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Yield Response and Production Risk: An Analysis of Integrated Pest Management in Cotton

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Production uncertainty is commonly believed to be an impediment to the adoption of less pesticide-intensive methods in agriculture such as integrated pest management (IPM). To investigate the effects of pest control inputs on yields and yield variability, data from a cross-section of San Joaquin Valley cotton producers were analyzed in a heteroskedastic production model. The results suggest that yields are increasing with soil quality, crop rotation, frequency of field monitoring, and the use of independent pest control advisors. Yield variability was not found to be significantly affected by production inputs, including pesticides and IPM practices with the exception of frequent contact with extension farm advisors which was found to contribute to reduced yield variability.

Key words: cotton, heteroskedasticity, integrated pest management, pesticides, stochastic production functions.

Introduction

Producer behavior under risk and uncertainty has long been an interest of economists and has been investigated widely by many researchers (e.g., Arrow; Pratt; Sandmo; Anderson, Dillon, and Hardaker; Robison and Barry). One of the strong implications drawn from both theoretical models and empirical research is that risk-averse producers optimally use less of a risk-inducing input than they would under certainty. This has important implications for the adoption and use of less chemical-intensive agricultural practices like those associated with integrated pest management (IPM) which have been considered more "risky" than pesticides by many producers. To reduce agricultural nonpoint source pollution and public and farm worker exposure to hazardous chemicals, agricultural research has focused on improving the knowledge and information available to farmers to control pests through a greater variety of methods and through methods that emphasize cultural practices that contribute to the interruption of pest life cycles.

In this article, the normative producer model presented by Antle (1989) is used to derive behavioral implications for input use under risk. These implications then are used to examine the recent use of IPM in the production of cotton in the San Joaquin Valley of California. The econometric production model of Just and Pope is applied to estimate the contribution of these IPM techniques to yields and risk. In the following section, the model of firm behavior under input risk and the econometric framework are presented.

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Next, the estimation procedure is described, followed by a presentation of the data and some summary details of the recent use of IPM in cotton production. The remainder of the article consists of a presentation and discussion of the results of the estimation, as well as a summary of the key points and policy implications of the analysis.

Input Choices under Input and Output Risk

Consider a simplified model of the decision problem confronting agricultural producers. Following Antle (1989), we define the short-run problem of the producer as choosing the quantities of a vector of agronomic and pest control inputs (X) to maximize expected utility (EU). The argument of the producer's utility function is assumed to be the distribution of net returns (π). Therefore, producers not only are concerned with the expected level of return, but also are affected by the spread and skew of the distribution of net returns. These characteristics are reflected in the moments of the distribution (e.g., mean, variance, and skew). Antle (1989) models producer utility as a function of the first three moments; however, in this article only the first two moments are modeled. Therefore, greater generalizations can be extended to the analysis and may be appropriate in some empirical situations. For the current analysis, this simplification is appropriate, since an examination of the yield data used in the empirical model does not suggest a skewed distribution (see fig. 1).[1]

Let m_1 and m_2 represent the location and dispersion (i.e., the first two moments) of the distribution of net returns, respectively. These moments are functions of the underlying production factors and characteristics such as a vector of producer's variable inputs (X), a vector of fixed and exogenous factors (Z) (e.g., soil quality and the intensity of pest damage), and the vector of associated production parameters (ϕ).[2]

With the expectations operator represented by E, the producer's problem is defined as:

$$\text{(1)} \qquad \operatorname*{Max}_{X} EU[m_1(X, Z, \phi), m_2(X, Z, \phi)],$$

where the expected utility function is assumed to be continuous and twice differentiable. Defining S_π as a bounded subset of Euclidean space from which possible net returns (π) are drawn, the first two moment functions are defined as:

$$\text{(2)} \qquad m_1(X, Z, \phi) = E[\Pi] = \int_{\Pi \in S_\pi} \Pi \, dF(\Pi \mid X, Z, \phi),$$

and

$$\text{(3)} \qquad m_2(X, Z, \phi) = E[\Pi - m_1]^2 = \int_{\Pi \in S_\pi} (\Pi - m_1)^2 \, dF(\Pi \mid X, Z, \phi).$$

Marginal utility of expected profit is defined as $dEU/dm_1 \equiv U_1$, and marginal utility of variance of profit is defined as $dEU/dm_2 \equiv U_2$. Utility is assumed to be increasing in expected profit, $U_1 > 0$; producers are assumed to be risk averse, $U_2 < 0$. These conditions simply conform to standard intuition that utility increases with increasing expected profit, and utility decreases with increasing variability. The first-order conditions (FOC) resulting from the solution of the optimization problem in equations (1)–(3) can be written as:

$$\text{(4)} \qquad \frac{dEU}{dx} = 0 \Rightarrow \frac{\partial m_1}{\partial x} + \frac{U_2}{U_1}\frac{\partial m_2}{\partial x} = 0 \qquad \text{for each } x \in X.$$

This equation characterizes the optimal input and strategy decisions of the producer in terms of the distribution of profit. Equations (2), (3), and (4) provide the structural form equations for a system that, in general, can be solved simultaneously for optimal input quantities. It will be useful to express equations (2)–(4) in terms of the function of net returns that the producer faces.

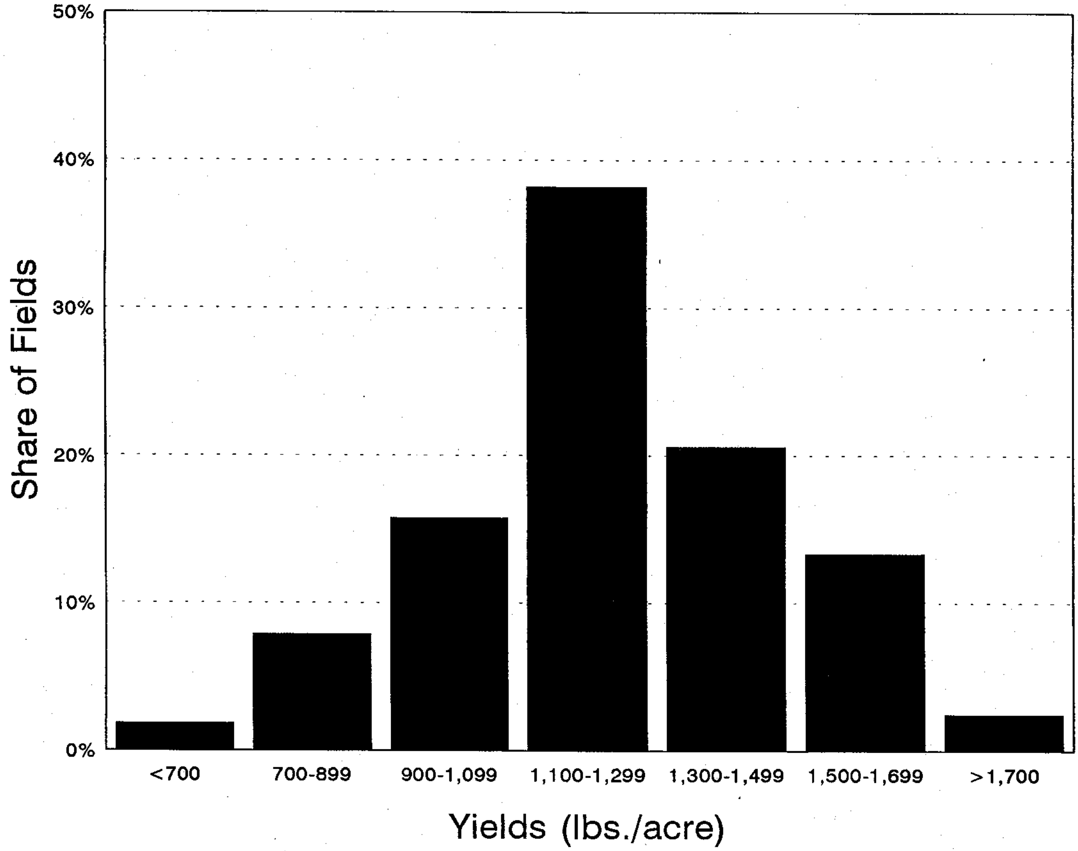

Figure 1. Frequency distribution of 1990 San Joaquin Valley cotton yields

Profits from agricultural production frequently are expressed in terms of net returns per acre, and this measure serves as the basic unit of the objective function of the agricultural firm.[3] To express the underlying stochastic nature of net returns, we use the stochastic production framework developed by Just and Pope. Used in several studies of production factors (e.g., Farnsworth and Moffitt; Griffiths and Anderson), this framework allows for the development of a significantly more flexible statistical model that accommodates both risk-increasing and risk-decreasing factors of production (in contrast to more simple and traditional models that impose specific risk behavior on inputs—see Just and Pope for examples).

Normalizing the profit function on the basis of output price (i.e., defining quantity units such that the output price is one), the one-period per acre profit function is defined as:

$$\Pi = f(X, Z, \alpha) + h^{1/2}(X, \beta)\epsilon - w'X, \tag{5}$$

where the function $f(\bullet)$ represents deterministic yields as a function of a vector of input choices (X), a vector of exogenous factors and pest levels (Z), and a parameter vector (α). The function $h^{1/2}(\bullet)$ models the interaction of input levels with random fluctuations in production (ϵ) that are assumed to be independent and normally distributed with a mean of zero and a variance of σ^2. The magnitude of this random disturbance is influenced by the vector of input choices (X) through the parameter vector (β).[4] Input prices, normalized by output price and given by the vector w, reflect the costs of both agronomic and pest control inputs.

The expression for net returns given in equation (5) exhibits the roles that input choices, pest conditions, and uncontrolled stochastic factors play in affecting agricultural yields.

The stochastic stocks in the model are the result of variability of weather and pest infestations, the use of latent and proxy variables that have not accounted fully for the effects of underlying physical processes, and the influence of other effects that are uncontrolled for in the analysis (e.g., nitrogen carryover in the soil).

Assuming that prices are known with certainty or, more generally, that they are statistically independent of the production disturbance, this model that is based on the model derived by Just and Pope is combined with the FOC [equation (4)] based on the work of Antle (1989). Together these equations characterize the producer's optimal input choice. From equation (5), we can express the expected value and variance of net returns as:

(6) $$E[\Pi] = m_1 = f(X, Z, \alpha) - w'X,$$

(7) $$V[\Pi] = m_2 = E[\Pi - m_1]^2 = E[h^{1/2}(X, \beta)\epsilon]^2 = h(X, \beta)\sigma^2.$$

Input choices can be seen to affect variance either positively or negatively depending on the partial effect of the input on the function $h(\cdot)$. The effect of the input on yield variability is given by the sign of the partial effect of the input on the function $h(\cdot)$, h_X, where the subscript indicates the partial derivative with respect to the function's arguments. Substituting the derivatives of equations (6) and (7) with respect to input choice into equation (4) results in the following expression for optimal input choice:

(8) $$f_X + \frac{U_2}{U_1} h_X \sigma^2 = w.$$

This expression equates the value of the marginal product (f_X) to the normalized marginal input cost (w), with an adjustment term that represents a premium for risk. Assuming risk aversion ($U_2/U_1 < 0$), the adjustment term is either positive or negative depending on the sign of h_X (i.e., whether the effect of the input is risk increasing or risk decreasing). Given inputs that affect variance and the risk preferences of producers, these conditions demonstrate the importance of risk in influencing input choice.

Estimation Procedure

The aim of the empirical application described below is to use data obtained from cotton producers to estimate the marginal contributions of inputs—in particular, pest management practices—to yields (f_X) and to yield variability (h_X). In order to estimate these relationships using the stochastic production function specified in equation (5), some further analysis is necessary. Let per acre yield (Q) be given by:

(9) $$Q = f(X, Z, \alpha) + h^{1/2}(X, \beta)\epsilon,$$

where $E[\epsilon] = 0$; $V[\epsilon] = \sigma^2$; and $E[\epsilon_i\epsilon_j] = 0,\ i \neq j$.

Assuming the correct functional specification of the model, the parameter vector α can be estimated without bias using ordinary least squares (OLS). However, given the effect of X on the variance of Q, the estimates are not efficient since the variance of the model is not constant across observations. This is the definition of heteroskedasticity and results in estimated standard errors that are biased. The correction for this problem leads both to an efficient estimation of the parameter α and to the estimation of the effects of the inputs to yield variance (i.e., estimates of β).

To correct for heteroskedasticity, a feasible generalized least squares (FGLS) estimator is used. This estimator requires the estimation of the error covariance matrix, Ω^{-1}, which, given the cross-sectional data analyzed in the model, is assumed to be diagonal (i.e., yields are assumed to be independent among the fields in the sample).[5] The FGLS estimator is defined as:

$$\alpha^* = (X'\hat{\Omega}^{-1}X)^{-1}X'\hat{\Omega}^{-1}Q.$$

To estimate the error covariance matrix, the estimated residuals from the OLS estimation are used since they are consistent estimates of the true error distribution and, hence, can be used to estimate the effects of input use on yield variance and to obtain an estimate of the error covariance ($\hat{\Omega}^{-1}$). The estimated residuals are given by:

$$(10) \qquad \hat{u} = Q - f(X, Z, \hat{\alpha}) = f(X, Z, \alpha) - f(X, Z, \hat{\alpha}) + h^{1/2}(X, \beta)\epsilon = h^{1/2}(X, \beta)\hat{\epsilon},$$

where $\hat{\alpha}$ is the estimated vector of expected production parameters and $h^{1/2}(X, \beta)\hat{\epsilon}$ is the estimated random disturbance.

To obtain consistent estimates of $\hat{\beta}$, given consistent estimates of $\hat{u}$, requires a functional specification that is unknown and must be maintained as a joint hypothesis in the model. Two general forms of heteroskedasticity have been addressed in the literature, additive and multiplicative (see Kmenta for a discussion of each form). In practice, however, there is a preference for using the multiplicative form because it has the desirable property of maintaining predicted variances that are positive, whereas the additive model can result in predicting negative variances.[6] Based on an analysis of these data, Hurd presents a comparison of the estimation of both forms of heteroskedasticity and rejects the additive specification based on statistical performance.

Therefore, the following specification is defined to estimate the error covariance and the effect of inputs on variance:

$$(11) \qquad \ln(\hat{u}^2) = \ln(h(X, \beta)\hat{\epsilon}^2) = \ln(h(X, \beta)) + \ln(\hat{\epsilon}^2) = X'\beta + v,$$

where $v = \ln(\hat{u}^2/\sigma^2)$; $E[\epsilon] = 0$; $E[\epsilon_i\epsilon_j] = 0$; and $V[\epsilon] = \sigma^2$.

If ϵ is normally distributed and if $\hat{u}$ converges in distribution to u, then (since v is the logarithm of a normal variate that has been squared) v is distributed as the logarithm of a χ^2 divided by its degrees of freedom. Therefore, v will be distributed asymptotically with a mean and variance given by Harvey as: $E[v] = -1.2704$ and $V[v] = 4.9348$. The results of these properties include inconsequential bias in the estimation of the constant term and an asymptotic covariance matrix of $\hat{\beta}$, given by $4.9348(X'X)^{-1}$.

To summarize, the estimation procedure involves three steps. The first step concerns the empirical specification of the model and the use of OLS to obtain consistent estimates of $\hat{\alpha}$ and $\hat{u}$ in equation (10). Next, the estimated residuals ($\hat{u}$) are squared and transformed by taking natural logarithms and then regressed on the inputs to obtain consistent estimates of $\hat{\beta}$. In the final step, these estimates of $\hat{\beta}$ are used to construct a feasible generalized least squares estimate ($\hat{\alpha}^*$) that is both consistent and efficient. In the next section, the data used in the estimation are described.

Data and Model Specification

Research and development into improved pest control practices has aided agriculture in the pursuit of methods that are effective in controlling pests while minimizing the negative effects of pesticide use. In our sample, cotton growers in the San Joaquin Valley have demonstrated familiarity with IPM and many of its practices, with 77% of the growers rating themselves as at least moderate users of IPM and only 2.4% reporting that they were not familiar at all with IPM. It is estimated from this study that IPM methods are practiced, at least partially, on nearly 70% of the acreage surveyed.

The data used in this study were obtained in 1990–91 from a field-based survey of IPM methods used in the production of cotton. The data consist of production and pest control information from a sample of 165 cotton fields. The survey, administered to approximately 90 farm managers by National Agricultural Statistics Service (NASS) enumerators, was based on "area frame" sampling protocols to produce an acreage-based representative sample of fields; therefore, some farm managers provided information on more than one field. After adjusting for missing data, a random selection of 30 observations was also removed to provide the basis for model validation.[7] The following econometric analysis was based on 94 observations of individual fields.

The distributions of yields are illustrated in figure 1; the yields are normally distributed (refer to endnote #1 for statistical confirmation), with a mean of 1,233 pounds of lint per

Table 1. Summary Statistics of Variables

Variable	Definition	Units	Expected Effect	Mean	Standard Deviation
Q	Pounds of harvest lint per acre	lbs.		1,232.6	241.0
SOIL	Soil quality (scale 1–10)	subjective number	+	6.94	1.67
N	Total pounds of applied nitrogen	lbs.	+	162.0	91.39
HU	Total seasonal accumulation of degree days (60°F)	degree days	+	2,547.3	147.4
CLTVS	Number of cultivations for weeds	number	+	3.19	1.61
CLT_WDS	Interaction variable crossing number of cultivations with the sum of reported weed intensities	subjective number (0–5)	+	26.27	28.75
PESTCOST	Expenditure on pesticide applications	dollars	+	54.31	44.66
MONITOR	Total number of times the field was monitored	number	+	30.12	11.32
YRSIPM	Years practicing IPM	years	+	11.13	10.09
ROTATE	Non-cotton crop planted within previous two years	0, 1	+	.55	.50
CDM	Crop development monitoring used in field	0, 1	+	.73	.45
BP	Biological preserves used in field management	0, 1	+	.08	.27
INDPCA	Independent pest control advisor was consulted	0, 1	?	.49	.50
ADV	Number of annual contacts with extension service	number	+	6.64	9.70
AGE	Age of the primary field operator	years	+	46.7	13.0
EDUC	Highest grade completed by primary field operator	grades	+	14.5	2.5
YRSCOT	Number of years experience growing cotton	years	+	22.85	11.45
BGRASS	Intensity of Bermuda grass problem in field	subjective number (0–5)	−	.55	1.03
JGRASS	Intensity of Johnson grass problem in field	subjective number (0–5)	−	.69	1.23
VERT	Concern about verticillium wilt in field	0, 1	−	.47	.50
MITES	Concern about mite infestations in field	0, 1	−	.92	.27
LYGUSCT	Highest monitored count of lygus per 50 sweeps	count	−	10.05	13.31

acre (2.5 bales) and a standard deviation of 241 pounds. The data included information on the use of several IPM strategies recommended by University of California IPM guidelines ("Integrated Pest Management for Cotton in the Western Region of the United States") and by extension farm advisors (Goodell; Kirby; Leigh). Summary statistics of these variables and others included in the analysis are presented in table 1.

The factors hypothesized to affect yield and yield variability included both variable inputs and other factors that are fixed in the given time period or exogenous to the producer. There were a number of limitations on model selection imposed by the data. First among these limitations was the binary nature of many of the pest control measures. In most cases, this reflected the use (or nonuse) of the practice. This limitation greatly influenced the choice of a linear/quadratic specification by ruling out logarithmic transformations of many of the independent variables.

The primary focus of this research was to investigate the role and effects of IPM in the production process. The analysis considered six IPM practices that have been developed and promoted by University of California Extension personnel. These practices include:

(1) *Crop Rotation:* Regular rotation of crops is practiced to interrupt the life cycles of insect and weed pests.
(2) *Crop Development Monitoring:* Systematic monitoring of plant growth and stage of

development is useful to identify specific crop stresses related to agronomic and/or pest factors.

(3) *Independent Pest Control Advisor (PCA):* Independent PCAs do not have a financial interest in pesticide sales and therefore may be less likely to recommend chemical controls prematurely.

(4) *Biological Preserves:* The practice of providing buffering habitat for beneficial insects is intended to aid in the biological control of insect problems.

(5) *Farm Advisor Contact:* Local extension farm advisors facilitate the communication of changing local conditions and the experience and practices of other area growers.

(6) *Intensive Field Monitoring:* In addition to crop development monitoring, the regular and systematic scouting for insect and weed problems and the testing of soil conditions can alert farmers to changing field conditions.

Consideration was given to combining these IPM-use variables to form a single index reflecting IPM intensity. However, after considering a simple count model and various weighting strategies (including factor analysis), it was decided that more useful interpretations of the results were obtained by treating each practice independently and thus identifying the relative contributions from various practices. In addition to IPM factors, the analysis included several variables that proxy for management ability and experience. Age, education level, and cotton production experience each were hypothesized to contribute to the successful production of cotton.

Some inputs were unobserved and proxy variables were substituted in the model. For example, actual soil conditions were unobserved; however, the survey measured perceived soil quality (*SOIL*) on a subjective scale, where the "least capable soil" was equal to 1 and the "very best soil in the Valley" was equal to 10. This variable was modeled linearly since it is fundamentally an ordinal measure (i.e., it cannot be assumed that a soil rated at 8 is twice as productive as a soil rated 4). Due to differences in perceptions across growers and difficulties relating the subjective scale to a physical measure of soil quality, this proxy variable may be a source of bias in the model due to errors-in-measurement problems. Also unobserved was the actual level of nitrogen available for uptake by the crop. As a latent variable that should be correlated with available nitrogen, we used a measure of nitrogen applied during the season.

Another agronomic variable included in the analysis was a measure of photosynthetic potential. Based on the accumulation of degree days (a measure of heat units) during the length of the season, this measure is a latent variable for sunlight in the growing process. Ideally, the measure should reflect the accumulation of degree days from planting through harvest and would vary by field. Unfortunately, such information was unavailable and was approximated by location-specific measurements and assumptions on season length. This measurement problem can have implications for the interpretation of the results, given that heat units beyond those necessary for the crop to reach maturity do not contribute to yield.

The analysis was further conditioned by several important cotton pests that can reduce productivity. These pests were controlled independently in the analysis to facilitate the identification of the impacts of particular problems. However, there were some important difficulties in measuring pest intensity relating to both pest dynamics and grower perception of intensity. For the two weed species (i.e., Bermuda grass and Johnson grass), the analysis was based on two proxy variables for competition from weeds. The proxies were based on responses of growers to subjective questions asking them to estimate the "intensity" of the problem on a scale of 1 (no problem) to 5 (very significant problem). The effects of verticillium wilt and spider mites on the cotton were more difficult to measure. Treatments for each of these problems generally are considered on a "presence/absence" basis (i.e., either the problem exists or it does not). Therefore, our measures reflect this either/or response with a binary variable based on the subjective concern of the grower. The control for lygus bugs was more consistent with the physical effect of lygus which is dependent on the relative population size, since measurements were based on a systematic count system.

Table 2. Estimated Effects of Inputs on Expected Yields and Yield Variance (lbs./acre)

Independent Variables	Estimated Coefficients (t-Statistics)		
	1 ($\hat{\alpha}$)	2 ($\hat{\beta}$)	3 ($\hat{\alpha}^*$)
SOIL	42.93*	.10	26.34*
	(3.79)	(.49)	(2.74)
N	2.99*	.0048	2.96*
	(4.60)	(.35)	(4.56)
N^2	−.0078*	.000015	−.0067*
	(−5.18)	(.46)	(−3.61)
HU	3.62	−.017	4.52
	(1.05)	(−.27)	(1.24)
HU^2	−.00077	.0000029	−.00095
	(−1.13)	(.23)	(−1.34)
CLTVS	3.15	.47	−54.30
	(.093)	(.81)	(−1.43)
$CLTVS^2$	−7.70*	−.054	−.11
	(−1.89)	(−.87)	(−.026)
CLT_WDS	4.90*	.0076	4.50*
	(4.87)	(.58)	(3.33)
PESTCOST	−.099	.036	.99
	(−.077)	(1.48)	(.94)
$PESTCOST^2$	−.0074	−.00018	−.021*
	(−.96)	(−1.40)	(−3.73)
MONITOR	49.57*	−.032	39.91*
	(3.14)	(−.10)	(2.24)
ROTATE	109.76*	.57	124.23*
	(3.45)	(.91)	(12.79)
CDM	−70.65	.98	−40.80
	(−1.52)	(1.03)	(−.86)
BP	85.32	−.14	146.17*
	(1.39)	(−.11)	(2.44)
INDPCA	194.94*	.12	182.94*
	(4.82)	(.14)	(4.87)
ADV	7.00	.18	18.02
	(.71)	(.99)	(1.60)
ADV^2	.54	−.025*	−.40
	(1.04)	(−2.47)	(−.55)
BGRASS	−36.48	—	−115.30*
	(−1.16)		(−3.05)
JGRASS	−10.23	—	22.65
	(−.52)		(1.75)
VERT	−121.28*	—	−192.45*
	(−3.31)		(−5.70)
MITES	2.13	—	−6.27
	(.035)		(−.11)
LYGUSCT	−4.60*	—	.48
	(−2.07)		(.26)
AGE	−4.64	.15	3.74
	(−.45)	(.71)	(.30)
AGE^2	.074	−.0016	−.045
	(.65)	(−.70)	(−.31)
EDUC	63.65	1.67	82.94
	(1.04)	(1.40)	(1.52)
$EDUC^2$	−1.97	−.065	−2.56
	(−.84)	(−1.45)	(−1.26)

Table 2. Continued

Independent Variables	Estimated Coefficients (t-Statistics) 1 ($\hat{\alpha}$)	2 ($\hat{\beta}$)	3 ($\hat{\alpha}^*$)
YRSIPM	−9.09	.19	−3.73
	(−1.36)	(1.39)	(−.65)
YRSIPM^2	.096	−.0058	.0080
	(.53)	(−1.56)	(.049)
YRSCOT	15.50*	.058	6.23
	(2.59)	(.51)	(.96)
YRSCOT^2	−.25*	−.0011	−.013
	(−1.98)	(−.45)	(−.089)
INTERCEPT	−4,853.9	13.65	−5,870.00
	(−1.09)	(.17)	(−1.26)
Adjusted R^2	.798	.191	.790
Mean of Dependent Variable	1,250.2	7.21	1,250.2
Sample Size = 94			

* Indicates a coefficient is statistically significant at the 5% level.

Cotton is a significant consumer of water in the San Joaquin Valley. Since 1990 was the fourth year of drought in this study area, water use was a highly sensitive issue and one that many growers were reluctant to discuss; as a result, there were many missing values for the quantity of water applied to the fields. Although state and federal water deliveries to growers were reduced slightly, cotton production did not appear to be affected significantly. Experts did not expect significant changes in water and crop allocation until the fifth year of drought. Since many growers have the capacity to supplement their surface water allotments with groundwater, and none of the growers indicated that their irrigation schedules were deficient, it does not appear that production practices were water-constrained because of the drought during the 1990 growing season. We assume in our empirical model, therefore, that sufficient water to grow the crop was available to all fields planted to cotton.

In specifying the functional form of the equations estimated, limitations on the types of data required a combined linear and quadratic specification. The quadratic specification allowed the model to reflect diminishing returns for many of the modeled inputs. However, in contrast to a logarithmic specification, the quadratic specification can produce results that are contrary to expectation. For example, the quadratic specification can result in estimating negative marginal products for input quantities beyond a certain range. In some cases this is consistent with expectations in which too much of a particular input may be detrimental; however, in general, the normal range of the input would correspond to a positive marginal product.

Results

Estimation results from the econometric analysis are presented in table 2 and some economic interpretation of the statistically significant results is provided in table 3. Columns labeled 1, 2, and 3 in table 2 depict coefficient estimates and t-statistics for the first-stage application of OLS on yields, for the second-stage variation models, and for the corrected FGLS model of the contribution of inputs to expected yields, respectively. These parameter estimates and associated t-statistics indicate the magnitude and strength of the relationships among various inputs, pest control practices, pest levels, and management variables and the expected value and variance of yields.

Table 3. Estimated Value of Marginal Products and Elasticities of Yield Mean and Variance

Inputs (Variable Name)	Estimated Value of Marginal Product of Input[a] PQ_{X_i}	Estimated Percentage Change in Yield Due to a Percentage Change in Input (@ variable mean) $\frac{\% \Delta Q}{\% \Delta X_i}$	Estimated Percentage Change in Yield Variance Due to a Percentage Change in Input (@ variable mean) $\frac{\% \Delta \sigma^2}{\% \Delta X_i}$
Soil (*SOIL*)	20.01	.15	—
Nitrogen (*N*)	.59	.10	—
Cultivations[b] (*CLTVS*)	12.92	.044	—
Monitoring Frequency (*MONITOR*)	5.30	.17	—
Crop Rotation (*ROTATE*)	94.42	.055	—
Pesticide Expenditure[c] (*PESTCOST*)	−.97	−.057	—
Biological Preserves (*BP*)	111.09	.009	—
Farm Advisor Contact (*ADV*)	—	—	−.00081
Independent PCA (*INDPCA*)	139.03	.073	—
Bermuda Grass (*BGRASS*)	−87.63	−.051	—
Verticillium Wilt (*VERT*)	−146.26	−.073	—

[a] Calculated at the average expected cotton price of \$.76/lb.
[b] Assumes moderate weed problems with four weed species (i.e., *WEEDS* = 16).
[c] Yields are increasing in *PESTCOST* up to an expenditure of \$23 per acre.

To express the estimation results more clearly, the associated estimates of elasticities and the values of the marginal products for the variables that were statistically significant are shown in table 3. The elasticity measures were calculated at the mean values reported for yield and inputs, and indicate the percentage changes for yields and variance expected to result from a percentage change in the level of the input. For example, from column 1, an increase in soil quality by level is estimated to add \$20 to expected net returns per acre.

Consider first the effects of the inputs and management factors on expected yield. Of the six IPM variables in the model, crop rotation (*ROTATE*), frequency of field monitoring (*MONITOR*), and the use of an independent pest control advisor (*INDPCA*) contribute significantly to yields, and after the correction for heteroskedasticity, the use of biological preserves (*BP*) also contributes significantly. The hypothesis that information provided by crop development monitoring (*CDM*) and farm advisor contact (*ADV*) contributes to yields is not supported by the evidence from this model. The coefficients on farm advisor contact (*ADV* and ADV^2) have the expected signs, indicating diminishing marginal productivity to farm advisor contact; however, they fall below typical levels of statistical significance, as do the estimates for crop development monitoring (*CDM*).

The significance of crop rotation is underscored in this analysis both by its statistical significance (t-statistic = 12.8) and its economic significance. The recent planting of crops other than cotton contributed nearly $94 per acre on average to gross returns (see table 3). The benefits from crop rotation, in enhancing nitrogen carryover and in avoiding the establishment of weed problems and other pests, have long been acknowledged by agronomists. This result indicates that, within this sample, rotated fields out-perform those that are not under a regular rotation schedule.

Due to the very small sample of growers reporting the use of biological preserves (only 13), the estimated yield effects and value of marginal product (*VMP*) associated with biological preserves are not well supported in the analysis. The estimated *VMP* of $111 is a surprisingly high value from a practice that does not contribute directly to productivity, but rather provides a habitat for beneficial insects and a trap crop for damaging pests. Biological preserves cannot be expected to perform as well as the estimates indicate, but should be considered as a subject for future research.

A second surprising result concerns the expected contribution from employing an independent pest control advisor. The estimated *VMP* of $139 is clearly a surprising result, and one that cannot be dismissed as a result of low frequency in the sample. Forty-six percent of the sample reported the use of in-house entomologists or independent pest control advisors. The expectation was that pest control advice would differ only slightly between chemical company representatives and independents, and thus it would be important to gather data on actual practices and not just source of advice, as had been done in many previous IPM studies (e.g., Hall; Burrows; Farnsworth and Moffitt). This unexpected result suggests that the quality of the advice may indeed be a function of its source and price.

Expenditures on pesticides ($PESTCOST$ and $PESTCOST^2$) perform according to expectations, with diminishing marginal returns. According to this specification, however, the marginal return to pesticides becomes negative after $23 per acre are expended. This result is consistent with the understanding that with increasing severity of pest problems, yields are likely to fall in spite of increasing pesticide expenditures. Several researchers have reported similar findings in attempts to measure the productivity of pesticides (e.g., Miranowski; Farnsworth and Moffitt). Farnsworth and Moffitt, estimating a stochastic production model using cotton production data from the early 1970s, found that greater insecticide use was associated with higher variance and lower expected yields. Again, the role of pesticides as a damage-control input suggests that their use will be greatest when pest damage is expected to be high.

Evidence of the detrimental effects of pests is found in the model. Significant losses of 115 lbs./acre and 192 lbs./acre are attributed by the model to both Bermuda grass (*BGRASS*) and verticillium wilt (*VERT*), respectively. The evidence from insect and arachnid pests (e.g., lygus and mites) was less clear. In the first-stage estimation, lygus was found to be significantly harming yields; however, the corrected model no longer supports a significant relationship.

The performance of the agronomic variables, soil (*SOIL*) and nitrogen (N and N^2), was consistent with expectations, with the latter indicating diminishing marginal returns. The coefficients on heating units (HU and HU^2) had the correct sign; however, they were not statistically significant. Cultivations for weed control ($CLTVS$, $CLTVS^2$, and CLT_WDS) appear to be effective and economical when there are significant weed problems present in the field.

While management ability and experience are expected to be productive assets in agriculture, the results do not support a systematic relationship between the management proxies (i.e., age, education, and cotton production experience) and yields. Experience growing cotton ($YRSCOT$ and $YRSCOT^2$) is significant, with expected signs on the coefficients in the initial OLS estimation, but it loses significance after correction for heteroskedasticity. Age (AGE and AGE^2) and education ($EDUC$ and $EDUC^2$) of the operator both have estimated coefficients with the expected sign (i.e., indicating diminishing marginal returns); however, neither achieves statistical significance. In either case, the magnitude of the coefficient indicates a relatively small effect associated with years of experience.

Considering the effect of these variables on the variability of yields, no support was found in this study for the view of pesticides as a risk-reducing input, as has been suggested by previous theoretical research (e.g., Antle 1989; Robison and Barry). Pesticide expenditures, regardless of the estimation specification, were found not to have any statistical relationship to the variance of yields. This is a significant finding because "excessive" pesticide use commonly is rationalized by the argument that the excess of the marginal cost over the expected value of the marginal product could be interpreted as a risk premium paid by risk-averse producers.

The only significant factor in explaining yield variance in this model was the frequency of farm advisor contact (*ADV* and ADV^2). The estimated coefficients for farm advisor contact indicate that yield variability begins to fall after four contacts per season. This is a curious result given that farm advisor contact is not significant in explaining expected yields; however, it is consistent with the expectation that frequent farm advisor contact is an effective information source, particularly if this information is sought several times throughout the growing season. In this model, neither pesticides nor IPM practices appeared to contribute to yield variability.

Conclusions

In this article, economic theory has been used to illustrate the importance of distributional attributes in affecting models of choice and behavior. These models of choice and behavior provide a foundation for an understanding of how individuals are likely to respond to changes in perceived risks and incentives. The adoption and use of new technologies in agriculture can be better understood and facilitated by the use of these models and their empirical investigation.

This examination of inputs, yields, and yield variability has shown that flexible models of production risk are valuable for analyzing the relationships between inputs and outputs, and can be useful for the assessment of new and changing technologies such as IPM. As research, development, and implementation of strategies and methods of pest control continue, and as farmers seek to reduce their losses from pest damage, statistical evidence is an important informational tool to improve decision making at a variety of levels.

The evidence found in this study confirms the important role of many production inputs such as soil quality, nitrogen, and crop rotation, and additionally identifies practices that have not been widely observed as important such as monitoring, independent pest control advice, and the potential of biological controls. The evidence further suggests that concern about the effects of these inputs on yield variability may be overblown. There was no empirical support suggesting that pesticides reduced risk, nor was there support for the claims that IPM is a "risky" technology. In fact, the evidence suggested that frequent contact with local extension advisors may serve to reduce risk. Analysis of the marginal risks for other commodities or for other regions may indicate that some pest control practices do increase or decrease yield variability significantly and, therefore, risk attributes of technology ought to remain a concern for producers.

Because the prevailing view of integrated crop and pest control systems for many commodities involves both inter- and intra-seasonal production diversity, the analysis of firm-level marginal risks should, when feasible, be structured in terms of a whole-farm approach. This suggests future research should consider a broader range of production that involves multiple crops and production over time. Additionally, pest control research needs to better incorporate the methods of analyzing the productivity of damage control inputs, and this requires methods for the measurement of crop damage (e.g., yield loss). This in turn requires a program of monitoring and the calibration of a model that measures the relationship between pest levels and production loss, neither of which were available for this study. Adoption of these suggestions would provide a more complete framework for the analysis of marginal risk in production and for the assessment of pest management practices that frequently involve production diversity and inter-temporal practices and effects.

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Notes

[1] This model can be generalized to include higher moments, as has been done by Antle (1983). There is a certain appeal to the relevance of the third moment (skew) in that risk-averse economic agents are particularly concerned about downside risk. However, in this study, there did not appear to be empirical support for extending the analysis beyond the first two moments. An analysis of the distribution of yields confirms the normality that appears in figure 1. The Shapiro–Wilk statistic, W, was computed to test the normalcy of the data. The resulting value ($W = .981$) is associated with a significance level of .48, so clearly the hypothesis of a normal distribution cannot be rejected. Based upon this result, we restrict our analysis to the first two moments.

[2] Later in this article, this production parameter will be partitioned into a mean effect (α) and a variance effect (β).

[3] The utility model that has been developed has as its arguments the moments of the distribution of total profits per season. Since the model has implicitly treated the marginal utility of wealth as constant across growers and ignores dynamic considerations such as investment, it should be viewed only as an approximation of the behavioral process of the grower. The approximate nature of the utility model is carried one step further below, as constant returns to scale are assumed. This assumption enables the analysis to consider per acre formulations of profit and production. On a per field basis, this assumption is clearly viable since growers typically manage fields and not specific acres within that field; however, they base many of their decisions on costs and yields that frequently are measured on a per acre basis. Consistent with the empirical observation that production scale did not affect either the expected yield or yield variance, discussion of profit and production analysis throughout this article will continue to indicate a per acre basis.

[4] This function is raised to the ½ power to allow a more convenient treatment of variance.

[5] This assumption may not hold strictly due to the fact that some fields in the sample were not independently managed. However, the sample included approximately 90 different managers who can be assumed to be reasonably independent. Given the small sample of potentially dependent fields, there is no reasonable method to account for systematic spatial autocorrelation in these data.

[6] Antle (1983) proposed a solution to this problem by using nonlinear programming methods to constrain the estimated variances to be positive. This procedure was rejected for this analysis due to a lack of theoretically justified support of the additive model and the unknown consequences on the estimated coefficients resulting from the binding of the nonnegativity constraints in a programming model.

[7] The sample of 30 observations was randomly pulled from the data prior to any estimation or data analysis. This sample of 30 observations provided a method of validating the model results by using the estimated model to predict out-of-sample observations. The results of this test indicate that the model has significant predictive ability (less than 10% error for most observations; see Hurd). The remaining loss in observations was due to missing or unreported data. It is not expected that these missing data were systematically related to the sample, and therefore this loss is not expected to adversely bias the sample.

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