STOCHASTIC TECHNOLOGY, RISK PREFERENCES, AND THE USE OF POLLUTING INPUTS.

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Abstract : In this paper, we develop a methodology for the estimation of stochastic technology and risk preference parameters. The estimates provide direct information on the manner in which pesticides and fertilizers, the two classes of polluting inputs in agriculture, affect random outputs. This information, in combination with the risk preference estimates computed, can be used in exercises involving the effects of agricultural and environmental policy.

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Introduction.

Considerable scholarly analysis has been addressed to the economics of agricultural pollution control. Naturally much of this has to do, directly or indirectly, with the use of pesticides and fertilizers as inputs into agricultural production.

Pesticides and fertilizers are now understood as affecting risky agricultural production in complicated ways. They are capable of affecting the mean, variance and higher moments of outputs. This factor, coupled with the widely-accepted notion of risk-aversion among producers, implies that the effects of environmental and agricultural policies on the use of polluting inputs are dependent on stochastic technology and risk preference parameters. Prior theoretical research in this area has shown that comparative static effects of policies such as input taxes and yield insurance on polluting input use are very sensitive to these parameters.

Much of the prior work analyzing the effects of policies on the use of polluting inputs has utilized experimental data and imposed ad-hoc assumptions on risk preference structure. Experimental data usually yield a set of technology points that are outside the realm of actual producer experience. Ad-hoc assumptions on risk parameters create a considerable margin for preference missspecification errors. In contrast, by utilizing observed farm-level economic data and estimating all parameters from these data, such risks can be minimized.

In this paper, we adopt the approach of estimating a complete set of such parameters from observed economic data using flexible representations of technology and utility. The theoretical model lays out a set of optimization conditions under risk-aversion and endogenous technological risk. The econometric model derives and applies a Generalized Method of Moments (GMM) estimator to these optimization conditions, on a panel dataset of Illinois grain production. This research focuses on developing a methodology that is more general than previous literature in this area, and yet computationally tractable.

Some of the important contributions we make are : (i) We utilize a novel, single equation approach to stochastic technology (Just-Pope production function) estimation that is robust to heteroskedasticity as well as serial correlation (ii) We present a methodology that can handle multiple-output production situations, and (iii) We exploit the advantages that panel datasets have to offer , including the consideration of "time" effects in production.

This paper presents the methodology and econometric results, but does not extrapolate to policy analysis. However, the results of this estimation process can be combined with numerical methods to indicate the implications of agricultural and environmental policies on polluting input use.

Theoretical Model.

The theoretical model is a very generally specified one which assumes that agricultural producers maximize the expected utility from (static) random profits deriving from multiple outputs. Since the application centers around corn-soybeans farmers in the midwest, the theory is developed in terms of two outputs, corn and soybeans.

Notation :

$U(., \theta)$: (flexible) utility function. θ is a vector of utility function parameters.

W : Endowed wealth.

Q^c, Q^s : Corn and Soybean outputs, respectively

p^c, p^s : Corn and Soybean output prices, respectively.

$\mathbf{X^c}, \mathbf{X^s}$: Vectors of variable inputs (such as pesticides and fertilizers) applied to the production of corn and soybeans, respectively.

$\mathbf{w_x}$: Vector of prices of variable inputs **X**.

$\mathbf{Z^c}$**,** $\mathbf{Z^s}$: Vectors of fixed inputs (such as land) used in the production of corn and soybeans, respectively. **Z** represents the total endowment of the fixed input, which is allocated to to the two crops as $\mathbf{Z^c}$ and $\mathbf{Z^s}$.

$\mathbf{w_z}$: Vector of prices of fixed inputs, **Z**.

Stochastic Technology is represented by a joint conditional density function, f(Q^c, Q^s / $\mathbf{X^c, X^s, Z^c, Z^s}$**;** $\boldsymbol{\alpha}$). (see, for example, Antle)**.** $\boldsymbol{\alpha}$ here denotes the vector of technology parameters.

Given the stated assumptions, the optimization problem for agent j is to choose input vectors ($\mathbf{X^s}$**,** $\mathbf{X^s}$**,** $\mathbf{Z^c}$**,** $\mathbf{Z^s}$) to solve :

$$Max \int_{Q^s} \int_{Q^c} U[W_j + (p^c Q_j^c - \mathbf{w}_x^{/}\boldsymbol{X}_j^{\boldsymbol{c}} - \mathbf{w}_z^{/}\boldsymbol{Z}_j^{c}) + (p^s Q_j^s - \mathbf{w}_x^{/}\boldsymbol{X}_j^{\boldsymbol{s}} - \mathbf{w}_z^{/}\boldsymbol{Z}_j^{s}) \; ; \; \boldsymbol{\theta}]$$
$$f(Q^c, Q^s / \boldsymbol{X}^c, \boldsymbol{X}^s, \boldsymbol{Z}^c, \boldsymbol{Z}^s \; ; \boldsymbol{\alpha}) \; dQ^c \; dQ^s$$

Subject to $\mathbf{Z_j^c + Z_j^s = Z_j}$

Representation of Technology.

In order to add further structure to the representation of stochastic technology, we make the following assumptions :

(i) Approximate Stochastic Nonjointness (AST). AST is a condition (Antle) that combines the statistical independence of different outputs with the assertion that the distribution of a certain output depends only upon inputs used in the production of that output. In our context , this condition is stated as :

$$F(Q^c, Q^s / \mathbf{X^c, X^s, Z^c, Z^s} \; ; \boldsymbol{\alpha}) = F^c(Q^c / \mathbf{X^c, Z^c} \; ; \boldsymbol{\alpha}^c) \, F^s(Q^s / \mathbf{X^s, Z^s} \; ; \boldsymbol{\alpha}^s) \quad .$$

(ii) Stochastic technologies for the two outputs are represented by Just-Pope production functions.. The Just-Pope function has well-established properties and estimation techniques, and retains all the conveniences associated with a production function representation of technology. Hence, it is the representation of our choice.

(iii) We assume in this paper that the allocation of capital (land) between the two outputs is not part of the optimization process. In other words, acres planted to corn and soybeans in each year can be considered as fixed inputs in corn and soybeans production, respectively. This assumption is made for two reasons : Firstly, the division of land between corn and soybeans (in the short run) is not very flexible owing to crop-rotation (biological) considerations. Secondly, the empirical application in this study covers the period 1990-94, and the base acres requirement for deficiency payments in this period had the effect of locking land into specific enterprises in the short run.

(iv) Our technology estimation is done on a per-acre basis, for convenience in estimation.[1]

We assume $F^c(Q^c / \mathbf{X^c}, \mathbf{Z^c} ; \boldsymbol{\alpha}^c) = A^c f^c(q^c / \mathbf{x^c}, \mathbf{z^c} ; \boldsymbol{\alpha}^c)$ and $F^s(Q^s / \mathbf{X^s}, \mathbf{Z^s} ; \boldsymbol{\alpha}^s) = A^s f^s(q^s / \mathbf{x^s}, \mathbf{z^s} ; \boldsymbol{\alpha}^s)$.

Here, A^c and A^s are acres in corn and soybeans, respectively, for individual farms. q, x and z are per-acre versions of Q, X and Z.

Given our specification of technology and the assumptions we have made, the objective function can be rewritten as follows :

$$Max\ E\ [\ \ U[W_j + A^c(p^c q_j^c - \mathbf{w}_x^{/}\mathbf{x}_j^{c} - \mathbf{w}_z^{/}\mathbf{z}_j^{c}) + A^s(p^s q_j^s - \mathbf{w}_x^{/}\mathbf{x}_j^{s} - \mathbf{w}_z^{/}\mathbf{z}_j^{s})\ ;\ \theta]\ \ ]$$

with respect to (per-acre) variable inputs for corn and soybeans, i.e., $\mathbf{x^c}$ and $\mathbf{x^s}$, and with (per-acre) stochastic technology specified as follows :

$q_j^c \; = \; f(\boldsymbol{x}_j^c, \; \boldsymbol{z}_j^c) \; + \; g(\boldsymbol{x}_j^c, \; \boldsymbol{z}_j^c, \; \epsilon)$ for Corn, and

$q_j^s \; = \; h(\boldsymbol{x}_j^s, \; \boldsymbol{z}_j^s) \; + \; k(\boldsymbol{x}_j^s, \; \boldsymbol{z}_j^s, \; \eta)$ for Soybeans.

ϵ and η are random error terms distributed with mean 0.

The vectors of first order conditions with respect to the variable inputs $\mathbf{x} \equiv (\mathbf{x}^c, \mathbf{x}^s)$ (including pesticide and fertilizer applications on corn and soybeans) are given by :

$$\boldsymbol{E} \; [\; \boldsymbol{U}'(.) \; (\; \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{x}_c} \; + \; \frac{\partial \boldsymbol{g}(\epsilon)}{\partial \boldsymbol{x}_c} \;) \;] \; = \; \mathbf{0} \qquad \mathbf{(1)}$$

$$\boldsymbol{E} \; [\; \boldsymbol{U}'(.) \; (\; \frac{\partial \boldsymbol{h}}{\partial \boldsymbol{x}_s} \; + \; \frac{\partial \boldsymbol{k}(\eta)}{\partial \boldsymbol{x}_s} \;) \;] \; = \; \mathbf{0} \qquad \mathbf{(2)}$$

The interpretation of **(1)** is that the expected marginal utility of producers with respect to pesticides, fertilizers and other variable inputs applied to corn is set to zero. **(2)** is a set of parallel first order conditions for the soybeans case.

Econometric Framework.

The risk-preference parameters θ, and stochastic technology (production function) parameters α that are of interest are embedded in the set of equations **(1)** and **(2)**. While the estimation of such a set of simultaneous, implicit[2], nonlinear equations is a challenging task in itself, separate identification of technology and risk-preference parameters poses a further difficulty.

The identification problem could be eased if the Just-Pope functions could be estimated separately to yield estimates of α , which could then be used in **(1)** and **(2)** to estimate θ.

A literature exists that believes that such separate technology estimation is not justified. The argument is that inputs are endogenous, which leads to a correlation of variable inputs with the production function error term. Separate estimation of production functions using economic (as opposed to experimental) data will thus yield inconsistent estimates. Papers by Love and Buccola (henceforth, L & B), and Saha, Shumway and Talpaz (henceforth, S, S & T) present complicated econometric techniques for the estimation of equation sets such as **(1)** and **(2)** based upon this argument.

However, in prior work, two of us have shown (Shankar and Nelson) that such an argument does not hold, and that separate estimation of Just-Pope production functions does indeed yield consistent estimates of technology parameters[3]. Based on that demonstration, we adopt the strategy of a two-step estimation process. Such a strategy enables us to avoid some undesirable features of the methodologies employed by L & B, and S, S & T. For example, S, S & T are compelled to use an observable proxy for the production error term that in reality is an unobservable residual.

A Two-Step Generalized Method of Moments Model.

Generalized Method of Moments (GMM) estimation techniques are ideally suited to handling sets of simultaneous, implicit, non equations involving expected values. Below, we outline our two-step panel GMM procedure.

Step 1 : GMM estimation of Just-Pope Production Functions.

Our empirical version of the Just-Pope production function for corn detailed before is specified thus :

$$q_{jt}^{c} = \alpha_{1c}P_{jt}^{c} + \gamma_{1c}(P_{jt}^{c})^2 + \alpha_{2c}F_{jt}^{c} + \gamma_{2c}(F_{jt}^{c})^2 + \alpha_{3c}O_{jt}^{c} + \gamma_{3c}(O_{jt}^{c})^2 + \alpha_{4c}S_{jt}^{c} + \gamma_{4c}(S_{jt}^{c})^2 + e^{\beta_{1c}P_{jt}^{c} + \beta_{2c}F_{jt}^{c} + \beta_{3c}O_{jt}^{c}} \epsilon_{jt}^{c}$$

$E(\epsilon_{jt}^{c}) = 0$, for all i, t. (3)

The additional notation is as follows :

P : Pesticide Input (per-acre) F : Fertilizer Input (per acre)

O : “Other” Variable Inputs (aggregated) (per-acre)

S : A Soil-Quality Index. c signifies corn.

j and t index individuals and time periods, respectively.

This four-input Just-Pope stochastic production function is our empirical specification of the general version introduced before. Pesticides, Fertilizers, and “Other Variable Inputs” are the variable inputs (the vector **x** in the general specification), while Soil Quality Index is an endowment (the vector **z** in the general specification). Note that all inputs can affect the mean of output, but only the variable inputs are allowed to affect the variance.[4] The production function for Soybeans is parallel to the Corn case.

The ϵ are idiosyncratic shocks. We seek estimates of stochastic technology parameter set $\boldsymbol{\alpha} \equiv \{ (\alpha_1..\alpha_4), (\gamma_{1..}\gamma_4), (\beta_1...\beta_3)\}$, and the GMM estimation technique to achieve this is outlined below :

(3) can be written as :

$$\epsilon_{jt} = \ln(q_{jt}^{\,c} - [\ \alpha_{1c}P_{jt}^{c} + \gamma_{1c}(P_{jt}^{c})^2 + \alpha_{2c}F_{jt}^{c} + \gamma_{2c}(F_{jt}^{c})^2 + \alpha_{3c}O_{jt}^{c} + \gamma_{3c}(O_{jt}^{c})^2 + \alpha_{4c}S_{jt}^{c} + \gamma_{4c}(S_{jt}^{c})^2\ ]\ ) - (\beta_{1c}P_{jt}^{\,c} + \beta_{2c}F_{jt}^{\,c} + \beta_{3c}O_{jt}^{c})$$

Orthogonality between the mean zero disturbance and a set of instruments (see, for example, Mairesse and Hall, or Ogaki), denoted by τ, implies $E[\epsilon_j(\boldsymbol{\alpha}) \otimes \tau_j] = 0$, where $\epsilon_j(\boldsymbol{\alpha}) = [\epsilon_{j1}(\boldsymbol{\alpha}), \epsilon_{j2}(\boldsymbol{\alpha}), ..., \epsilon_{jT}(\boldsymbol{\alpha})]$, $\tau_j = [\tau_{j1}, ..., \tau_{jm}]$ (m instruments per year) and $\otimes$ is the Kronecker delta. These moment conditions have sample equivalents given by :

$$\phi(\boldsymbol{\alpha}) = \frac{1}{N} \sum_{j=1}^{N} \epsilon_j(\boldsymbol{\alpha}) \otimes \tau_j$$

GMM estimates of $\boldsymbol{\alpha}$ are then obtained by minimizing the quadratic form

$\zeta(\boldsymbol{\alpha}) = \phi'(\boldsymbol{\alpha})\ A\ \ \phi(\boldsymbol{\alpha})$ with respect to $\boldsymbol{\alpha}$.

A can be chosen to make the estimator consistent and asymptotically efficient.[5]

A parallel derivation of the GMM estimator applies to the technology parameters attached to soybeans production.

The GMM estimation of technology outlined above has several advantages. Firstly, no distributional assumption needs to be made regarding the production error term. In all prior literature, normality of production error has been assumed, which implies that agricultural output itself is normally distributed. This dubious implication is avoided by the GMM model described above. Secondly, GMM techniques allow fully for heteroscedastic and serially correlated errors. Thirdly, consistency and asymptotic efficiency properties are well-established.

Step 2 : GMM estimation of risk parameters from first order conditions, conditional on step 1 technology parameters.

For expositional convenience, we collapse the sets of first-order conditions **(1)** and **(2)** into the following term :

$$\boldsymbol{E\ [\ U'(W_{jt},\ \theta)\ \Gamma(\alpha)\ ]\ =\ 0} \qquad \textbf{(5)}$$

Here, $W_{jt} = W_{jt}^{o} + \pi_{jt}^{c} + \pi_{jt}^{s}$. W_{jt}^{o} is initial wealth, π^{c} and π^{s} profits from corn and soybeans respectively. W_{jt} is final wealth, a random variable. This is a set of six first-order conditions, three each for corn and soybeans cases, and in each case with respect to pesticides, fertilizers and other variable inputs. The technology terms have been indicated by the function $\boldsymbol{\Gamma(\alpha)}$. The set of technology parameters, α, has of course been estimated in the first step.

Idiosyncratic errors are possible in optimization, and hence an empirical version of the set of FOC's **(5)** can be written as :

$$\boldsymbol{E}\ [\ \boldsymbol{U}^{/}(\boldsymbol{W}_{jt},\ \theta)\ \Gamma(\alpha)\ ] = \nu_{jt}\ , \qquad \boldsymbol{E}(\nu_{jt}) = \mathbf{0}, \quad \text{for all j, t.}$$

As before, if expectations are rational, all variables in the agent's information set at time t are orthogonal to the errors ν_{jt}, and can be used as instruments.

We use the popular power utility function for our parameterization of preferences. The power utility function is given by $U(W_{jt}) = \frac{W_{jt}^{\rho}}{\rho}$. This utility function imposes Decreasing Absolute Risk Aversion (DARA) and Constant Relative Risk Aversion (CRRA). This choice of utility functions was prompted by two considerations : (i) It enabled an easier estimation process, and (ii) There is a large volume of evidence in support of DARA, including at least two recent studies of farmer risk-aversion (Chavas and Holt; Saha Shumway and Talpaz).

Data.

Our dataset is a panel of 50 Illinois grain farms over the time period 1989-92. Several thousand farmers maintain accounting records with the Illinois Farm Business Farm Management (FBFM) association. However, the expenditure records maintained in this databank are generally not output-specific. A smaller subset of farmers do maintain output-specific input expenditure records with FBFM, aside from information on most other variables essential for our analysis, such as corn and soybean outputs, acreage, etc. This unique dataset is intersected with a financial dataset containing initial wealth (net worth) information needed for this analysis.

The use of accounting data for production analysis is quite widespread in agricultural economics. A common approach to inferring quantity and price information from such data involves the use of weighted prices from state or national-level data (see, for example, Saha, Shumway and Talpaz). Price aggregates for the fertilizer and pesticide input categories were computed using Illinois state level price and quantity data on commonly used pesticides and fertilizers, with quantity shares as weights. The pesticide and fertilizer expenditures of individual farms in our dataset were divided by these constructed price aggregates to obtain measures of pesticide and fertilizer input quantities. Other variable input expenditures such as seed, hired labor and fuel were aggregated into a composite input category called ‘Other variable inputs’. A price aggregate for this category was computed using expenditure shares. All nominal variables were deflated to 1989 dollars using the Consumer Price Index for the Northcentral United States.

Technology Parameter Estimates.

The GMM estimates of (3) are presented in table 1 for corn, and table 2 for soybeans. The following instruments were used in the base case for corn : time dummies, (t-1) and (t-2) values of corn and soybean yields, (t-1) and (t-2) values of pesticides, fertilizers and other variable inputs applied to corn. As explained before, the estimation is robust to conditional heteroskedasticity and serial correlation.

Column (1) in table 1, our model of choice for the corn stochastic production function, demonstrates that the model is a very good fit to the data. All parameters are uniformly significant at the 1% level. Since more orthogonality conditions are available than are needed for identification of the parameters, we can test model specification by performing Hansen’s overidentifying restrictions test. Hansen’s J-statistic (Hansen and Singleton) is a random variable distributed as chi-square, under the null hypothesis that the overidentifying restrictions are not rejected. The p-value for this statistic, shown in column 1, is 0.708, providing us with evidence that the overidentifying restrictions are indeed, not rejected.

The soybeans technology estimates are presented in column (1) of table 2. Aside from two, all parameters are significant at the 1 or 5% level. The p-value for the overidentiying restrictions test is 0.808, and therefore, once again we cannot reject the overidentifying restrictions.

“Time effects” can be very important in agricultural production. While the production errors, ϵ and η, capture idiosyncratic shocks, the presence of *aggregate* shocks, common to all producers in a year, can invalidate all estimates if not accounted for. Since our sample consists of producers in Illinois, an abnormally good or bad year of weather for the state can create such effects. The logic of the GMM estimation procedure provides a very convenient way to test for the presence of time effects. If time effects are indeed present, then time dummies would be invalid instruments (Runkle; Ziliak and Kniesner). Therefore a test could be constructed as follows : estimate two different models, one with and the other without time dummies as instruments. The difference in the J statistics between the two models is distributed asymptotically as a chi-square random variable (Eichenbaum, Hansen and Singleton) under the null hypothesis of the absence of time effects. The models for corn and soybeans without time dummies are presented in Columns 2 of tables 1 and 2 respectively. The test statistics and p-values at the bottom of the tables demonstrate, surprisingly, that time effects do not exist in our sample years.

The estimates reveal that all three variable aggregate input categories, pesticides, fertilizers and other variable inputs, are “risk-increasing”, for both corn and soybeans. Table 3 presents estimates of the elasticities of the mean and variance of corn and soybeans outputs with respect to fertilizers and pesticides, evaluated at the sample mean. Comfortingly, all three variables are seen to also increase the expected value of production. Slightly surprising is the variance-increasing effect of pesticides, which would seem contrary to conventional wisdom. However, it is important to remember that the input categories here are aggregate, and there is little a-priori information about the manner in which such aggregate input categories affect risk.[6] Also, evaluated at the sample mean, the elasticity of corn output variance with respect to pesticides is quite small : a 10% increase in pesticide input on corn increases corn variance only by 1.48 %, while increasing the expected corn output by 5.54%. In contrast, a 10% increase in fertilizer input on corn increases corn variance by 9.34%, and the expected output of corn by 17.86%.

In general, relative strengths of the effects of pesticides and fertilizers on corn and soybeans is not symmetric. In corn production, the mean and variance elasticities of fertilizer input are large compared to the mean and variance elasticities of pesticide input. The reverse is true in the case of soybeans.

Risk Preference Estimate.

The GMM estimate of the Utility function parameter ρ is presented in table 4. The instrument set consisted of time dummies, (t-1) and (t-2) values of net worth and (t-1) and (t-2) pesticide and fertilizer inputs into corn and soybeans.

The negative value of the estimated ρ implies that the marginal utility of final wealth is indeed, positive, as one would expect. The value $(1-\rho)$ is the “unit-free” coefficient of relative risk aversion, and is suitable for comparison across studies. Our estimated coefficient of relative risk aversion is 1.831. Chavas and Holt report that previous estimates of the relative risk coefficient in agriculture have varied from 0 to over 7.5, with a median estimate around 1. Thus out estimate is quite consistent with previous findings, and indicates only a “moderate” degree of risk aversion on part of Illinois farmers.

The p-value on the overidentifying restrictions test is 0.178, and once again, we cannot reject the overidentifying orthogonality conditions.

Conclusion : In this paper, we have developed a methodology for the estimation of stochastic technology and risk preference parameters. The estimates provide direct information on the manner in which pesticides and fertilizers, the two classes of polluting inputs in agriculture, affect random outputs. This information, in combination with the risk preference estimates computed, can be used in exercises involving the effects of agricultural and environmental policy.

The methodology developed is robust to heteroskedasticity and serial correlation in production. Tests of time effects, model specification, etc, can be accomplished in a facile manner with this approach. Multiple output production situations can be handled quite easily, and the computational burden is small compared to alternative methods.

Our findings indicate that both aggregate classes of polluting inputs, fertilizers and pesticides increase corn as well as soybeans production risk at the margin. At the sample mean, both inputs also increase the expected value of output at the margin. The marginal effects of pesticide input are stronger for soybeans as compared to corn, while the marginal effects of fertilizer input are stronger for corn as compared to soybeans. Time effects do not seem to have significantly affected production in the sample period. Farmers are found to be moderately risk averse.

Table 1 : Technology Estimates for Corn Production[a]

Parameter	Col 1 : Model with time dummies	Col 2 : Model without time dummies
α_{1c}	889.960 (200.825)***	805.522 (431.133)*
γ_{1c}	-493.374 (135.665)***	-862.891 (404.682)**
α_{2c}	4.0884 (0.287873)***	2.31084 (0.591851)***
γ_{2c}	-0.0073 (0.005526)***	-0.003911 (0.00114)***
α_{3c}	64.7786 (4.4236)***	7.79413 (7.76016)
γ_{3c}	-8.55662 (0.560416)***	0.087154 (0.543138)
α_{4c}	-25.1672 (2.20842)***	-17.6580 (4.57713)***
γ_{4c}	0.171874 (0.013737)***	0.155953
β_{1c}	0.832264 (0.224798)***	(0.033295)***
β_{2c}	0.00862856 (0.00036)***	2.80415 (0.409148)***
β_{3c}	0.093715 (0.010315)***	0.006155 (0.00067)***
J-Stat. (degrees of freedom)	20.7238 (25)	-0.004616 (0.01842)
P-value for overid. test :	0.708	17.2363 (22)
χ^2 statistic for test of time		0.750
effects (deg. of freedom) :		
P-value :		3.4875 (3)
		0.32239

a Standard errors are in parantheses. *, **, *** denotes significance at the 10, 5 and 1 % levels respectively. As stated before, all parameters with subscript 1 are "attached" to pesticide input, those with subscript 2 are attached to fertilizer input, those with subscript 3 are attached to other variable input, and those with subscript 4 are attached to soil quality.

Table 2 : Technology Estimates for Soybeans Production[a]

Parameter	Col 1 : Model with time dummies	Col 2 : Model without time dummies
α_{1s}	54.2549 (15.8763)***	41.4444 (15.3374)***
γ_{1s}	-107.719 (29.7944)***	-82.3053 (28.8834)***
α_{2s}	-0.060353 (0.022206)***	-0.017477 (0.061791)
γ_{2s}	-0.000061 (0.00014)	-0.000368 (0.000497)
α_{3s}	3.17183 (0.956568)***	2.75817 (0.994519)***
γ_{3s}	-0.179924 (0.064271)***	-0.179853 (0.083661)**
α_{4s}	0.382872 (0.16744)**	0.441174 (0.227664)*
γ_{4s}	0.0003438 (0.00148)	0.000062 (0.002466)
β_{1s}	3.25643 (0.266767)***	2.94303 (0.318943)***
β_{2s}	0.0026017	0.003234 (0.00148)**
β_{3s}	(0.00073)***	0.082605 (0.012891)***
J-Stat. (degrees of freedom)	0.068866 (0.010242)***	18.5250
P-value for overid. test :	18.7728	0.674
χ^2 statistic for test of time effects (deg. of freedom) :	0.808	0.2478 (3)
P-value :		0.96953

a Standard errors are in parantheses. *, **, *** denotes significance at the 10, 5 and 1 % levels respectively. As stated before, all parameters with subscript 1 are "attached" to pesticide input, those with subscript 2 are attached to fertilizer input, those with subscript 3 are attached to other variable input, and those with subscript 4 are attached to soil quality.

Table 3 : Elasticities of Moments.[a]

	Pesticide Input	Fertilizer Input
Corn : Expected Output	5.548	17.866
Corn : Variance of Output	1.489	9.341
Beans : Expected Output	2.929	0.251
Beans : Variance of Output	6.121	0.722

a Evaluated at the sample mean.

Table 4 : Risk Preference Estimate.

ρ : -0.831425. J-Statistic : 56.8867

Standard Error : 0.1378 Degrees of Freedom : 48.

Significant at 1% level. P-value for test of overidentifying restrictions : 0.178.

Endnotes.

1. There are two problems with estimation on the basis of aggregate outputs and inputs at a farm level : First, there is a lack of sufficient variability in acreage levels across the cross-section. Two, all other aggregate inputs tend to be highly correlated with acreage.

2. Explicit forms for input demand functions usually do not exist in such frameworks, unless the researcher is willing to make drastic assumptions regarding utility and technology functional forms.

3. This paper is available upon request.

4. There is no a-priori reason to believe that soil quality should affect the variance of output. To restrict parameter proliferation, we specify soil quality to affect only the mean of output.

5. Further elaboration on GMM procedures for panel data is beyond the scope of this paper. Ogaki provides an excellent review.

6. This brings up an implicit assumption made in this paper : that our input categories are robust to aggregation issues. It also points to a need for research on input aggregation under endogenous technological risk. While the use of farm-level accounting data is preferable to experimental data in several ways, it does preclude detailed information at the level of disaggregate inputs.

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