\mathbf{PZ}_1, \mathbf{PZ}_2, ..., \mathbf{PZ}_M)$.

In the first step, the system is estimated with the usual 3SLS estimator (Greene 2000); $\hat{\boldsymbol{\delta}}_{3SLS} = \left[\hat{\mathbf{Z}}'\left(\boldsymbol{\Sigma}^{-1} \otimes \mathbf{I}_M\right)\hat{\mathbf{Z}}\right]^{-1} \hat{\mathbf{Z}}'\left(\boldsymbol{\Sigma}^{-1} \otimes \mathbf{I}_M\right)\mathbf{y}$, where $\boldsymbol{\Sigma} = n^{-1}\mathbf{e}'\mathbf{e}$, $\mathbf{e} = [\hat{\mathbf{e}}_1, \hat{\mathbf{e}}_2, ..., \hat{\mathbf{e}}_M]'$, and $\hat{\mathbf{e}}_j$ is the residual vector of the jth equation estimated with two–stage least squares; $\hat{\mathbf{e}}_j = \mathbf{y}_j - \mathbf{Z}_j\left(\mathbf{Z}_j'\mathbf{PZ}_j\right)^{-1}\mathbf{Z}_j'\mathbf{y}_j$. Using the 3SLS residuals, K&P apply their minimum distance (MD) estimator (Kelejian and Prucha 1999) to obtain a spatial error AR term (λ) for each equation. Given a consistent estimator of λ for each equation, $\mathbf{Z}_j$ and $\mathbf{y}_j$ are spatially detrended with the corresponding λ_j using a Cochran–Orcutt filtering device; $\widetilde{\mathbf{Z}}_j(\lambda_j) = (\mathbf{I}_n - \hat{\lambda}_j\mathbf{W})\mathbf{Z}_j$, and $\widetilde{\mathbf{y}}_j(\lambda_j) = (\mathbf{I}_n - \hat{\lambda}_j\mathbf{W})\mathbf{y}_j$. The 3SLS estimator is constructed again using these transformed variables, and the process is repeated until a convergence criterion is satisfied.

2.3.3 Heteroskedastic–robust minimum distance estimation of spatial error processes

Recent advances in estimation of the spatial error AR term (λ) allow for heteroskedastic error terms (Kelejian and Prucha 2007). The Minimum Distance estimation of the error AR term was developed by K&P in 1999 under the assumption of homoskedastic disturbances. Relaxing this assumption implies that $E[\mathbf{uu}'] = \boldsymbol{\Omega}$, where $\boldsymbol{\Omega}$ is a positive–definite matrix n by n. Estimation of the spatial error (SE) process for the jth equation (e.g., $\mathbf{e}_j = \lambda_j\mathbf{W}\mathbf{e}_j + \mathbf{u}_j$) applies a recently developed minimum distance procedure that allows heteroskedastic–robust estimation of the error autoregressive term when disturbances are nonspherical (Kelejian and Prucha 2006).

The key difference between the heteroskedastic and heteroskedastic–naïve SE–MD estimators relates to the construction of the moment conditions. In the heteroskedastic–robust version of the SE–MD estimator (SE–MD_{HET}), the moment conditions are re–specified as the difference between the sum of squares of appropriately filtered error terms and the trace of the product of the spatial weights matrices re–scaled by the residual terms. See Kelejian and Prucha (2006) for details.

Given the general structure of the F3SGLS–SARAR(1,1) estimator and a heteroskedastic–robust estimator for the spatial error process in each equation, the GMM–SARAR(1,1) estimator naturally follows with some minor modifications. First, an iterative approach is applied similar to the one taken for the F3SGLS–SARAR(1,1) estimator. Second, the same procedure used in the above steps is used to estimate the spatial error AR terms. What differs with this approach is treatment of the covariance terms in the system estimator.

The SAR(1) spatial lag model is clearly a special case of a GMM estimator. In the GMM setting, a system of SAR(1) equations implies the following moment conditions for equation j (Greene 2000), $E[\mathbf{q}_i \mathbf{e}_{ji}] = E[\mathbf{q}_i(y_{ji} - \mathbf{z}'_{ji}\boldsymbol{\delta}_j)] = \mathbf{0}$, $i = 1,..., N$ observations, $j = 1,..., M$ equations. We use the GMM approach outlined in Greene (2003) to estimate a heteroskedastic – robust version of the SARAR(1,1) model. Anselin (1988) first suggested this estimator for the single SAR(1) equation.

2.4 Forecasting demand for open space, lot size and distance to the CBD

The research applies a novel approach for generating forecasts from the SARAR(1,1) model. Kelejian and Prucha (2007) recently noted that few (if any) studies applying conventional spatial econometric techniques have used estimates to generate forecasts, even though one of the main reasons for estimating such models is predictive. Second, of the studies that had generated spatial predictions using spatial lag, spatial error, or SARAR(1,1) models, *they had done so incorrectly*. This research applies an *unbiased and efficient predictor* for generating forecasts from the SARAR(1,1) equation system to facilitate comparisons between the regular property tax scheme (baseline) to the alternative land value tax scenarios. In their study, Kelejian and Prucha (2007) compared two "intuitive" SARAR(1,1) predictors commonly used in the literature to alternative predictors that include information about the correlations between the lagged dependent variable and the error terms. The unbiased and efficient predictor we apply in this research is; $\hat{y}_{ij} = \hat{\rho}_j w_{i.} y_j + \mathbf{z}_i' \hat{\boldsymbol{\delta}}_j + \mathrm{var}(w_{i.} y_j)^{-1} \mathrm{cov}(e_{ij}, w_{i.} y_j) w_{i.} [\mathbf{y}_j - (\mathbf{I} - \hat{\rho}_j \mathbf{W})^{-1} \mathbf{Z}_j \hat{\boldsymbol{\delta}}_j]$, with $\mathrm{cov}(e_{ij}, w_{i.} y_j) = \hat{\sigma}_{\varepsilon_j}^2 \hat{\sigma}_{i.}^{u_j} (\mathbf{I} - \hat{\rho}_j \mathbf{W}')^{-1} w_{i.}$ ($\hat{\sigma}_{i.}^{u_j}$ is the *i*th row of $\hat{\boldsymbol{\Psi}}^{u_j}$, $\hat{\sigma}_{\varepsilon_j}^2 = n^{-1} \hat{\mathbf{e}}_j' \hat{\mathbf{e}}_j$), and $\mathrm{var}(w_{i.} y_j) = \hat{\sigma}_{\varepsilon_j}^2 w_{i.} (\mathbf{I} - \hat{\rho}_j \mathbf{W})^{-1} \hat{\boldsymbol{\Psi}}^{u_j} (\mathbf{I} - \hat{\rho}_j \mathbf{W}')^{-1} w_{i.}'$. Given estimates of the lag and error autoregressive terms ($\hat{\rho}$, $\hat{\lambda}$) and $\hat{\boldsymbol{\delta}}$, demand for open space, lot size, and distance to the CBD can be forecasted, allowing *ex ante* comparisons between values generated under the regular property tax scheme and the alternative land value tax scenarios. We modify their approach to accommodate the system of equations.

3. Study Areas and Data

This research focuses on Knox County in the Knoxville MSA. The area consist of both rapid and slow housing growth regions. Recently, low–density sprawl in West Knox County is found to be driven by newer houses on smaller lots (Cho and Roberts 2007).

Specifically, single−family houses in the Town of Farragut in West Knox County are newer (by 9 years), in lower density areas (by 0.6 houses per acre), and on smaller lots (by 2,409 square feet) relative to all of Knox County.

Five primary GIS data sets are used: individual parcel data, satellite imagery data, census–block group data, boundary data, and environmental feature data. Individual parcel data, i.e., sales price, lot size, structural information, and boundary data, i.e., high school district and jurisdiction boundaries, can be obtained from county offices. The individual parcel data are from the Knoxville, Knox County, Knoxville Utilities Board Geographic Information System (KGIS 2007) and the Knox County Tax Assessor's Office. The boundary data are from the Knoxville–Knox County Metropolitan Planning Commission (MPC 2006).

Land cover information is derived from Landsat 7 imagery for 2001. The classified national land cover database from the multi-resolution land characteristics consortium (NLCD 2001) includes the GIS map used in the analysis to identify open space in the study area. Of the 21 classified land covers in the NLCD 2001 database, 11 classifications will be considered open space in our study.[5] The open–space classification is loosely based on the definition of "open area" or "open space" in Section 239–y of the General Municipal Law (Open space inventory 1999).[6] To define open–space demand for individual households, the space in the 11 open–space classifications is aggregated within a 1.0–mile radius (buffer) of each housing sales transaction. Buffer sizes found in the

[5] The 11 classifications include "developed open space, barren land (rock/sand/clay), deciduous forest, evergreen forest, mixed forest, shrub/scrub, grassland/herbaceous, pasture/hay, cultivated crops, woody wetlands, and emergent herbaceous wetlands" (NLCD 2001).

[6] Section 239–y defines "open area" as "any area characterized by natural beauty or, whose existing openness, natural condition or present state of use, if preserved, would enhance the present or potential value of abutting or surrounding development or would offer substantial conformance with the planning objectives of the municipality or would maintain or enhance the conservation of natural or scenic resources" (Open space inventory 1999).

literature were not consistent, resulting different estimates of open space value (McConnell and Walls 2005). For example, Geoghegan *et al*. (2003) used two buffers, a 100–meter radius around the property and a 1,600–meter radius. Acharya and Bennett (2001) also used a 1,600−meter buffer. Nelson *et al*. (2004) used 0.1−mile, 0.25−mile, and 1.0 mile buffers and Irwin (2002) used a 400−meter buffer. Lichtenberg *et al.* (2007) used buffers of 0.5, 1, and 2 miles. Although buffer sizes are arbitrarily chosen without using a systematic framework, a 1−mile buffer is chosen for this study because the 1−mile distance is what can be seen within an easy walk and can be referred to as the neighborhood.

Environmental feature data including water bodies and golf courses are found in Environmental Systems Research Institute Data and Maps 2004 (ESRI 2004). Information from census–block groups, e.g., income, housing density, unemployment rate, vacancy rate, will be assigned to houses located within the boundaries of the block groups.

4. Policy Implications

Given consistent estimates of the demand system parameters, and procedure to accurately forecast open space demand, the prevailing property tax rate is varied (subject to certain conditions) to test *ex ante* hypotheses about how demand for open space, lot size, and proximity to the CBD change in particular, and how a land value tax affects the pattern of urban sprawl in general. This information provides insight into where in a sprawling area a land value tax might be most successful for encouraging compact development, given significant spatial heterogeneity.

We hypothesize that the demand for these goods under the land value tax scheme will exhibit varying degrees of spatial heterogeneity across the housing market, depending on the weight placed on land value, holding other factors constant. *Ex ante* evidence of heterogeneous policy effects on demand for these goods suggests that a sliding land value tax scale may be useful in targeting critical sprawl areas.

References

Acharya, G., and L. L. Bennett, 2001. "Valuing open space and land-use patterns in urban watersheds." *The Journal of Real Estate Finance and Economics* 22:221–237.

Anselin, L., 1988. *Spatial Econometrics: Methods and Models*, Dordrecht: Kluwer Academic Publishers.

Anselin, L., and R. Florax, 1995. *New Direction in Spatial Econometrics*, Berlin: Springer.

Bao, S., M. Henry, and D. Barkley, 2004. Identifying Urban-Rural Linkages: Tests for Spatial Effects in the Carlinao-Mills Model, Chapter 15, pp. 321-334. In: Anselin, L., R.J.G.M. Florax and S. J. Rey (Eds.). Advances in Spatials Econometrics: Methodology, Tools and Applications, New York: Springer-Verlag.

Boarnet, M. G., S. Chalermpong, and E. Geho, 2005. "Specification issues in models of population and employment growth." *Papers in Regional Science* 84:21–46.

Brueckner, J. K., 1986. "A modern analysis of the effects of site value taxation." *National Tax Journal* 39:49–58.

Brueckner, J., and H. Kim, 2003. "Urban sprawl and the property tax." *International Tax and Public Finance* 10:5–23.

Case, K. E., and J. H. Grant, 1991. "Property tax incidence in a multijurisdictional neoclassical model." *Public Finance Quarterly* 19:379–392.

Cho, S., and R. K. Roberts, 2007. “Cure for urban sprawl: Measuring the ratio of marginal implicit prices of density-to-lot-size.” *Review of Agricultural Economics* 29:572–579.

Cho, S., S. Kim, C. D. Clark, and W. M. Park, 2007. “Spatial analysis of rural economic development using a locally weighted regression model.” *Agricultural and Resource Economics Review* 36:24–38.

Cho, S., C. D. Clark, W. M. Park., and S. Kim, 2008. “Spatial and temporal variation in the housing market values of lot size and open space.” *Land Economics*, forthcoming.

Cliff, A. D., and J. K. Ord, 1973. *Spatial Autocorrelation,* London: Pion.

Cliff, A. D., and J. K. Ord, 1981. Spatial Processes - Models and Applications, London: Pion.

Cohen, J. P., and C. J. M. Paul, 2005. “Agglomeration economies and industry location decisions: the impacts of spatial and industrial spillovers.” *Regional Science and Urban Economics* 35:215–237.

Environmental Protection Agency, 2007. Smart Growth, About Smart Growth. Available at http://www.epa.gov/dced/about_sg.htm.

ESRI, 2004. ESRI Data & Maps 2004. Available at http://www.esri.com/library/whitepapers/pdfs/datamaps2004.pdf.

Expansion Management, 2005. Expansion Management survey of site consultants. Available at http://www.expansionmanagement.com/smo/articleviewer/default.asp?cmd=articledetail&articleid=16977.

Geoghegan, J., L. Lynch, and S. Bucholz, 2003. "Capitalization of open spaces into housing values and the residential property tax revenue impacts of agricultural easement programs." *Agricultural and Resource Economics Review* 32:33–45.

Gordon, P., and H.W. Richardson, 1998. "Prove it." *Brookings Review* 16:23–26.

Greene, W. H., 2000. *Econometric Analysis, 4th ed*. Upper Saddle River, N.J.: Prentice–Hall.

Hanham, R., and J. S. Spiker, 2005. *Geo-Spatial Technologies in Urban Environments*, Berlin a Heidelberg: Springer.

International City/County Management Association, 2007. Getting to Smart Growth. Available at http://www.smartgrowth.org/pdf/gettosg.pdf.

Irwin, E. G., 2002. "The effect of open space on residential property values." *Land Economics* 78:465–480.

Kelejian, H. H., and I. R. Prucha, 1999. "A generalized moments estimator for the autoregressive parameter in a spatial model." *International Economic Review* 40: 509–533.

Kelejian, H. H., and I. R. Prucha, 2004. "Estimation of simultaneous systems of spatially interrelated cross sectional equations." *Journal of Econometrics* 118:27–50.

Kelejian, H. H., and I. R. Prucha, 2006. Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances, Working paper, Department of Economics, University of Maryland.

Kelejian, H. H., and I. R. Prucha, 2007. "The Relative Efficiencies of Various Predictors in Spatial Econometric Models Containing Spatial Lags." *Regional Science and Urban Economics* 37:363–374.

KGIS, 2007. Knox net Where. Knoxville, Knox County, Knoxville Utilities Board Geographic Information System. Available at http://www.kgis.org/KnoxNetWhere.

Lambert, D. M., K. McNamara, and M. Garret, 2006. "Food industry investment flows: Implications for rural development." *Review of Regional Studies* 36:140–162.

Lichtenberg, E., C. Tra, and I. Hardie, 2007. "Land use regulation and the provision of open space in suburban residential subdivisions." *Journal of Environmental Economics and Management* 54:199–213.

Mathis, E. J., and C. E. Zech, 1982. The economic effects of land value taxation, *Growth and Change* 13, 2-5. Available at http://www.blackwell-synergy.com/doi/abs/10.1111/j.1468-2257.1982.tb00382.x.

McConnell, V., and M. Walls, 2005. The value of open space: Evidence from studies of non-market benefits, Working Paper, Washington DC: Resources for the Future.

Mills, E.S., 1998. The Economic Consequences of a Land Tax, In: Netzer, D. (Eds.). Land Value Taxation: Could It Work Today? Cambridge, MA: Lincoln Institute of Land Policy.

Mills, D. E., 2001. "Land value taxation." *Regional Science and Urban Economics* 31:765–770.

Monchuk, D. C., J. A. Miranowski, D. Hayes, and B. Babcock, 2007. "An analysis of regional economic growth in the U.S. Midwest." *Review of Agricultural Economics* 29:17–39.

Moreno, R., E. López-Bazo, E. Vayá, and M. Artis, 2004. External Effects and Cost of Production, In: Anselin, L., R.J.G.M. Florax, and S. J. Rey (Eds.). Advances in Spatial Econometrics: Methodology, Tools and Applications, Berlin: Springer.

MPC, Knoxville/Knox County Metropolitan Planning Commission, 2006. Directory of Neighborhood Organizations. Available at http://www.knoxmpc.org/director/orgs/ndhome.htm.

Nechyba, T. J., 1998. Replacing Capital Taxes with Land Taxes: Efficiency and Distributional Implications with an Application to the United States Economy, In: Netzer D. (Eds.). Land Value Taxation: Can It and Will It Work Today? Cambridge, MA: Lincoln Institute of Land Policy.

Nelson, N., Kramer, E., Dorfman, J., and B. Bumback, 2004. Estimating the economic benefit of landscape pattern: A hedonic analysis of spatial landscape indices, Institute of Ecology, University of Georgia. Available at http://www.rivercenter.uga.edu/publications.htm.

NLCD, 2001. National Land Cover Database 2001. Available at http://gisdata.usgs.net/website/MRLC/viewer.php.

Oates, W. E., and R. M. Schwab, 1997. "The impact of urban land taxation: The Pittsburgh experience." *National Tax Journal* 50:1–21.

Open space inventory, 1999. Village of Dobbs Ferry Westchester County, New York. Available at http://www.dobbsferry.com/village/Committees/openspace/FinalInventory.doc.

Skaburskis, A., 1995. "The consequences of taxing land value." *Journal of Planning Literature* 10:3–21.

Skaburskis, A., 2000. “Housing prices and housing density: Do higher prices make cities more compact?” *Canadian Journal of Regional Science* 23:455–487.

Thorsnes, P., 2002. “The value of a suburban forest preserve: Estimates from sales of vacant residential building lots.” *Land Economics* 78:426–441.

Tracy, S., 2003. Smart Growth Zoning Codes: A Resource Guide, Local Government Commission.

U.S. Census Bureau, 2007. Available at http://www.census.gov/.

Whittle, P., 1954. “On stationary processes in the plane.” *Biometrika* 41:434–449.

Wojan, T. R., D. Lambert, and D. A. McGranahan, 2008. “Emoting with their feet: Bohemian attraction to creative milieu.” *Journal of Economic Geography*, forthcoming.

Table 1. A Complete List of Exogenous Variables Hypothesized to Explain the Demand for Open Space, Lot Size, and Proximity to the CBD in Matrix X^A

Variable	Definition
Tax variable	
Property tax	Prevailing property tax rate times the assessed value of structures and land
Structural variables	
Age	Year house was built subtracted from 2008
Brick	Dummy variable for brick siding (1 if brick, 0 otherwise)
Pool	Dummy variable for swimming pool (1 if pool, 0 otherwise)
Garage	Dummy variable for garage (1 if garage, 0 otherwise)
Bedroom	Number of bedrooms in house
Stories	Height of house in number of stories
Fireplace	Number of fireplaces in house
Quality of construction	Dummy variable for quality of construction (1 if excellent, very good or good, 0 otherwise)
Condition of structure	Dummy variable for condition of structure (1 if excellent, very good or good, 0 otherwise)
Finished area	Total finished square footage of house ($feet^2$)
Environmental variables	
Distance to greenway	Distance to nearest greenway (feet)
Distance to railroad	Distance to nearest railroad (feet)
Distance to sidewalk	Distance to nearest sidewalk (feet)
Distance to park	Distance to nearest park (feet)
Park size	Size of nearest park ($feet^2$)
Distance to golf course	Distance to nearest golf course (feet)
Distance to water body	Distance to nearest stream, lake, river, or other water body (feet)
Size of water body	Size of nearest water body ($feet^2$)

Variable	Definition
Other spatial dummy variables	
City	Dummy variable for City (1 if in city boundary, 0 otherwise)
ACT	American College Test score by high school district
Flood	Dummy variable for 500-year floodplain (1 if in stream protection area, 0 otherwise)
Interface	Dummy variable for rural-urban interface (1 if in census block of mixed rural-urban housing, 0 otherwise)
Urban growth boundary	Dummy variable for urban growth boundary (1 if in urban growth boundary, 0 otherwise)
Planned growth area	Dummy variable for planned growth area (1 if in planned growth area, 0 otherwise)
Season	Dummy variable for season of sale (1 if April through September, 0 otherwise)
Census block-group variables	
Housing density†	Housing density for census-block group (houses/acre)
Vacancy rate†	Vacancy rate for census-block group in 2000
Unemployment rate†	Unemployment rate for census-block group in 2000
Travel time to work†	Average travel time to work for census-block group in 2000 (minutes)
Income†	Median household income ($)
Real estate market variables	
Prime interest rate†	Average prime interest rate less average inflation rate

† Indicates exogenous instruments explaining the implicit price of open space in the matrix $\mathbf{X}^B$.