Cotton Production Under Risk:  
An Analysis of Input Effects on  
Yield Variability and Factor Demand

Richard L. Farnsworth and L. Joe Moffitt

The risk flexible production model developed by Just and Pope is estimated for the case of cotton in California's San Joaquin Valley and the implications of the model for factor demand are examined. Results indicate risk-reducing roles for farm machinery, labor, and fertilizer in contrast to restrictions imposed by traditional stochastic production specifications. Qualitative assessment of estimated risk effects on factor employment under risk aversion are evaluated by comparison to the risk-neutral solution.

The lead U.S. agriculture maintains in worldwide production of food and fiber can be attributed largely to the use of innovative, energy-intensive farm machinery and contemporary farming practices, such as irrigation, fertilization, and pest management. However, the public has become more concerned in recent years over the possible adverse effects of agricultural inputs on the environment and society as a whole; e.g., both pesticides and farm mechanization are now controversial issues. For intelligent regulation of the use of productive factors, government agencies must be aware of the roles various inputs play in production and the implications of their roles on factor employment.

For example, farm machinery may be employed to reduce uncertainty associated with labor supply during harvest. Analyses of policies designed to mitigate farm labor displacement should account for this effect. Additionally, pest control input usage is supposedly influenced by production risk considerations [Feder]. Since these inputs may be used both to increase output and to decrease output variability, changes in the availability of pesticides have implications regarding variability of output. Production function analyses of regulation should account for this potential impact. Such models of the productive process should be sufficiently flexible to assess the impacts of inputs on both absolute output and output variance. Unfortunately, a review of previous empirical and theoretical production studies indicates little or no attention has been directed toward the issue of input effects on output variability. Traditional models have implicitly introduced assumptions that prevent the opportunity to investigate this issue.

Just and Pope recently showed the unduly restrictive nature of traditional stochastic models of agricultural production processes. Their results demonstrate that for the class of traditionally specified log-linear stochastic production functions — including the Cobb-Douglas, translog, generalized power, CES, and transcendental — the marginal impact of an input on yield variability and marginal product are always positive and always negative, respectively. To facilitate more flexibility regarding risk in both empirical and theoretical investigations, they proposed a technical relationship incorporating separate effects of inputs on the mean and variance of output. Our purpose here is to provide an empirical test of this production framework to determine if a priori assumptions regard-
ing the impact of input use on yield variability are supportable and to consider implications of the empirical results for derived demand.

Production Model and Derived Demand

The general form of the production function employed for this study is

\[ y = f(x;\alpha) + h^{1/2}(x;\beta)\varepsilon \]

where \( E[\varepsilon] = 0 \); \( E[\varepsilon^2] = 1 \); and \( y \) is output, \( x \) is a vector of inputs, \( \alpha \) and \( \beta \) are vectors of unknown parameters. Just and Pope developed this production model and its properties with emphasis on its flexibility with respect to an input’s impact on the variance of output.

The risk-flexible technology depicted in equation (1) may be incorporated into a firm decision model and implications for derived factor demand can be examined if very specific assertions regarding firm behavior and technology are made in the conceptual development of the demand model. First, it is assumed that the firm produces output subject to the technical conditions expressed in (1) and that the error term, \( \varepsilon \), is distributed according to the standard normal density. Second, product price, \( p \), and a k-vector of input prices, \( \gamma \), are assumed known and given. Third, firm behavior is characterized by selection of a k-vector of inputs, \( x \), to maximize expected utility, \( E[U(\cdot)] \), a monotonic function of profit, \( \pi \).

Under these assumptions, a firm’s objective function is given by

\[ E[U(\cdot)] = \int_{-\infty}^{\infty} U(\xi)g_\pi(\xi)\,d(\xi) \]

where \( \pi = p[f(x;\alpha) + h^{1/2}(x;\beta)\varepsilon] - \gamma'x \) and

\[ g_\pi(\xi) = \left[2\pi p^2h(x;\beta)\right]^{-1/2} \exp \left(-\frac{1}{2}\frac{(\xi - pf(x;\alpha) + \gamma'x)^2}{ph^{1/2}(x;\beta)}\right) \]

Fourth, it is further assumed that the firm’s decision-maker exhibits constant risk averse behavior characterized by the following exponential function:

\[ U(\xi) = a - b \exp[-c\xi] ; a, b, c > 0 \]

Hence:

\[ E[U(\pi)] = a - b \exp[-c(pf(x;\alpha) - \gamma'x) + (1/2)[cph^{1/2}(x;\beta)]^2] \]

and necessary conditions characterizing the firm’s postulated optimal behavior require that

\[ \frac{\partial E[U(\pi)]}{\partial x_i} = 0 ; i = 1, 2, \ldots, k \]

or that

\[ p\frac{\partial f(x;\alpha)}{\partial x_i} = \gamma_i + (1/2)cp^2 \left[\frac{\partial h(x;\beta)}{\partial x_i}\right] ; i = 1, 2, \ldots, k \]

Sufficient conditions indicate that the matrix with elements \( H_{ij} \) given by

\[ H_{ij} = p[p^2f(x;\alpha)/(\partial x_i\partial x_j)] - (1/2)cp^2 \left[\frac{\partial h(x;\beta)}{\partial x_i\partial x_j}\right] ; i, j = 1, 2, \ldots, k \]

is negative definite. Thus, equation (2) suggests that a firm employs an input to the point of equality between the value of marginal product and the input price plus a term involving the marginal effect of the input on risk.

In the case of risk-increasing inputs (derivative of \( h(\cdot) \) positive), strict concavity of the mean of output satisfies conditions for a local maximum by equation (3). On the other hand, for risk-reducing inputs (derivative of \( h(\cdot) \) negative), optimality requires the value of marginal product to be steeper than the subjective value of the marginal impact on risk. As an illustration, the value of marginal product (VMP) and “value of marginal risk” (VMR) curves depicted in Figure 1 for the

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1The exponential utility was chosen to simplify computations.
case of a risk-increasing and risk-reducing input satisfy these conditions. Likewise, a corresponding derived input demand function for a risk-reducing and a risk-increasing input is also shown in Figure 1. Note that in this figure the value of marginal product curve is shifted according to the marginal effect of the input on risk. Specifically, at input price $\gamma_i$, employment of input $x_i$ is displaced from its level under risk neutrality, $x_i^0$, to either $x_i^1$ or $x_i^2$ when risk aversion is introduced. Only a downward shift is permitted when the traditional stochastic production model is combined with risk-averse behavior. Figure 1 depicts the intuitive hy-
The hypothesis that risk averse behavior implies more (less) of an input is employed if it has a decreasing (increasing) impact on risk than would be employed in the absence of risk aversion.

**Estimation**

Coefficient estimates based on (2) are difficult to obtain directly due to problems of identifiability. However the production model in equation (1) may be independently estimated, and resulting estimates can be used with other data to make inferences about input demand. The latter procedure is used in this empirical analysis. Consistent and efficient estimation of the parameters in equation (1) is provided by the following four-step procedure:

1. **Stage 1** Application of nonlinear ordinary least squares to:
   \[ y_t = f(x_t; \alpha) + u_t \]
   to obtain \( \hat{\alpha} \) and \( \hat{u}_t = y_t - f(x_t; \hat{\alpha}) \).

2. **Stage 2** Application of ordinary least squares to:
   \[ \ln|u_t| = \ln[h^{1/2}(x_t; \beta)] + v_t = (1/2)\ln(u_t^2) \]
   to obtain \( \hat{\beta} \).

3. **Stage 3** Application of nonlinear generalized least squares to:
   \[ y_t = f(x_t; \alpha) + u_t \]
   with consistent covariance matrix estimate developed from the results of stage 2. Results provide, \( \alpha^* \), an efficient estimate of \( \alpha \).

4. **Stage 4** Application of linearized maximum likelihood to obtain an efficient estimate of \( \beta \) given by:
   \[ \beta^* = \hat{\beta} + .6352e_1 - 1/2 \left[ \sum_{t=1}^{T} 1n x_{it} 1n x_{it} \right]^{-1} \]
   \[ \sum_{t=1}^{T} [1 - \hat{u}_t^2 \cdot \exp(-21n x_{it} (\hat{\beta} + .6352e_1))] 1n x_{it} \]
   where \( \hat{\alpha} \) and \( \hat{\beta} \) are defined in Stages 1 and 2 respectively, and \( e_1 \) is a \( k \)-vector with first element 1 and remaining elements zero.

In the following estimation, the four-step method is applied to a Cobb-Douglas production function which incorporates the stochastic aspects of (1), and is given by

\[ y_t = \alpha k x_{it}^{\alpha_i} + \beta k x_{it}^{\beta_i} \varepsilon_t; \]
\[ t = 1, 2, \ldots, T \]

where
\[ E[\varepsilon_t] = 0 \text{ and } E[\varepsilon_t \varepsilon_{t'}] = \begin{cases} 1, & \text{if } t = t' \\ 0, & \text{otherwise} \end{cases} \]

**Data**

The data used to estimate the model in equation (4) consist of records from a random sample of 41 cotton growers in California’s San Joaquin Valley. The data pertain to yield and input levels in 1974.\(^2\) Variables included in the model are:

- \( y_t \) = cotton lint (pounds per acre)
- \( x_{1t} \) = irrigation (acre feet per acre)
- \( x_{2t} \) = labor (dollars per acre)
- \( x_{3t} \) = machinery (dollars per acre)
- \( x_{4t} \) = fertilizer\(^3\) (pounds per acre)
- \( x_{5t} \) = insecticides\(^4\) (pounds per acre)

Table 1 presents summary statistics, the matrix of simple correlation coefficients of the data, and F-statistics which were used on an

\(^2\)The use of cross-section data raises the possibility of estimation bias which can result from omitted interfirm factors. The extent of such bias is an empirical question dependent on the data set under consideration. The absence of suitable managerial variables prevents investigation of the extent of this bias.

\(^3\)Fertilizer use included manure as well as the popular chemical fertilizers.

\(^4\)Includes miticides.
Cotton Production Under Risk

TABLE 1. Data Summary Statistics\(^a\).

<table>
<thead>
<tr>
<th>Item</th>
<th>Lint</th>
<th>Irrigation</th>
<th>Labor</th>
<th>Machinery</th>
<th>Fertilizer</th>
<th>Insecticides(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>976.424</td>
<td>3.071</td>
<td>79.564</td>
<td>127.352</td>
<td>2641.550</td>
<td>14.857</td>
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<tr>
<td><strong>Standard Deviation</strong></td>
<td>211.263</td>
<td>1.182</td>
<td>48.739</td>
<td>73.738</td>
<td>5129.560</td>
<td>16.377</td>
</tr>
<tr>
<td><strong>F-statistic</strong></td>
<td>-2.083</td>
<td>1.489</td>
<td>.840</td>
<td>2.074</td>
<td>1.331</td>
<td></td>
</tr>
</tbody>
</table>

Matrix of Simple Correlation Coefficients

<table>
<thead>
<tr>
<th>Item</th>
<th>Lint</th>
<th>Irrigation</th>
<th>Labor</th>
<th>Machinery</th>
<th>Fertilizer</th>
<th>Insecticides(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cotton lint</strong></td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Irrigation</td>
<td>.197</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor</td>
<td>.198</td>
<td>-.065</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machinery</td>
<td>.278</td>
<td>-.184</td>
<td>.260</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fertilizer</td>
<td>.047</td>
<td>-.194</td>
<td>-.205</td>
<td>.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Insecticides</td>
<td>.066</td>
<td>.373</td>
<td>.107</td>
<td>-.203</td>
<td>-.109</td>
<td>1.000</td>
</tr>
</tbody>
</table>

\(^a\)Based on 1974 data, sample size = 41.
\(^b\)Includes miticides.

F-test for evaluation of collinearity in variables (see Farrar and Glauber).

Production Estimates

Just and Pope show that the traditionally specified Cobb-Douglas production function is a special case of the risk-flexible production function (1) when, among other conditions, \( \alpha_i = \beta_i; i = 1,2, \ldots , k \). Hence for comparison purposes, Table 2 reports both the usual stochastic production model, estimated in log-linear form by ordinary least squares, and the risk flexible model of equation (4).\(^6\) Least squares estimates (shown in the first column of numbers) indicate positive output elasticities for all inputs; however, none of the coefficient estimates are significantly different from zero. The corresponding efficient output elasticity estimates of the risk-flexible formulation (reported in the fifth column of Table 2) differ considerably from the ordinary least squares results; moreover, all input coefficients are significant, with the notable exception of insecticides. The latter coefficient possesses a negative sign and is statistically insignificant. Furthermore, efficient estimates of risk impacts (presented in column 6) reveal statistically significant risk-increasing and reducing roles for irrigation and farm machinery, respectively. For the remaining inputs, parameter estimates of labor and fertilizer suggest risk-reducing impacts whereas the parameter estimate for insecticides suggests a risk-increasing impact on output. Considering the different parameter estimates resulting from the alternative model specifications, the hypothesis, \( \alpha_i = \beta_i \), was tested to aid in model selection. Application of Hotelling’s \( T^2 \) test led to rejection of the hypothesis \( \alpha_i = \beta_i \), which suggests that the risk-flexible form is more appropriate than the traditionally specified Cobb-Douglas production function.

Input Productivities and Risk Impacts

In empirical work, the usefulness of the risk-flexible model lies in its ability to sepa-
TABLE 2. Estimates of Risk Flexible Production Function for Cotton, San Joaquin Valley, California

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Ordinary Least Squares</th>
<th>4-Step</th>
<th>4-Step</th>
<th>4-Step</th>
<th>4-Step</th>
<th>4-Step</th>
<th>4-Step</th>
<th>Direction of Impact</th>
</tr>
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<tr>
<td></td>
<td>( \hat{\alpha}_i )</td>
<td>( \hat{\alpha}_i )</td>
<td>( \hat{\beta}_i )</td>
<td>( \hat{\beta}_i )</td>
<td>( \hat{\alpha}_i )</td>
<td>( \hat{\beta}_i )</td>
<td>Mean</td>
<td>Variance</td>
</tr>
<tr>
<td>Constant</td>
<td>5.9549</td>
<td>5.3639</td>
<td>8.1681</td>
<td>4.5907</td>
<td>7.1502</td>
<td></td>
<td></td>
<td>+</td>
</tr>
<tr>
<td>Irrigation</td>
<td>.1964</td>
<td>.2409</td>
<td>.5153</td>
<td>.2121</td>
<td>.4902</td>
<td></td>
<td></td>
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<td></td>
<td>(.1144)</td>
<td>(.0980)</td>
<td>(.4007)</td>
<td>(.0606)</td>
<td>(.2869)</td>
<td></td>
<td></td>
<td>+</td>
</tr>
<tr>
<td>Labor</td>
<td>.0005</td>
<td>.0167</td>
<td>-.0516</td>
<td>.1052</td>
<td>-.0608</td>
<td></td>
<td></td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>(.0282)</td>
<td>(.0352)</td>
<td>(.0989)</td>
<td>(.0429)</td>
<td>(.0708)</td>
<td></td>
<td></td>
<td>- e</td>
</tr>
<tr>
<td>Machinery</td>
<td>.1101</td>
<td>.1699</td>
<td>-.4349</td>
<td>.2666</td>
<td>-.3452</td>
<td></td>
<td></td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>(.0713)</td>
<td>(.0678)</td>
<td>(.2496)</td>
<td>(.0576)</td>
<td>(.1788)</td>
<td></td>
<td></td>
<td>- e</td>
</tr>
<tr>
<td>Fertilizer</td>
<td>.0245</td>
<td>.0415</td>
<td>-.1824</td>
<td>.0492</td>
<td>-.0867</td>
<td></td>
<td></td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>(.0304)</td>
<td>(.0243)</td>
<td>(.1065)</td>
<td>(.0183)</td>
<td>(.0763)</td>
<td></td>
<td></td>
<td>- e</td>
</tr>
<tr>
<td>Insecticides</td>
<td>.0086</td>
<td>.0052</td>
<td>.0228</td>
<td>-.0139</td>
<td>.0058</td>
<td></td>
<td></td>
<td>- e</td>
</tr>
<tr>
<td></td>
<td>(.0202)</td>
<td>(.0193)</td>
<td>(.0707)</td>
<td>(.0158)</td>
<td>(.0506)</td>
<td></td>
<td></td>
<td>+</td>
</tr>
</tbody>
</table>

aBased on 1974 data, sample size = 41.
bAssumes multiplicative, homoscedastic disturbances.
cIncludes miticides.
dNumbers in parentheses are estimated asymptotic standard errors.
eIndicates a change in sign from traditional stochastic specification.

rate the effect each input has on mean output and variability of output. Since traditional production models have confounded these effects, it is important to assess each input's separate effects qualitatively and to compare with commonly held beliefs in the agricultural community.

Irrigation positively affects mean yield and yield variability (columns 7 and 8 of Table 2). As expected, this input has a positive marginal product, yet it also increases output variability. The risk-increasing aspect of irrigation may appear counterintuitive since establishment of an irrigation schedule supposedly mitigates the role played by nature in the production process. Several illustrations complicate this supposedly simple hypothesis. For example, irrigation may interact positively with random variations in weather variables such as sunlight and temperature, to promote above average yields. On the other hand, growth problems associated with an insufficient number of degree days are exacerbated by an irrigation schedule that could further lower soil temperature and contribute to plant disease. Moreover, the ability of growers to respond to other farm management problems is somewhat restricted during periods when irrigation limits mobility in the field. Finally, California-based agricultural consultants have noted the major role of irrigation in aggravating farm problems, such as crop protection and crop nourishment.

Each of the next three inputs in Table 2 — labor, machinery, and fertilizer — has the same sign configurations, suggesting a positive marginal product and a risk-reducing role in production. In the cases of labor and machinery, increasing these inputs should permit growers to respond more rapidly to problems, particularly during harvest when a rapid response may be crucial in reducing crop losses. Finally, fertilizers appear to reduce yield variability perhaps by helping maintain plant vitality despite adverse weather conditions or agricultural pests that find the fertilizer-induced overgrowth a prime breeding ground and unlimited food source.

Most surprising and interesting in Table 2 are the apparently anomalous results for insecticides. Although both estimates of marginal product and the impact on output vari-
bility are insignificant, the signs are the op-
posite of what one might ordinarily expect.
Several prior production studies [Headley,
Fischer, Campbell] indicate large and signifi-
cant mean returns to insecticide treatments
and thereby foreshadow potentially large
costs for regulating insecticide use. It is also
generally accepted that growers apply addi-
tional insecticides as a form of self-insurance
against losses. Justification for insurance-
spraying centers around the idea that insec-
ticides reduce the likelihood of pest popula-
tions attaining economically damaging levels.

Nevertheless, closer scrutiny of the most
recent pest management economics litera-
ture indicates several factors which satisfac-
torily explain the finding in this study. First,
depletion of the effectiveness of the insec-
ticide arsenal (increased degree of resistance
by insects), resurgence, and secondary pest
outbreaks threaten the viability of insec-
ticides in agricultural production. For exam-
ple, Carlson's analysis of nationwide cross-
section data during three separate years indi-
cates a decining expenditure elasticity for
insecticides over time that was not signifi-
cantly different from zero in the most recent
year considered (1969). Second, Feder used
decision analysis to show that excessive in-
ssecticide use by risk-averse growers may oc-
cur. Hence, in the presence of overuse and
decling effectiveness, parameter estimates
indicating substantial gains from additional
insecticide application might not be expect-
ed. Third, insecticide elasticity estimates
based on cross-section data, which include
the previously cited reports, are conditioned
on the typically used level of the pest
population. Extraneous qualitative evalua-
tion here indicates that relevant infestation
levels were quite low during the sample
period, thus further limiting the importance
of insecticides in the production process.

Finally the phytotoxic effects of insecticides
on plants cannot be ruled out. In summary,
the negative sign attached to insecticides
may be attributed to these factors or to sam-
pling variation. Additional research is neces-
sary to verify the trend of declining effec-
tiveness of insecticides and to identify the
relevant factors.

Factor Demand

Expected marginal productivities and ex-
pected marginal impacts of input use on yield
variability were evaluated and are reported
in Table 3. Table 4 shows the expected value
of marginal product and average input prices
paid by farmers in the San Joaquin Valley of
California. Earlier behavioral postulates indi-
cate that the value of marginal product ex-
ceds factor price for risk-increasing inputs
and is less than factor price when an input
functions so as to reduce risk. The following
results were obtained for irrigation, labor,
and fertilizer. The value of marginal product
for irrigation exceeds unit cost, whereas for
the risk-reducing inputs, labor and fertilizer,
the opposite occurs. Results in the cases of
fertilizer and irrigation are highly significant.
Implied factor demands under constant risk
aversion indicate decreased (increased) em-
ployment of risk-increasing (risk-decreasing)
inputs compared with the risk neutral solu-
tion for a range of risk coefficients. This result
is most evident in the case of risk-reducing
inputs. Thus, in particular, these inputs tend
to support a priori expectations regarding
derived demand under risk.

Conclusions

This paper investigates the supposedly
twofold role inputs have on mean output and
output variability and assesses qualitatively
what effect risk impacts may have on factor
employment. The traditionally specified
Cobb-Douglas production function and the
risk-flexible production function, developed
by Just and Pope, were estimated and com-
pared. Based upon the available cross sec-
tional sample data obtained from 41 Califor-
nia cottongrowers, the econometric analysis led to rejection of the hypothesis implicitly assumed in the Cobb-Douglas production function; namely, that all inputs increase output variability. Results from estimating the risk-flexible production function for cotton suggest a significant risk-increasing role for irrigation and a significant risk-reducing role for farm machinery. Results also indicate labor and fertilizer reduce yield variability and insecticides increase yield variability.

Given the quantitatively different roles inputs have on output variability, a simple decision model was specified to aid in qualitative assessment of risk effects on factor demand. The assumption of constant risk-averse behavior was incorporated into the decision model, and the intuitive hypothesis that demand for an input is inversely related to its risk impact was examined. Results tend to support this hypothesis for risk-reducing inputs.

Some caution about these conclusions should be exercised since the cross-section data employed are region and crop specific and do not necessarily permit general inference regarding risk impacts of agricultural inputs. However, the importance of correctly identifying the role of inputs on output variability cannot be overestimated. This is especially true for chemical inputs that have potentially large negative externalities as-

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### TABLE 3. Expected Marginal Mean and Variance Impacts on Inputs for Cotton, San Joaquin Valley, California*a.

<table>
<thead>
<tr>
<th>Input</th>
<th>Expected Marginal Productb</th>
<th>Expected Marginal Impact on Yield Variabilityb</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS 4-Step</td>
<td>OLS 4-Step</td>
</tr>
<tr>
<td>(pounds per acre/input unit)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Irrigation</td>
<td>65.1517 70.3598</td>
<td>11,374.2137 323,311.3782</td>
</tr>
<tr>
<td>Labor</td>
<td>.0261 5.5167</td>
<td>4.5774 -5117.8223</td>
</tr>
<tr>
<td>Machinery</td>
<td>3.0069 7.2810</td>
<td>524.9442 -22464.4719</td>
</tr>
<tr>
<td>Fertilizer</td>
<td>.0311 .0624</td>
<td>5.4223 -437.3457</td>
</tr>
<tr>
<td>Insecticides</td>
<td>1.2946 -2.0924</td>
<td>226.0063 6491.3931</td>
</tr>
</tbody>
</table>

*aBased on estimates reported in Table 2.

*bEvaluated at the geometric mean.


<table>
<thead>
<tr>
<th>Input</th>
<th>Unit</th>
<th>Expected Value of Marginal Product</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Irrigation</td>
<td>dollars/acre foot</td>
<td>33.35 (9.5287)c</td>
<td>4.50</td>
</tr>
<tr>
<td>Labor</td>
<td>dollars/hour</td>
<td>2.70 (.3677)</td>
<td>2.90</td>
</tr>
<tr>
<td>Machinery</td>
<td>dollars/hour</td>
<td>3.46 (.2486)</td>
<td>3.00</td>
</tr>
<tr>
<td>Fertilizer</td>
<td>dollars/pound</td>
<td>0.03 (.0109)</td>
<td>0.21</td>
</tr>
<tr>
<td>Insecticides</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

*aBased on the estimates reported in Tables 2 and 3.

*bOutput elasticity of insecticides was insignificant.

Numbers in parentheses are estimated asymptotic standard errors.
associated with their use. Policy-makers should be particularly aware of yield variation attributable to inputs when evaluating costs associated with regulatory controls on input use. The risk-flexible production model presented by Just and Pope provides a practical framework for examining both input-yield variability interaction and government policies designed to reduce risks in agriculture.

References


