Modeling the Determinants of Farmland Values in the United States

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Abstract

Farmland has long represented a significant component of both farm sector and farm household assets. This chapter provides a comprehensive overview of significant developments in modeling farmland values, with attention to methodological challenges and recent modeling innovations. After outlining the capitalization model that provides the theoretical underpinnings for most farmland value studies, the merits and efficacy of dynamic models using aggregate data, as well as increasingly popular cross-sectional hedonic models that use spatially disaggregate data are presented. Estimation issues in hedonic models are reviewed, with a focus on those deserving special consideration in the context of farmland values such as spatial dependence and heterogeneity and sample selection bias. Promising future research directions include greater use of nonparametric approaches, quasi-experimental designs, panel data analyses, and structural econometric models, which take advantage of spatially explicit farmland values data but avoid the restrictive assumptions of standard spatial lag and spatial error models.

Keywords: farmland values, capitalization model, dynamic models, hedonic models, sample selection bias, spatial dependence

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[1] This work was completed when Zhang was a graduate student in the Department of Agricultural, Environmental, and Development Economics at the Ohio State University.

Although once distributed for free to the earliest settlers in the United States, land has long been traded in private markets. For most of the past 100 years, real estate (land and structures) has comprised a significant portion of the wealth of many landowners. This is particularly true for the farming sector, which also is a major user of land—51% of the US land base in 2007 was in agricultural use (Nickerson et al. 2012). Valued at $1.85 trillion in 2010, farm real estate accounted for 85% of total US farm assets (US Department of Agriculture, Economic Research Service [USDA-ERS] 2012). Because it comprises such a significant portion of the balance sheet of US farms, changes in the value of farm real estate have an important bearing on the farm sector's financial performance. Farm real estate also represents the largest single investment item in a typical farmer's investment portfolio; as a principal source of collateral for farm loans and a key component of many farmers' retirement funds, changes in its value can affect the financial well-being of landowners.

Because of the longstanding significance of land values to both the farming sector and landowners, understanding the determinants of farmland values has been the subject of a great deal of economic research. Although the earliest studies date back well more than 100 years, most methodological and empirical advances in the study of farmland values have occurred more recently. The farmland valuation models developed and tested in the ensuing decades have generally evolved to help explain changes in farmland values that began to diverge from trends in returns to farming. The foci of the research have shifted over time partly due to recognition that existing models were not very well explaining significant swings in farmland values observed both at national and regional levels. The direction of research has also been influenced by the types of data available for empirical analysis, with the availability of increasingly detailed data spawning new opportunities to explain the determinants of farmland values and changes in those values.

In this chapter, we provide a comprehensive overview of significant developments in modeling farmland values. In doing so, we cover a wide variety of models and give particular attention to methodological challenges and recent modeling innovations. We begin by outlining the capitalization model, which has been—and continues to be—widely used as the theoretical basis in economic studies on this topic. We next discuss modeling efforts to address perceived shortcomings of this basic model in the context of farmland values. Dynamic modeling approaches using aggregate data to explain changes in farmland values have been heavily used for this purpose. We then turn attention to cross-sectional hedonic models that use spatially disaggregate or individual-level data to examine the influence of particular determinants on farmland values, which in recent decades have become the mainstay of modeling techniques in the farmland values literature. We describe estimation issues that arise in hedonic modeling of farmland values, devoting most attention to those methodological issues that deserve special consideration in the context of farmland values, including spatial dependence and sample selection bias. In the course of doing so, we focus less on the specific findings of the studies (of which there are many) and more on the models themselves.

Because many of the advances in the study of farmland values occurred due to changes in farmland markets over time and to the applications of new modeling techniques, it is instructive to proceed in a more or less linear fashion, beginning with the earliest models, and describe the conditions that induced changes in modeling. We conclude with the most recent advances in modeling the determinants of farmland values and a discussion of what we perceive to be promising future research directions.

1. The Basic Capitalization Model

David Ricardo's (1817) formulation of an economic theory of rent, which was originally developed in the context of the value of farmland, is an important theoretical cornerstone in the basic model of land rents and land values. Ricardo's key insight was that land that differs in quality and is limited in supply generates rents that arise from the productive differences in land quality or from differences in location. Ricardo's work and that of others (e.g., Malthus' concept of residual surplus and von Thünen's theory of rent differentials arising from distance from a central market) form the basis of our modern understanding of land rents and land values (Barlowe 1986).

In the basic model, farmland is recognized as a fixed factor of production. Farmland prices are comprised of the discounted stream of economic returns generated by the land, where returns are defined as the return above all variable factors of production. Formally, the model is written as

$$P_t = \int_{t=0}^{\infty} A_i(t) e^{-rt}\, dt \qquad (1)$$

where P_t is the price of farmland in period t, A_i is annual net returns from farming, and r is the discount rate. The use of this basic model underlies not only farmland values research but also is used to model landowner decisions about land use choices.

Throughout the early decades of the 1900s, even though commodity prices experienced both rapid increases and significant declines, farmland prices and net returns remained relatively closely correlated. Farmland values began diverging from net returns in the 1950s, with farmland values increasing fourfold relative to farm income between 1952 and 1964 (Chryst 1965). Around this time, several studies attempted to model farmland values in a simultaneous equations framework (e.g., Herdt and Cochrane 1966; Tweeten and Martin 1966). However, this direction of research was short-lived, due primarily to concerns about identifying classic supply equations in a market with inelastic farmland quantities (e.g., Falk 1991), and subsequent research that determined the ability of these models to explain changes in farmland prices was very sensitive to the time period of the data (Pope et al. 1979).

3. Developments Using Time Series Models and Aggregate Data

Dramatic changes in farmland prices occurred in the following decades, with rapid appreciation in the 1970s followed by large declines in the 1980s. These changes raised a number of questions about the usefulness of the basic capitalization model in explaining changes in farmland values. In addition to assuming that land is valued only for its economic returns (which are known with certainty), the model assumes a constant discount rate, risk neutrality, and no effects from capital gains, inflation, transaction costs, and taxes. These issues lend themselves to examination using dynamic approaches, and many of the ensuing studies used time series techniques used to study stock price movements to test empirically these and other assumptions. These studies also used highly aggregated data in most cases—often state-level averages—due at least in part to the lack of more disaggregated, high-quality data available for farmland.

An issue receiving early attention is the specification of A, net returns. Melichar (1979) pointed out that net farm income may not be the best measure of returns because it includes returns to all productive assets, labor, and management time. As a result, many subsequent papers used net rents instead of net farm income as the measure of returns. However, other studies support the use of imputed returns (Mishra et al. 2004).

3.1 Distributed Lag and Vector Autoregressive Models

Several time-series studies used distributed lag models to test the relative effects of returns and inflation on farmland price movements. Because returns anticipated in the future are not observable, these models used observed returns in previous years to proxy for expected returns. The models placed less weight on returns earned in the most recent years than in earlier years, reasoning that changes are capitalized into land values only if they persist. Using different specifications of distributed lags with different aggregated data, both Alston (1986) and Burt (1986) found returns to be the major explanation of land prices and the effects of inflation to be small at most. Alston's study used data from eight US Midwestern states between 1963 and 1982, whereas Burt used data from Illinois over a similar time period. A study by Moss (1997) suggested that the relative effects of returns and inflation vary by region, with returns providing more explanatory power in regions relying more heavily on government payments.

Vector autoregressive (VAR) techniques were also used to test the basic capitalization model. These models capture interdependencies by defining an equation for each variable that is based on own-value lags, as well as on lags of the other variables in the model. An often cited study is that by Featherstone and Baker (1987), who simultaneously estimated equations for farmland values, returns, and interest rates to examine the time path of farmland value adjustments to changes in returns and interest rates. Using annual data on US farmland values for 1910–1985, their results suggest that speculative factors seem important: that is, farmland values overreact to shocks in values, real returns, or interest rates, and the reaction lasts for up to six years. Others have used VAR methods to test whether the discount rate in the capitalization model was time-varying (e.g., Falk 1992). Assuming the trend series was difference-stationary rather than stationary, Falk and Lee (1998) used VAR and Iowa data from 1922–1994 and concluded that the capitalization model explained farmland price movements in the long run; in the short run however, they concluded that overreactions to temporary shocks caused deviations between prices and predictions of the capitalization model.

3.2 Cointegration Analysis

Advances in the study of time series data led to challenges of the stationarity assumptions used in traditional time series representations. A number of ensuing studies were influenced by the work of Campbell and Shiller (1987), which showed that if the PV model were to hold, (1) land prices and rents must both have the same time-series properties, and (2) certain restrictions were required on the VAR representation of the changes in rents and the spread between rents and land prices (see Falk 1991, p. 3–4). These studies used cointegration analysis to overcome spurious results that could occur when using traditional time series approaches with data characterized by nonstationarity and unit roots. A number of these studies reject the present value model on the basis of an inability to find that farmland prices and rents are cointegrated (e.g., Falk 1991; Tegene and Kuchler 1993; Clark et al. 1993). However, Gutierrez et al. (2007) argue that this lack of support may be due to previous studies' not taking into account structural breaks and also assuming that states' data are independent of each other—which they point out is unlikely to hold, given the common boom-bust cycles in the data typically employed. Using recent advances in modeling nonstationary panel data and data from 31 US states over 1960–2000, they find that, by controlling for structural breaks, they cannot reject the present value model. Using a cointegration approach and error-correction models, Erickson, Mishra, and Moss (2003) also found support for the present value model, but note that the results are sensitive to the specification of the economic returns to land.

Cointegration analysis has also been used to examine whether discount rates vary by income source. Weersink et al. (1999) found government payments tended to be discounted less than market-based returns in Ontario. Schmitz (1995) found the opposite in Saskatchewan, which Weersink et al. (1999) posit is a result of farmers viewing government payment programs in the former province as a more stable source of income than the ad hoc transfers that are more characteristic of payments in the latter.

3.3 Structural Models

The conflicting evidence these studies find on the role of expectations, inflation, time-varying discount rates, and other factors is attributed by some to the use of econometric approaches that examine possible influences in isolation and which use specifications that are not based on economic theory (e.g., Just and Miranowski 1993; Chavas and Thomas 1999; Weersink et al., 1999). In a seminal paper, Just and Miranowski (1993) developed a comprehensive structural model to examine the multidimensional effects of inflation on capital and savings-return erosion and real debt reduction, as well as of changes in the opportunity cost of capital, while accounting for risk preferences and transaction costs. Using state-level pooled cross-section data from 1963–1986, they found increased returns to farming, inflation, and opportunity cost were major explanations of the large increases in farmland prices in the 1970s, whereas only the latter two factors primarily explained subsequent large declines in the 1980s. Their results also suggest that inflation and opportunity cost explained the tendency of changes in land prices to exceed changes in rents (Featherstone and Baker 1987; Falk 1991). They did not find the results were sensitive to the expectations regime used. Although the study did not account for nonstationarity of the data as pointed out by Lence (2001), a subsequent study that did and which used very similar data found similar results (Awokuse and Duke 2006).

In another particularly notable paper, Chavas and Thomas (1999) developed a model at the microeconomic level that incorporates risk aversion, transaction costs, and dynamic preferences. Recognizing that time series data have been available almost exclusively only at an aggregate level, they described the conditions necessary for maintaining consistency between microlevel decision rules and aggregate price data—and the particular challenges for empirical modeling of the role of transaction costs. Using data on US farmland values over 1950–1996, they found that both risk aversion and transaction costs affected land prices and helped explain the inadequacies of the static present value model.

3.4 Other Dynamic Modeling Approaches

Other dynamic modeling approaches have been employed in the farmland value literature, although they have not been adopted as widely as the models just discussed.[1] Several of these techniques were utilized to specifically examine the influence of government payments. Because agricultural payment programs in the United States have been in place since the Agricultural Adjustment Act of 1933, several studies using dynamic modeling approaches considered the impact of government payments on changes in farmland values. Several studies found that US government payments had little effect on annual changes in farmland prices in the United States (e.g., Just and Miranowski 1993; Gardner 2003), attributing the findings of limited impacts on price fluctuations to the stabilizing effects of the payments. Studies using cointegration techniques suggest the relative responsiveness of land values to changes in government payments in Canada may depend on the proportion of government payments to total income (Weersink et al. 1999).

Estimating the impacts of government programs with precision in a dynamic modeling framework is challenging because these programs have been subject to change during the course of Farm Bill reauthorizations that occur approximately every five years, and the complexity of farm policies has increased over time. For many years, payments were tied to production or market conditions, so payment amounts could vary substantially across Farm Bill periods. Changes in the programs also mean that estimated effects of past farm programs may not be representative of effects of current farm programs. In particular, through 1950, commodity programs provided relatively little support, but during the next 15 years or so new programs were introduced that provided more support (Gardner 2003). Farm legislation in the 1980s and 1990s shifted away from market-distorting policies, with the addition of income-supporting (as opposed to price-supporting) commodity loan programs in 1985 and the introduction of planting flexibility on acres qualifying for commodity program payments in 1990. The Federal Agricultural Improvement and Reform Act of 1996 (i.e., the 1996 Farm Bill) eliminated all cropping restrictions; commodity payments previously tied to current planting decisions were decoupled from current production decisions and replaced with payments based on historical production choices (Nelson and Schertz 1996).

A few studies accommodated these program complexities by using different empirical techniques to model explicitly whether the land value effects of US commodity payment programs have varied across Farm Bill periods. Gardner (2003) used pooled county-level data between 1950–1992 and found only weak evidence that the rate of growth in farmland values in counties with substantial amounts of program crops was higher than it would have been in the absence of commodity programs (i.e., compared to “non-program crop” counties). Gardner (2003) posits that the evidence was not stronger because farmland may benefit more uniformly from the existence of commodity programs (i.e., if farms are not enrolled, the value attached to the option to enroll would be capitalized into the value of the land). Also, although payment impacts may be evident in the short run, the effect could be dampened in the long run if a larger share of program benefits goes to commodity buyers.

Using a recursive model to account for identification issues arising from the counter-cyclical nature of some farm program payments, Shaik et al. (2005) find that farm program payments may have increased farmland values by as much as 30–40% during 1940–1980, but that the effect declined to 15–20% during 1980–2002. Mishra et al. (2011) used an information measure and found that impacts on land value changed after passage of the 1996 Farm Bill, noting less divergence between the distributions of farmland values and government payments in the post-1996 Bill period. Nonetheless, a challenge continues to be that modeling the impacts of government payments with aggregate data is problematic. That, coupled with the recognition that government payments are likely to also affect input and output markets, helps explain a shift in modeling the incidence of policies away from the effects on prices (Sumner et al. 2010).

Collectively, studies employing dynamic modeling techniques demonstrate that these approaches offer several benefits in the context of modeling farmland values. Among the most important are that these models inform on the relative importance of macroeconomic factors, such as interest rates and inflation, whose identification requires temporal variation. The contributions they provide to informing farmland value forecasting models are also important (Erickson et al. 2003). Criticisms include a lack of a behavioral basis, as well as the potential for aggregation bias; a continuing challenge is obtaining consistent results. Although recent advances in nonstationary panel techniques may help improve consistency or the identification of some impacts (e.g., Gutierrez et al. 2007), and extensions that incorporate demands for land in alternative uses could be useful (Moss and Katchova 2005; Shaik et al., 2005), they may not fully address the criticisms noted above.

4. Developments Using Cross-Sectional Models and Spatially Explicit Data

In more recent decades, the increasing availability of cross-sectional and spatially disaggregated data provided new opportunities to model the determinants of farmland values with data at a scale that more closely matched economic behavioral decisions (Irwin et al. 2010). A strain of farmland values literature evolved that exploited these increasingly disaggregate data and adapted property value modeling approaches that were common in the urban economics literature. In particular, application of these techniques to farmland markets in urbanizing areas became widespread. This occurred in part due to the recognition that, in many regions, farmland can earn returns not just from agricultural production and government payments, but also from "nonfarm" sources. Principal among the nonfarm sources of returns first considered was the expected future rent increases arising from returns from future development for residential uses for farmland in close proximity to urban areas. Capozza and Helsley's (1989) seminal work laid the theoretical foundation for this literature and showed how the value of expected future rent increases could be quite large, especially in rapidly growing cities. That is, in such areas, farmland values are represented by (setting aside uncertainty):

$$P_t = \int_{t=0}^{u} A_i(x_i, t)e^{-rt}\, dt + R_i(x_i, u)e^{-ru} \quad (2)$$

where P_t is the price of farmland in period t, A_i is annual net returns from farming, R_i is the one-time net returns from converting the land to an urban use at the optimal conversion time u, x_i is a vector of exogenous parcel characteristics, and r is the discount rate. In this specification, farming returns are no longer earned once time u arrives. The returns to conversion are represented as a one-time payment to reflect the typical lump sum payment that landowners receive when land is converted to an urban use. This model could also be expanded to include other sources of nonfarm income—income from hunting leases, for example—that generate a stream of payments that are earned in addition to farming returns.

Hedonic models quickly became the most widely used property value model in the study of the determinants of farmland values. Because of its extensive use, we provide an overview of the basic model and issues that require attention when estimating the model. We note that hedonic models are not the only models used to explain nonfarm influences. For example, Hardie et al. (2001) adapt an urban growth model and used a simultaneous equation approach with county-level data to explain residential and farm real estate prices. Others used ordinary least squares (OLS) regressions with farm-level survey data to study the impacts of both various forms of government payments (disaggregated by program type) and potential returns from future development (Goodwin et al. 2003*a*, 2003*b*).

4.1 Hedonic Models: Conceptual Approach

Hedonic models are a revealed preference technique based on the notion that the price of a good observed in the marketplace is a function of its attributes or characteristics. A seminal article by Rosen (1974) develops the model for differentiated consumer products (as noted by Palmquist [1989]; Freeman [1974] also developed a similar model). These models provide the theoretical underpinnings for empirical models that estimate marginal prices for a product's characteristics. The theory of hedonic property value models is thoroughly described in Freeman (1993) and in Palmquist (2006); however, those models were confined to residential properties. Under the assumption of perfect competition, the hedonic price function represents an equilibrium price schedule that is comprised of the market-clearing bid-and-offer curves of heterogeneous agents (Rosen 1974). This equilibrium price of a property is a function of property attributes and location characteristics, and each characteristic is valued by its implicit price. Although studies have shown that these implicit prices could be used to identify marginal willingness-to-pay (MWTP) functions in the second stage estimation of hedonic models (e.g., Freeman 1993), most current studies only focus on the first stage estimation of implicit prices due to potential endogeneity concerns (Bartik 1987; Epple 1987; Bishop and Timmins 2011).

The equilibrium conditions of the hedonic model have been criticized because they require instantaneous adjustment in demand or supply. In particular, when market forces are moving continuously in one direction (or are expected to move in one direction), the imperfect adjustments of the market to changing conditions of supply and demand might introduce bias in the estimates of MWTP using observed implicit prices from hedonic regressions (Freeman 1993). As a result, researchers should be especially cautious in applying hedonic models when markets are changing rapidly. However, in most circumstances, divergence from hedonic equilibrium will only introduce random errors, and, even in cases of rapidly changing markets, hedonic estimates could still serve as the upper (or lower) bound of the MWTP estimates and provide useful information to infer the direction of biases.

In a seminal paper, Palmquist (1989) adapts the model for differentiated factors of production and applies it in the context of farmland rental markets. That paper assumes farmland owners and buyers are profit-maximizing farmers who own and buy land strictly for its productive capacity. Palmquist and Danielson (1989) discuss modifications needed in models using farmland sales as opposed to rent data but did not explicitly model them. Specifically, they note that the interpretation of the coefficients can differ depending on whether rents or sales prices are used in the hedonic model. Differences can arise when the marginal value of a characteristic differs in a short amount of time (within the length of the rental lease) relative to a longer period that would be capitalized into the value of the land. For example, being adjacent to a national park might reduce the rental price of farmland due to potential wildlife damage of crops but could increase the sales price if close proximity is expected to provide positive benefits in the more distant future.

The Palmquist and Danielson framework also does not account for the fact that, for many farm parcels, the land provides benefits beyond the net returns earned from farming, such as the value associated with the option to convert the land to residential use at some point in the future as modeled in (2) above, and benefits from close proximity to open space or other natural amenities that do not contribute specifically to the land's productive capacity. Indeed, US Department of Agriculture data reveal that most farmland owners in 1999 (the most recent data available on farmland ownership) did not operate farms as their primary business (US Department of Agriculture, National Agricultural Statistics Service [USDA-NASS] 2001). Some farmland owners farm on a part-time basis, but about 25% of farmland in 2007 was farmed by operators who were retired or operated a farm primarily for residential or lifestyle reasons (Hoppe and Banker 2010). The point that farmland has value both as a factor of production and as a consumption good has been recognized by some (e.g., Henneberry and Barrows 1990; Ma and Swinton 2012), although it appears that most researchers who estimate hedonic models in all but the most rural areas cite Rosen's theory related to consumer goods.

Many of the early applications of hedonic models to farmland markets used the approach to estimate the marginal value of both farm and nonfarm characteristics of farmland in urbanizing areas. One of the earliest and most well-cited papers is Chicoine (1981), who used sales data on unimproved farmland parcels in Will County, Illinois and found that the influence of factors affecting potential development returns R were far greater than soil productivity, the sole characteristic included in A as a proxy for farm returns. Numerous subsequent studies have also modeled the impact of urban proximity on farmland values; in areas that are more urbanized or have rapid population growth, these studies find that the demand for land for urban uses is the most significant nonfarm factor affecting farmland values (e.g., Shi et al. 1997; Plantinga et al. 2002; Huang et al. 2006; Guiling et al. 2009).

Hedonic models have also been used to examine the role of environmental factors and recreational opportunities on farmland prices. In response to concerns about farmland erosion resulting from the 1970s agricultural export boom and increases in nonpoint water pollution, a number of studies during the 1980s examined the effect of soil erodibility, as well as drainage, on farmland values (e.g., Ervin and Mill 1985; Miranowski and Hammes 1984; Gardner and Barrows 1985; Palmquist and Danielson 1989). Ervin and Mill (1985) also noted that such studies are useful for identifying the extent to which private markets capture the value of changes in a land characteristic that have implications for both on-site productivity and off-site environmental quality. Other studies examine the impact of wildlife recreation opportunities (e.g., Henderson and Moore 2006) and other amenities (see Bergstrom and Ready 2009 for a review), as well as the impact of restrictions on land uses, such as zoning (e.g., Chicoine 1981; Henneberry and Barrows 1990), agricultural district and greenbelt designation (Vitaliano and Hill 1994; Deaton and Vyn 2010), and farmland protection easements (e.g., Nickerson and Lynch 2001; Lynch et al. 2007). Several recent studies have considered the impact of bioenergy policies by analyzing the impact of proximity to ethanol plants on farmland values (e.g., Henderson and Gloy 2009; Blomendahl et al. 2011; Zhang et al. 2012).

4.2 Empirical Issues in Hedonic Modeling of Farmland Prices

A number of well-known econometric problems may arise when estimating hedonic models. One issue that has particular significance in the context of farmland markets relates to the geographic extent of the market. A key assumption of the equilibrium hedonic price schedule is that sales transactions are drawn from a single market. This assumption is particularly restrictive in studies using farmland price data, since the historical thinness of the market limits the number of transactions within narrowly defined geographic areas. Indeed, recent surveys reveal that less than

2% of farmland is sold annually (Sherrick and Barry 2003; Duffy 2011). Previous studies have utilized transactions data at various levels, from a single county (e.g., Chicoine 1981; Henneberry and Barrows 1990), to a single state (e.g., Guiling et al. 2009), and to entire regions (e.g., Roka and Palmquist 1997; Barnard et al. 1997). However, the appropriate size will likely vary depending on the topic of the study. Studies on the value of farmland in urbanizing areas could arguably have markets covering a much smaller geographic area compared to studies on farmland values in rural areas, for example.

The historical thinness of farmland markets also raises two other important issues unique to farmland values studies. The first is about the construction of the dependent variable, given the fact that sales prices reflect the value of both land and structures in the presence of farm structures, residential dwellings, or both. Previous researchers have included a dummy variable indicating the presence of structures (e.g., Palmquist and Danielson 1989), subtracted the value of improvements from the total sales price (e.g., Guiling et al. 2009; Zhang et al. 2012), or simply excluded the parcels with structures (e.g., Chicoine 1981). Although information on the attributes or even presence of farm buildings is rarely available, including the value of structures in the dependent variable is not inconsistent with theory (Freeman 1993). The other issue relates to the choice of the data source. Whereas use of survey data (e.g., Roka and Palmquist 1997; Henderson and Gloy 2009) can yield more observations than microlevel sales transaction data, it raises a question about how well survey respondents' assessments of farmland values represent true market prices.[2]

A particularly important empirical issue that requires consideration in farmland value hedonic studies is omitted variable bias, in which the correlation of observed variables and unobserved attributes lead to biased estimates of the implicit prices of characteristics of a property, a land parcel, or a product (Palmquist 2006). Bias resulting from spatial dependence and sample selection due to observables and unobservables are two distinct types of omitted variable bias that researchers have begun address in recent farmland value studies. Agricultural land parcels are essentially spatially ordered data, and achieving unbiased and efficient estimates requires addressing the inherent spatial dependence (Anselin 1988). This dependence has long been recognized in the areas of regional science and geography and was nicely summarized in Tobler's (1970, pg. 236) *First Law of Geography*—"everything is related to everything else, but near things are more related than distant things." In the presence of spatial dependence, the standard OLS assumptions of uncorrelated error terms and independent observations are violated, and thus the parameter estimates from the standard hedonic regressions will be biased and inefficient. A sample selection problem occurs when a nonrandomly selected sample used to estimate behavioral relationships is not representative of the desired population (Heckman 1979), which could arise from selection on the unobservables (Heckman 1979) or on the observed characteristics (Heckman and Robb 1985). If left uncontrolled, the sample selection problem will result in biased parameter estimates of the hedonic models.

Two other well-known problems that may affect any hedonic study are the functional form of the empirical model and multicollinearity. Although the choice of functional form can affect both the magnitude and significance of coefficients, as noted by most studies, economic theory offers little guidance regarding model specification and restrictions on functional form. In practice, data availability and the goodness of fit often dictate the choice among different functional forms; farmland value studies have used a variety of forms, including transcendental, linear, semi-log, and double-log; some researchers prefer the flexibility afforded by the Box-Cox functional form, which lets the data determine the appropriate form (Palmquist and Danielson 1989; Roka and Palmquist 1997; Nivens et al. 2002). Another key specification issue in hedonic models is the multicollinearity that often arises from the attempt to control for all relevant characteristics of the land. This problem arises at least in part from difficulties in obtaining enough data for ideal model specifications, which is challenging given the thinness of farmland markets. As noted by Freeman (1993), including collinear variables increases the variance of coefficient estimates and affects inference.

Substantial research effort has been devoted to alleviating all of these econometric problems imbedded in hedonic models. In the context of research on farmland values, recent econometric developments have largely been focused on addressing biases arising from spatial dependence and addressing sample selection bias due to observables and unobservables. Our discussion of these techniques in the following sections describes these developments. We also draw on the wider hedonics literature, in which several developments are sufficiently recent that they have not been often embraced in models of farmland values.

4.3 Recent Developments in Addressing Spatial Autocorrelation and Spatial Heterogeneity

To account for spatial dependence in hedonic models of farmland values, two parametric spatial econometric models are primarily applied: spatial lag (spatial autoregressive) models and spatial error (spatial autocorrelation) models. Spatial lag dependence means the dependent variable in one location is affected by independent variables in that location and other locations. The standard spatial lag model solves this problem by adding a weighted average of nearby values of the dependent variable as an additional set of explanatory variables, which instead of the traditional model $y = X\beta + u$ yields

$$y = \rho W y + X\beta + u = (I - \rho W)^{-1}(X\beta + u)$$

$$= (I + \rho W + \rho^2 W^2 + \ldots)(X\beta + u) \qquad (3)$$

where W is an n x n spatial weight matrix, and the scalar ρ is the spatial coefficient.

As can be seen in the last equation of (3), the Leontief inverse reduced form, spatial lag of the dependent variable implies a spatial diffusion process or a so-called “spatial multiplier” effect, in which each observation is potentially influenced by all other observations (Anselin 2001), and such influence decays with the increase in distance between observations.

Spatial error dependence or spatial autocorrelation, in which the correlation of error terms is across different spatial units, is typically caused by measurement error or omitted spatial variables, or by a modifiable areal unit problem (i.e., results differ when the data are aggregated in different ways) (Griffith 2009). In contrast with the spatial lag model, in which the spatial interaction is the process of interest, the spatial error model offers a more common and direct treatment of the spatial dependence among error terms of the observations, in which the spatial dependence is a nuisance:

$$y = X\beta + u, \qquad with\, u = \theta W u + e$$

$$y = X\beta + (I - \theta W)^{-1} e \quad (4)$$

where W is an n x n spatial weight matrix, and the scalar θ is the spatial coefficient.

Opportunities to account explicitly for spatial dependence among observations in farmland values studies have grown in recent years, due to increased availability of spatially explicit data on farmland, the explosive diffusion of Geographic Information System software, and the dramatic increase in the ability of statistical packages to handle large spatial matrices. Using county-level data in the Corn Belt, Benirschka and Binkley (1994) offer one of the first treatments of spatial autocorrelation in studies of the relationship between agricultural land price variations and distances to markets, in which the spatial correlation of error terms across counties are represented by a standard spatial error model specification, with *W* being a simple binary continuity matrix. In a spatial lag, serially correlated hedonic pricing framework, Huang et al. (2006) further control for serial correlation using a first-order autoregressive process along with the assumed time-invariant spatial lag dependence using a Kronecker product of the spatial matrix *W* and a $T \times T$ identity matrix. A similar spatiotemporal weight matrix is also used by Maddison (2009). In a study of effects of natural amenities on Michigan farmland values, Ma and Swinton (2012) use a spatial error specification to account for spatial dependence, in which the spatial weights matrix is defined using the inverse distance formula with a cutoff distance of 600 meters from the parcel centroids beyond which no correlation is assumed. The spatial error model structure was determined through diagnosis and tests of the structure of spatial correlation.

Due to improved computational speed and functional simplicity, spatial lag and spatial error models have become routine fixes for nearly any model misspecification related to space (McMillen 2012). However, these standard spatial econometric models are far from problem-free. In particular, most spatial econometric models face an ironic paradox that their very use is an admission that the true model structure is unknown, yet the common estimation technique of maximum likelihood relies heavily on knowing the true structure in advance (McMillen 2010). Other criticisms include identification problems and usually exogenously imposed spatial weights matrix, which can result in biased parameter estimates if misspecified.[3]

As emphasized by McMillen (2010, 2012), standard spatial econometric models are simply another form of spatial smoothing, and they should be viewed as additional statistical tools for model specification tests and convenient robustness checks, rather than as the primary means of analyzing spatial data. In general, applications of spatial models should be guided by economic theory (e.g., Brueckner 2006) and by actual empirical questions (Pinkse and Slade 2010). Instead of focusing solely on spatial lag and spatial error models, researchers have advocated alternatives, such as semiparametric and nonparametric approaches (McMillen 2010), and “experimentalist paradigm” approaches, such as instrumental variables (IV) and spatial differencing (Gibbons and Overman 2012).

These alternative approaches have gained popularity in residential real estate valuation studies, for which spatially explicit data has traditionally been more readily available than farmland data. Two recent studies using these approaches are worth noting. The first is a nonparametric analysis of capitalization of proximity to rapid transit lines in residential house prices in Chicago, in which McMillen and Redfearn (2010) illustrate that, unlike standard parametric spatial models, nonparametric estimators control for spatial variations in marginal effects and spatial autocorrelation while using highly flexible functional forms, without imposing an arbitrary weight matrix. The second is a study that identifies the influence of spatial land use spillovers on housing values. Carrión-Flores and Irwin (2010) exploit a natural discontinuity in the data and show that a partial population identification strategy solves the endogeneity problem and is a superior alternative to the common spatial error model for eliminating spatial error autocorrelation and identifying spatial interactions.

Some progress in addressing spatial autocorrelation and spatial heterogeneity has also been made in studies of farmland values beyond the spatial lag and error models. Cotteleer et al. (2011) tried to resolve specification uncertainty in selecting explanatory variables and weighting matrices in parametric spatial econometric models by employing Bayesian Model Averaging in combination with Markov chain, Monte Carlo model composition. In this framework, no single correct model specification is assumed and learning from the data is allowed, but prior information is needed. Using parcel-level data in Northern Ireland, Kostov (2009) generalized the linear spatial lag model by employing a flexible, semiparametric IV quantile regression approach, which not only allowed for varying effects of the hedonic attributes, but also varying degrees of spatial dependence. In two similar Northern Ireland studies, Kostov et al. (2008) and Kostov (2010) employed two different nonparametric approaches and found that buyer characteristics and personal relationships exert nonuniform and nonlinear effects on the implicit prices of farmland characteristics. Using intramunicipal-level French data, Geniaux et al. (2011) extended Capozza and Helsley's (1989) model to account for uncertainty in future land use zoning and used mixed geographically weighted regression estimations of a spatial hedonic model to recover intramunicipally heterogeneous impacts of land use conversion anticipation on farmland prices.

4.4 Recent Developments in Addressing Sample Selection Bias

Sample selection problems may arise from a variety of selection mechanisms, including self-selection by the data units (Heckman 1979) and the so-called incidental truncation problem, in which data on a key variable are available only for a clearly defined subset (Wooldridge 2002); for example, farmland rental rates can only observed for those land that are actually rented. In such cases, unobserved factors determining inclusion in the subsample are correlated with unobservables influencing the variable of primary interest, leading to biased parameter estimates of the hedonic models.

Heckman's 1979 seminal paper offers the first and the most widely applied correction model of sample selection (or selectivity) bias. The sample selection problem is characterized by two latent variable equations, the selection or participation equation and the outcome equation, which are allowed to have correlated errors. Correction of the sample selection bias is commonly achieved through a limited-information two-step estimation procedure (Greene 2012), in which the inverse Mills ratios are formulated from the estimated parameters of the first-stage probit selection equation to control for selectivity bias. This Heckman-style selection model has become a standard solution to the sample selection problem in various fields of economics, especially in the literature of program evaluation. In the context of research on land values, especially farmland values, this model is also widely applied. In a study of residential land value functions in which land use is determined by zoning, McMillen and McDonald (1989) find evidence of selectivity bias for undeveloped and multifamily residential land uses in which the "self-selectivity" arises when local governments use land values to guide zoning decisions. However, in the context of farmland markets, sample selection was not detected in two recent studies that addressed it using Heckman selection model (Nickerson and Lynch 2001; Kirwan 2009).

The Heckman selection models address selection on the unobservables; however, in a broader sense, sample selection could also occur when the unobserved disturbance in the outcome function is correlated with the observed explanatory variables in the selection model, which is introduced as "selection on the observables" by Heckman and Robb (1985). As a result, when estimating the average treatment effect, the assumptions about the distributional equality of the covariates across the treatment and control subsamples imposed by hedonic regressions could be problematic, and the differences between covariates among treatment and control units may need to be adjusted for (Imbens and Wooldridge 2009). Matching offers a straightforward and effective way to balance these differences, which facilitates the identification of the causal treatment effect. Intuitively, matching solves the sample selection on the observables by selecting treated observations and comparison observables with similar covariates, by covariates X (e.g., Rubin 1980), or by propensity score p (e.g., Rosenbaum and Rubin 1983).

In this section, we focus on propensity score matching (PSM) methods, which use propensity score (the probability of selection into treatment conditional on covariates) in matching, because these methods are most commonly used and have been shown to be reliable under certain regularity conditions (Todd 2007). PSM presents several key advantages over the least squares hedonic approach. Most importantly, PSM does not require a parametric model linking outcomes and program participation (Dehajia and Wahba 2002; Smith and Todd 2005; Ravallion 2007). In addition, unlike standard regression methods, PSM ensures that observations in treatment and control groups share the common support (Ravallion 2007), and, finally, unlike Heckman selection model, PSM does not assume a particular functional form for the price equation (Heckman and Navarro 2004). Matching estimators such as PSM are justified if the selection is only on the observables (Imbens and Wooldridge 2009), and the performance of PSM depends crucially on the set of covariates included in the estimation (Heckman et al. 1998; Todd 2007). However, instead of elaborating on the methodological and implementation details on PSM, we aim to highlight specific applications of PSM in farmland values. The reader is referred to Caliendo and Kopeinig (2005), Smith and Todd (2005), Todd (2007), Zhao (2004), and the *Towe, Lewis, and Lynch[oxfordhb-9780199763740-e-027]* chapter in this Handbook for detailed discussions on the matching methods.

PSM has become a popular approach to estimate causal treatment effects and has been used in some recent studies of farmland values. In an analysis of the selection problem due to the voluntary nature of farmland easement programs analyzed also in Nickerson and Lynch (2001), Lynch et al. (2007) use a PSM approach in which observed variables closely related to the future development option values, and variables affecting eligibility or probability of program participation are included as conditioning variables. Specifically, in contrast with results from hedonic models but consistent with findings by Nickerson and Lynch (2001), they find little evidence that preserved parcels sell for a significantly lower price than nearby unrestricted land.

Using a sample of UK cereal farms, Sauer et al. (2012) incorporates the PSM approach with a production theory based multi-output, multi-input directional distance function framework and find that different agri-environmental schemes significantly affect production behavior at farm level.

However, systematic differences in unobservables may still bias these PSM estimators. Various extensions have been proposed as a response, including combining PSM and linear regression (Imbens and Wooldridge 2009), allowing for selection on unobservables by imposing a factor structure on the errors and estimating the distribution of unobserved errors (e.g., Carneiro et al. 2003), and controlling for time-invariant unobserved heterogeneity using a difference-in-difference (DID) matching estimator as defined in Heckman et al. (1997). Here, we focus on the DID PSM estimator, which has attracted more interest in the farmland value literature. When estimating average treatment effect, the conditional DID PSM estimator compares the conditional before-after outcomes of treated units with those of nontreated units. This DID PSM estimator is attractive because it permits selection to be based on potential program outcomes and allows for selection on unobservables (Heckman et al. 1997). A study by Ciaian et al. (2011) is worth mentioning because, rather than using the conventional binary PSM estimator to identify the effects of European Union government programs, it employed a generalized propensity score (GPS) method proposed by Hirano and Imbens (2005), which allows for estimation of the capitalization rates into farmland values for different levels of government payments as multivalued, continuous treatments. Two very recent US farmland value studies have used a DID PSM estimator to identify the impact of an expanding ethanol market. Using a panel dataset of US farmland parcels from 2001 to 2007, Towe and Tra (2013) investigate the differential impacts of the construction of new ethanol facilities before and after the Renewable Fuel Standard legislation passed. Their results suggest that the RFS created expectations of higher returns to agriculture, beyond those derived from higher commodity prices. Zhang et al. (2012) instead combine the regular binary PSM estimator with DID regressions and apply them on parcel-level agricultural land sales data in Ohio 2001–2010 and find evidence of a structural change in the marginal value of the proximity to ethanol plants induced by the 2007 residential housing market bust and concurrent expansion of ethanol facilities.

4.5 Addressing Omitted Variable Bias Using Instrumental Variables Approach

To address the omitted variable bias and endogeneity concerns other than sample selection bias, some recent studies have employed the standard instrumental variables (IV) approach to identify the impact of governmental subsidies. Although land studies in this area are all on farmland rental rates, the techniques are very amenable to examining the impact of government payments in the context of farmland value studies. Using US farm-level data, Kirwan (2009) designed an IV strategy to overcome the attenuation bias induced by the expectation error, which is the difference between actual agricultural subsidies and expected subsidies. Specifically, he instrumented the 1992–1997 subsidy change using the post-FAIR Act 1997 subsidy level and addressed the measurement error problem with a second instrument, the county-level average subsidy per acre. Following Lence and Mishra (2003) and using data in Northern Ireland, Patton et al. (2008) adopted an IV strategy combined with GMM technique to recognize the fact that payments are not known when rental contracts are determined and therefore instruments using lagged realizations of the “pre-2002 SAP” payments are needed in the presence of expectation error. Using a rich dataset of pooled cross-sections at the farm level, Goodwin et al. (2010) instrumented the expected payment benefits using a four-year historical average of real payments per farm acre in the county where the farm is located. They argued that this measure better represents the long-run potential benefits associated with agricultural policy, whereas the common measure, realized payments, may, in contrast, reflect individual policy choices and characteristics of the farms.

5. Conclusion and Future Research Directions

The continued significance of farmland values to both the farm sector and to many farm households means that understanding the key determinants of farmland prices will remain of perennial interest. In this chapter, we have sought to identify major modeling approaches used to model farmland values and to describe recent innovations. As this chapter highlights, both dynamic time series and static cross-sectional approaches have been utilized by a large number of studies, with each contributing unique insights. In this section, we identify several areas in which future research may yield the highest return both in terms of advances in modeling and in terms of topics of interest to policy makers.

Dynamic models reveal important information about macroeconomic factors affecting rates of change in farmland values. However, criticisms of ad hoc econometric specifications that could contribute to misleading results have plagued many of these studies. A natural direction for these studies would be to utilize some of the more recent advances in time series techniques in ways that are supported by an underlying structural model that is both consistent with individual behavior and that captures critical market relationships (along the lines of Just and Miranowski 1993). In particular, a better (or at least more current) understanding is needed of how expectations by landowners are formed over prices, costs, and other key variables. Also, how changes in determinants are transmitted through expectations as suggested by Just and Miranowski (1993) could be useful, especially if the studies can illuminate how quickly farmland values react to changes in its determinants.

Furthering our understanding of the dynamics of farmland markets in these ways seem useful for at least three reasons. First, the rapid onset of and large (double-digit) annual increases in farmland values that we have witnessed in recent years is occurring under different conditions than increases that occurred in the 1970s, so the primary drivers of change are different. In particular, studies that consider the formation and role of price expectations, market relationships, and incidence may help inform decision makers about how quickly high farmland values could erode (or could be further enhanced) due to policy changes under their control (e.g., government farm program payments, bioenergy policies that increase demand for biofuel crops like corn and soybean, and macroeconomic policies such as interest rates). Second, nonfarm influences on farmland are growing, and models that incorporate these influences can help inform on how changes in related land markets are influencing farmland values.[4] Finally, advances in these areas could help inform efforts to link farmland value models and models of land use and land use change. We return to this last point below.

In terms of future directions in cross-sectional hedonic studies, we note several compelling opportunities to better address omitted variable bias—which is arguably among the most important econometric issues requiring treatment in farmland value studies using disaggregated, parcel-level data. Exploiting the ever-widening range of new spatially explicit modeling approaches allows researchers to reveal the rich spatial heterogeneity of the influences of determinants of farmland values with fewer restrictive assumptions. These approaches include the nonparametric approaches, quasi-experimental (QE) designs, and structural econometric models, many of which we mentioned in section 4 in this chapter. In the following sections, we highlight some examples relevant for farmland values research.

Minimizing the bias and inefficiency caused by untreated spatial dependence in cross-sectional studies has spurred the adoption of a variety of techniques in land values studies. Although largely applied in land markets in or near urbanizing areas, the inherent spatially correlated processes underlying many farmland value determinants means the results of farmland valuation studies that do not consider spatial dependence are likely to be suspect. Standard spatial lag and spatial error models have yielded insights regarding the magnitude of the bias that can result if spatial dependence is left untreated. However, future research using spatially ordered farmland transactions data would likely benefit by embracing newer techniques that avoid the restrictive assumptions of these models. In particular, these newer techniques enable researchers to control for spatial dependence without imposing a certain spatial structure a priori. Approaches such as those relying on quasi-randomness, such as the "partial population identifier" used in Carrión-Flores and Irwin (2010), and semiparametric and nonparametric approaches employed by McMillen and Redfearn (2010) seem particularly fruitful in this regard. However, the standard spatial econometric models still serve as a useful toolbox for model specification tests and robustness checks, and a spatial lag model is still justified if the objective is to identify the effects of neighboring values on the dependent variable and the empirical model rests on economic theory (McMillen 2010).

In contrast with the standard hedonic models, QE designs popular in labor and regional economics, such as matching approaches and regression discontinuity design (RDD), present some interesting alternatives. By controlling for observable covariate differences and time-invariant unobserved heterogeneity, the DID PSM estimators illustrated in section 4.4 can yield more plausible results than traditional hedonic estimators, if correctly implemented. Researchers may also benefit by using matching estimators other than PSM. A good candidate is covariate matching, including the common Mahalanobis metric (e.g., Rubin 1980), or the recently developed genetic matching method (Diamond and Sekhon 2013).

Although, to our knowledge, RDD has not yet been applied in the studies of farmland values, it has been enthusiastically embraced in the literatures of political science, epidemiology, and other fields of economics, such as real estate studies.[5] Future farmland values studies could benefit by explicitly considering RDD, especially when estimating the impact of state or local governmental programs and the effects of strict agricultural zoning policies. However, caution must be exercised regarding the potential spatial spillover problems when geographic borders are used in RDD, in which case a robustness check using matching estimators may be helpful.

The importance of addressing sample selection is a well-known empirical issue in the farmland values literature. Given that a wide array of government policies and programs support the agricultural sector and the increasing reliance on mechanisms with voluntary participation, advances in addressing this issue could be particularly fruitful. However, current applications of Heckman selection models in farmland values research are limited to the original Heckman (1979) model, which has a rather limited structure and is highly parameterized (Vella 1998). Besides the aforementioned QE approaches, future research may adopt a broader view and consider more generalized selection models with less restrictive modeling assumptions, such as those used by Lee (1982, 1983), Heckman and Robb (1985), and Puhani (2000). Other methods, such as control functions, could also prove to be beneficial in certain circumstances (e.g., Heckman and Navarro 2004; Navarro 2008; Imbens and Wooldridge 2007).

As we mentioned earlier in this section, more work can be done in the farmland values literature to inform on efforts to uncover the structural parameters of the demand and supply of farmland, which helps link changes in farmland values with land use change models described (see for instance *Irwin and Wrenn[oxfordhb-9780199763740-e-012]* in this Handbook). Modeling dynamic aspects that take into account the formulation of expectations by farmland owners over prices, costs, and other key variables is crucial to estimating the supply of farmland and necessitates a dynamic modeling approach for the structural estimation of farmland supply. Current reduced-form models, such as hedonics and QE designs, are static, and they do not take these dynamics into account. However, as illustrated by *Irwin and Wrenn[oxfordhb-9780199763740-e-012]* in this Handbook, the complexity of dynamic discrete choice models makes it sometimes infeasible empirically. Nevertheless, incorporating feedback or forward-looking expectations in structural hedonic models of farmland markets remains a crucial unsolved issue. In the hedonics literature, some notable advances have been made to identify the marginal willingness-to-pay functions, including the IV approach by Ekeland et al. (2004), the new econometric inversion estimation by Bishop and Timmins (2011), and the dynamic hedonic model by Bishop and Murphy (2011), which allows for forward-looking behavior of decision-makers. However, as mentioned in section 4, researchers need to be cautious about using hedonic approaches when market forces are changing rapidly (Freeman 1993).

The ability of researchers to move forward on many of these fronts will be contingent on the increasing availability of spatially disaggregated data. Previous studies on agricultural land values that have employed aggregate data often mask important differences in the spatially disaggregated determinants of farmland values, such as distance from urban centers and proximity to agricultural delivery points like ethanol plants, grain elevators, and agricultural terminals. Aggregate data also hinder the application of new modeling approaches from related fields such as residential land/housing values research to studies on farmland values. A data challenge will continue to be the cost of developing parcel-level panel datasets via surveys and the thinness of farmland markets of developing pooled parcel-level sales data over time. Nonetheless, with more spatially explicit data available and techniques like nonparametric approaches and panel data analysis, researchers will have improved opportunities to analyze spatial variation as well as potential structural changes in certain determinants of farmland values.

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[1]For example, see papers included in Moss and Schmitz, eds. (2003).

[2] Ma and Swinton (2012) found tax assessor estimates of farmland values were particularly likely to underestimate the value of surrounding natural amenities.

[3] See Pinkse and Slade (2010), McMillen (2010, 2012), Gibbons and Overman (2012), and Brady and Irwin (2012) for further discussions of the criticisms of standard spatial econometrics models.

[4] We also note that the increasing influence of urban demands on farmland raises questions about whether time series properties differ between farmland subject to urban influence and farmland that is not.

The reader is referred to van der Klaauw (2008), Imbens and Lemieux (2008), and Lee and Lemieux (2010) for excellent reviews of RDD, and to Black (1999), Chay and Greenstone (2005), Greenstone and Gallagher (2008), and Grout et al. (2011) for applications of RDD in urban housing market studies.