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Spatial Economic Analysis in Data-Rich Environments

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Abstract

Controlling for spatial effects in micro-economic studies of consumer and producer behavior necessitates a range of analytical modifications ranging from modest changes in data collection and the definition of variables to dramatic changes in the modeling of consumer and producer decision-making. This paper discusses conceptual, empirical, and data issues involved in modeling the spatial aspects of economic behavior in data rich environments.

Attention is given to established and emerging agricultural economic applications of spatial data and spatial econometric methods at the micro-scale. Recent applications of individual and household data are featured, including models of land-use change at the urban-rural interface, agricultural land values, and technological change and technology adoption.

JEL Classifications: C21, Q10, Q12, Q15, Q56

1. Introduction

Spurred by recent advances in data and software, as well as in economic theory and econometric methods, spatial economic analysis is on the rise (for reviews see Anselin, Florax, and Rey 2004 and Florax and van der Vlist 2003). Anselin, Florax, and Rey (2004) attribute this increase to the following five factors: a renewed interest in the role of space and spatial interactions in social science theory; the increased availability of large socio-economic datasets with geo-referenced observations; the existence of low cost geographic information systems to manipulate spatial data; heightened activity in terms of methodological research; and increased availability of software to implement empirical spatial economic methods (e.g., MATLAB (Pace and Lesage spatial statistics toolbox and Lesage spatial econometrics toolbox, R (R-geo)), S-Plus, Stata, Geoda, and Space-Stat). Recent research of agricultural, natural resource, and environmental economists reflects the escalating prominence of spatial interactions and provides support for the significance of these five factors in changing analytical research methods (Anselin 2001a, Anselin 2002, Bateman et al. 2002, Bateman et al. 2006). Since the 2002 special volume of *Agricultural Economics* (Nelson 2002), which provided an introduction to spatial analytical approaches, agricultural, resource, and environmental economists have increasingly been open to spatial analysis. In what follows, we bring attention to a subset of these recent efforts, giving emphasis to applications involving micro-level spatial data.

Controlling for spatial effects in micro-economic studies of consumer and producer behavior necessitates a range of analytical modifications ranging from modest changes in data collection and the definition of variables to dramatic changes in the modeling of consumer and producer decision-making. Modest changes evolve from improved and readily available spatial data and result in spatial analysis that supplements conventional economic research. The ability to overlay multiple layers of spatial data using geographic information systems (GIS) gives researchers tremendous power and flexibility to describe the spatial aspects of economic problems. For example, parcel-level models of land-use change commonly now rely on the use of spatial data and modeling software that permit rich descriptions of parcels' locations (e.g., proximity to numerous features; viewscapes, road network access and congestion), land features (e.g., soil, slope, vegetation, water), and surrounding neighborhoods (e.g., neighboring land uses, demographics, school quality, crime rates) as well as relevant public policies (e.g., zoning laws, habitat regulations, or agricultural easements) (Irwin et al. 2003). In addition, the employment of

a spatial perspective affords researchers tremendous benefits in terms of conceptualizing spatial effects or patterns. Examining the spatial distribution of one or more variables may suggest spatial heterogeneity or spatial dependence. For example, studies of technology adoption that employ mapping may reveal structural breaks in terms of decision-making or evidence of knowledge spillovers (Zhang et al. 2002). Likewise, basic maps showing the temporal and spatial distribution of invasive pests, infectious diseases, and wildfires provide valuable measures of the spatial heterogeneity in risk and damage surfaces (Holmes et al. 2006; Beck et al. 2002; and Schmidt et al. 2002). Similarly, visualizing the results of policy analyses in map form may offer valuable information about the distributional impacts of specific policies or the potential cost savings from geographical targeting (e.g., Irwin et al. 2003, Yang et al. 2005, Newburn et al. 2006). Overall, these changes in data collection, variable definition, and communication of results have proved quite complementary to standard, empirical economic research methods.

More dramatic changes are evolving from the adoption of spatial econometric models and estimation approaches (Anselin 1988; Anselin, Florax, and Rey 2004; LeSage 1999; LeSage and Pace 2004). In some cases, these changes coincide with modifications to traditional regression models. For example, the spatial error and spatial lag models popularized by Anselin's spatial econometrics research and software (Anselin 1988; Anselin 2001b, Anselin 2002) are progressively more common in the applied economics literature. These models respectively incorporate spatial correlation among regression disturbance terms and dependent variable observations. In addition, test statistics related to these two models are now an expected component of empirical research. In other instances, these changes are inspiring fundamentally different models and empirical methods such as agent-based (Berger 2001), Bayesian (Holloway et al. 2002), and geographically weighted regression models (Lesage 2004). Spatial and spatiotemporal econometric methods modify the representation of consumer and producer decision-making by bringing attention to spatial interactions among these decision-makers. Using spatial GIS data, the strength of interaction between two agents is typically modeled as a function of physical distance or a measure of physical proximity. It is important to note, however, that these modeling frameworks support a variety of non-physical distance measures, such as economic or market distances.

This paper discusses conceptual, empirical, and data issues involved in modeling the spatial aspects of economic behavior in data rich environments - environments that support a rich description of decision-makers and natural resources and often permit the unit of analysis to correspond with that of the relevant decision-maker. Particular attention is given to recent applications of individual and household data, including models of land-use change at the urban-rural interface, agricultural land values, technological change and technology adoption. Together, this mix of studies illustrates how spatial economic analysis can improve our understanding of economic behavior and regulatory and management approaches. The remainder of the paper is organized into 3 sections. Section 2 provides an overview of micro-scale spatial economic analysis. Section 3 summarizes recent applications of spatial analysis. Lastly, Section 4 offers concluding remarks and points to directions for future research.

2. Spatial Economic Analysis using Micro-Scale Data

Because our review of applications focuses on data rich environments, some of the discussion is most applicable to the United States and other developed countries in which local and national governments are significant providers and managers of spatial data. In these countries, parcel-level land, road network, and street address data are electronically recorded and managed using Geographic Information System (GIS) software. In addition, designated spatial areas are standard units of analysis and data collection by government agencies and researchers (e.g., US Census geography). These resources facilitate integration of databases, such as the merging of tax assessment records with land parcel boundary files or demographic data with place or area boundary files, and the conversion of non-spatial to spatial databases via geocoding or address-matching. In addition, government oversight of core data collection and management has also resulted in data quality and metadata standards and data review processes.

The boundaries of micro-scale spatial analysis are expanding to include developing countries, as spatial datasets are made available because of technical advances in global positioning system (GPS) and remotely-sensed data collection and infrastructural enhancements at established research sites. While not as many high resolution spatial datasets may be available for these countries, the returns to creating such datasets appear high. For example, Vance and Geoghegan (2002) integrate satellite imagery land cover data with data collected from farm households whose agricultural plots were geo-referenced using a global positioning system (GPS) to

examine forest clearing in an agricultural frontier of southern Mexico. Similarly, Caviglia-Harris and Sills (2006) geo-referenced household lots using a global positioning system (GPS) in their study of the dynamic relationship between cattle intensification and forest clearing in Rondonia, Brazil. Both of these studies make use of the knowledge of ownership boundaries in examining land use dynamics and cleverly combine micro- and macro-scale spatial datasets.

2.1 Micro-scale

For the purposes of this paper, micro-scale data are defined as data describing individual units such as firms, farms, households, or land parcels. There are advantages and disadvantages to working with spatial data at a micro-level scale. These were reviewed at length in Bell and Irwin (2002) and are summarized again here briefly. The primary advantage extends from using data at a scale that corresponds to the economic decision of interest. In addition, micro-level models that can spatially aggregate up individual-level decisions to other relevant scales (e.g., city; labor or agricultural market; village) provide a unique means to assess the consequences of individual decisions. For example, Bell and Irwin (2002) emphasize the utility of spatially articulated models of individual land use conversion that provide a means to transition from individual-level behaviors to aggregate-level outcomes. Because micro-scale approaches link predicted outcomes with the underlying behavior of individual actors, they can also directly incorporate policies and improve predictions for policy analysis (Irwin et al. 2003; Bockstael 1996). Lastly, because the unit of observation corresponds directly with the scale at which the underlying spatial process takes place, data measurement problems are minimized, which reduces a source of spatial error autocorrelation (e.g., spatial mismatch).

Despite these advantages, there are clear challenges to developing spatial, micro-level models in a data-rich environment. Datasets may be massive in size, necessitating extensive data management and computer resources. In addition, as datasets grow in size, the challenges of modeling correspondingly increase, as researchers strive to assess possible interactions among a growing set of decision-makers and must manipulate larger spatial weight matrices (e.g., Bell and Bockstael, 2000).

2.2 Empirical Micro-Scale Models

The diverse interests in spatial microeconomic theory exhibited by agricultural and resource economists mirror those expressed by other social science researchers (Anselin 2002)¹. Agricultural and resource economists study a diverse set of decision-makers, giving rise to myriad forms of spatial interactions. A unifying theme among these studies is the emphasis given to how individual consumers and producers interact with a host of natural resources. Spatial interactions, in turn, are driven both by relationships among decision-makers as well as the spatial heterogeneity of natural resources.

Our discussion of spatial models focuses on two basic models: the spatial lag and spatial error models (Anselin 1988; Anselin 2001b). Both models are adaptations of a standard linear regression model. The former addresses spatial interactions among choices of decision-makers or agents, capturing substantive spatial dependence by allowing for relationships among observations of the dependent variable. The latter addresses correlation of the regression disturbance terms over space or nuisance spatial dependence. Together, these two models account for the majority of recent spatial economic applications by agricultural and resource economists.

From a theoretical perspective, the spatial lag model is intriguing because it relaxes the assumption of independent decision-making and necessitates consideration of spatial interactions. Explaining how and why these interactions occur is of utmost importance when employing this framework. Anselin (2002) and Brueckner (2003) present two distinct microeconomic theoretical models that are consistent with the spatial lag model. Brueckner discusses these models in the context of spatial interaction in public economics (Brueckner 2003). Anselin (2002) extends Brueckner's intuition to agricultural and resource economic problems. Following their intuition and notation closely, we summarize the spillover and resource flow models in the context of a consumer utility maximization problem. The same intuition can be used to motivate these models in the context of a profit maximization or cost minimization problem. Using their terminology, a spillover model is one in which an agent i chooses the level of a decision variable, y_i , but the values of the y chosen by other agents (y_{-i})

¹ For example, the significance of individual agent behavior and the relationships among these agents are emphasized in social network theory and agent-based modeling research (Dietz 2002; Conley and Topa 2002; Brock and Durlauf 2002). Space is also central to the literature related to the new economic geography (Fujita and Krugman 2004).

affects the agent's objective as well. Therefore, the utility function of an agent includes her choice and the choices of all other agents:

$$U(y_i, y_{-i}; x_i),$$

where x' is a vector of exogenous characteristics of agent i , which are associated with variation in agent preferences. In a spatial context, the spillover model may be used to motivate spatial dependence as the product of direct interactions with neighboring agents. In addition, the extent of interaction among agents may be differentiated as a function of proximity. Interactions take on some form of strategic interaction manifested as competition, copy-cat behavior, or diffusion of knowledge. For example, some studies of technological adoption examine the influence of past adoptions by neighboring decision-makers on current adoption rates. In contrast, a resource flow model arises not from direction interaction as in the case of the spillover model but rather as a function of a shared resource. Spatial interaction arises from the distribution of the shared resource across all agents, s , which is a function (H) of the exogenous characteristics of the agents, x , and the consumption of the resource by all agents (y_i and y_{-i}). Using this modeling framework, the utility function of an agent includes her choice and the stock of resource available to her, which is a function of the choices of all other agents. The utility function of and resource available to an agent are expressed as follows:

$$U(y_i, s_i; x_i)$$

$$s_i = H(y_i, y_{-i}; x_i)$$

where H is a function describing the stock of resource available to agent i .

As demonstrated by Brueckner (2003) and Anselin (2002), when embedded in a utility maximization problem, the spillover model and the resource flow model both generate the same reaction function to describe the maximization solution². This reaction function can broadly be thought of as: $y_i = R(y_{-i}, x_i)$. This general reaction function, which stresses the interdependence of an agent's choice and the choices of other agents, may be used to motivate

the spatial lag model. The spatial lag model extends a standard linear regression model by adding a spatial lag term (Wy),

$$y = \mathbf{r}Wy + \mathbf{X}\beta + \mathbf{e},$$

where y is an n by 1 vector of the dependent variable, W is a n by n spatial weights matrix representing the structure of the spatial interaction among agents, X is an n by k matrix of exogenous explanatory variables, ρ is the spatial autoregressive parameter to be estimated, β is a k by 1 vector of parameters to be estimated, and ϵ is a n by 1 vector of random disturbance terms. The spatial lag term (Wy) and its estimated parameter, ρ , describe the spatial dependence among agents or decision makers. Specifically, it assumes a linear function form for R and limits interactions among agents using W .

The spatial lag term is an endogenous variable. Because ordinary least squares estimation of this model ignores this endogeneity, its estimates will be biased and inconsistent. Maximum likelihood and generalized method of moments are the most common methods used to estimate the lag model. A variety of statistical tests have been developed to examine the appropriateness of the spatial lag model (e.g., Moran's I, Kelejian-Robinson, and Lagrange Multiplier). In practice, the standard linear regression model is estimated first by OLS and these test statistics build from the results of this regression and a designated spatial weight matrix. Applications of spatial lag models include descriptions of patterns among sales prices of land and housing, expenditures and policies of local governments, and technology adoption. In practice, the spatial lag model is employed as an alternative to a standard linear regression model or to adapt a discrete choice model by modifying the specification of a latent variable.

The second, most common application of spatial economic analysis arises from data measurement issues rather than a modified theoretical model. Spatially correlated residuals, which may be caused by spatial correlation of omitted variables or spatial mismatch in data measurement, violate the standard assumptions of the linear regression model. Specifically, the assumption of independent, homoskedastic residuals must be relaxed. An autoregressive representation of this correlation alters the standard linear regression as follows:

²Anselin (2002) discusses the issues associated with this result in the context of the classic inverse problem. In short, it is unclear what economic process or mechanism supports the spatial lag model.

$$y = X\beta + \epsilon,$$

$$\epsilon = rW\epsilon + u,$$

where y is an n by 1 vector of the dependent variable, W is a n by n spatial weights matrix representing the structure of the spatial interaction among residual terms, X is an n by k matrix of exogenous explanatory variables, ρ is the spatial autoregressive parameter to be estimated, β is a k by 1 vector of parameters to be estimated, ϵ is a n by 1 vector of random disturbance terms, and u is a n by 1 vector of random, iid disturbance terms. This modification assumes an autoregressive structure for the error terms. Alternative error structures are also possible, including moving average and error components. Similar to the case of the spatial lag model, a variety of statistical tests have been developed to examine the appropriateness of the spatial error model. These test statistics are calculated using OLS results and rely on the specification of a spatial weight matrix. If this form of correlation is present and ignored, ordinary least squares estimates will be unbiased but inefficient. Within agricultural and resource economics, the most common application of the spatial error model is in hedonic property value studies. In these studies, the spatial correlation of residuals is often explained as the result of omitted variables that are spatially correlated. In practice, researchers often struggle trying to sort out both types of dependence (spatial lag and spatial error) and heteroskedasticity problems.

When estimating the spatial lag and spatial error models using micro-scale data, a major issue for researchers is the specification of the spatial weight matrix, W . Spatial weight matrices are central to spatial error and lag models, imposing a great deal of structure on spatial interactions. Careful consideration is required in micro-data environments. In contrast to macro scale studies, where units are broad geographic areas such as countries, states, or villages, micro observations are often scattered throughout a landscape and agents do not share borders that crisply define neighbors. Instead, researchers are often forced to specify weights as a function of distance. Key questions that must be resolved in any microanalysis include: how should the weights be defined; should the weight matrix be row-standardized (e.g., asymmetry); and should some observations be allowed to have 0 neighbors (e.g., islands). Economic theory and knowledge of the data generation process may help with the specification of W , but there is typically considerable uncertainty about the appropriate form of W . Very little guidance is offered to researchers when specifying W (Anselin 2002), and, in some cases, the lack of

justification of W can detract from a study³. As a result, sensitivity analyses showing variation in parameter estimates across alternate weight matrices are commonly completed (e.g., Bell and Bockstaal 2000).

In their review of the economics literature, Anselin, Florax, and Rey (2004) noted the bulk of spatial economic applications since 2001 still involve linear regression (spatial error and lag) models. This is perhaps not surprising, as these models are most similar to conventional models, are relatively easy to estimate, and are incorporated into statistical software packages. In the future, it is likely that common applications will include panel data models (Baltagi and Li 2004) and discrete choice models (Fleming 2004). However, to date, these latter models may not be estimated using readily available statistical software packages.

3. Applications

In this section, we summarize recent spatial economic analysis applications in three areas: land-use change at the rural-urban interface; hedonic models of agricultural and residential land values; and technological change and technology adoption. The review is intended to wet researchers' appetites for learning more about spatial economic analysis in data-rich environments. Curious readers are encouraged to refer to the original works cited in this section for the full details of their analysis. It is our hope that this review will raise awareness of recent advances and illustrate the novelty and breadth of data rich environments for spatial economic analysis. There are other examples we have omitted due to brevity.

3.1 Land-use change at the Rural-Urban Interface

Studies of land-use change have long stressed the significance of space. von Thunen's nineteenth century writings, which emphasize the role of distance to a central market, have shaped generations of land-use models (see Plantinga and Irwin (2006) for a recent review). A variety of empirical models have been employed by agricultural and resource economists to describe land-use change. A recent change in the literature, resulting from the rise of spatial data and GIS modeling tools, is an increased emphasis of spatial heterogeneity in theoretical (Segerson, Irwin, and Plantinga 2006) and empirical models of land-use change (Plantinga and

³ A notable shortcoming arises from having these models accessible in readily available software packages. In short, some researchers opt to estimate models using default specifications (e.g., inverse distance) with little consideration for the uniqueness of their research problem, sample, or data properties.

Irwin 2006). Specifically, there is less reliance on a single measure to capture spatial heterogeneity, such as distance to the central business district. In addition, GIS and other database advances have facilitated the use of parcel-level data. Prior to these advances, most economic models of land-use change used aggregate data on land-use, such as US Census tracts, county acreage estimates, or county land-use shares data.

Land-use change models utilizing parcel-level data are excellent examples of micro-scale models featuring spatial heterogeneity. To date, these models have been applied to explain land conversion in rapidly developing areas of the U.S. (see Plantinga and Irwin (2006) and Bell and Irwin (2002) for recent reviews). The majority of these applications are designed to address the conversion of undeveloped lands to developed lands at the rural-urban interface. These conversions are significant from a policy perspective because of potential external costs ranging from changes in environmental quality and rural character to changes in public service costs.

Data rich environments supporting such studies tend to be in areas with higher resources devoted to land-use planning. These environments afford researchers a unique setting in which to study land-use change, as GIS data management and organization has facilitated unparalleled detailed data on land parcels. Such data include spatially-articulated tax and assessment records describing the parcel's physical, structural, financial, and use history; zoning and other land management ordinances; natural resource characteristics including slope, soil type, vegetation, water resources; access to public services and other relevant networks such as transportation corridors; and proximity to relevant amenities and disamenities. From a researcher's perspective, there is great value in knowing both the absolute value of these features for a given land parcel and the relative values of these features among neighboring land parcels.

The benefits of a data-rich environment are perhaps best illustrated by the recent land-use research efforts centered at University of Maryland and spearheaded by Professor Nancy Bockstael. Parcel-level land-use data and other GIS and electronic data available in the State of Maryland have been scrutinized by a team of researchers to explore the utility of alternative modeling approaches and support public decision-making. Early work from this team of researchers raised awareness of micro-level spatial data, spatial econometric issues, and spatial interaction (e.g., Bockstael 1996). Subsequent efforts have focused on a range of issues arising in the estimation of micro land-use change models, including, among other issues, spatial

dependence, sample selection, and identification issues (Irwin et al. 2003; Irwin and Bockstael 2004a; Irwin and Bockstael 2004b; Towe et al. 2005a; and Towe et al. 2005b).

Parcel-scale models of land-use change have primarily taken advantage of improved spatial data and the alignment of the decision unit and observed unit of analysis. Contemporaneous spatial dependence (e.g., spatial lag) is rarely accounted for and may be due to the relative difficulty of adapting discrete choice rather than linear regression models. Instead, interactions are examined by modeling the impact of the land use of surrounding parcels on the likelihood of a particular land-use change.

Many recent models underscore the importance of understanding the dynamics of land-use change and employ duration modeling techniques. These same models also illustrate the utility of integrating spatially-explicit policy data into land-use change models. This latter advance enables much improved assessments of the effectiveness of policies and their influence on the spatial pattern of development patterns. Irwin et al. 2003 estimate a proportional hazards model to explain residential development in Calvert County, Maryland. Numerous GIS-derived variables are used in this analysis to distinguish the influences of development costs, locational features, neighboring land-use variables, public services, zoning regulations, and smart growth policies. A simulation-based analysis of potential policy changes finds that spatially-based policies such as priority funding (targeted growth) areas have a significant influence on conversion decisions. In addition, the results suggest open space and agricultural land protection programs may be more effective when coupled with targeted growth area policies. Hite et al. 2003 employ a parametric accelerated failure time survival model to examine land-use change in Delaware County, Ohio. Again, numerous GIS-derived variables are used to explore the impacts of taxes on the rate and timing of conversions of agricultural land to industrial, commercial, and residential use. Emphasis is given to the role of proximity to a variety of features, including roads, utility lines, water resources, and the city center as well as to the spatial variation in property tax rates used to fund schooling and infrastructure. Their results indicate higher property tax rates do delay conversion of agricultural lands to residential use, with infrastructure taxes having a greater negative influence than school taxes. In addition, their findings suggest commercial development follows residential development and densely residential areas repel industrial development.

Other studies focus on spillover effects of past land-use conversion decisions on future decisions. Irwin and Bockstael (2004a) refine the approaches of the previously discussed work by emphasizing the potential for statistical identification problems when estimating land-use change models. Their findings raise concerns with previous findings on the impacts of neighboring land uses on land conversion decisions. Unobserved heterogeneity associated with land parcels is likely to be strongly correlated in space and to complicate the identification of endogenous interaction effects. If omitted variables are invariant over time and spatially correlated over space, then it will be difficult to distinguish between the influence of such unobserved spatial effects and those of true spatial externalities from surrounding land uses. They pose an identification strategy, estimate a proportional hazards model of land conversion in Calvert County, Maryland, and conduct simulations to explore. Results demonstrate support for land-use change models that incorporate exogenous explanatory variables and the endogenous interaction effects of neighboring land uses. Findings also indicate the relevancy of these interaction effects to the design of policies intended to curb sprawl or scattered development patterns. This latter point is featured in a second paper (Irwin and Bockstael 2004b), where estimates from a proportional hazards model provide additional empirical evidence of interdependencies among neighboring land uses. Results indicate that parcels with greater amounts of preserved open space nearby are more likely to be converted to residential use in the future. In contrast, neighboring commercial and industrial development has a depressing effect on the likelihood of conversion. The findings with respect to open space suggest clustered development policies may have the potential to exacerbate scattered development patterns.

Econometric and other statistical issues are the focus of other recent studies. Carrion-Flores and Irwin (2004) stress the potential for spatially correlated residuals (the spatial error model) in their analysis of land-use change in Medina County, Ohio. A test for spatially correlated residuals in a probit model framework is conducted and a spatial sampling routine is implemented to address the spatial correlation. Newburn and Berck (2006) estimate a parcel-scale model of land-use change in Sonoma County, California using a random-parameter logit model. This analysis emphasizes the potential for heterogeneous responses to zoning regulations among areas with different development densities. Findings indicate potential problems with models of land-use change that bundle all forms (densities) of residential development into a single class and provide support for increased consideration of the heterogeneity among

development density classes. Lastly, Towe et al. (2005a and 2005b) emphasize the potential for applying real options theory to the study of land-conversion. Towe et al. (2005b) employs a durations model to explore real options in the context of land-use change, including whether price uncertainty measured as the variance in returns to development impacts decisions to convert farmland to developed uses and whether the presence of an option to preserve farmland in a purchasable development right program delays development decisions. Results demonstrate significant empirical evidence that variance in returns (price uncertainty) and having the option to sell a purchasable development right easement delays the conversion of farmland land to developed uses. Towe et al. (2005a) extends this real options theory research to examine the significance of spatial interaction effects among land-owner decisions. Interaction effects are examined using both a hazard regression model and a quasi-controlled experiment (using propensity score matching) approach. Statistically significant evidence of a positive interaction effect between neighboring preserved land and the likelihood of development of neighboring parcels is found using both empirical approaches. These findings raise further concern about the unintended policy consequences of open space and other land preservation policies.

3.2 Hedonic Property Models of Agricultural Land Values

Hedonic property value studies have also benefited from recent advances in spatial data and modeling tools. Of note is the tremendous flexibility and power afforded to researchers by GIS data and software when conducting a hedonic property value analysis. The return to this flexibility is evident when reviewing recent studies of agricultural and residential land values (Patton and McErlean 2003, Ready and Abdalla 2005, Boxall et al. 2005, Beron et al. 2004, Geoghegan et al. 2003, Irwin 2002, Paterson and Boyle 2002, Gayatri and Lewis 2001, Leggett and Bockstael 2000, Bell and Bockstael 2000). The bulk of such studies not only incorporate a range of GIS-derived spatial explanatory variables but also complete testing for spatial dependence and implement spatial econometric techniques, as necessary.

Recent studies of agricultural land values stress heterogeneity over space, effects from urbanization pressures, and impacts of public programs such as farmland preservation programs. Patton and McErlean (2003) estimate spatial lag models that jointly address substantive spatial dependence and spatial heterogeneity (e.g., spatial regimes or submarkets) to explain variation in farmland prices in Northern Ireland. The spatial lag model is attributed with the circular

influence of appraisals on land prices, notably the use of neighboring land parcels as comparables. Their findings illustrate the potential bias in parameter estimates when these spatial econometric issues are ignored. Considerable differences in parameter estimates emerge, including a reversal in sign for parcel size from negative to positive in some sub-markets. Cavailhes and Wavresky (2003) examine the variation in transaction prices of farmland parcels in Dijon France using a random effects model, where the random effect is intended to capture, among other things, the spatial heterogeneity among communes (e.g., suburban or exurban areas). Evidence of inter- and intra-commune level spatial autocorrelation between disturbances is found. Findings illustrate the mixed role of agricultural factors and expectations of future returns from development. The impact of urbanization is examined from multiple perspectives, including the premium of subdivision effects and barriers to entry for non-farm investors and the decline in urban premium with distance from the city. Recently, the effect of urban pressure on farmland values was decomposed into the net returns to agriculture, non-farm opportunity costs and a speculative component equation (related to conversion risk) in a 3SLS framework corrected for spatial autorcorrelation (Livanis et al. 2005). The results largely called to question the valuation of farmland based solely upon the net present value of productive capacity and offered a tripartite explanation of land values: changes in net agricultural returns, non-farm opportunities and land speculation. These findings are especially relevant for areas that have large population growth or are located close to metropolitan areas.

Nickerson and Lynch (2001) explore the effects of agricultural purchasable development right programs on farmland values using parcel-scale data from three Maryland counties. A sample selection model is used to account for the potential sample selection bias of parcels enrolled in purchasable development right programs. An hedonic property value model is estimated as the second stage, explaining price as a function of parcel size, soil characteristics, proximity to streams, urban areas, and the nearest farm enrolled in the program, the extent of forest land cover, and county effects. Contrary to expectations, the results reveal little statistical evidence that purchasable development right programs decrease farmland prices.

Increased attention given to spatial data and dependence is also evident in the related literature examining variation in residential land values. Studies of the impacts of open space (Irwin 2002; Geoghegan et al. 2003) and the effects of rural disamenities such as livestock operations (Ready and Abdalla 2005; Bayoh, Irwin, and Roe 2004) and oil and natural gas

facilities (Boxall et al. 2005) on residential property values employ GIS-derived explanatory variables and test and correct for spatially correlated residuals. Additional studies making use of spatial data and spatial econometric methods continue to refine our knowledge of the impacts of environmental quality on residential property values (Paterson and Boyle 2002; Leggett and Bockstael 2000; Beron et al. 2004).

3.3 Technology Adoption and Agricultural Production

Spatially explicit data has been used in several areas of applied agricultural production economics including information acquisition on technologies and agricultural practices, new technology adoption, explanation of diffusion patterns, agricultural land pricing, strategic behavior of agribusinesses as well as linking agricultural production to resource usage and environmental services. Studies have employed, plot- household- and village-level data as well as spatially explicit regional data.

Information acquisition and sharing as well as technology adoption and diffusion are areas that have rapidly incorporated physical and social distances into non-spatially explicit modeling by necessity of social and economic exchange. One early application examined regional-scale data over 25 years to derive neighborhood effects on the path and speed of the adoption of high yielding varieties in India (Zhang, Fan and Cai 2002). Using a land allocation model, the asymmetric influence of successful and unsuccessful adopters on followers was identified. Adoption decisions have also been modeled at the individual decision making level using a Bayesian spatial Probit model (Holloway, Shankar and Rahman 2002) or in individual land allocation models (Langyintuo and Merkuria 2005). In the former, accessible iterative procedures are used to identify the spatial influence of neighbors and the error associated with ignoring spatial dependencies. In the later case a spatial lag model was applied in a Tobit framework to household-level data and found significant neighborhood effects on land allocation decisions.

Technology adoption and diffusion models now regularly integrate GIS-derived variables in order to disaggregate neighborhood effects between the inertia generated by proximity to, or the mass of, previous adopters (Abdulai and Huffman 2005). Secondly, the ease of access to data on controlling environmental factors and the influence of heterogeneous production features that condition adoption decisions can be joined with behavioral factors to enrich adoption models

(Moreno and Sundig 2005). Sarmiento and Wilson (2005) developed a game theoretic framework to explain inter-firm rivalry and the spatial correlation of the payoff matrix between neighbors and neighbors' adoption decisions of new grain handling technology. To do so, a spatially lagged dependent variable (the adoption decision) was modeled in a logistic framework and empirically estimated with an algorithm that concentrated inter-firm correlation coefficients in the likelihood function. Results indicate that strategic and market expansion is dependent upon competitors' adoption but that the influence declines with distance.

Market participation decisions have been examined in terms of distance to markets, as well as in terms of neighborhood effects, in a manner similar to adoption and diffusion. Staal et al (2002) provided an example of georeferenced farm units and linked their market participation behavior to a set of location-specific attributes. From these models, public policy interventions related to road infrastructure were investigated to determine their relationship to transaction costs and ultimately technology adoption. Inertia and neighbor's participation decisions were identified using a spatial autoregressive function in a Bayesian Probit framework in order to identify the human determinants of market participation in addition to physical transaction costs and barriers (Lapar, Halloway and Ehui, 2004). Market distance functions also were used to capture demand-side characteristics influencing livestock adoption decisions and ultimately the individual decision on market participation (Abdulai and Huffman 2005).

Technology adoption and market participation studies have largely pointed to the flow of information through proxy measures and not the information itself. In studies of knowledge intensive technologies, such as integrated pest management, whether (or not) the study accounts for neighborhood effects can have dramatic effects upon performance outcome and the evaluation of information dissemination programs (see Feder, Murgai and Quizon 2004 and Yamazaki and Resosudarmo 2006 for contrasting results). One natural counterpart to geographic space and proximity is the role of ethnicity or other social boundaries that define information sharing networks. Social boundaries are examined jointly with geographic measures of communities to generate a "social proximity" measure and explain access to extension and other sources of information (Romani 2005).

Technology adoption, diffusion and information sharing require that the technology under scrutiny provide some aspect that is superior to the existing technology. The profitability of site-specific nitrogen application, and the attendant investment in variable rate technology and

yield monitors, was evaluated in frameworks that controlled landscape position with spatial error, spatial lag and non-spatial regression models (Anselin, Bongiovani, and Lowenberg-Deboer 2004). Profitability assessment of the technology was dependent on whether yield response functions were modeled as spatially autoregressive or not.

Beyond technology adoption, spatial economic models have emerged in the measurement of technical and allocative efficiency and in explaining the linkage between environmental services and agricultural production. In the former, technical and allocative efficiency of dairy firms was examined to determine whether performance among firms was spatially dependent and whether the patterns suggested localization or urbanization economies and Marshall-Arrow-Romer or Jacobs' externalities (Bragg, 2005; Bragg and Dalton, 2006). Failing to adjust for spatial dependence and omitting exogenous variables from the frontier estimation process resulted in biased efficiency estimates.

The spatial dependence between forest ecosystem services, and the effect these service have upon agricultural production and attendant welfare, was recently modeled using spatial lag, error and lag and error models and then compared to non-spatially explicit models (Pattanayak and Butry, 2005). Ignoring the spatial dependence related to economic interactions and ecological systems undervalues forests to downstream agricultural producers. By contrast, Swinton (2002) was able to model spatial dependencies between production and natural resource degradation using a random effects regression as opposed to a spatial lag or error model. The spatial dependency between agricultural systems and environmental performance has also been modeled in mathematical programming systems integrating GIS and plot-level land allocation information to evaluate the impact of green payments and the elimination of commodity support programs on farm welfare (Cobourn 2004, Antle et al 2003).

4. Conclusions

Our review of the literature since the 2002 special volume of *Agricultural Economics* (Nelson 2002) demonstrates increasing interest in the use of spatial data and spatial analysis tools. However, as noted previously, there appears to be a lag in terms of methodological advances and applications but several very recent advances Current applications of spatial econometric methods tend to be linear regression models, such as the spatial lag and error models. Applications of panel data models (Baltagi and Li 2004), models of limited dependent

variables (Fleming 2004), and hazard or durations models that address spatial dependence are not commonly found in the literature. It will be interesting to see if the increased analytical and programming requirements of such applications delay their widespread use by agricultural economists. But, in addition, if analyses continue to demonstrate that research without spatial factors suffer omitted variable bias, we expect to see greater incorporation of these tools into the applied analyst's toolbox.

A second observation is the advancement of thinking in terms of understanding spatial interactions. The structure of spatial dependencies is central to any spatial economic analysis of consumer or producer behavior. While causality, dependency, exogeneity or endogeneity are regularly stressed in applied economic training, thinking "spatially" or in terms of other natural groupings that are not captured by simple dichotomous dummy variables, needs emphasis to advance social learning. Further refinement is necessary in this area.

Lastly, technological advances are closing the gap between micro and macro spatial data. It will be interesting to track the expansion of micro-spatial data availability. We are already exposed to spatial-temporal models, but scale-differentiated models that provide more information for sub-groups is developing. Currently, applications often study individual micro-level behavioral issues conditioned upon village, country or other "superstructure." We could evaluate the impact of micro-, meso-, or macro-level variation (instead of dichotomous controls) and incorporate these factors into identifying social behavior in a more refined manner.

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