ANALYSIS OF GOVERNMENT FARM SUBSIDIES ON FARMLAND CASH RENTAL RATES USING A FIXED EFFECT SPATIAL DISTRIBUTED LAG MODEL AND A TRANSLOG COST MODEL

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ABSTRACT

The objective of this study is to examine how factors such as government payments, soil productivity ratings, commodity selling price, corn and soybean production, and spatial attributes affect cash rental rates. Baseline estimates of the effects of government payments on cash rents are determined using a fixed effect, distributed lag model. The results of this model are compared to a distributed lag model that incorporates spatial effects. A second model estimates the impact of government subsides on farm cost structure. This is accomplished estimating a fixed effect, translog cost function that also incorporates spatial effects. The data used in the analysis is the Illinois Farm Business Farm Management (FBFM) Economic Management Analysis (EMA), containing more than five thousand Illinois FBFM clients annually from 1996 to 2001.

Keywords: Government payments, fixed effects model, translog cost function, spatial regression

Introduction

The new farm bill was launched into action in spring, 2002. The new legislation calls for funds exceeding $67 billion over the 1996 Federal Agricultural Improvement and Reform (FAIR) Act base (Goodwin, Mishra, and Ortalo-Magné). With this level of government backing, two questions asked in this study are: (1) do government subsidies capitalize into cash rental rates or farmland value?; and (2) do these support measures affect farm-level demand for inputs vis-à-vis lower total production costs and higher product revenue?

There is a well-developed literature with respect to analysis of the factors affecting farmland values in general, and cash rents in particular. Alston used cash rents to proxy income from land. Likewise, Lence and Mishra considered cash rents representative of the observed price of land as an input in production. Cash rents are a function of several factors such as land productivity, government support programs, inflation and interest rates, individual skill and success, and expected commodity market prices. For the most part, farmland price models incorporate Melichar's idea that land prices are linked to real growth in payments to land, and to Feldstein's hypothesis that growth in land prices arises from increases in the inflation rate. Turvey summarizes the attributes of these classical approaches towards modeling farmland pricing. In general, economic rents are estimated by measuring then capitalizing the area below marginal revenue and above marginal cost. Marginal revenue is random without income stabilization or deficiency payments, and land values are capitalized relative to expected marginal revenue. However, with access to government payments, marginal revenue (and therefore economic rents) should increase.

Weersink et al.'s analysis of farmland prices in Canada was one of the first studies to decompose farmland prices into returns from market income and payments from government programs. Goodwin, Mishra, and Ortalo-Magné separated government payments and farm output from net income, allowing different capitalization rates for these income sources. They found that Loan Deficiency Payments (LDP) and Agricultural Market Transition Act (AMTA) payments increased farmland value by \$6.55 and \$4.39/acre, respectively. But not surprisingly, conservation reserve program (CRP) payments decreased land value by \$15.15/acre. Roberts, Kirwin, and Hopkins found that government assistance under FAIR could increase land values between \$6.80 and \$8.20/acre at a 5% discount rate. Lence and Mishra examined the impact of market loan assistance, production flexibility contracts (PFC), CRP, and LDP payments on cash rents in Iowa from 1997 to 2001. They assumed that cash rents were not impacted whether owners or renters received government payments. Their model also assumed that total economic rents accrued only to the owners: that it is the present value of cash rents that determines farmland price (Turvey). Depending on the discount rate used, Lence and Mishra found that the aggregate impact of government assistance significantly increased cash rental rates between \$2.62/acre and \$1.31/acre (for discount rates of 5% and 10%, respectively). For PFCs, and assuming a 5% discount rate, farmland values should increase between \$14.20 and \$26.80/acre.

In lieu of these studies, the effects of government support on farmland prices in Illinois between 1996 and 2001 are estimated. The FAIR Act of 1996 was the farm bill legislation effective from 1996 to 2002. This legislation created AMTA payments and implemented LDPs. Program participants received nearly \$7.5 billion in government subsidies from 1996 to 2002 in Illinois as a result of the FAIR Act. Midwestern farmers have tended to use these payments in bidding or negotiating new cash rent leases (Barry, Escalante, and Moss). For producers in some counties, cash rents may substantially contribute to farm revenue. Farmers producing only corn and soybeans in Central and Northern Illinois owned 14 and 21% of land farmed, respectively. In 2000, these producers cash rented 43% of their farmland in Northern Illinois and 21% in Central Illinois. AMTA payments are derived from a farm's historical yields, the number of acres enrolled in the government program, and a rate set by the FAIR Act. These payments are fixed income transfers based on historical production. As such, they are considered 'decoupled' from production. AMTA payments were also scheduled to end in 2002. LDP's are basic price supports that pay on the difference between posted county crop prices and loan rates.

Payment Effects on Input Cost Structure: An Extension to the Cash Rent Analysis

As an extension to the cash rent section of this study, the effects of these instruments are also investigated with respect to farm-level input factor demand and product revenue. A translog cost function was estimated, including input share equations for fertilizer, pesticide, labor, land rent, and product revenue equations for corn and soybean. Next, LDP and AMTA payments are included in the cost function and its derivatives, and the model was re-estimated. Differences between the baseline factor demand and input-output price elasticities are compared. This approach is different from the 'present value' approaches looking at effects of government support on farmland value in that the farm cost structure is the primary focus, and any interpretation regarding effects of these support measures on land values are inferred by way of changes in demand elasticities for land. If results from this model are to be extended to farmland policy price analysis, then the working assumption behind this approach is that if government support measures increase the demand for land, then farmland prices should increase.

The Issue of Spatial Dependence

Because of the spatial nature of farmland price data, a reasonable conjecture is that location matters with respect to farmland price determination, local variations in posted county prices, and levels of government payments received. Realization of cash rents or grain output for one farm may be a function of cash rents or output realized by neighboring farms. Moreover, farmland prices are also likely a function of 'suburban sprawl' dynamics (Hardie, Narayan, and Gardner). The same kind of spatial effects possibly exist with respect to grain production and related input demand, particularly when topography or other geographic characteristics are taken into consideration. If there is data for these spatially dependent variables, it should be included in the model. There are many reasons why neighboring farms or counties may be similar in the Midwest in general and Illinois in particular. There is also the likelihood that errors amongst nearby observations are negatively or positively correlated in models that use georeferenced data. If this is indeed the case, then any regression results based on these relations may be improved in terms of precision and efficiency of estimates when spatial dependence or autocorrelation is appropriately modeled.

Spatial dependence is an econometric issue that has recently received attention in the real estate literature (Pace and Barry), urban geography (Elhorst), economic growth studies (Silveira-Neto, Raul, and Azzoni), analysis of precision agriculture technologies (Hurley, Malzer, and Kilian; Lambert, Malzer, and Lowenberg-DeBoer), technical change and adoption in agriculture (Druska and Horrace; Holloway, Shankur, and Rahman), crop insurance (Wang and Zhang), and deforestation (Swinton; Munroe). Some farmland price literature in agricultural economics has also used spatial econometric approaches (for example, Benirschka and Binkley; Hardie, Narayan, and Gardner; Lence and Mishra). These studies recognized that determinants such as local or regional 'spill-over' effects linked to geography, transportation infrastructure, plant pathogen epidemiology, or other spatially dependent processes may be important factors determining farmland prices or grain output at the farm level. If, for example, data for these variables are not directly observable, they may be modeled through spatial autoregressive (SAR) parameters using matrices that identify proximity and relative importance of spatial relations between observations.

The Objectives of This Study

The objectives of this study are twofold. The first objective is to examine how AMTA and LDP payments affect cash rental rates. The second objective is to determine the effect of these government support instruments on farm-level cost structure and concomitantly, input demand given input and output price changes. The data used to examine the effects of these government programs on cash rental rates and output is a panel data set comprising 470 farms representing 74 counties in Illinois between 1996 and 2001. This data is from a portion of the Illinois Farm Business Farm Management (FBFM) Economic Management Analysis (EMA), containing more than five thousand

Illinois FBFM clients annually from 1996 to 2001. Because some survey participants did not participate in the survey every year, only 74 counties are used in the analysis. Because of the spatial nature of the Illinois FBFM data set used in this analysis, diagnostics for spatial autocorrelation was used to detect spatial structure in errors or between observations. When spatial structure is present between observations or model residuals, a spatial econometric approach can be used to exploit this information.

Empirical Methods

Three econometric models are developed to test whether AMTA and LDP payments (i) significantly increased cash rents on a per acre basis in Illinois between 1996 and 2001; and (ii) significantly affected input factor demand and input-output price elasticities over the same time period. To test (i), two models are considered: (a) Lence and Mishra's deconstruction of a profit-maximization model developed to specifically evaluate the impacts of government payments on farmland values; and (b) following Hausman, Hall, and Griliches, a fixed-effect (FE), distributed lag model. The FE model allows for farm-specific effects in the regression analysis such as the producers' skill, or other unobserved sources of heterogeneity. To test objective (ii), an indirect translog cost function (Capalbo) was estimated with and without LDP and AMTA payments. A FE model was also specified to capture unobserved production heterogeneity between farms in the translog cost model.

Spatial Lag and Spatial Error FE Models

In spatial econometrics, an n x n spatial weights matrix ($\boldsymbol{W}$) is often used to define neighborhoods of observations. By including $\boldsymbol{W}$ into the regression model, relations between the dependent variable y_{it}(or residual u_{it}) with neighboring y_{jt}'s(u_{jt}'s) are defined for spatial lag(error) processes. Consider the standard FE model (Wooldridge), $\boldsymbol{y}_t = \boldsymbol{x}_t\boldsymbol{\beta} + \boldsymbol{c} + \boldsymbol{u}_t$, where $\boldsymbol{y}'_t = [\boldsymbol{y}_{it},...,\boldsymbol{y}_{nt}]'$, $\boldsymbol{x}'_t = [\boldsymbol{x}_{it},...,\boldsymbol{x}_{nt}]'$, $\boldsymbol{c}' = [c_1,...,c_n]'$, $\boldsymbol{u}_t$ is a disturbance term, and $n = 1,\ldots,470$ farms and $t = 1996,\ldots,2001$.

For spatial lag processes, the FE regression model becomes $\boldsymbol{y}_t = [\boldsymbol{R_T} \otimes \boldsymbol{W}]\boldsymbol{y}_t + \boldsymbol{x}_t\boldsymbol{\beta} + \boldsymbol{c} + \boldsymbol{u_t}$; where $\boldsymbol{R_T}$ is a T x T block diagonal matrix with zeros on the off-diagonals, and SAR lag terms ρ_t for each period in the panel series for explaining dependence of y_{it} on neighboring y_{jt}'s. The disturbance term $\boldsymbol{u_t}$ is an independent and identically distributed (iid), non-heteroskedastic, uncorrelated disturbance term ~$N(0, \sigma^2)$.

The FE spatial error model is specified as $\boldsymbol{y}_t = \boldsymbol{x}_t\boldsymbol{\beta} + \boldsymbol{c} + \boldsymbol{\varepsilon}_t$ with $\boldsymbol{\varepsilon_t} = [\boldsymbol{\Lambda_T} \otimes \boldsymbol{W}]_{\boldsymbol{n}}\boldsymbol{\varepsilon}_t + \boldsymbol{u_t}$. The error term $\boldsymbol{\varepsilon_t}$ defines a spatial error autoregressive process for each period in the panel series. $\boldsymbol{\Lambda_T}$ is a T x T block diagonal matrix with zeros on the off-diagonals and λ_t SAR parameters on the diagonal.

Note that when $\boldsymbol{\Lambda_T} = \mathbf{0}$ or $\boldsymbol{R_T} = \mathbf{0}$ ordinary least squares (OLS) is the best linear unbiased estimator of the FE model. Depending on the assumptions made by the researcher, λ or ρ may be constrained to be the same across all periods (for example, Lence and Mishra; Elhorst) or separate SAR terms can be estimated for each time period (Druska and Horrace; Lambert, Malzer, and Lowenberg-DeBoer; Anselin).

Detecting Spatial Lag or Error in an FE Model

Moran's I is sometimes used to test for spatial dependence. However, rejection of the null hypothesis of "no spatial dependence" does not provide indication of the type of spatial dependence present in the residuals. Instead, Lagrange Multiplier (LM) tests can be used to identify spatial error *or* spatial lag processes. The single-equation LM(error) test (Anselin) is:

$$LM_t = \frac{\left[\boldsymbol{u}_t'\boldsymbol{W}_n\boldsymbol{u}_t/\sigma^2\right]^2}{tr\left[\left(\boldsymbol{W}_n'+\boldsymbol{W}_n\right)\boldsymbol{W}_n\right]} \tag{1}$$

where $\sigma^2 = n^{-1}\boldsymbol{u}_t'\boldsymbol{u}_t$, tr is the trace operator, and LM_t is the LM test for spatial error in each period t. By extension, a joint LM(error) test for the FE model may be written as:

$$LM_{(error)}^{Joint} = \frac{\left[\boldsymbol{u}'\left(\boldsymbol{I}_T \otimes \boldsymbol{W}_n\right)\boldsymbol{u}/\sigma^2\right]^2}{T\left(tr\left[\left(\boldsymbol{W}_n'+\boldsymbol{W}_n\right)\boldsymbol{W}_n\right]\right)} \tag{2}$$

where T is the number of periods in the panel series, and $\sigma^2 = \boldsymbol{u}'\boldsymbol{u}/Tn$.

For FE models, the LM(lag) test (Anselin) is re-written as:

$$LM_{(lag)}^{Joint} = \frac{\left[\boldsymbol{u}'\left(\boldsymbol{I}_T \otimes \boldsymbol{W}_n\right)\boldsymbol{y}/\sigma^2\right]^2}{\left[\hat{\boldsymbol{y}}'\boldsymbol{W}_n'\boldsymbol{M}\boldsymbol{W}_n\hat{\boldsymbol{y}}/\sigma^2 + T\left(tr\left[\boldsymbol{W}_n'\boldsymbol{W}_n + \boldsymbol{W}_n^2\right]\right)\right]} \tag{3}$$

where $\boldsymbol{M} = \boldsymbol{I} - \boldsymbol{X}\left(\boldsymbol{X}'\boldsymbol{X}\right)^{-1}\boldsymbol{X}'$. Both statistics are $\sim \chi^2_{(T)}$ variates.

Baltalgi, Song, and Koh recently suggested a Standardized LM(error) test (SLM) developed specifically for random error component (ECM) models. Their statistic is, by extension, modified to account for the unobserved effects included in the FE model. The SLM statistic is $E[SLM] = \frac{d - E[d]}{\sqrt{VAR[d]}}$, where $d = \frac{\boldsymbol{u}'\left(\boldsymbol{I}_T \otimes \boldsymbol{W}_n\right)\boldsymbol{u}}{\boldsymbol{u}'\boldsymbol{u}}$, $E[d] = \frac{tr[\boldsymbol{MW}]}{S}$, $S = NT - N - k$ (modified for the inclusion of fixed effects; T is the number of periods, N is the number of fixed effects, or farms in the survey, and k is the number of explanatory variables), and:

$$VAR[d] = 2\left(S \times tr[(\boldsymbol{I}_T \otimes \boldsymbol{W}_n)\boldsymbol{M}]^2 - [tr((\boldsymbol{I}_T \otimes \boldsymbol{W}_n)\boldsymbol{M})]^2\right) / \left(S^2(S+2)\right) \tag{4}$$

The SLM test statistic is ~$N(0,1)$. There is presently no spatial lag SLM analogue.

The alternative of the LM(error) and SLM tests is that residuals follow a spatial pattern, while the alternative for the LM(lag) test is that individual observations on explanatory and/or the dependant variables are correlated with the average of other values of the same variables in a given neighborhood of observations. Rejection of the null for the LM(lag) test means that the researcher is faced with an omitted variable problem; FE model estimates are biased and inconsistent. If the null of the LM(error) test is rejected, the researcher faces an efficiency problem; FE model estimates are not biased, but they are inefficient.

Lence and Mishra's Model Testing H_o: Government Payments do not affect Cash Rental Rates

Lence and Mishra recently proposed a model to describe how government payments affected cash rental rates in Iowa between 1996 and 2001. Their model is important becasue it links government payments to economic theory by way of the producer's optimization problem as a function of payment instruments. To determine the effects of government payments on cash rental rates, the t-period regression equations including spatial effects they propose is (in terms of the variables in this study):

$$\begin{aligned} r_{i,t} &= \beta_{0,t+1}(1-\lambda) + \beta_1 z_{corn,i,t+1} + \beta_2 z_{soybean,i,t+1} + \beta_{AMTA} z_{AMTA,i,t+1} + \beta_{LDP} z_{LDP,i,t+1} + \\ &\lambda r_{(-i),t} - \beta_1 \lambda z_{corn,(-i),t+1} - \beta_2 \lambda z_{soybean,(-i),t+1} - \beta_{AMTA} \lambda z_{AMTA,(-i),t+1} - \beta_{LDP} \lambda z_{LDP,(-i),t+1} + u_{i,t+1} \end{aligned} \tag{4}$$

where $r_{(-i),t} \equiv \sum_{i \neq j} w_{ij} r_{j,t}$, $z_{k(-i)t+1} \equiv \sum_{i \neq j} w_{ij} z_{k,i,t+1}$, w_{ij} is an element in a spatial weights matrix, $\boldsymbol{W}$; t = 1996,…,2001 and i = 1,…,470 farms; λ is a SAR parameter; z_{corn} and $z_{soybean}$ are revenues from corn and soybean (calculated using real prices); and $u_{i,t+1}$ is an independent and identically distributed (iid) disturbance term for farm i in period t, with $E[u_{i,t+1}] = 0$. The β_k's are restricted to be the same for all t equations. Each of the t equations identifies a period in the panel. Insignificant t-values for β_{AMTA} and β_{LDP} would suggest that government payments have no effect on cash rental rate. The system of t equations is estimated using iterated general method of moments (ITGMM). Details on estimation details are found in Lence and Mishra.

Lence and Mishra restricted the SAR parameter to be identical across all periods. Elhorst proposed similar restrictions for panel data sets. Hardie, Narayan, and Gardner also assumed identical SAR terms across their analysis of land prices in the Mid-Atlantic States. An alternative interpretation of spatial process in panel data sets allows each period in the panel series to have its own SAR term (for example, Anselin; Lambert, Lowenberg-DeBoer, and Malzer; Druska and Horrace). This makes sense because, although spatial proximity between farms and counties are generally invariant, the outcome of varying temporal effects over a fixed spatial array may be considerably different. Following Lence and Mishra, no diagnostics are used to evaluate residuals across the t equations: their model assumes *a priori* spatial error autocorrelation exists, and this is assumed to be the case when applying their model here. A likelihood ratio (LR) test is used to determine whether inclusion of period-specific SAR parameters is warranted.

Lence and Mishra also use a different specification of proximity than the one used in this study. They used an inverse distance matrix with the typical w_{ij} elements $d_{ij}^{-\delta} \big/ \sum_j d_{ij}^{-\delta}, i \neq j$, where the parameter ($\delta$) weights the distance between observations (d_{ij}) is simultaneously estimated with the model parameters. In this study, a row-standardized, exogenous contiguity matrix is used because records of Cartesian coordinates were not available for individual farms.

Distributed Lag Model Testing H_o: Government Payments do not Affect Cash Rental Rates

The FE distributed lag model used to estimate the effects of AMTA and LDP payments on cash rental rates between 1996 and 2001 is a linear version of Hausman, Hall, and Griliche's non-linear FE distributed lag model (Wooldridge):

$$r_{i,t} = \theta_t + \beta_{AMTA} AMTA_{i,t-1} + \beta_{LDP} LDP_{i,t-1} + \beta_{corn\ revenue} (P_{corn} {*} CORNYIELD)_{i,t}$$
$$+ \beta_{bean\ revenue} (P_{soybeans} {*} BEANYIELD)_{i,t} + \beta_{SPR} SPR_{i,t} + \beta_{ACRES\ OWNED} ACRESOWNED_{i,t} +$$
$$+ \beta_{CASH\ RENTED\ ACRES}\, CASHRENTACRES_{i,t} + \beta_{SHARE\ ACRES}\, SHAREACRES_{i,t} + c_i + u_{it} \qquad (5)$$

where r is the cash rent acre^{-1} for farm i = 1,…,470 in period t = 1997,…,2001; *LDP* (\$/acre) and *AMTA* (\$/farm) are the government payments received by farm i in the previous period; *CORNYIELD* and *BEANYIELD* are the corn and bean yields (bu/acre) produced by farm i in period t; P_{corn} and $P_{soybean}$ are the real corn and soybean prices received by farm i in period t; *ACRESOWNED*, *CASHRENTACRES*, and *SHAREACRES* are the farmed acres that are owned, cash rented, or share-rented by farm i in period t, respectively. Finally, c_i are unobserved, heterogeneous farm-specific effects (for example, the producer's farming skill); θ_t is a time-varying intercept; and u_{it} is defined above. Insignificant *t*-values for β_{AMTA} and β_{LDP} would suggest that these government instruments do not have an effect on cash rental rates.

Indirect Translog Cost Function Testing H_o: Government Payments do not Influence Farm-level Factor Demand Elasticities

An indirect translog cost function is specified to estimate the effects of government support on factor demand elasticities and input-output price elasticities:

$$\ln C = \alpha_0 + \sum_i \psi_i \ln q_i + \frac{1}{2}\sum_i \sum_j \varphi_{ij} \ln q_i \ln q_j + \sum_k \beta_k \ln w_k + \frac{1}{2}\sum_k \sum_l \gamma_{kl} \ln w_k \ln w_l$$
$$+ \sum_i \sum_k \eta_{ik} \ln q_i \ln w_k + \sum_t^{T-1} \tau_t d_t + \sum_i \sum_t^{T-1} \zeta_{ti} d_t \ln q_i \qquad (6)$$
$$+ \sum_k \sum_t^{T-1} \vartheta_{tk} d_t \ln w_k + \sum_f^{F-1} c_f^C + \varepsilon$$

where C are total costs for farm i; q_i is total corn and soybean yield for farm i (bu); w_k are input costs/acre for pesticides, fertilizer, labor, and land; d_t are time dummy variables (t = 1997,…,2001), and c_f are unobserved, individual farm-specific effects, and ε is a disturbance term which may or may not be spatially dependent on other error terms. Equation 6 is an approximation of the conventional indirect cost function since input levels are not directly observed. For integrability, the interactions between the linear cost and quantity terms are multiplied by the fixed effects. The following behavioral, cost-minimizing restrictions are imposed: homogeneity restrictions; $\sum_l \gamma_{kl} = 0, \sum_j \varphi_{ij} = 0$ and an additivity restriction; $\sum_k \beta_k = 1$. The homogeneity restrictions imply symmetry in the $\boldsymbol{\gamma}$ and $\boldsymbol{\varphi}$ matrices. The input share equations (s_k) and product revenue equations (R_i) are derived using Shepard's Lemma:

$$s_k = \frac{\partial \ln C}{\partial \ln w_k} = \beta_k + \sum_l \gamma_{kl} \ln w_{kl} + \sum_i \eta_{ik} \ln q_i + \sum_t^{T-1} \vartheta_{tk} d_t + \sum_f^{F-1} c_f^{s_k} + u_k \qquad (7)$$

$$R_i = \frac{\partial \ln C}{\partial \ln q_i} = \psi_i + \sum_j \varphi_{ij} \ln q_j + \sum_k \eta_{ik} \ln w_k + \sum_t^{T-1} \zeta_{it} d_t + \sum_f^{F-1} c_f^{R_i} + v_i \qquad (8)$$

where u_k and v_i are disturbance terms which may or may not be spatially dependent on other u_k's or v_i's. An additional restriction is imposed in the fixed effects parameters; $c_f^C = c_f^{s_k} = c_f^{R_i} \forall C, k, i \in f$ because the same, farm-specific heterogeneous effects are assumed to operate across all of the equations similarly.

Because LDP's are linked to production, corn and soybean product revenues are adjusted as $R_{i,t}^{LDP,i,t} = \left(P_{i,t}Q_{i,t} + LDP_{i,t-1}\right)/C_{i,t}$. On the other hand, there are no direct linkages between AMTA payments and input or output. To model the effects of AMTA payments on farm-level cost structure, AMTA payments enter the indirect cost function as an extra term in the intercept; $\tilde{\alpha}_0 = \alpha_0 + \delta \ln AMTA_{t-1}$.

The system of equations is estimated using iterated seemingly unrelated regression (ITSUR). Lagrange multiplier tests are used to separately test for spatial dependence in each period in each equation. Z-tests are used to statistically compare elasticities derived from the cost system with and without LDP and AMTA payments.

Specification of the Spatial Weights Matrices Used in this Analysis

A spatial weights matrix was constructed to capture farm-farm effects within a given county and farm-county links across counties in Illinois. The weight matrix is therefore a combination of two spatial contiguity patterns. The first weight matrix identifies farms belonging to the same county ($\boldsymbol{W}^F$); all farms belonging to the same county receive a '1' entry in $\boldsymbol{W}^F$. The second matrix identifies neighboring counties in the dataset based on a 'queen' or a 'rook' criterion ($\boldsymbol{W}_{Rook}^c$ or $\boldsymbol{W}_{Queen}^c$). The 'rook' criterion identifies counties whose borders are perpendicular to a given county. The ‘queen’ criterion identifies counties whose borders are perpendicular and diagonal to a given county. A visual analogy would be that of the moves rooks or the queen pieces take on a chessboard. Neighboring counties of a given county receive a ‘1’ entry in this matrix according to the ‘queen’ or ‘rook’ criterion. $\boldsymbol{W}^{c}_{Rook}$, $\boldsymbol{W}^{c}_{Queen}$, and $\boldsymbol{W}^{F}$ are row standardized. After combining the farm-farm and farm-county matrices as $\boldsymbol{W}^{R} = \boldsymbol{W}^{c}_{Rook} + \boldsymbol{W}^{F}$ and $\boldsymbol{W}^{Q} = \boldsymbol{W}^{c}_{Queen} + \boldsymbol{W}^{F}$, the resulting matrices ($\boldsymbol{W}^{\boldsymbol{R}}$ and $\boldsymbol{W}^{\boldsymbol{Q}}$) are row standardized.

Druska and Horrace interpret the weighting matrices used in their farm technical efficiency analysis as a mechanism that models production shocks of farm i as a function of productivity shocks experienced by neighboring farms j. Lence and Mishra interpret their weighting matrix as a mechanism to capture error correlation across counties in their study of farmland prices in Iowa. A similar interpretation from both of these studies is applicable here, but the shocks not only capture localized effects (for instance, farms located in the same county), they capture other effects that operate at the inter-county level (for example, effects attributable to water-shed drainage, regional soil types, similarities in posted inter-county crop prices, local competition, or weather patterns).

General Moments Estimation of the Spatial Error FE Model (SARE-GM)

Elhorst outlines the estimation steps of the spatial FE model using maximum likelihood (ML). Kelejian and Prucha proposed an alternative method for estimating the spatial autoregressive model that does not require estimation of eigenvalues of $\boldsymbol{W}_n$ or the log determinant, $\ln\left|\left(\boldsymbol{I}_n - \boldsymbol{\Lambda}_T \otimes \boldsymbol{W}_n\right)\right|$, greatly decreasing computation time. Druska and Horrace modified Kelejian and Prucha’s approach to accommodate FE models. The approach they used is employed here to estimate the spatial error FE model. The following system of general moment equations solves for λ_t for a single equation in period t:

$$\boldsymbol{\Gamma}_t = \frac{1}{n}\begin{bmatrix} 2\boldsymbol{u}_t'\boldsymbol{W}_n\boldsymbol{u}_t & -(\boldsymbol{W}_n\boldsymbol{u}_t)'\boldsymbol{W}_n\boldsymbol{u}_t & n \\ 2(\boldsymbol{W}_n^2\boldsymbol{u}_t)'\boldsymbol{W}_n\boldsymbol{u}_t & -(\boldsymbol{W}_n^2\boldsymbol{u}_t)'\boldsymbol{W}_n^2\boldsymbol{u}_t & tr(\boldsymbol{W}_n^2) \\ \left(\boldsymbol{u}_t'\boldsymbol{W}_n^2\boldsymbol{u}_t + [\boldsymbol{W}_n\boldsymbol{u}_t]'\boldsymbol{W}_n\boldsymbol{u}_t\right) & -(\boldsymbol{W}_n\boldsymbol{u}_t)'\boldsymbol{W}_n^2\boldsymbol{u}_t & 0 \end{bmatrix} \tag{9}$$

where $\boldsymbol{\Xi}_t = [\lambda_t, \lambda_t^2, \sigma_t^2]'$, $\boldsymbol{\gamma}_t = \frac{1}{n}\left[\boldsymbol{u}_t'\boldsymbol{u}_t, (\boldsymbol{W}_n\boldsymbol{u}_t)'\boldsymbol{W}_n\boldsymbol{u}_t, \boldsymbol{u}_t'\boldsymbol{W}_n\boldsymbol{u}_t\right]'$ and

$$\arg\min_{\Xi_t}\left\{(\boldsymbol{\Gamma}_t\boldsymbol{\Xi}_t - \boldsymbol{\gamma}_t)'(\boldsymbol{\Gamma}_t\boldsymbol{\Xi}_t - \boldsymbol{\gamma}_t) : \lambda_t \in [-1,1], \sigma_t^2 \geq 0\right\} \tag{10}$$

The moment conditions are solved, and the slope estimates are found conditional upon the λ_t's as $\boldsymbol{\beta}^* = \left(\ddot{\boldsymbol{X}}'\boldsymbol{\Omega}\ddot{\boldsymbol{X}}\right)^{-1}\ddot{\boldsymbol{X}}'\boldsymbol{\Omega}\ddot{\boldsymbol{Y}}$, $\ddot{\boldsymbol{X}} = (\boldsymbol{I}_{nT} - \boldsymbol{\Lambda}_T \otimes \boldsymbol{W}_n)\boldsymbol{Q}\boldsymbol{X}$, $\ddot{\boldsymbol{Y}} = (\boldsymbol{I}_{nT} - \boldsymbol{\Lambda}_T \otimes \boldsymbol{W}_n)\boldsymbol{Q}\boldsymbol{Y}$, where the time de-trending matrix $\boldsymbol{Q} = diag(\boldsymbol{I}_{nT} - \boldsymbol{\iota}_{nT}\boldsymbol{\iota}_{nT}'/T)$, $\boldsymbol{\Lambda}$ is a T x T matrix of zeros with diagonal elements λ_t, and $\boldsymbol{\iota}$ is a vector of ones. Druska and Horrace use a weighting matrix $\boldsymbol{\Omega} = \boldsymbol{\sigma}_{\boldsymbol{T}}^{-2} \otimes \boldsymbol{I}_{\boldsymbol{n}}$ because the SARE FE error model is, by construction, heteroskedastic.

Instrumental Variable Estimation of the Spatial Lag FE Model (SARL-IV)

The spatial lag model can be estimated using an instrumental variable (IV) approach (Lee). In the first stage of this approach, the spatially lagged dependent variable (***Wy***) is regressed on the set of dependent variables (***X***), the lagged and squared lagged values of the explanatory variables (***WX*** and $\boldsymbol{W}^2\boldsymbol{X}$). In the second stage, the predicted values of ***Wy*** are included in equations 5, or 6, 7, and 8. The spatial lag AR parameters (ρ) explain the correlation between observation y_i and surrounding y_j neighbors. Explanatory and endogenous variables are time-detrended with the $\boldsymbol{Q}$ matrix for fixed effect estimation.

Diagnostics for Spatial Autocorrelation

Lence-Mishra Cash Rent Model

There are no diagnostics for the Lence-Mishra model because it is assumed *a priori* there is spatial error dependence.

Distributed Lag Cash Rent Model

The LM test for spatial error was significant for the ‘queen’ and ‘rook’ weight specifications (LM(error) = 12.07 and 11.36, respectively; LM critical value = 11.07 at the 5% level). The SLM test was also significant for ‘queen’ and ‘rook’ weight specifications (SLM = 5.08 and 4.95, respectively, Z critical value = 1.96 at the 5% level). Spatial lag was not detected in the residual terms when ‘queen’ or ‘rook’ weight specifications were used (LM(lag) = 7.83 and 7.56, respectively). Based on these diagnostics, equation 5 was re-estimated using SARE-GM adjusted for fixed effects.

Translog Cost Model

The LM(lag) tests for the indirect cost function, the input share equations, and the corn and soybean revenue equations were highly significant (Table 2). LM(error) tests also indicated the presence of spatial error, but the magnitude compared to the LM(lag) results was much less. Similar results obtained when LDP and AMTA payments were included in the cost system. Based on these results, the translog cost model with and without government payments was re-estimated using the SARL-IV approach.

Regression Results and Analyses

Lence-Mishra Cash Rent Model

The Lence-Mishra model was estimated restricting SAR terms to zero, using a single SAR term, and allowing each period to have a SAR coefficient. Although the coefficients of determination were very low, AMTA and LDP payments significantly increased cash rents in each of the specifications (Table 3). However, the coefficient for corn revenue was negative when the SAR terms were restricted to be zero and when a single SAR term was used for the entire series. When each period was allowed a separate SAR term, the expected signs for revenue were obtained for corn and soybean. SAR terms were significant in 3 of the 5 years. The null hypothesis of no spatial error autocorrelation across all periods was rejected at the 5% level (likelihood ratio test, LR = 33, df = 5). LDPs increased cash rent \$2.34/acre at a 5% discount rate, based on the estimates for the model allowing a SAR term for each period (estimated as $\beta_{Govtpayment} / \delta$, where δ is a discount rate, Turvey). These results for LDPs are similar in magnitude to those found in the Lence-Mishra study. AMTA payments positively contributed to cash rents, but at a magnitude much less than that of LDPs (\$0.006/acre).

Distributed Lag Cash Rent Model

It is worth noting that ordinary least squares(OLS) results are generally in agreement with (although not the same magnitude as) the Lence-Mishra results: AMTA and LDP payments significantly increase farmland values (Table 4). The null hypothesis of 'no fixed effects' was rejected at the 5% level (F = 3.96, numerator df = 470, denominator df = 1863), indicating that a FE specification is appropriate with this panel series. When individual, farm-level heterogeneity is permitted, the effect-magnitude of AMTA and LDPs decreases, and the effects are no longer significant.

In general, the results of the FE model estimated with SARE-GM were not different from the ordinary FE estimates. AMTA and LDP payments still positively (but insignificantly) impact farmland value ($0.0045 and $3.50/acre, respectively, 5% discount rate).

Considering the Lence-Mishra and the Distributed Lag model results, the relatively small magnitude of the effects of AMTA payments may not be surprising. AMTA payments were scheduled to terminate by 2002. If producers considered these payments to be transitory compared to income from the market, government payments as an income source will be discounted more heavily than income received from selling grain (Weersink et al.). If this is true, then the expected impact of transitory government payments on farmland prices should be minimal.

Translog Cost Model

Model fit statistics for the translog cost model estimated with and without AMTA and LDP payments were similar (Table 5). It is difficult to generalize a trend with respect to changes in the parameters estimated with and without LDP and AMTA payments. However, there are some differences between estimates including government payments, and those that do not (Table 6).

The biggest difference is apparent in corn and soybean output intercept coefficients (ψ) in the revenue equations. This is not surprising because LDPs are added to corn and soybean product revenue when the model is estimated with government payments. As expected, the AMTA slope coefficient (δ) is negative (and significant). All of the spatial lag terms (ρ) were bounded between –1 and 1.

All inputs substitute for one another given respective price changes. Input own- and cross-price elasticities were inelastic, while factor demand elasticities with respect to corn and soybean output were elastic (Table 7). The greatest change in factor demand with respect to a 1% increase in corn output was observed with the demand for labor (2.24%). For soybean, after including AMTA and LDPs, the demand for land increases by 1.55% given a 1% increase in soybean output.

AMTA and LDP payments significantly impact the magnitude of the factor demand and input-output price elasticities (Table 7). Own-price elasticities for fertilizer, pesticide, and land are significantly different when AMTA and LPDs are included in the cost model. It is interesting to note too that the own-price elasticity for land and the cross-price elasticities between land and the other inputs are significantly different from the base (without payment) elasticities. This is to be expected because the land cost share (46%) is twice as large as cost shares for fertilizer, pesticides, and labor (19%, 16%, and 19%, respectively). Like the factor demand elasticies, input-output elasticities were significantly different when the cost model was estimated with and without AMTA and LDP payments. The greatest changes compared to the base were observed with labor demand, given a 1% increase in soybean output, and demand for land, given a 1% increase in corn output.

The mechanism driving the changes in factor demands given an increase in output is clear for LDP payments, coupled with the cost burden of land representing 46% of the total costs. These payments directly enter the product revenue terms for corn and soybean. If corn (or soybean) output were to increase, and LDPs are concomitantly received for corn (or soybean), then the producer has incentive to purchase more inputs to increase production of these crops. The biggest boost in factor demand after government payments are included in farm cost structure comes from a change in corn output, followed by an increase in demand for land. This might be expected because corn yield is generally higher than soybean yield, and that land supply is, in the short run at least, fixed.

The story is slightly different considering changes in soybean output, factor demand, and LDP payments. Fertilizer, pesticide, and labor demand significantly increase by about 0.2% with the addition of support payments. However, demand for land decreases less. This might be attributable to the corn-soybean rotation pattern generally observed throughout the Midwest. Because corn is historically the dominant crop in Illinois, many producers may consider it the 'decision' crop; soybean cycles generally follow corn.

The role of AMTA payments in these changes is less clear. As a sensitivity check, the translog cost model was estimated adding only LDP payments. The results were not significantly different from the present results, indicating that, based on the assumptions maintained here about how government payments enter farm production costs, LDP payments seem to be driving changes in factor demand-output relations. Alternative specifications might model land rent as a price expectation model with lagged AMTA payments on the right hand side.

Conclusions

While it has been long known that government subsidies tend to be capitalized into land farmland values and cash rental rates, these results indicated there are no changes in cash rental rates could be attributed to AMTA or LDP payments, assuming that the FE model is the correct specification. One explanation is that because the 1996 FAIR act was a continuation of previous farm legislation subsidies, farmland cash rental rates were already artificially inflated from older farm bills. If during the FAIR act years, government subsidies ceased then this study may have documented decreases in cash rental rates. While this is one explanation, it is not surprising that slight changes in replacement farm legislation would significantly change land values and rents that have been affected by subsidies for several decades.

However, cost structure is affected by LDP and AMTA payments with respect to land and the substitute inputs; fertilizer, labor, and pesticides. The substitution effect towards other inputs away from land is significantly less in the presence of these instruments. This suggests that farmers place more importance on land in terms of production than marginal dollars spent on alternative inputs when payments are available. Input use with respect to output elasticities are also much greater in magnitude with corn compared to soybeans. This suggests that farmer's input decision making is driven by the corn portion of the rotation. Additionally, input-output elasticities appear to significantly increase with payments for corn and soybeans.

Table 1. Descriptive statistics covering farms used in the study: 1996-2001

Variable	*Mean*	*Std*	*10th percentile*	*90th percentile*
Cash rent (\$ acre^{-1})	119	45	71	154
Corn price (\$ bu^{-1})	2.80	0.37	2.37	3.24
Soybean price (\$ bu^{-1})	6.43	1.07	5.37	7.83
Soybean revenue (\$ acre^{-1})	313	73	238	413
Corn revenue (\$ acre^{-1})	423	83	324	523
Corn yield (bu acre^{-1})	151	24	120	179
Soybean yield (bu acre^{-1})	49	7	40	57
Owned acres	173	246	0	440
Shared acres	418	457	0	979
Cash rented acres	413	369	88	815
LDP (\$ acre^{-1})	68	30	19	95
AMTAF (\$ farm^{-1})	15966	11407	6448	26697

Table 2. Lagrange multiplier tests for spatial lag and error in the translog cost model

	Without Payments		*With Payments*	
	LM(error)*,**	LM(lag)	LM(error)	LM(lag)
Total Cost	263	1899	253	895
Fertilizer Share Eq.	101	1143	97	1040
Pesticide Share Eq.	37	181	38	158
Labor Share Eq.	32	775	32	808
Bean Revenue Eq.	1150	10484	1329	11370
Corn Revenue Eq.	1597	10674	2146	12230

*5% Critical level for LM(lag) and LM(error) tests is 11.07; **The results using the 'queen' matrix are presented here. In all cases, rejection was stronger using the 'queen' weights.

Table 3. Parameter estimates using Lence and Mishra's GMM spatial model

Parameter	*Estimate*	*T*	*Estimate*	*T*	*Estimate*	*T*
λ			0.0086	0.46		
$\lambda(97)$					-0.0222	-1.12
$\lambda(98)$					0.1818	3.90
$\lambda(99)$					0.0600	1.45
$\lambda(00)$					0.2341	5.12
$\lambda(01)$					0.4955	10.03
Constant 97	108.2559	66.34	108.1704	65.94	104.7415	62.17
Constant 98	109.6168	64.91	109.5734	63.89	107.2765	54.21
Constant 99	103.2691	47.57	103.4370	46.23	99.6808	40.81
Constant 00	104.7231	45.89	104.9343	44.26	102.6290	37.35
Constant 01	105.0438	44.25	105.2895	42.47	112.4214	29.78
β_{corn}	-0.00468	-1.30	-0.0052	-1.40	0.0011	0.30
β_{soy}	0.025093	6.25	0.0260	6.31	0.0224	5.34
β_{amta}	0.000216	5.43	0.0002	5.43	0.0003	7.05
β_{ldp}	0.102077	3.84	0.0991	3.66	0.1170	4.31

Table 3 (continued). Parameter estimates using Lence and Mishra's GMM spatial model

Equation	Adjusted R^2		
1997	0.0019	0.0028	0.0008
1998	0.0190	0.0197	0.0423
1999	0.0231	0.0229	0.0276
2000	0.0112	0.0115	0.0343
2001	0.0250	0.0255	0.0525

Table 4. Farm-level, cash rented acres distributed lag model (Standard Errors in parentheses). Dependent variable is cash rent acre^{-1}

Variable	*OLS*	*FEM*	*FEM GMM SAR*
Intercept	-6.480	53.130	49.820
	(7.714)	(57.750)	(50.037)
AMTA(t-1)	0.001*	1.000E-04	1.906E-04
	(1.858E-04)	(3.448E-04)	(2.239E-04)
LDP(t-1)	0.320*	0.150	0.175
	(0.129)	(0.118)	(0.102)
Soybean revenue	0.026	0.004	0.005
	(0.020)	(0.017)	(0.016)
Corn revenue	0.060*	0.030*	0.023
	(0.015)	(0.017)	(0.014)
Soil Productivity	1.170*	0.530	0.567
	(0.085)	(0.624)	(0.547)
Owned acres	0.004	0.084*	0.080*
	(0.005)	(0.016)	(0.014)
Cash rented acres	-0.010*	-0.030*	-0.028*
	(0.003)	(0.009)	(0.007)
Share rented acres	-0.001	0.021*	0.019*
	(0.003)	(0.008)	(0.007)
Time dummy(1998)	-7.230*	-0.440	1.057
	(3.242)	(3.385)	(3.940)
Time dummy(1999)	-14.020*	-6.120	-4.519
	(3.749)	(3.600)	(3.949)
Time dummy(2000)	-31.210*	-13.470	-12.536
	(10.369)	(9.621)	(8.782)
Time dummy(2001)	-31.330*	-13.240	-13.472
	(11.393)	(10.592)	(9.523)
*Spatial AR coefficients***			
λ(*97*)			0.50
λ(*98*)			0.15
λ(*99*)			0.21
λ(*00*)			0.27
λ(*01*)			0.33
Adjusted R^2	0.19	0.60	0.61

*Significant at the 5% level; **Standard errors are not reported for SARE-GM since they are not estimable (Kelejian and Prucha).

Table 5. Translog model fit statistics

	Root Mean Squared Error		*Squared Correlation Coefficient*	
Equation	No Payments	Payments	No Payments	Payments
ln Cost	0.3976	0.4116	0.9272	0.9289
Fertilizer share	0.0533	0.0528	0.9578	0.9568
Pesticide share	0.0485	0.0508	0.9389	0.9348
Labor share	0.0616	0.0651	0.9546	0.9516
Soybean revenue	1.5454	1.6302	0.9966	0.9973
Corn revenue	1.0885	1.1831	0.9968	0.9970

Table 6. Fixed effect, translog cost model estimates with and without AMTA and LDP payments*

Parameter	*Estimate*	*T*	*Estimate*	*T*
	Without LDP and AMTA Payments		With LDP and AMTA Payments	
α_0	2.6945	59.88	2.9740	69.29
δ_{AMTA}			-0.0039	-2.07
ψ_{bean}	0.1948	5.38	0.2300	6.44
ψ_{corn}	0.5139	13.56	0.5093	13.61
$\varphi_{bean, bean}$	0.0306	33.06	0.0291	32.01
$\varphi_{bean, corn}$	0.0212	6.59	0.0208	6.53
$\varphi_{corn, corn}$	-0.0131	-1.92	-0.0114	-1.70
$\beta_{fertilizer}$	0.0540	5.23	0.0700	6.85
$\beta_{pesticide}$	0.0488	5.28	0.0529	5.79
β_{labor}	0.3491	31.11	0.3331	30.10
β_{land}	0.5482	66.34	0.5440	65.89
$\gamma_{fertilizer, fertilizer}$	0.0045	15.46	0.0034	12.05
$\gamma_{fertilizer, pesticide}$	-0.0065	-14.00	-0.0065	-13.95
$\gamma_{fertilizer, labor}$	0.0057	14.25	0.0055	13.63
$\gamma_{fertilizer, land}$	-0.0037	-8.66	-0.0024	-5.48
$\gamma_{pesticide, pesticide}$	0.0037	15.49	0.0031	13.38
$\gamma_{pesticide, labor}$	0.0035	8.20	0.0032	7.32
$\gamma_{pesticide, land}$	-0.0007	-1.98	0.0001	0.39
$\gamma_{labor, labor}$	0.0004	2.20	0.0003	1.81
$\gamma_{labor, land}$	-0.0096	-20.98	-0.0089	-19.45
$\gamma_{land, land}$	0.0141	77.82	0.0112	64.70
$\eta_{bean, fertilizer}$	0.0020	1.18	0.0017	0.98
$\eta_{bean, pesticide}$	0.0022	1.54	0.0020	1.40
$\eta_{bean, labor}$	-0.0014	-0.77	-0.0013	-0.72
$\eta_{bean, land}$	-0.0028	-2.16	-0.0024	-1.78
$\eta_{corn, fertilizer}$	0.0126	6.90	0.0118	6.48
$\eta_{corn, pesticide}$	0.0123	7.94	0.0129	8.31
$\eta_{corn, labor}$	-0.0121	-6.17	-0.0097	-4.96
$\eta_{corn, land}$	-0.0129	-9.38	-0.0149	-10.71

Table 6 (continued). Fixed effect, translog cost model estimates with and without AMTA and LDP payments*

Spatial Lag Coefficients				
ρ(Cost, 1997)	-0.0010	-0.23	-0.0035	-0.87
ρ(Cost, 1998)	0.2641	1.44	0.2537	1.50
ρ(Cost, 1999)	0.1742	0.83	0.1625	0.83
ρ(Cost, 2000)	0.2256	2.10	0.1881	1.89
ρ(Cost, 2001)	-0.0375	-1.79	-0.0283	-1.52
ρ(Fertilizer, 1997)	-0.0026	-1.10	-0.0036	-1.60
ρ(Fertilizer, 1998)	-0.0070	-2.93	-0.0075	-2.94
ρ(Fertilizer, 1999)	-0.0056	-0.07	-0.0152	-0.17
ρ(Fertilizer, 2000)	0.1719	1.52	0.1619	1.38
ρ(Fertilizer, 2001)	0.0311	0.48	0.0433	0.63
ρ(Pesticide, 1997)	-0.0157	-0.88	-0.0130	-0.67
ρ(Pesticide, 1998)	-0.0030	-0.13	-0.0078	-0.30
ρ(Pesticide, 1999)	-0.0066	-3.43	-0.0059	-2.86
ρ(Pesticide, 2000)	0.0687	0.82	0.0366	0.41
ρ(Pesticide, 2001)	0.2361	2.09	0.2287	1.92
ρ(Labor, 1997)	0.0201	0.29	-0.0183	-0.24
ρ(Labor, 1998)	0.0367	1.80	0.0344	1.50
ρ(Labor, 1999)	-0.0742	-2.37	-0.0643	-1.87
ρ(Labor, 2000)	-0.0058	-3.52	-0.0054	-2.99
ρ(Labor, 2001)	0.1606	1.95	0.1593	1.76
ρ(Bean revenue, 1997)	0.9675	1.07	0.9865	1.12
ρ(Bean revenue, 1998)	-0.1609	-0.34	-0.1424	-0.30
ρ(Bean revenue, 1999)	0.0072	0.05	-0.0016	-0.01
ρ(Bean revenue, 2000)	0.0025	0.01	-0.0250	-0.10
ρ(Bean revenue, 2001)	0.0156	6.54	0.0091	4.16
ρ(Corn revenue, 1997)	-0.3872	-0.66	-0.3400	-0.60
ρ(Corn revenue, 1998)	0.7040	1.13	0.6446	1.06
ρ(Corn revenue, 1999)	0.3147	0.93	0.1361	0.41
ρ(Corn revenue, 2000)	0.0200	0.19	0.0244	0.23
ρ(Corn revenue, 2001)	-0.0364	-0.21	-0.0468	-0.28

*Time dummy variables and interaction terms available upon request.

Table 7. Input Factor Demand and Factor-Output price Elasticities (Standard Errors)

	---*With Payments*---					
	Fertilizer	Pesticide	Labor	Land	Corn	Soybean
Fertilizer	-0.8257	0.1269	0.1782	0.5206	2.2291	1.5026
	(0.0018)	(0.0030)	(0.0026)	(0.0029)	(0.0060)	(0.0440)
Pesticide	0.1140	-0.8121	0.1610	0.5371	2.2096	1.5102
	(0.0027)	(0.0014)	(0.0026)	(0.0022)	(0.0054)	(0.0396)
Labor	0.1905	0.1646	-0.8557	0.4735	2.2423	1.4974
	(0.0028)	(0.0030)	(0.0011)	(0.0032)	(0.0064)	(0.0471)
Land	0.1477	0.1697	0.1256	-0.4430	2.0921	1.5563
	(0.0008)	(0.0007)	(0.0009)	(0.0003)	(0.0017)	(0.0125)
	---*Difference (With Payments Elasticity – Without Payments Elasticity)**---					
Fertilizer	-0.0074	0.0004	-0.0018	0.0088	0.1992	0.2039
Z-score→	(-4.01)	(0.13)	(-0.70)	(3.08)	(33.36)	(4.64)
Pesticide	0.0004	-0.0035	-0.0021	0.0052	0.2002	0.2028
Z-score→	(0.13)	(-2.54)	(-0.81)	(2.38)	(37.35)	(5.12)
Labor	-0.0020	-0.0025	-0.0005	0.0050	0.1985	0.2047
Z-score→	(-0.70)	(-0.81)	(-0.49)	(1.55)	(31.11)	(4.35)
Land	2.5E-03	0.0017	1.3E-03	-0.0055	0.2063	0.1962
Z-score→	(3.09)	(2.37)	(1.55)	(-17.02)	(122.04)	(15.70)

*Critical values for Z-scores: 1.96 and 2.58 for 5%, and 1% levels, respectively.

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