Spatial Analysis of Illinois Agricultural Cash Rents

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Introduction

Who benefits from commodity price increases? During the summer of 2008, corn futures prices rose 119.8% compared to the previous year. The resulting nominal prices were the highest in history. Agricultural land values quickly followed suit with Illinois experiencing a 19.3% increase in cropland values between 2007 and 2008, the largest year-over-year increase ever in the Corn Belt (USDA, 2008*a*). After the dramatic price shock in 2008, anecdotal evidence implied that much of these benefits accrued to land owners through increased land values and cash rent levels. In this article, we use unique farm-level data for the state of Illinois to determine how farmland rents are affected by changes in commodity prices and government payment levels, while controlling for farm and regional characteristics.

A number of studies have investigated the relationship between land prices and residual returns (Awokuse and Duke, 2006; Phipps, 1984), government payments, conservation and land retirement programs (Goodwin, Mishra, and Ortalo-Magné, 2003; Goodwin and Ortalo-Magné, 1992; Nickerson and Lynch, 2001; Shaik, 2007; Shaik, Helmers and Atwood, 2006; Taylor and Brester, 2005), global warming (Mendelsohn and Dinar, 2003), and urbanization pressures (Livanis et. al, 2006; Plantinga, Lubowski and Stavins, 2002). However, we see little consensus on the degree to which land prices capture changes in profit.

One method for observing capitalization is by considering land rents, where one might expect to see a more rapid response to changes in agricultural revenue. As Ricardian theory would predict, a couple initial studies on cash rents show that soil productivity and yield potential have positive effects, such as Forster et al. (2003) in Ohio and Kurkalova, Burkart, and Secchi (2004) in the Upper Mississippi River Basin. A recent focus in the cash rent literature is the estimation of the incidence of government payments (e.g, Kirwan, 2009; Goodwin, Mishra, and Ortalo-Magné, 2005; Lence and Mishra, 2003). Data used in these studies have ranged from national farm-level data to regional data at the county-level and the estimates of incidence rates have varied considerably. More recently, Du et al. (2007) analyze how cash rents in Iowa have responded to factors including growth in the ethanol industry, scale of the local livestock industry, and adoption of genetically engineered crops.

The purpose of this study is to revisit the question of how farm land markets change in response to changes in commodity prices. Using unique farm-level, longitudinal data from the Illinois Farm Bureau Farm Management (FBFM) Association, we estimate a spatial hedonic model of the determinants of Illinois' cash rents and derive the marginal contributions of changes in commodity prices and government payment levels, while controlling for inherent parcel and regional characteristics. This study makes several important contributions and extensions to this literature.

First, our panel data set includes farm-level observations for cash rents and other characteristics that were unavailable to researchers in previous studies. Our results indicate a significant difference between the farm-level results and those obtained from the same data aggregated to the county level. Second, existing studies have tended to focus on eras of relatively stable commodity prices from the late 90's through the mid 00's. We include data from 1996 through 2008, a period which encompasses the sharp increase in commodity prices that began in 2005, as well as two significant changes in farm policy – the 1996 and 2002 farm bills.

Finally, this analysis extends the literature on the valuation of heterogeneous agricultural land. By explicitly accounting for variations in soil quality, urbanization pressures, economies of scale, and economic characteristics, a clearer view of how commodity price changes ultimately flow through to rental markets is observed. Also, the degree of regional correlation among rental rates is typically quite high, which causes efficiency problems in classical econometric estimation. Thus, we allow for heterogeneity across tenant farmers while explicitly controlling for the spatial nature inherent in the data by using a leading-edge spatial panel error component estimation method (Kapoor et al. 2007) which simultaneously accounts for the spatial and temporal correlations. The application of this estimator is unique to this literature.

Similar to previous work, we find that marginal output price changes and government payment levels have a significant effect on cash rents. In contrast to predictions of Ricardian rent theory, we find that the majority of increased revenues are accumulated by the tenant farmer in lieu of the landowner. We also observe that the move to more predictable government payments resulted in substantial increases in the amount of the subsidy capitalized into land costs. The results also provide substantiating evidence that both cross-county and intra-county soil productivity variations have considerable impacts on cash rent levels, as well as the existence of strong spatial effects. Parcels within relatively rural areas as well as those operated by farmers with large scale operations are also likely to pay slightly higher rents. Last, we find limited evidence of a risk premium in Illinois.

Background

The use of hedonic modeling approaches has been common in the literature on the determinants of farmland values (e.g. Palmquist and Danielson, 1989; Xu, Mittelhammer, and Barkley, 1993; Oltmans, Chicoine, and Scott, 1988; Craig, Palmquist, and Weiss, 1998). Huang et al. (2006) were the first to incorporate both spatial and temporal correlations into their estimation procedures within a hedonic framework. They estimate the determinants of farmland values in Illinois from 1979 to 1999 using a spatial lag model after first transforming their data to correct for temporal correlations assuming an AR(1) process.

Hedonic approaches within the cash rent literature have been less common. For example, Du et al. (2007) use the variable profit function approach in their study of cash rents in Iowa. Using annual, county-level survey data and employing a spatial error autoregressive model, they find that a 1$ increase in relative prices increases cash rents by approximately $79 in the short run. While, like us, they control for spatial correlation, they use county-level data to ask how cash rents are affected by the local ethanol and livestock industries, and the level of adoption of genetically modified crops within the county.

A growing number of cash rent studies have focused on the impact of government payments. Lence and Mishra (2003) use county-level data from Iowa to estimate the effect of a variety of government payment types on cash rent levels. Their results imply that marketing loan assistance and production flexibility contract payments increase cash rent levels by $0.70 to $0.90 per dollar of program payment. Goodwin, Mishra, and Magné (2005) find similar incidence rates for decoupled farm programs in the United States based on farm-level data from the USDA's annual Agricultural Resource Management Survey (ARMS) covering the period 1998 to 2001. Patton et al. (2008) also estimate high incidence rates outside of the United States using data on government payments for beef and sheep in Northern Ireland.

Using farm-level data from the 1992 and 1997 Census of Agriculture, Roberts, Kirwan, and Hopkins (2003) find much lower incidence rates, roughly half the size of those found by

Lence and Mishra (2003). A recent study by Kirwan (2009) reports even lower incidence rates – approximately 25% - in the United States using data from the 1992 and 2007 Census of Agriculture and the 2005 ARMS survey. While the methods employed by the authors and the data sets upon which their results are based differ, the wide range of incidence estimates suggest further work in this area is needed.

Our study is differentiated from these in a number of ways. We use a data set which covers a more recent time period (1996-2008) and provides a true panel of farms in Illinois. Our data also includes both farm and parcel characteristics which are not available from the data sources used by other authors (e.g., soil productivity).

Additionally, we have combined a hybrid of the methods previously applied in the land value and cash rent literatures. Rather than relying on realized sales or returns, the use of which has been noted to introduce estimation error (Roberts et al., 2003), we include futures prices to account for (expected) changes in profitability over time. We also include trend yields, a measure of soil productivity, and a measure of yield variability to account for farm-level heterogeneity in terms of both profitability and risk. Our estimation method, while similar to those used by Huang et al. (2006) and Du et al. (2007) in that they account for correlation across both spatial and temporal dimensions, is unique in that it simultaneously accounts for the spatial and temporal factors within the estimation process.

Methods

Within the context of cropland cash rents, the hedonic framework suggests that the equilibrium rent per acre is a function which maps individual attributes of the land into a single price. The relationship can be represented by the hedonic equation:

(1) $$\boldsymbol{R} = \boldsymbol{f}(\boldsymbol{z}),$$

where R is the rental price of the parcel per acre, and $z = (z_1, \ldots\ldots, z_n)$ is a vector of n unique characteristics of the land (Palmquist, 1989).

The hedonic approach has been extensively employed in the study of agricultural land values (Bastian et al 2002, Chicoine 1981, Shi et al 1997, Palmquist 1989, Palmquist and Danielson 1989, Huang et al. 2006). Parcel characteristics such as soil type, fertility levels, and location reflect the production potential of the land. Commodity prices assign a value to this production potential. Collectively, these factors contribute to its equilibrium rental price.

Characteristics of the tenant farmer represent a source of heterogeneity for cash rent levels. Observing measures of the tenant farmer's ability and risk preferences are typically not available to the econometrician and must be absorbed into the error component of the model, suggesting a random effects panel framework. Other unobserved characteristics such as varying degrees of information within land rental markets are also captured in the error term, and are likely spatially correlated. Assuming linearity, these factors imply that the hedonic model can be written as:

(2) $$\boldsymbol{R_{it}} = \boldsymbol{\alpha} + \boldsymbol{Z_{it}\beta} + \boldsymbol{V_{it}\gamma} + \boldsymbol{P_{it}\delta} + \boldsymbol{u_{it}},$$

where Z is a matrix of parcel characteristics such as soil quality, V is a matrix of regional characteristics such as yield variation, and P is a matrix of economic characteristics such as price and government payments, where these independent variables together are simplified as the matrix *X*: [*Z,V,P*]=*X*. The vectors of model parameters to be estimated are given by α, β, γ and δ. Finally, u represents the model error whose structure includes both temporal and spatial correlation.

The specification in (2) is assumed to follow a typical spatial error process where i is the cross-sectional index and t is the index for the time dimension (Baltagi, 2008). Focusing on the spatial effects, the observations can be thought of as stacked cross sections with u_t denoting an N x 1 vector of disturbance terms characterized by a first order spatial autoregressive process:

(3) $$\boldsymbol{u_t} = \boldsymbol{\rho W u_t} + \boldsymbol{\varepsilon_t},$$

where ρ is the scalar spatial autoregressive parameter, W is the N x N time invariant spatial weights matrix and $\boldsymbol{\varepsilon_t}$ is an N x 1 vector of innovations (Anselin, 2002).

Similar to a shift operator used in time series analysis (e.g. $t-1$), spatial econometrics constructs the so-called "spatial lag operator", a new variable consisting of the weighted averages of neighboring observations as specified through the weights matrix. Stacking the observations in the panel, the vector of spatially lagged error terms for the above equation is as follows:

(4) $\boldsymbol{Wu} = (\boldsymbol{I_T} \otimes \boldsymbol{W_N})\boldsymbol{u}$,

with I_T an identity matrix with dimension T. The disturbance process can be rewritten in stacked notation as:

(5) $\boldsymbol{u_N} = \boldsymbol{\rho}(\boldsymbol{I_T} \otimes \boldsymbol{W})\boldsymbol{u_N} + \boldsymbol{\varepsilon_N}$,

or,

(6) $\boldsymbol{u_N} = (\boldsymbol{I_T} \otimes \boldsymbol{B^{-1}})\boldsymbol{\varepsilon_N}$,

where $B = (I - \rho W)$ and is commonly recognized as the *spatial filter*. We assume the remainder error component ε may be temporally autocorrelated, but is not spatially correlated across units. The remainder error ε is specified as a one way error component model to allow for the innovations to be correlated over time:

(7) $\boldsymbol{\varepsilon_N} = (\boldsymbol{\iota_T} \otimes \boldsymbol{I_N})\boldsymbol{\mu_N} + \boldsymbol{v_N}$,

with μ_N the N *x* 1 vector of cross-sectional random components (i.e. the unobservable and time-invariant individual specific effect) and v_N the remainder disturbance varying over both the cross-sectional and temporal dimensions and ι_N is a vector of ones.

Following Kapoor et. al (2007), we assume the remaining error components, μ_{it} and v_{it}, are i.i.d. with mean zero, variance σ_μ^2 and σ_v^2, respectively, and have finite fourth moments. In estimating the spatial autoregressive parameter and variance components, a generalized method of moments estimator is used as suggested by Kelejian and Prucha (1999). The GMM estimators use all moment conditions and an optimal weighting scheme based on the inverse of the variance covariance matrix of the sample moments at the true parameter values under the assumption of normally distributed residual errors, ε. Kapoor et al. (2007) note that, while this matrix may not be strictly optimal in the absence of normality, it can be viewed as a reasonable approximation of the true variance covariance matrix.

The estimates of the spatial coefficient and variance components are then used to define a feasible generalized least squares estimator (FGLS) by further transforming the already spatially transformed model by pre-multiplying it by $I_{NT} - \theta_{Q_1}$, where I_{NT} is an identity matrix, $\theta = 1 - {}^{\sigma_v}/_{\sigma_\mu}$ and $Q_1 = e_T e'_T / T \otimes I_N$, the standard transformation matrix well known in the error component literature. The result is a doubly transformed model with estimators identical to that of OLS (Baylis, Garduño-Rivera, and Piras 2009). Thus, the coefficient estimator is given by:

$$(8) \qquad \hat{\beta} = \left\{X_N^*(\hat{\rho})'\left[\Omega_{\varepsilon,N}^{-1}\left(\hat{\sigma}_{v,N}^2, \hat{\sigma}_{\mu,N}^2\right)\right]' X_N^*(\hat{\rho})\right\}^{-1} X_N^*(\hat{\rho})'\left[\Omega_{\varepsilon,N}^{-1}(\hat{\sigma}_{v,N}^2, \hat{\sigma}_{\mu,N}^2)\right] R_N^*(\hat{\rho}),$$

where the parameter $\hat{\rho}$ is an estimate of the spatial correlation. The matrices X^* and R^* are spatially-filtered independent and dependent variables respectively, thus $X_N^*(\hat{\rho}) = [I_T \otimes (I_N - \hat{\rho} W_N) X_N]$ and $R_N^*(\hat{\rho}) = [I_T \otimes (I_N - \hat{\rho} W_N) R_N]$. The variance-covariance matrix of residual errors, ε, $\Omega_{\varepsilon,N}^{-1}$ is based on estimates of the variance of the spatial and temporal errors, $\hat{\sigma}_{v,N}^2, \hat{\sigma}_{\mu,N}^2$. For details, please see Kapoor et al (2007).

Data

This study employs farm-level data from the Illinois Farm Business Farm Management Association (FBFM), county-level yield data from the National Agricultural Statistics Service, and corn futures settlement prices from the Chicago Board of Trade (CBOT). The FBFM data span the years 1996 through 2008, and contains financial, management, and agronomic variables for more than 6,000 cooperating farmer members.

The full FBFM data set was cleaned of a number of reporting errors and outliers.[1] Cash rents and soil productivity ratings (SPR) reported as negative or zero were excluded. Farms which reported positive cash rent levels, but had zero cash rented acres or zero operator acres were also removed. One constraint of our estimation methodology is that a balanced panel is required, thus we consider only farms for which observations are available for the entire 13 year period of our data. The resulting balanced panel of farm level data includes 408 individual farmers. The county-level data consists of 78 of Illinois'102 counties per cross-section. Table 1 reports selected summary statistics for the county- and farm-level datasets used in the spatial error component analysis.

The dependent variable for each analysis is cash rent per acre. Expected corn prices and government payments received are included as measures of the land's potential to generate returns to the farmer. The parcel characteristics considered are expected corn yields, intra-county soil productivity differences, crop yield risk, and measures of urbanization pressure and farm size. All financial measures are adjusted to 2008 dollars using a farmer specific producer price index based on non-land costs.[2]

In defining our measure of expected corn prices, we assume farmers typically enter into rental agreements in the winter prior to the following crop year. The *PRICE* variable is defined as the average settlement for corn futures in November for harvest futures contract (December) for the following crop year. Government payments received by the farm are available in the FBFM database. These include all Farm Service Agency payments. For the Illinois farms in our dataset, program payments would come primarily from decoupled direct payments, the price-based counter-cyclical program, production flexibility contracts, marketing loans, conservation programs, and disaster assistance.[3]

Parcel characteristics measuring both yield potential and yield risk are also included. Expected trend yields for each farm serve as a measure of *inter*-county productivity across Illinois farms. The ExpYield variable is defined as the detrended county yield level based on a simple linear trend fit to NASS county yield data from 1972 through 2008. Intra-county differences in yield potential are captured using the soil productivity rating (SPR) information reported at the farm-level in the FBFM database. The variable *FtoCSPR* is defined as the ratio of the farm-level SPR rating to average SPR for farms in the same county. Yield risk is measured by the coefficient of variation(*CV*) of county-level yields based on a 15-year rolling average. The yield risk measure is updated every year within the panel to account for potential changes in yield risk over time.[4] Following Huang et al. (2006), the effect of urbanization pressures on cash rent levels is controlled using the USDA-ERS Beale Rural-Urban Continuum Code. Finally, a measure of farm size is included and defines as total acres (*Acres*) of the operation as reported in the FBFM database.

To capture spatial correlation, we use a block weights matrix based on the county for the individual farm-level data, and a queen-contiguity weights matrix for the county-level data analyses. Because we do not observe individual locations of farms within a county, we are constrained to only using a coarse measure of spatial correlation. However, given county-level tax policies and local information flow, we feel using a county-level block weight to identify neighbors does capture a key component of the spatial relationship.

Some data limitations should be noted. Although a portion of cash leases are renegotiated each year, the length of individual contracts is unknown. The actual timing of the lease signing is also unknown. We assume rents are renegotiated annually prior to the beginning of crop year, which is consistent with previous work in this area. Furthermore, we provide results from alternative specifications to investigate any bias that this assumption might introduce.

In addition, it is likely that some reported rental rates are ones in which the landowner rents directly to a family member, increasing the likelihood that the reported cash rent level does not reflect the true market value of the land's hedonic characteristics. Anecdotal evidence indicates that share rental or hybrid agreements might be more highly favored in family situations (Forster, 2003). Since our data excludes non-cash agreements, and we have made efforts to remove outliers, we are confident that this is not a major issue in the context of our analysis.

The representative nature of the farms included in the FBFM database might also cause concern. FBFM cooperators do not comprise a randomly-selected sample, nor are the farm observations weighted as is the case in the USDA ARMS database. To further investigate whether selection bias may be an issue in our data, we compared FBFM summary statistics for cash rent levels across the time period within our panel to average cash rents for the state of Illinois as reported by NASS. Figure 1 illustrates these averages on an annual basis from 1996 through 2008. The NASS and FBFM cash rent averages are very similar in magnitude and tend to trend together throughout the years of observation. This evidence suggests that the FBFM data is in fact representative of cash rents paid by farmers throughout the state of Illinois.

Results

Table 2 reports the estimation results from the balanced panels at the county- and farm-levels. The estimation results from a standard random effects panel estimator are also provided for comparison to those generated from the spatial error component estimator described in the Methods section. All reported specifications regress cash rent per acre against the attributes discussed in the Data section. The last two columns of table 2 report estimation results from the spatial error component estimator for two different time periods defined by the changes to government programs included in the 2002 Farm Bill.

The signs and significance of the coefficient estimates are all as expected, with the exception of *CV* and *Beale*. With the exception of the random effects estimates at the county level, the measure of urbanization was found to have a statistically insignificant effect on cash rents. The estimated effect of yield risk was not robust across estimators and the level of data aggregation.

The findings suggest there are significant spatial error correlations present at both levels of aggregation with $\rho = 0.43$ for the county-level data, and 0.278 for the complete farm-level dataset. Because our methods assume that the spatial nature remains unchanged over the time period, we estimated yearly Moran's I statistics, which calculate the correlation between cash rents and spatially-weighted cash rents. These statistics were very consistent over our 13-year time-period, ranging from 0.19 to 0.30 at the farm level, and 0.70 to 0.85 at the county. All yearly statistics showed spatial correlation at the 0.01 level of significance.

We find strong evidence that the expected output price has a positive effect on real cash rents. The county-level results vary significantly across estimators. At the farm-level, the estimated price effect for the SEC estimator is nearly double that obtained using the county-level data, and is robust across estimators and time periods. The level of intra-county variability in Illinois cash rents, as measured by the standard deviation of rent level reported within a county, ranged from approximately $30 to more than $60 per acre. For comparison, inter-county variability, or the standard deviation of county-level rents across the state of Illinois, averaged approximately $25 per acre within our panel. This suggests that the use of county-level data, and the resulting loss of information through aggregation, can results in significantly different results and conclusions with regard to the effect of changes in prices or returns on cash rent levels.

Cash rents are estimated to increase by approximately $37 per acre given a $1 per bushel increase in the expected corn price. However, even our farm-level estimates are much lower than the $79 dollars estimated by Du et al. The difference may arise from the fact that they estimate a production function, and consider the effect of a relative price increase while holding input prices constant. We also control for changes in input prices, but instead by deflating prices based on the bundle of inputs used. Thus, our estimates are deflated by increasing input prices.

Estimates from our farm-level SEC estimator indicate an incidence rate of 27% percent for government payments. The RE estimator generated a slightly higher, but similar incidence rate estimate. These results are similar to those recently estimated by Kirwan (2009) using farm-level survey data for the entire U.S. Similar to the case of the estimated effect of corn prices on cash rents, the county-level estimates of the relationship between government payments and cash rents were much smaller.

The 2002 Farm Bill introduced a number of changes to commodity programs, including the introduction of the direct payment program which provides a fixed level of support each year. Thus, we split our panel into two time periods. The first covers the years 1996 through 2001 while the second covers 2002 through 2008. Estimates of the effect of changes in price levels on cash rent levels do not differ significantly across the two time periods. However, our results indicate that the incidence of government payments on cash rent levels has increased significantly over time.

For the early time period, our incidence rate estimate is just 8 percent. Following introduction of the 2002 Farm Bill, we estimate an incidence rate of nearly 50% percent of government payments. We find this result intuitive, based on the shift towards programs which offer support on a more consistent basis. The more certain is the level of government support received, the greater the proportion of those payments that may be bid into cash rent levels.

Each additional bushel of expected yield is estimated to increase cash rents by $1.80 per acre. Relative farm-level soil productivity increases (decreases) cash rents by approximately $8 per acre for every 10% increment above (below) the county SPR mean. We also find statistical evidence of increasing returns to scale. However, the impact of farm size is very small in practical terms with cash rents increasing by less than $10 per acre if farm size increase by 1,000 acres. The estimated effects of production risk and urban pressures lack robustness and statistical significance.

The requirement of the use of a balance panel for our SEC estimator may raise selection bias concerns among readers. To address this issue, we also provide estimates across the entire (unbalanced) panel of FBFM farms in the first column of table 3 using a standard RE estimator.

The results are strikingly similar to those obtained from the balance panel using the SEC estimator.

The assumption that cash rents are negotiated annually is another potentially weak assumption. In practice, cash rent agreements may be negotiated for multiple crop years and thus the true impact of changes in price levels may not be reflected in cash rent values each year. As a further robustness check, we also provide results which were based on farms for which reported cash rent levels had changed from the previous year. These results are reported in columns 2 and 3 of table 3 and, with the exception of the corn price effect, are also strikingly similar to the other farm-level specifications.

When only farms with changing rent levels are analyzed, the effect of the changes in prices increases. This result is intuitive in that changing rent levels imply some level of renegotiation, which would be expected to involve the use of current market information and expectations. In contrast, rent levels that do not change may be the result of a multi-year rental agreement, and would thus not be impacted by year-to-year changes in expected price levels.

Finally, table 4 reports estimation results for a variety of fixed-effects spatial estimators using the balance panel of farms in the FBFM data. Previous work has noted the importance of unobserved farm characteristics which may be correlated with observed values, biasing the estimation results in these contexts (Kirwan, 2009). While the incorporation of time fixed effects results in a smaller estimate of the government payment incidence rate, the inclusion of farm fixed effects does not significantly change our results. Cash rents are still estimated to increase by $35 to $40 per acre given a $1 increase in the real corn futures price. The estimated incidence rate for government payments falls in the range of 20 to 30 percent.

Summary and Conclusions

This study employs a novel spatial panel econometric approach using farm-level data from Illinois to estimate the incidence of price shocks and government payments. We find that while rental rates do fluctuate with both price movements and changes in government subsidies, the tenant farmer is able to capture much of the revenue generated by changes in futures prices. Specifically, we find that for a 1$ increase in the corn futures price, at a 2008 average yield of 169.88 bushels, tenant farmers capture $131.30 of the extra revenue, while land owners only receive \$37.58. That said, we underestimate the land owners take when we consider only county-level average rents, implying that within county variation has a large effect on rental outcomes. That said, our results show a lower estimate compared to those from Du et al (2007) who use a variable profit approach.

Like other papers, we also consider the effect of government payments on cash rents, to estimate how they are shared among the various affected parties. Holding input costs constant. we find that on average, an extra dollar of government payments results in a \$0.27 per acre increase in land rents. This result is very similar to that found by Kirwan (2009), who found that land owners only captured 25% of government payments, with the rest going to producers. Interestingly, when we split our data to align it with the 1996 and 2002 farm bills, we find a substantial difference in the degree to which payments are capitalized into land costs. During the 1996 farm bill, we find that only \$0.08 on the dollar is going to landowners, whereas during the 2002 farm bill, that amount jumps to \$0.47. This increase might result from the fact that the 2002 farm bill made the fixed payments permanent, and therefore more predictable, and entrenched many of the ad hoc disaster payments into permanent programs such as the countercyclical payments.

To test whether we introduced bias by considering only farms that remained in our data over the entire 13-year period, we also estimate the same model using an unbalanced panel, and find very similar results on the pass-through rates of both price and government payments. Second, because we know many producers may not renegotiate their rental rates each year, we consider a subset of our data where rental rates change yearly. Perhaps unsurprisingly, here we see a higher pass-through rate of prices, where rental rates increase by \$45 for a one dollar increase in corn futures. Interestingly, more frequent adjustments to rental rates do not appear to greatly affect the pass-through rate of government subsidies, which remain around \$0.20 on the dollar.

In terms of other factors, we find rents differ as expected across relative soil productivity ratings, and we find evidence of returns to scale with larger farms paying higher cash rents. In contrast, the estimated effects of urbanization pressures and yield risk are inconsistent across our model specifications. We find very limited evidence to support Ricardian theory with a majority of increased revenues as a result of high commodity prices being captured by the tenant farmer.

Last, our findings suggest that the use of farm level data outperforms that of aggregated county level, and that these data are best considered using a model that accounts for spatial correlation. Explicitly taking into account spatial considerations within the empirical model gives additional confidence when applying statistical inference to the coefficients as the standard BLUE assumptions are fully met. Future research pertaining to cash rents and their land value counterparts can benefit from the spatial observations presented in this study and aid researchers in deciding whether explicitly accounting for spatial connectedness between neighbors is an appropriate assumption and avoiding erroneous inferences from ordinary least squares estimation.

Endnotes

[1]An observation was deemed an outlier if the observed rent was three times the interquartile range for each county-year. Discussions with FBFM staff indicated that rents in excess of $600 per acre, were most likely the result of data collection errors.

[2] Non-land costs include fertilizer, seed, pesticide and fuel & oil expenditures. We chose to construct a farm-specific producer price index rather than using an aggregate measure such as the PPI supplied by the Bureau of Labor Statistics. A 2008-base index was created for each farmer (county) given their individual per acre costs reported for each year. The index was used to deflate all variables given in dollar amounts (cash rent, futures prices, and government payments) to equivalent values for the 2008 crop year.

[3] Fixed direct payments and the counter-cyclical program were introduced in 2002. Production flexibility contract payments have been largely irrelevant in Illinois since 2002, and were completely phased out beginning in 2006.

[4] The construction of the *CV* variable takes into consideration that the perceived yield risk of a farmer will change over time with the accumulation of additional information. As more history is observed, the farmer is assumed to update their information set.

Tables and Figures

Table 1. Variable Means (Standard Deviations) for the County- and Farm-Level Panels

Variable	County-Level	Farm-Level
Cash Rent	171.71 (52.02)	190.61 (77.00)
Price	3.99 (0.71)	4.11 (1.31)
ExpYield	156 (18)	164 (12)
CV	0.15 (0.03)	0.15 (0.03)
Beale	4.80 (2.35)	4.80 (2.35)
SPR	-	
Acres	-	885.16 (566.83)
GovPay	41.20 (41.55)	38.85 (44.98)

Note: County- and farm- level summary statistics differ due to use of acreage-weighting in the aggregation process.

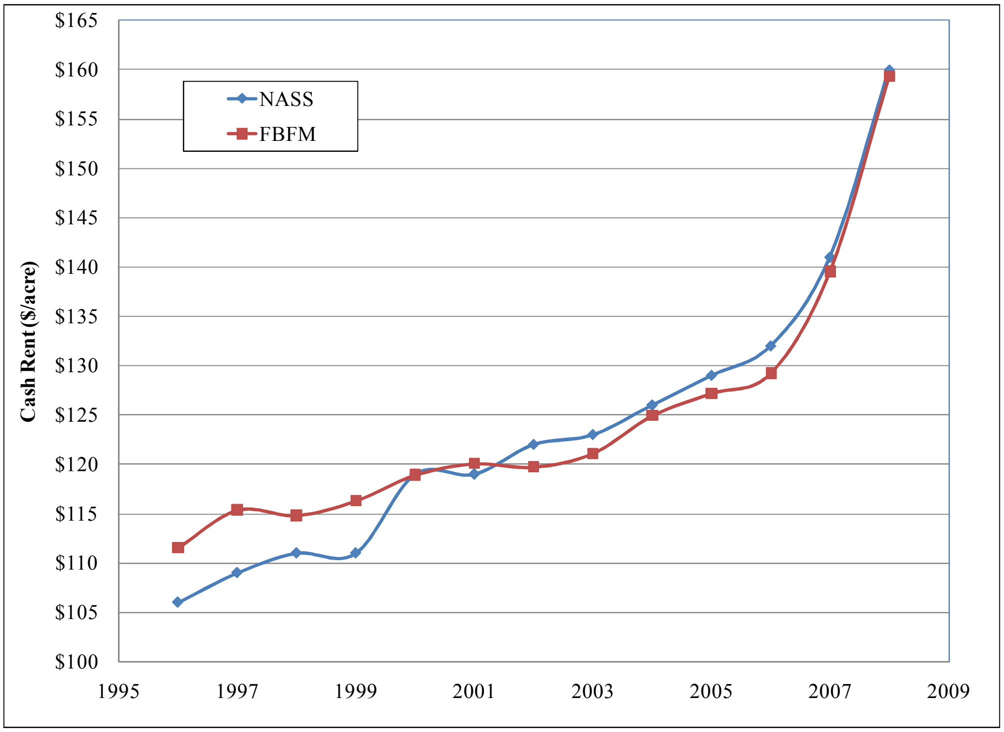

Figure 1. Average Cash Rents in Illinois, 1996 - 2008

Table 2. Random Effects (RE) and Spatial Error Component (SEC) Results

	County-Level		Farm-level			
	RE	SEC	RE	SEC	SEC 1996-2001	SEC 2002-2008
Intercept	-303.41*** (-12.68)	-270.01*** (-7.98)	-372.19*** (-12.07)	-358.51*** (-9.64)	-296.97*** (-6.47)	-627.83*** (-13.71)
Price	11.90*** (9.48)	20.93*** (12.99)	37.32*** (128.55)	37.58*** (120.07)	36.76*** (39.15)	34.28*** (88.06)
ExpYield	2.41*** (19.78)	2.11*** (12.03)	1.84*** (13.54)	1.80*** (9.95)	1.69*** (8.04)	2.71*** (13.62)
CV	242.01*** (4.31)	109.70 (1.49)	29.17*** (0.77)	-2.27 (-0.05)	-516.75*** (-6.57)	1013.4*** (10.96)
Beale	1.75* (2.09)	1.18 (1.39)	0.43 (0.50)	0.25 (0.22)	-0.70 (-0.53)	1.36 (1.20)
SPR			81.21*** (4.83)	80.64*** (4.95)	125.98*** (5.94)	62.37*** (3.41)
Acres			0.008*** (3.88)	0.009*** (4.27)	0.015*** (4.26)	.001*** (4.49)
GovPay	0.17*** (9.21)	0.12*** (4.82)	0.34*** (28.27)	0.27*** (19.88)	0.08*** (3.76)	0.47*** (25.62)
ρ		0.432		0.278	0.251	0.257
σ_v^2	537.73	451.72	1685.38	1578.7	1502.10	1219.29
σ_1^2	238.08	3493.30	920.39	13174	8709.84	7462.69
θ	0.615	0.640	0.647	0.654	0.58	0.60
$\hat{\sigma}^2/\sigma^2$		0.3224		0.647	0.636	0.886
$corr(y,\hat{y})^2$	0.433†	0.6812	0.890†	0.851	0.204	0.915
N	1014	1014	5291	5291	2442	2849

Asterisks (*, **, ***) indicate that the statistic is significantly different from zero at the 10%, 5%, and 1% hypothesis level. T-statistics are given in parenthesis.
†R-Squared

Table 3. Farm Level Robustness Checks for Selection Bias

	All Farms (Unbalanced)	ΔRent $\neq 0$ All Farms†	ΔRent $\neq 0$ No Time Gaps††
Intercept	-401.11*** (-27.08)	-444.51*** (-21.70)	-462.63*** (-17.94)
PRICE	35.26*** (116.42)	45.13*** (142.99)	45.22*** (120.74)
ExpYield	1.92*** (33.99)	2.00*** (25.94)	2.06*** (21.65)
CV	10.48 (0.36)	-153.65*** (-3.71)	-160.26*** (-3.02)
Beale	0.71* (2.02)	0.72 (1.48)	1.61*** (2.96)
SPR	110.46*** (12.88)	132.87*** (11.12)	140.62*** (9.20)
Acres	0.012*** (10.19)	0.012*** (7.65)	0.008*** (4.73)
GovPay	0.29*** (22.70)	0.19*** (9.72)	0.24*** (10.56)
R-Squared	.423	.487	0.477
N	29,879	24,623	18,300

Asterisks (*, **, ***) indicate that the statistic is significantly different from zero at the 10%, 5%, and 1% hypothesis level. T-statistics are given in parenthesis.
†Includes all farms which were present in the FBFM data for at least two-consecutive years.
††Includes all farms for which a multi-year time gap did not exist.

Table 4. Results for Farm and Time Fixed Effects Specifications

	Farm FE Spatial Lag	Time FE Spatial Lag	Time and Farm FE Spatial Lag	Farm FE Spatial Error
Price	35.93*** (122.61)	42.33*** (113.93)	41.09*** (128.14)	37.47*** (120.23)
ExpYield		1.78*** (30.14)		
CV	-37.94 (-0.91)	60.29** (2.00)	1.34 (0.02)	-65.67 (-1.06)
Beale		0.16 (0.45)		
SPR	18.61 (0.63)	110.00*** (14.08)	20.31 (0.77)	14.55 (0.52)
Acres	0.003 (1.07)	0.014*** (12.21)	0.003 (1.17)	0.003 (1.16)
GovPay	0.32*** (28.01)	0.04** (2.69)	0.10*** (6.93)	0.24*** (17.77)
ρ	.076***	.075***	0.06***	0.39***
$\hat{\sigma}^2/\sigma^2$	0.74	.84	.79	0.75
$corr(y, \hat{y})^2$	0.91	0.93	0.91	0.91
N	5291	5291	5291	5291

Asterisks (*, **, ***) indicate that the statistic is significantly different from zero at the 10%, 5%, and 1% hypothesis level. T-statistics are given in parenthesis.

References

Awokuse, T., and J.M. Duke. 2006. "The Causal Structure of Land Price Determinants." *Canadian Journal of Agricultural Economics*. 54(2): 227-245.

Baltagi, B.H. 2008. Econometric Analysis of Panel Data, 4th edition. New York: Wiley.

Du, X., D.A. Hennessy, and W.M. Edwards. 2007. "Determinants of Iowa Cropland Cash Rental Rates: Testing Ricardian Rent Theory." *Working Paper 07-WP 454*.

Forster, L., C.A. Pohlman, M.T. Batte, and B.L. Sohngen. 2003. "Ohio Farm Real Estate Markets." *Technical Report*. Department of Agricultural, Environmental, and Development Economics, Ohio State University.

Goodwin, B. K., and F. Ortalo-Magné. 1992. "The Capitalization of Wheat Subsidies into Agricultural Land Values." *Canadian J. Agricultural Econonics.* 40 (March):37–54.

Goodwin, B., A.K. Mishra, F. Ortalo-Magné. 2005. "Landowners' Riches: The Distribution of Agricultural Subsidies." *Working Paper*. School of Business, University of Wisconsin.

____. 2003. "What's Wrong with our Models of Agricultural Land Values?" American Journal of Agricultural Economics 85(3): 744-752.

Huang, H., G. Miller, B. Sherrick, and M. Gomez. 2006. "Factors Influencing Illinois Farmland Values." *American Journal of Agricultural Economics*. 88(2): 458-470.

Kapoor, M., Kelejian, H.H., & Prucha, I.R. 2007. "Panel data model with spatial correlated error components." *Journal of Econometrics*. 140(1): 97-130.

Kelejian, H.H., & Prucha, I.R. 1999. "A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model." *International Economic Review*. 40(2): 509-533.

Kirwan, B. 2009. "The Incidence of U.S. Agricultural Subsidies on Farmland Rental Rates." *Journal of Political Economy*. 117(1): 138-164.

Kurkalova, L., C. Burkart, and S. Secchi. 2004. "Cropland Cash Rental Rates in the Upper Mississippi River Basin." *Technical Report*. Center for Agricultural and Rural Development, Iowa State University.

Lence, S.H. and A.K. Mishra. 2003. "The Impacts of Different Farm Programs on Cash Rents." *American Journal of Agricultural Economics* 85(3): 753-761.

Livanis, G., C.B. Moss, V.E. Breneman, R.F. Nehring. 2006. "Urban Sprawl and Farmland Prices." *American Journal of Agricultural Economics*. 88(4): 915-929.

Mendelsohn, R., A. Dinar. 2003. "Climate, Water, and Agriculture." *Land Economics*. 79(3): 328-341.

Nickerson, C., L. Lynch. 2001. “The Effect of Farmland Preservation Programs on Farmland Prices.” *American Journal of Agricultural Economics*. 83(2): 341-351.

Patton, M., P. Kostov, S. McErlean, J. Moss. 2008. “Assessing the Influence of Direct Payments on the Rental Value of Agricultural Land.” *Food Policy*. 33(5): 397-405.

Phipps, T. 1984. “Land Prices and Farm-Based Returns.” *American Journal of Agricultural Economics*. 66(4): 422-429.

Plantinga, A., R. Lubowski, R. Stavins. 2002. “The Effects of Potential Land Development on Agricultural Land Prices.” *Journal of Urban Economics*. 52(3): 561-581.

Roberts, M., B. Kirwan, and J. Hopkins. 2003. “The Incidence of Government Program Payments on Agricultural Land Rents: The Challenges of Identification.” *American Journal Agricultural Economics*. 85 (August): 762–69.

Shaik, S. 2007. “Farm Programs and Land Values in Mountain States: Alternative Panel Estimators.” *Paper prepared for presentation at the 2007 Western Agricultural Economics Association Annual Meeting, Portland, Oregon, July 29- Aug. 1, 2007*.

Shaik, S., G.A. Helmers, J.A. Atwood. 2006. “Farm Programs and Agricultural Land Values: The Case of Southern Agriculture.” *Paper prepared for presentation at the 2006 Southern Agricultural Economics Association Annual Meeting, Feb. 5-8, 2006*.

Taylor, M.R., G.W. Brester. 2005. “Noncash Income Transfers and Agricultural Land Values.” *Review of Agricultural Economics*. 27(4): 526-541.

USDA, National Agricultural Statistics Service. 2008*a*. *Land Values and Cash Rents 2008 Summary*. National Agricultural Statistics Service, USDA, Washington, D.C.