*Journal of Rural Development 8 (December 1985): 197~214* 

# ECONOMETRIC MODELING OF PEST MANAGEMENT TECHNOLOGY AND ENDOGENEITY OF PESTICIDE INPUT

PARK SEONG-KWAE*

## Introduction

The aim of this paper is twofold: econometric modeling of pest management technology and development of an appropriate estimation method under the conditions of input endogeneity, nonlinearity in endogenous variables, and heteroskedasticity. In the modeling of pest management technology risk and output dynamics are an important joint consideration. Agricultural crops pass through several growth stages in the course of a season's growth. The biological plant dynamics (i.e., output dynamics) accompanies pest incidence at each growth stage so output dynamics and associated pest problems lead a farmer to choose pesticide input sequentially (Antle 1983a, 1983c). Thus, pesticide input becomes an endogenous variable.

A standard statistical procedure for empirically analyzing production risk is the method of moments. Several studies (Day, Roumasset, Anderson) applied this method to the experimental data. However, the method of moments has serious limitations since hypothesis tests for probability distributions requires a large body of cross-section data over a considerable period of time. Just and Pope suggests econometric procedures for estimating the mean and variance of output as a functions of inputs. Their model is based on an heteroskedastic additive error specification which can appropriately reflect the effects of inputs on output variance. In a study of optimal choice among alternative technologies with random yield, Yassour et al. developed an expected utility, moment-generating function technique, considering the first moments of output distribution. Applications of this methodology include Moffitt et al., and Liapis and Moffitt. Taylor presents a hyperbolic trigonometric transformation procedure for estimating the form as well as the parameters characterizing the probability density function or the cumulative function. The Taylor's technique may be useful for safty-first and stochastic dominance consideration, but the computation of expected utility requires numerical integra-

* Research Associate, Korea Rural Economic Institute, Seoul, Korea.

tion using this method. Most risk analyses in the area of agricultural pest management (Carlson 1970, Willey, Farnsthworth, Feder, Lazarus and Swanson) have been based on the expected utility hypothesis. Carlson (1984) observed that pesticide input endogeneity can provide inconsistent estimates. Few empirical studies have taken such input endogeneity into consideration.

This paper applies the flexible moment-based approach (Antle 1983b) to risk analysis of a worm monitoring program for processing tomato production in the Sacramento Valley. This model has several advantages in production risk analysis: mitigating enormous data requirement of Day's approach, providing a systematic method of approximating moments, avoiding arbitrary restrictions on stochastic production functions, providing manageable econometric estimation technique. The empirical models of tomato net output and worm damage are specified as quadratic in production inputs and as linear in relevant dummy variables. Thus, nonlinearity in an endogenous variable (i.e., insecticide input) is associated with the quadratic functional specifications while heteroskedasticity is the inherent characteristic of the moment-based model.

The first section of the paper develops the theoretical basis for this study and discusses the pesticide input endogeneity prolem. The second section discusses data and variables in the model, empirical model specification, estimation method (nonlinear instrumental variable-generalized least squares technique), hypothesis test statistics, and empirical results.

## Theoretical Considerations

An important source of risk in agricultural crop production is damage from pests. This is a particular concern to farmrs where there are quality standards (e. g., in processing tomato production there is a 2 percent worm damage tolerance level set by the State of California). Pest damage directly affects the proportion of crop marketed and thus a farmer's profit. Hence the farmer's pest management and other input decisions are directed toward reducing damage from pests (or meeting the quality requirement).

Assume that output and input prices are nonstochastic. The relationship between profit normalized by output price ($\pi$), the amount of crop marketed ($Q^a$), gross output ($Q^g$), and worm damage ($Q^d$) can be given in terms of production inputs by

$$(1) \qquad \begin{aligned} \pi &= Q^a(P, L) - W_pP - W_lL \\ &= Q^g(P, L)V(P, L) - W_pP - W_lL \end{aligned}$$

where $\pi$ and W's are profit and input prices normalized by output; $V$ is $[1\text{-}Q^d\,(P,\ L)]$; $Q^d$ is percentage of worm damage; $P$ is pesticides; $L$ is pest monitoring labor. In addition to $P$ and $L$, other inputs are related to yield and worm damage, although not all directly affect the yield and quality of product. For simplicity in this presentation, all variables other than pesticides and pest monitroing efforts are assumed to be applied in an optimal manner. The model can be generalized to allow choice of all variable inputs.

The farmer views growth output ($Q^g$), damage rate ($Q^d$), and net output ($Q^a$) as random variables due to the uncertainty of surrounding weather conditions and pest populations during the growing season. Thus, the farm manager is faced with the entire probability distribution of $Q^g$ and $Q^d$ functions instead of being faced with single means. The probability distributions of the variables are related to the farmer's production input decisions. Therefore, the random variables can be defined as follows: means are $M_1{}^d$, $M_1{}^d$, and $M_1{}^g$; $Q^a \sim h_a\ (Q^a|P, L)$; $Q^g$ and $Q^d \sim h(Q^g, Q^d|P, L)$.

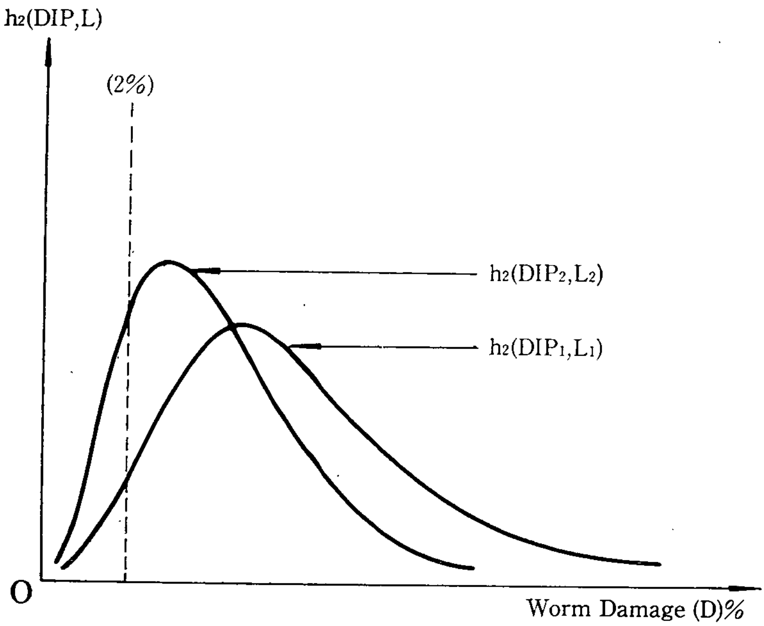
Agricultural crops pass through several stages in the course of a season's growth: seedling establishment, vegetative growth, flowering, and harvest (or fruiting). These stages all differe in nutrient requirements and susceptibility to pests. Near harvesting time is when crops are most susceptible to insect pests and when worm damage most often occurs, while $Q^g$ is largely determined during the first three stages. The assumption of independence between the two rand omvariables, $Q^g$ and $Q^d$, is supported by crop plant biology. The three above random variables ($Q^a$, $Q^g$, and $Q^d$) are non-negative and bounded. Therefore, all moments for each variable exist and uniquely determine the conditional probability distribution on production inputs. It follows that all economically relevant characteristics of the production technology must be embodied in the relationships between inputs and moment. Therefore, the farmer's behavior under production risk can always be defined in terms of the moents of the probability distributions of $Q^a$, $Q^g$, and $Q^d$ (Antle 1983b). Since the distributions of $Q^a$, $Q^d$, and $Q^g$ are assumed independent and are defined as $h_a\ (Q^a|P, L)$, $h_d\ (Q^d|P, L)$, and $h_g\ (Q^g|P, L)$, respectively, the moments of $Q^a$, $Q^d$, and $Q^g$ can be expressed as

$$
\begin{aligned}
(2) \qquad & M_1{}^n = \int Q^n h_n(Q^n|P, L)dQ^n \\
& M_i{}^n = \int (Q^n - M_1{}^n)^i h_n(Q^n|P, L)dQ^n, \qquad i \geq 2 \text{ and } n = a, d, g
\end{aligned}
$$

Note that the distributions of $Q^g$ and $Q^d$ directly influence the distribution of $Q_a$.

The damage rate and the shape characteristic of $Q^d$ probability distribution $-M_1{}^d$ and $M_i{}^d$, $i \geq 2$-are hypothesized to be of concern to the farmer because $Q^d$ is directly related to $Q^a$ and hence to the farmer's economic returns. The farm manager's decisions on input combinations may result in different probability distribution of worm damage. For example,

FIGURE 1




Worm damage ($Q^d$) probability distributions associated with different input combinations (** worm damage tolerance level set by the State of California).

as shown in figure 1, one input combination ($P_1$, $L_1$) can result in a quite different probability distribution of $Q^d$ from another ($P_2$, $L_2$). If input combination ($P_2$, $L_2$) is more effective in reducing the variance of $Q^d$ and "cutting off" the upside tail of the $Q^d$ distribution than ($P_1$, $L_1$) the farmer would choose the pest management strategy which is associated with input combination ($P_2$, $L_2$).
Note that by attempting to move the $Q^d$ distribution towards the origin, the farmer is "cutting off" the lower tail of the $Q^g$ (or $Q^a$) distribution. This kind of behavior (often called aversion to downside risk) has been ascribed to a disaster avoidance motive (Menezes et al.).

In this study it is hypothesized that the farm manager chooses production inputs to maximize expected utility of profit. Assume that a Taylor's series expansion of the underlying utility function converges. The Taylor's series expansion of the utility function is used to express the expected utility as a function of moments of profit. Terms beyond those involving the third moment of profit are ignored since they add little precision (Anderson; Dillon; Hardaker). It is also generally recognized that the first three moments of output distribution may be a basis for ascertaining the degree of production uncertainty (Heady; Anderson;

Roumasset; Antle 1983b; Antle and Goodger). Furthermore, under the quality standard on worm damage the farmer is concerned with the risk of $Q^d$ falling above the quality requirement so the third moment of $Q^d$ (or $Q^a$), representing the asymmetry or skewness of the distribution, may be an important consideration in pest management and other input decisions. In the empirical analysis the three moment functions for each of $Q^a$ and $Q^d$ are estimated.

Letting $X$ and $W$ be input and input price vectors, the average farmer's decision problem can be written in terms of the mean, variance, and third moment of normalized profit as follows:

$$(3) \qquad \max EU(\pi) = U(M_1{}^a(X) - WX),\ M_2{}^a(X),\ M_3{}^a(X)].$$

Note that $M_i{}^a$, $i = 2, 3$, are the moments of $Q^a$ since $\pi = Q^a - WX$ and thus $(\pi - E(\pi))^i = (Q^a - M_1{}^a)^i$, $\quad i = 2, 3$.

First order conditions for maximizing expected utility are obtained by taking the derivatives of equation (3) with respect to the decision variables and setting the results equal to zero:

$$(4) \qquad (dM_1{}^a/dX_k) + (U_2/U_1)(dM_2{}^a/dX_k) + (U_3/U_1)(dM_3{}^a/dX_k) = W_k.$$

where $U_i$ is partial derivatives with respect to moment $i$. Equation (4) can be rewritten in terms of moment elasticities:

$$(5) \qquad n_{1k} + (U_2/U_1)(M_2{}^a/M_1{}^a)n_{2k} + (U_3/U_1)(M_3{}^a/M_1{}^a)n_{3k} \\ = (W_kX_k)/M_1{}^a$$

where $n_{ik} = (dM_i{}^a/dX_k)(X_k/M_i{}^a)$, $\quad i = 1, 2, 3$.

Equation (5) is the condition for optimal input decisions (on pest management) and can be used to analyze decision making under production risk. $(U_2/U_1)$ and $(U_3/U_1)$ can be interpreted as Pratt's absolute risk aversion coefficient ($r^*$) and down-side risk aversion coefficient ($r^{**}$), respectively. The terms $n_{ik}$, $i$=2, 3, denote the marginal impact of input $k$ on moment $i$. Determination of the sign and magnitude of $n_{ik}$ is an empirical question. The expression $[(U_2/U_1)(M_2{}^a/M_1{}^a)n_{2k}]$ represents marmarginal adjustment to variance and $[(U_3/U_1)(M_3{}^a/M_1{}^a)\ n_{3k}]$ denotes marginal adjustment to skewness at the optimum. Thus, $[(U_2/U_1)(M_2{}^a/M_1{}^a)\ n_{2k} + (U_3/U_1)(M_3{}^a/M_1{}^a)\ n_{3k}]$ is the total marginal risk adjustment factor in equilibrium. These imply that at the optimum the expected value of marginal product, after risk adjustment, is equal to the normalized factor price. If a grower is risk-neutral, the relative factor share will be equal to the production elasticity with respect to input $k$. A risk averter taking into account the mean and variance of $Q^a$ will choose inputs such that the first two terms on the left-hand side of equation (5) equal the right-hand side, while a downside-risk averter will employ production inputs in equilibrium by setting all three terms equal to the relative factor shares.

The sum of two terms involving the derivatives of the second and third moment with respect to input $k$ on the left-hand side of equation (4) is the maximum monetary value which a grower would be willing to pay in order to get the value of expected marginal product, $dM_1{}^a/dX_k$, at the optimum. This is equivalent to the value of input $K$ applied for insurance purposes, compared with risk neutrality. Therefore, the quantity $[dM_2{}^a(X)/dx_k+dM_3{}^a(X)/dX_k)]$ can be interpreted as marginal risk emium. It's magnitude depends on $r^*$, $r^{**}$, and $dM_i{}^a(X)/dX_k$ $i$=2,3. Equation (5) can be interpreted in the same way. If given pest control technologies yield the same expected profit, the growers would prefer to choose the pest management method incurring smaller risk premium.

## Pesticide Input Endogeneity

In agricultural production most input $X_k$'s are determined in the early production stage. However, pesticides play a role as an intermediate input due to pest activities associated with plant growth stages (i.e., output dybamics and associated pest problem). Both pest infestations and crop plant growth are influenced by random events such as weather conditions occurring over the growth stages. This leads farmers to choose ininsecticides sequentially and as a result pesticide input becomes an endogenous variable (see Antle 1983a for detailed discussion of this issue). This is especially true in the case of the pest control technology supported by a systematic pest monitoring technique which specifies a formal procedure by which growers collect information on pest populations and spray accordingly (e.g., the worm monitroing prgram for processing tomato production developed by the University of California). More systematic and precise pest control techniques may not necessarily reduce pesticide treatments.

## Moment Model Specification and estimation

Equation (2) implies that the $Q^a$ and $Q^d$ moments may be functions of production input $X$. Thus, under the assumption that there are linear relationships in parameters between production inputs and the $Q^a$ and $Q^d$ moments, $Q^n$ of the $j$th farm (or field), $n=a$, $d$, can be written as their means $M^a_{1j}(X_j)$ plus an error $\varepsilon_{1j}$ with zero expectation:

$$(6) \qquad Q^n_j + M^n_{1j}(X_j) + \varepsilon_{j1},\ E(\varepsilon_{j1}) = 0, \qquad n = a,\ d$$

where $\varepsilon_{1j}$ is assumed to be independently distributed. Similarly, noting that $E[Q_j - M^a_{1i}]^i = E(\varepsilon^{ia}_{1j})$, $i = 2, 3$, and $n$ = a, d, it follows that

$$(7) \qquad \varepsilon^i_{1j} = M^a_{ij}(X_j) + \varepsilon_{ij},\ E(\varepsilon_{ij}) = 0, \qquad i = 2, 3.$$

In estimation of the moment models, there are two important econometric problems: pesticide input endogenity and heteroskedasticity. In addition, non-linearity problem in endogenous variables is discussed here because in the following sections the empirical models of $Q^a$ and $Q^d$ have linear-in-parameters quadratic functional spedifications.

When farmer use systematic pest control techniques, the final output $Q^a$, damage $Q^d$, and pesticide applications $I$, are functions of the pest population, a random variable. Hence, equation (6) and (7) violate the assumption, required for consistent estimation, that the explanatory variables $X$ be independent of the error terms $\varepsilon_{ij}$, $i=1, 2, 3$. Given the endogeneity, application of an *OLS* regression provides inconsistent parameter estimates (Theil, Kmenta). To solve the endogeneity problem, the correlations between $I$ and the disturbance must be purged. One way to do this is to find an optimal instrumental variable $I$ for $I$ which is orthogonal to the disturbance term in the probability limit. An optimal $I$ can be obtained from the first stage of the two stage least squares (2SLS) techniques since the first stage purges correlation with the second stage error, and the second stage involves a usual OLS regression. Hausman showed that 2SLS is the best instrumental variable (IV) estimator. However, the IV and 2SLS estimators remain identical only so long as all predetermined variables are used to form the istrumental variable. Thus, insecticide quantity I is expressed as a function of all the variables (but $I$) ($X$) in the moment model and other exogenous variables ($H$) such as input and output prices as follows:

$$(8) \qquad I = (X; H)$$

$\hat{I}$ is the fitted value from the corresponding OLS regression. If, however, the functional form is nonlinear in the endogenous variable $I$ such as the quadratic here, the use of $I^2$ in the quadratic specification results in an inconsistent estimator because the instrument $\hat{I^2}$ will not be orthogonal to its estimated residual (see Kelejian, P. 374). Thus $I^2$ must be treated as an additional endogenous variable. To solve this inconsistency problem, after squaring I, the instrument $\widehat{I^2}$ of $I^2$, is estimated by regression equation (8). Thus, the separate estimation of instruments of $I$ and $I^2$ allows the instruments ($\hat{I}$ and $\widehat{I^2}$) to be orthogonal to each estimated residual and hence second-stage consistent estimates can be obtained.

Heteroskedasticity is an inherent property of this moment model. Therefore, the appropriate model in this study should be one with hetero skedastic distrubances. Under the condition of heteroskedasticity the least squares estimators are consistent but do not have the smallest variance so they are not asymptotically efficient but still consistent under OLS. This violates hypothesis testing rules of estimator variance consistency.

For notational consistency, define $Z$ as a matrix of the explanatory variables with the instrumental variables and $\tilde{\varepsilon}_i$ as a corresponding error vector of the $i$th moment function. To derive the feasible GLS estimators for the $Q^a$ moment model parameters, the following assumptions on the distrubance terms and the $Z$ matrix are made:

(9) $E(\bar{\varepsilon}_{ij}\bar{\varepsilon}_{is}) = 0$ for all $j \neq s$ and $i = 1, 2, 3$.
(10) Plim $(N^{-1}Z'Z) = \Sigma_{zz}$ exists and a positive nonsingular matrix.
(11) Plim $(N^{-1}Z'H) = \Sigma_{ZH}$ exists and is non-singular.
(12) Plim $(N^{-1}Z'\bar{\varepsilon}_i) = 0$ for all $i = 1, 2, 3$.

Under these assumptions, an OLS regression of $Q^a$ on $Z$ provides a consistent estimator $\hat{\beta}_1^0$ of $\beta_1$. Also we can obtain a consistent estimators $\hat{\beta}_i^0$ of $\beta_i$ for any $i=2, 3$, by an OLS regression of $\bar{\varepsilon}_{1j}^i$ on $Z_j$ where $\hat{\varepsilon}_{1j}$ is the regression residual vector (Antle 1983b).

To treat the heteroskedasticity problem, Weighted least squares procedures can be applied to construct the feasible GLS estimators by (i) dividing each observation (both dependent and independent variables) by the standard deviation of the error for that observation and (ii) applying the usual OLS procedures to the transformed data.

The covariance matrices $\Omega_i$ of the moment function errors $\bar{\varepsilon}_i$, $i = 1,2,3$, are estimated directly from the regression residuals $\hat{\varepsilon}_i$ . Let

(13) $\bar{\varepsilon}_{ij}^2 = Z_j\alpha_i + V_{ij}, \qquad E(V_{ij}) = 0,$ for all $i$.

where $V_{ij}$ is assumed to be independently distributed and $\alpha_i$ is a parameter vector conformable to $Z_j$. Assumptions (9) through (12) and equation (13) imply that the OLS estmates $\hat{\alpha}_i$ of $\alpha_i$, $i=1, 2, 3$, are consistent (*i.e.* $E(\bar{\varepsilon}_{ij}^2) = \text{Plim}(Z_j\hat{\alpha}_i)$). Therefore, $\Omega_i$, $i=1, 2, 3$, can be defined as the diagonal matrices of $Z_j\alpha_i$ and $\hat{\Omega}_i$, $i=1, 2, 3$, as the diagonal matrices of $z_{ij}\hat{\alpha}_i$. However, $\hat{\Omega}_i$'s may be negative due to small sample bias or to sampling error in the est·mate of $\beta_i$. To overcome the non-negativity problem and obtain consistent estimates of the error variances of the moment functions, the MINOS program can be utilized to impose non-negativity constraints as described in Antle (1987b). Given the estimated convariance matrices, feasible GLS estimators for the $\beta_i$ are

(14) $\beta_i^* = (Z'\hat{\Omega}_i^{-1}Z)^{-1}Z'\hat{\Omega}_i^{-1}Y_i, \qquad i = 1, 2, 3.$

where $Y_i$, $i=1, 2, 3$, are vectors of $Q_j$, $\bar{\varepsilon}_{1j}^2$, and $\bar{\varepsilon}_{1j}^3$. The GLS estimators are asymptotically efficient because the covariance matrix of the OLS estimator exceeds that of the GLS estimator by a positive semidefinite matrix in view of Aitken's theorem (Theil, p. 238).

Therefore, assuming that the sample in this study is sufficiently large for the asymptotic properties of the estimators to be valid, the following NLIV-GLS estimation procedures can be used to obtain consistent, efficient estimates of the model parameters:

(1) Estimate the optimal instrumental variables for $I$ and $I^2$ and replace $I$ and $I^2$ in matrix $H$ with $\hat{I}$ and $\hat{I^2}$.
(b) Estimate the mean function of $Q^a$ and compute the residual

vector, $\hat{\varepsilon}_1$.

(c) Estimate regressions $\hat{\varepsilon}^i_{1j} = Z_j\beta_i + \bar{\bar{\varepsilon}}_{ij}$ and compute the residual vectors, $\hat{\varepsilon}_i$, $i = 2, 3$.

(d) Estimate $\alpha_i$, $i = 1, 2, 3$, by using the MINOS program:
min $\alpha_i$ $[\hat{\varepsilon}^2_{ij} - Z_j\alpha_i]^2$
$s.t,\ Z_j\alpha_i \geq 0$.

(e) Transform data sets $[Q_j\ Z_j]$ and $[\hat{\varepsilon}^i_{1j}\ Z_j]$ by dividing by $(Z_j\hat{\alpha}_1)^{1/2}$ and $(Z_j\hat{\alpha}_i)^{1/2}$, $i=2, 3$.

(f) Apply the usual OLS procedures to obtain NLIV-GLS estimators (14).

All hypothesis tests are performed based on the above statistical results which are derived from the assumption that the NLIV-GLS parameter estimates are asymptotically normally distributed.

## Risk in a Worm Monitoring Program for Processing Tomato Production

The Sacramento Valley is located in northern California. The Sacramento Valley area centered in Yolo county produces some 65 percent of the California processing tomatoes. The survey covered five counties including Yolo, Solano, Colusa, Sutter, and Sacramento. In this area, planting of processing tomatoes extends from February to mid-June and harvest is from July to October.

## The Worm Monitoring Program

Recently, the IPM (integrated pest management) Impementation Group and Department of Entomology (UC Davis) developed a worm monitoring program for processing tomato production, supported by systematic sampling techniques and in 1984 started the first formal trials on about 2,000 acres of tomatoes to demonstrate to growers its reliability and economic feasibility. The worm monitoring program (WMP) specifies a formal procedure by which growers collect information on pest populations and spray accordingly. A difference between the WMP and the conventional pest monitoring method (CPM) lies in worm monitoring techniques. CPe is based on non-systematic sampling methods such as visual observations of the pest situations in the fields.

## Description of Data and Variables in the Model

A detailed discission of the data and variables is in Park. Here, a brief description is given to the variables which are used to estimate the moment models.

The processing tomato production information collected is two year non-experimental data (1983–1984) consisting of farm production records of 21 WMP fields and 85 CPM fields: the WMP fields are the ones which participated in the university's worm sampling project; the CPM fields represent the fields which used non-systematic sampling techniques such as visual observations of pest situation. The field level data collection method substantially reduced aggregation problems.

In the following statistical analysis, ten variables are utilized. The variables include acreage ($A$), fertilizers ($F$), irrigation ($W$), insecticides ($I$), worm damage ($Q^d$), net tomato weight ($Q^a$), and dummy variables. Several important variables have been omitted due to measurement problem. Machinery utilization data could not be obtained (either from written records or memory recall) because agricultural firms use many different kinds of machinery which are utilized for a variety of operations. Only a few growers kept labor records (or costs) by field. Thus, most field-level labor input figures were obtained from a grower's recall. However, since the production technology is quite uniform in the Sacramento Valley with respect to mechanization and labor utilization, it is reasonable to assume that these inputs are used in fixed proportions with acreage. Information on Worm monitoring labor hours also was obtained from the grower's recall so its accuracy at the field level is questionable. Thus, the data were not used in the econometric model. However, since the information was believed to be indicative of acreage worm monitoring activities in CPM and WMP, a simple regression of worm monitoring hours on a WMP dummy variable (*i.e.*, $IN=1$ if WMP field, $IN=0$ otherwise) was used to test for a mean difference in monitoring hours between the WMP and the CPM.

Accurate field acreage figures were obtained for 106 processing tomato fields. Fertilizers were used for starter fertilization and side-dressings. In general, complete fertilizers were used as starters while most of the growers used only nitrogen in side-dressings. There were many different formulations of fertilizers in different units. The original quantity data were converted into a standardized unit (*e.g.*, lbs). Irrigation information was difficult to obtain, since many growers did not keep water use records in terms of acre-feet. In many cases, water quantities were computed based on per hour pumping rate (*e.g.*, gallons per hour) and total pumping hours during the season. Water prices per acre-foot were calculated by using electricity costs, tax assessments, and water charges. Insecticide data were obtained from the reports of pesticide treatment and crop history required by processors and were converted into pounds of active ingredient. Insecticides are heterogeneous in quality (*i.e.*, effectiveness and toxicities associated with different active ingredients). Therefore, quality adjustment is desirable. However, experimental information necessary for quality adjustment was not available. Market prices could be used for adjusting quality, since market prices may be indicative of quality differences. However, prices reflect other economic phenomena as well as quality. Therefore, the insecticide variable was used in the model without quality adjustment. Worm damage data were collected only for the 1984 season because the tomato commodity group of Statewide IPM project started the first formal field trials in 1984. Fruit damage caused by tomato fruitworms and beet armyworms was estimated in the field according to the sampling technique suggested by the university's IPM group shortly before or during harvest from mid-July, 1984 to September, 1984. Net tomato weight accepted by processors is determined through by quality grading at inspection stations. Grading results are sent to individual growers and processors. The grading sheets contain gross tomato weight delivered to the inspection station, paid tomato weight, and quality records. Thus, accurate net output data for each field were available from the grading sheets or growers' summary records. There are six dummy variables: one is associated with pest monitoring techniques ($IN=1$ if WMP field, $IN=0$ otherwise); there with planting seasons ($D1=1$ is early, $D2=1$ if middle, $D3=1$ if late, $D1=D2=D3=0$ otherwise); two outliers ($OT1=1$ if $Q^a \geq 45$ tons/acre, $OT2=1$ if $Q^a \leq 15$ tons/acre, $OT1=OT2=0$ otherwise).

## Empirical Model Specification

Although many problems associated with choice of functional form remain unsolved, quadratic moment models are employed as flexible representions of output and worm damage moment functions because (i) there is little a priori information about their functional structures and (ii) given a data set, Cobb-Douglas or log-linear functions impose a priori arbitrary constraints on production processes.

The $Q^a$ moment model is specified as a full quadratic in acreage ($A$), fertilizer ($F$), water ($W$), and insecticides ($I$). Three dummy variables-WMP ($IN$), mid-season planting ($D2$), and late planting ($D3$)-are included in linear form by stratifying the data by worm sampling techniques and by planting seasons. In addition, the $Q^a$ moment functions contain two outlier dummy variables ($OT1$ and $OT2$). The linear-in-parameters quadratic moment functions are specified as follows:

$$
\begin{aligned}
(15) \qquad M^a_{ij} = \beta_{0i} &+ \sum_{k}^{R} \beta_{ki} X_{kj} \\
&+ (1/2) \sum_{K}^{R} \sum_{1}^{R} \beta_{k1i} X_{kj} X_{1j} \\
&+ \sum_{t}^{T} \beta_{ti} X_{tj} \\
&i = 1, 2, 3, \; j = 1, \ldots, 106 \qquad R = 4, \qquad T = 5,
\end{aligned}
$$

where $j$ is the $j$-th processing tomato field; $\beta_i$ is a parameter vector of the $i$-th moment function; $X_{kj}$'s are production inputs—$A$, $F$, $W$, and $I$; $X_{ij}$'s are 5 dummy variables—$OT1$, $OT2$, $IN$, $D2$, and $D3$. For WMP economic research the moment model of worm damage ($Q^d$) may be more important than the $Q^a$ moment model because WMP is directly associated with $Q^d$ but only indirectly with $Q^a$. The functional specifications follow those of the $Q^a$ moment model. The only differences are in dependent variable name and dimensions of dependent and explanatory variables. The worm damage data include 52 field observations for the 1984 season. Acreage and fertilizer variables are not included in the model becuase there is little evidence that they ifleunce $Q^d$. Thus, the $Q^d$ moment model has a ful quadratic expansion in $W$ and $I$ and is linear in $IN$, $D2$, and $D3$. One problem with quadratic specifications is that a large number of parameters must be estimated when there are many inputs. Thus, when the sample is small, these may be subject to a substantial loss in degrees of freedom. Another problem is multicollinearity because of interaction terms between the variables. The above quadratic specifications with the given input variables, however, were not found to exhibit serious multi-collinearity while limiting the parameters to a manageable number.

To solve the input endogeneity problem, $I$ and $I^2$ are expressed as functions of all the variables (but $I$, $I^2$, and interaction terms with $I$) in the output moment model and input and output prices as follows:[1]

$$(16) \qquad (I \text{ or } I^2) = (\text{INTERCEPT}, A, W, F. A^2, A.W, A.F, W^2, W.F, F^2, ISP, WP, FP, TMP, MP, HBP, FGP\ OT1, OT2, IN, D2, D3, \delta)$$

where $ISP$ is insecticide price; $WP$ is water price; $FP$ is fertilizer price; $TMP$ is tomato price; $MP$ is miticide price; $HBP$ is herbicide price; $FGP$ is fungicide price; $\delta$ is disturbance. $\hat{I}$ and $\hat{I^2}$ are the fitted values from the corresponding OLS regression and are substituted for $I$ and $I^2$ in equation (15).

Derivaties of equations (15) with respect to input $k$ are marginal impacts of input $k$ on $M_i^a$, $i=1, 2, 3$. The moment elasticities with respect to input $k$ are

$$(16) \qquad n_{ik} = [(dM_i^a)/(dX_k)]/[X_k/M_i^a] = [\beta_k + \sum_1^R \beta_{k1i} X_{1j}]/[X_k/M_i^a], \qquad i = 1, 2, 3.$$

and can be computed at sample means. This formua also is utilized for estimating the moment elasticities of worm damage.

[1] Note that in the case of quadratic functional forms interaction terms between $I$ and $X$, where $X$ is an exogenous variable, are not nonlinear in the instruments' residual and thus do not result in inconsistency.

## Hypothesis Test Statistics

This empirical study requires four main hypothesis tests: (i) there are systematic relationships between $Q^a$ and $Q^d$ distributions and production inputs ($HI1$); (ii) WMP and CPM are associated with different distributions for $Q^a$ and $Q^d(HP2)$; (iii) there is a difference in worm monitoring hours between the WMP and the CPM($HP3$); and (iv) a difference in insecticide use exists between the two pest management technologies ($HP4$). In addition, it is hypothesized that planting time results in different mean and risk of $Q^a$ and $Q^d$ ($HP5$). These hypotheses are tested based on the following test statistics.

Under the large sample assumption, asymptotically valid chisquare ($\chi^2$) statistics can be used. The $\chi^2$ is constructed in terms of constrained error sum of squares ($CESS_i$) (i.e., all slope coefficients are zero) and unconstrained error sum of squares ($UESS_i$) as follows:

$$\chi_i^2(K_i - 1) = [(CESS_i - UESS_i)/(K_i - 1)]/[UESS_i] \tag{18}$$

where $i$ indicates the $i$th moment, and $K_i$ is the number of parameters of the $i$th moment. The distribution has ($K_i$—1) degrees of freedom.

The $Q^a$ and $Q^d$ moment models and equation (12) all contain 3 dummy variables (i.e., $IN$, $D2$, and $D3$) associated with $HP2$, $HP4$, and $HP5$. The $IN$ coefficients are the mean differences in the $Q^a$ and $Q^d$ moments and the insecticide use between WMP and CPM, while the coefficients of $D2$ and $D3$ represent the mean differences between the planting seasons. Testing the significance of the dummy variables is, in fact, testing $HP2$, $HP3$, and $HP4$.

It is postulated that the monitroing hours ($MH$) are given by

$$MH = G(INTERCEPT, IN) \tag{19}$$

The coefficient of WMP variable ($IN$) is the mean difference in monitoring hours between the two pest control techniques and is associated with the test for $HP4$.

To test the above hypotheses associated with individual dummy variables, asymptotic t-statistics are defined in terms of the ratio of dummy variable's coefficient (i.e., mean difference of a dependent variable) and its standard error.

## Empirical Results

This section discusses the role of instrumental variables under the condition of input endogeneity by comparing the NLIV-GLS and GLS estimates, the relevant hypothesis test results based on the NLIV-GLS estimates of the model parameters, and the marginal impacts of production inputs

TABLE 1 NLIV-GLS Parameter Estimates of Output Moments

| Var. name | Moments | | | | | |
|---|---|---|---|---|---|---|
| | First | | Second | | Third | |
| | B1 | t-ratio | B2 | t-ratio | B3 | t-rario |
| IN | —.0887 | —1.0856 | —.0002 | —.0188 | —.0177 | —2.4800*** |
| D2 | —.0391 | —.9184 | —.0096 | —.8736 | —.0078 | —1.1013 |
| D3 | —.1728 | —2.5856** | —.0019 | —.1163 | .0117 | 1.5547* |
| $\chi^2$ | 19519*** | | 258.47*** | | 778.5*** | |

Note all tables for: * indicates significant at the 10 percent significance level; ** indicates significant at the 5 percent significance level; *** indicates significance at the 1 percent significance level.

TABLE 2 GLS Parameter Estimates of Output Moments

| | | | | | | |
|---|---|---|---|---|---|---|
| IN | .1372 | —2.1877** | .419 | 2.3972** | .0309 | 3.0228*** |
| D2 | —.1960 | —2.9176*** | .0077 | .4137 | —.0418 | —1.3253* |
| D3 | —.1268 | —2.1492** | .0409 | 2.7726*** | —.0019 | —.3002 |
| $\chi^2$ | 5819.3*** | | | 614.32*** | | 298.32*** |

TABLE 3 NLIV-GLS Parameter Estimates of Worm Damage Moments

| | | | | | | |
|---|---|---|---|---|---|---|
| IN | —.6712 | —1.9915** | —.3155 | —1.1835 | .0277 | .0816 |
| D2 | .5549 | 1.9405** | .1279 | .6101 | —.0506 | —.2017 |
| D3 | 1.0011 | 2.3643*** | .3809 | 1.1500 | .1940 | .4761 |
| $\chi^2$ | 1156*** | | 1078.7*** | | 650.11*** | |

TABLE 4 GLS Parameter Estimates of Worm Damage Moments

| | | | | | | |
|---|---|---|---|---|---|---|
| IN | —.1405 | —.4772 | —.0455 | —.2662 | .1514 | .5384 |
| D2 | .2925 | 1.1449 | .0651 | .5093 | —.0313 | —.1477 |
| D3 | —.3350 | —.8492 | —.0780 | —.3293 | —.1538 | —.4122 |
| $\chi^2$ | 230.48*** | | 53.769*** | | 2.9037 | |

TABLE 5 NLIV-GLS Moment Elasticities of Output

| | Moment elasticities | | | | | |
|---|---|---|---|---|---|---|
| | First | t-ratio | Second | t-ratio | Third | t-ratio |
| A | .3333 | 1.4717* | 1.0558 | .9955 | —25.141 | —1.2745* |
| F | .5593 | 2.5542*** | 1.2529 | 1.1366 | —16.068 | —.6981 |
| W | .4986 | 2.4934*** | —.9549 | —.7555 | —17.767 | —.8286 |
| I | .3607 | 3.7575*** | —.8973 | —1.2932* | —26.154 | —4.2586*** |

TABLE 6 GLS Moment Elasticities of Output

| | | | | | | |
|---|---|---|---|---|---|---|
| A | .6987 | 2.7246** | —3.4607 | —2.0938** | —6.2843 | —.0691 |
| F | .2938 | 1.4889* | —.6933 | —.7402 | 180.4300 | 2.4436*** |
| W | .2355 | 1.2494* | 1.5088 | 1.0272 | —143.0600 | —1.2947* |
| I | —.0116 | —.2238 | —.5336 | —1.6632** | —4.7728 | —.2947 |

TABLE 7 NILY-GLS MOMENT ELASTICITIES OF WORM DAMAGE

| | | | | | | |
|---|---|---|---|---|---|---|
| W | —.3501 | —1.5802* | —.5745 | —1.3348* | .2869 | .1193 |
| I | —.4150 | —3.3652*** | —.8306 | —3.2846*** | —3.9972 | —2.5515*** |

TABLE 8 GLS MOMENT ELASTICITIES OF WORM DAMAGE

| | | | | | | |
|---|---|---|---|---|---|---|
| W | —1.1364 | —4.3645*** | —.3989 | —.7226 | —2.3633 | —.5028 |
| I | .0920 | .9452 | .4396 | 1.6036* | .5421 | .5378 |

on the $Q^a$ and $Q^d$ moments. Here, the dummy variable estimates and moment elasticities are presented in Tables 1 through 4.

First, there are sign differences in the first moment elasticities of $Q^a$ and $Q^d$ with respect to insecticide input. It is believed that insecticides have a positive impact on the mean of output but negative effect on the mean of worm damage. However, as presented in tables 6 and 8, the GLS estimates showed a negative marginal product of insecticide input and a positive marginal impact on worm damage. These results are consistent with the Carlson's observation (1984) that it is quite possible to estimate negative marginal productivity of pesticides due to input endogeneity. Second, the significance of the moment elasticities of $Q^a$ and $Q^d$ with respect to insecticide input differ: in the GLS run all the moment elasticities of $Q^a$ and $Q^d$ with respect to I expect for those of the second moments of $Q^a$ and $Q^d$ are insignificant at all conventional significance levels; those obtained by the NLIV-GLS all are significant. Third, there is a difference in significance of the *IN* variable coefficients between the NLIV-GLS and GLS runs. As seen in Tables 1, 2, 3, 4 all the *IN*'s in the GLS run of the output moment functions are much more significant than those in the NLIV-GLS estimation but the GLS IN's of the worm damage moment model are much less significant. In addition, there are differences in the $\chi^2$ values between the NLIV-GLS and GLS. All the NLIV-GLS $\chi^2$ values except for that of the $Q^a$ second moment are much lower than those for the GLS. The above different GLS results from those of the NLIV-GLS can be attributed to estimation bias owing to the input endogeneity problem in the moment models.

The $\chi^2$ tests accepted, at the 1 percent level, the hypothesis that there are systematic relationships between inputs and the first three moments of the output and damage distributions. The moment elasticity estimates suggest that the magnitude and direction of marginal impacts of production inputs on the output distribution may depend on many factors such as crop, climate, and soil conditions. It has been found in other studies that water and pesticides are risk reducing inputs, and that fertilizer is a risk-increasing input (Carlson 1979, Just and Pope 1978). The results indicate that water and insecticides decrease output variance but increase downside-risk; fertilizer increases the variance and downside risk of output, and thus is risk-increasing. For worm damage, water reduces the mean and variance while insecticide input reduces the mean, variance, and positive skewness of worm damage. These results for the insecticide input support the general view that pesticides can be used as an insurance input.

The empirical results show: (i) the WMP uses the same amount of insecticide as the CPM; (ii) the WMP increases pest monitoring labor but the incremental cost per acre is very small relative to average gross income per acre; (iii) no mean output difference exists between the WMP and the CPM at the 10 percent significance level; (iv) the evidence on the effect of the WMP on output ris, is inconclusive, due to the small sample size; (v) the WMP reduces the mean and variance of worm damage (iv) the mid- and late-season plantings not only increase the mean worm damage but also decrease the mean output, supporting the field observation that the early planting allows growers to avoid serious worm damage and reduce insecticides use.

Taken together, the above results imply that the WMP results in a significant reduction in mean worm damage and worm damage risk in tomato production without substantially increasing other production costs.

## Conclusions

This paper develops a nonlinear instrumental variable-generalized least squares technique (NLIV-GLS) under the conditions of input endogeneity, nonlinearity in endogeneous variables, and heteroskedasticity. This econometric estimation technique is applied to risk analysis of the worm monitoring program for processing tomato production. The empirical results show that, under the existence of input endogeneity, instrumental variable approach is a useful method to obtain consistent estimators.

An important limitation of the empirical study is the use of a relatively small sample size which causes the instability of the moment models. Another limitation is the use of a static model since detailed data by growth stage are not available. However, dynamics (i.e., multi-stages in plant growth over a single production period) and risk are an important joint consideration in this study.

Future research should utilize larger and more complete data samples. Also, future research should explicitly model dynamics and risk jointly to further explore an agricultural firm's behavior under production dynamics and uncertainty.

### REFERENCES

Anderson, Jock R., John L. Dillon and B. Hardaker, *Agricultural Decision Analysis,* Ames: The Iowa state University Press, 1977.

Anderson, Jock R., "Sparse Data, Climate Variability, and Yield Uncertainty in Response Analysis." *Amer. J. Agr. Econ.* 56(1974): 77–83.

Antle, J. M., "Sequential Decision Making in Production Models," *Amer. J. Agr. Econ.* 65(1983a): 282–290.

______, "Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach," *J. of Bus. and Econ. Stat.* 3(1983b): 192–201.

______, "Incorporating Risk in Production Analysis," *Amer. J. Agr. Econ.* 65 (1983c): 1099–1106.

Antle, J. M. and W. J. Goodger, "Measuring Stochastic Technology: The Case of Tulare Milk Production," *Amer. J. Agr. Econ.* 66(1984): 342–350.

Carlson, G. A., "A Decision Theoretic Approach to Crop Disease Prediction and Control," *Amer. J. Agr. Econ.* 52(1970): 216–223.

Calson, G. A., "Risk Reducing Input Related to Agricultural Pests," *In Risk Analysis for Agirucltural Production Firms: Concepts, Information Reqouirements and Policy Issues,* Department of Agricultural Experiment Station, University of Illinois at Urban-Champaign, 1984: 164–175.

Day, R. H., "Probability Distributions of Field Crops," *J. Farm Econ.* 47(1965): 713–741.

Feder, G., "Pesticides, Information, and Pest Management under Uncertainty," *Amer. J. Agr. Econ.* 61(1979): 97–103.

Farnsthworth, R. L., "*A Decision Theoretic Analysis of Alternative Pest Control Strategies: A Case Study of Cotton Growers in California,*" Unpublished Ph.D. Dissertation. University of California, Berkeley, 1980.

Fuss, M. and D. McFadden, eds. "*Production Economics: A Dual Approach to Theory and Applications,*" New York: North-Holland, 1978.

Hausman, Jerry A., "Specification and Estimation of Simultaneous Equation Models," in Zvi Griliches and Michael D. Intriligator (ed), *Handbook of Econometrics,* New York: North-Holland, 1983: 408–413.

Heady, Earl O., "*Economics of Agricultural Production and Resource Use,*" New York: Prentice-Hall, 1952: Chap. 15.

Just, R. E. and R. D. Pope, "Stochastic Specification of Production Functions and Economic Implications," *J. of Econometrics,* 7(1978): 67–86.

______, "Production Function Estimation and Related Risk Considerations," *Amer. J. Econ.* 61 (1979): 277–284.

Kelejian, Harry H., "Two-Stage Least Squares and Econometric Systems Linear in Parameters but Nonlinear in the Endogenous Variables," *J. Amer. Stat. Ass.* 66(1971): 373–374.

Kmenta, Jan, "*Elements of Econometrics,* McMillan Publishing Co. Inc., 1971.

Lazarus, W. F. and E. R. Swanson, "Insecaticide Use and Crop Rotation under Risk: Rootworm Control in Corn," *Amer. J. Agr. Econ.* 65(1981): 738–747.

Menezes, C., G. Geiss and J. Tressler, "Increasing Downside Risk," *Amer. Econ. Rev.* 66(1980): 904–910.

Moffitt, L. J., Thomas M. Burrows, John L. Baritelle and Vahram Sevacherian, "Risk Evaluation of Early Termination for Pest Control in Cotton," *Western J. of Agr. Econ.* 9(1984): 145–151.

Roumasset, J. A., "*Rice and Risk: Decision Making Among Low-Income Farmers,*" New York: North-Holland 1976.

Taylor, C. R., "A Flexible Method for Empirically Estimating Probability Functions," *Western J. of Agr. Econ.* 9(1984): 66–76.
Theil, Henri, "*Principles of Econometrics*," John Wiley and Sons, Inc., 1971: p. 238.
Yassour, Joseph, David Zilberman and Gorden C. Rausser. "Optimal Choices among Alternative Technologies with Stochastic Yield," *Amer. J. Agr. Econ.* 63(1981): 719–723.