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# Econometric Production Models with Endogenous Input Timing: An Application to Ecuadorian Potato Production

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In this article, a model was developed in which the quantity and timing of input and harvest decisions are endogenous. The endogenous timing model allows all of the information about input and harvest behavior to be utilized, and it provides a basis for linking econometric production analysis to the time-specific analyses in other scientific disciplines used to assess the environmental or human health impacts of agricultural production practices.

The case study of fungicide use on Ecuadorian potatoes was conducted with a unique data set containing detailed information on both quantity and timing of input use. The results showed that both quantity and timing of chemical use were responsive to economic variables.

*Key words:* chemical use, Ecuadorian production, endogenous input timing, potato production, production models, sequential models.

## Introduction

Econometric production models typically are specified with inputs aggregated over time during the production process. Antle (1983) argued that input decisions in agricultural production processes usually are made sequentially, and showed that sequential decision making has important econometric implications for specification and estimation of production models.

In implementing dynamic production models with sequential input decisions, the researcher must choose how to define the production stages. For example, Antle and Hatchett define three production stages in relation to the growth stages of the wheat crop to study water input decisions; Mjelde, Dixon, and Sonka model the corn production cycle with eight production stages; and Skoufias divides the production process into planting and harvest stages to investigate labor input decisions. In so doing, these authors assume that the number and timing of sequential production decisions are exogenously determined. Put somewhat differently, the existing literature treats the duration of time or the length of time intervals between input decisions and the number of decisions as exogenous.

In many agricultural production processes, however, the number and timing of input decisions may be more important than the quantity of inputs used. The classic example of this would be an integrated pest management technology, where managers sample the pest population and then apply a standard treatment when the population passes a threshold level. Another example is the timing of harvest activities for perishable crops.

The purpose of this article is to develop and estimate a sequential production model for which the number and timing of production decisions are *endogenous* to the production

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process. This study demonstrates that the endogenously-determined timing of input decisions can be formulated as the duration of time between production decisions. The sequential decision model of Antle (1983) is a special case of the model developed here. The endogenous timing model is applied to fungicide use in Ecuadorian potato production where the timing of decisions is an important characteristic of the production process. This case study utilizes a unique data set containing detailed information on the quantity and timing of pesticide use.

There are several other reasons why it may be important to treat the timing of production decisions as an endogenous variable. The recent emphasis on the environmental and health impacts of agricultural production creates a need for researchers in economics to develop models that can be linked to models from other disciplines that are location and time specific (Antle and Capalbo; Opaluch and Segerson; King et al.). For example, models of surface and ground water contamination by agricultural chemicals utilize data on the location and time of chemical application in relation to the time of weather events (Wagenet and Rao). Models of exposure of farm workers to pesticides utilize information on both the amount and frequency of pesticide use (Antle and Pingali). Thus, if economic production models are to be linked with biophysical and health models, they must be able to represent the timing of input decisions in relation to the timing of physical and health-related events.

There are also econometric reasons why the timing of input and harvest decisions should be specifed as endogenous rather than as predetermined decisions. One obvious reason is for statistical efficiency and accuracy: if timing of decisions conveys important information about the production process and about decision making, ignoring it will lead to biased and inefficient estimates. A second econometric consideration is that if production stages are defined exogenously, then some stages may be observed with zero input levels. Because the input quantities are endogenous variables, the econometrician then must use models for limited dependent variables with complex error distributions. Consistent and efficient estimation of these models necessarily requires the use of nonlinear estimation procedures which are particularly complex in dynamic models (Pudney). Moreover, the problem of choosing a functional form becomes problematic with zero input levels. The log-linear model, one of the few that yields closed-form solutions to dynamic input demand functions, does not readily accommodate zero input levels. In contrast, the approach presented in this article utilizes all of the information contained in the data, and can be implemented with linear or log-linear models.

The remainder of the article proceeds as follows. A review of the dynamic production model with exogenously determined timing of input decisions is presented in the first section. In the second section, the theoretical model is developed with endogenous timing of input and harvest decisions. A discussion of econometric issues that arise in translating the theoretical model with endogenous timing into an applied model can be found in the third section. In the next section, the model is applied to fungicide use decisions in Ecuadorian potato production. The article concludes with some observations about the implications of the endogenous timing model for production economics research design.

## Dynamic Production Models with Exogenous Timing

In this section, the sequential decision model is reviewed with exogenous timing of input decisions, and its econometric implications, following the discussion in Antle and Hatchett. Consider a production process with three sequential operations, such as pest management. The decision maker is assumed to solve

$$\underset{\{x_0,x_1,x_2\}}{\text{Max}}\ E_t[\pi] = E_t[pq_2] - \sum_{j=0}^{2} E_t[w_jx_j],$$

where $\pi$ is profit, $p$ is output price, $q_2$ is final output, $w_j$ is the price of input $x_j$, and $E_t$

represents the mathematical expectation conditional on information available at time $t$. The timing of each production decision is predetermined at the beginning of the production process in this model. The input quantity decisions are made either at the beginning of the production process, and thus are also predetermined, or are made sequentially based on information that becomes available during the production process.

The technology is represented by the stage-level production functions

$$q_0 = q_0(x_0, \epsilon_0) \quad \text{and}$$
$$q_t = q_t(x_t, q_{t-1}, \epsilon_t), \qquad t = 1, 2,$$

where $\epsilon_t$ is the random component in production due to weather, disease, etc., and $q_{t-1}$ is the previous state of the crop, assumed to embody the effect of all inputs and random components in earlier stages. Observe that these stage functions have a recursive structure and that substitution of $q_0$ and $q_1$ into $q_2$ gives what Antle and Hatchett referred to as the composite production function:

$$q_2 = q(x_0, x_1, x_2, \epsilon_0, \epsilon_1, \epsilon_2).$$

The sequence of events in the decision-making process is as follows: The input $x_0$ is chosen at the beginning of the production process, given initial expectations of prices, future crop states, and decision rules for optimal inputs $x_1^*$ and $x_2^*$, given by

$$x_1^* = x_1(w_1, q_0, \omega_1) \quad \text{and}$$
$$x_2^* = x_2(w_2, q_1, \omega_2),$$

where $\omega_t$ denotes the parameters of the decision maker's subjective distributions of future output and prices at time $t$. Thus, at the beginning of the production process, the farmer chooses $x_0$ to solve

$$\operatorname*{Max}_{x_0} E_0[pq_2 - w_0x_0 - w_1x_1^* - w_2x_2^*],$$

subject to the production functions defined above. After $x_0$ is chosen, production begins; stage 0 production disturbance $\epsilon_0$ and state variable $q_0$ are realized. At the beginning of stage 1, the farmer observes $q_0$, and using an expectation of $x_2^*$, chooses $x_1$ to solve

$$\operatorname*{Max}_{x_1} E_1[pq_2 - w_0x_0 - w_1x_1 - w_2x_2^*],$$

subject to the production functions. After $x_1$ is chosen, stage 1 production begins, disturbance $\epsilon_1$ is realized, and state variable $q_1$ is realized. At the beginning of stage 2, the farmer observes $q_1$ and chooses final input $x_2$ to solve

$$\operatorname*{Max}_{x_2} E_2[py_2 - w_0x_0 - w_1x_1 - w_2x_3],$$

subject to the production functions.

Intermediate outputs $q_0$ and $q_1$ usually are not observed by the econometrician; thus the system of equations that is estimated is represented by the factor demand functions $x_1^*$ and $x_2^*$, with the intermediate outputs recursively substituted out of the model. The resulting system of equations is thus of the form:

$$\begin{aligned} &x_1 = x_1(w_1, w_2, x_0, \epsilon_0, \omega_1); \\ (1)\qquad &x_2 = x_2(w_2, x_0, x_1, \epsilon_0, \epsilon_1, \omega_2); \quad \text{and} \\ &q_2 = q(x_0, x_1, x_2, \epsilon_0, \epsilon_1, \epsilon_2). \end{aligned}$$

The recursive structure of this system shows that the intermediate inputs $x_1$ and $x_2$ are functions of the production errors when the input decision problem is solved sequentially and farmers update their information set before each decision. Therefore, estimates of the production function or the factor demand functions which do not account for the correlation of the inputs with the production function disturbances generally are biased.

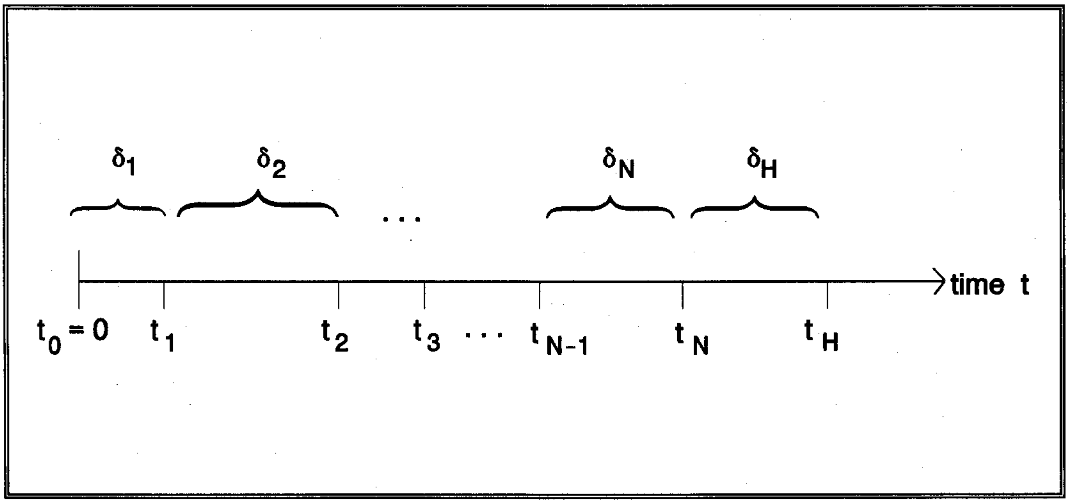


**Figure 1. Decision times ($t_i$) and intervals ($\delta_i$)**

Another problem that arises in the application of this model is that zero input quantities may occur, and this is especially likely in production processes where inputs such as pesticides are used. This precludes using the Cobb–Douglas model or other models involving logarithmic transformations of the variables.

## Dynamic Production Models with Endogenous Timing

The timing of production decisions is now assumed to follow the pattern illustrated in figure 1. Time $t$ is defined as continuous on the nonnegative real line, and production activities occur at discrete points in time. There are $N + 2$ decisions occurring at times $t_i$, $i = 0, 1, \ldots, N, H$, with land preparation, planting, and related activities at time $t_0 = 0$, intermediate production activities at times $t_1, \ldots, t_N$, and harvest at $t_H$. The intervals between decisions are defined as $\delta_i = t_i - t_{i-1}$, $i = 1, \ldots, N$, and $\delta_H = t_H - t_N$, so that

$$\sum_{i=1}^{H} \delta_i = t_H$$

is the time from planting to harvest.

Define a random vector $\epsilon_i$ on time interval $\delta_i$ to represent weather events on that interval (e.g., temperature, rainfall). For each partition of time $\delta = (\delta_1, \ldots, \delta_N, \delta_H)$, define the conditional density of weather events as $\phi(\epsilon_i \,|\, {}^{i-1}\epsilon)$, where the vector of errors that occurred in earlier stages is ${}^{i-1}\epsilon = (\epsilon_1, \ldots, \epsilon_{i-1})$. Henceforth, this notation is used to denote a vector of previously determined variables.

A general representation of a discrete, time-dependent production process then can be written as

$$\begin{aligned} q_0 &= q_0[x_0, \epsilon_0], \\ q_t &= q_t[x_t, q_{t-1}, \epsilon_t], \qquad 0 < t < t_H, \\ q_H &= q_H[x_H, q_t, \epsilon_H], \end{aligned}$$

where the subscripts on the functions indicate that the response of output to inputs depends on when the inputs are applied. For empirical purposes, this representation is not useful because in continuous time there are an infinite number of possible times at which input applications could occur on the (0, $H$) interval, and thus, by implication, there are an infinite number of possible production functions. One way to operationalize this model is to specify the production function with time-varying parameters. This type of varying parameter model is parameter intensive and is likely to suffer from the multicollinearity problem (see Mundlak and Hellinghausen). Moreover, in applications of these models, it typically is assumed that the model is log-linear and that the coefficients are linear functions of exogenous "state" variables. If one of these state variables was the time interval between input decisions, and the length of this interval was assumed to be an endogenous variable, then the log-linear variable coefficients model would become nonlinear in the parameters and would not possess a closed-form solution to the input decision problem.

The approach followed here is to represent the production process in each stage as a function of inputs employed and the time the activity occurs in relation to other activities in the production process. The $i$th production activity occurs at time $t_i = t_{i-1} + \delta_i$, and production $q_i$ is a function of: output from the previous stage, $q_{i-1}$; the time interval $\delta_i$; the input vector $x_i^*$; and the random events $\epsilon_i$ that occurred during $\delta_i$:

$$
\begin{aligned}
q_0 &= q_0[x_0, \epsilon_0], \\
q_i &= q_i[x_i, q_{i-1}, t_{i-1}, \delta_i, \epsilon_i], \qquad i = 1, \ldots, N, \\
q_H &= q_H[x_H, q_N, t_N, \delta_H, \epsilon_H].
\end{aligned} \tag{2}
$$

According to this model, parameters vary by stage of production rather than being explicit functions of time. The functions $q_i[\cdot]$ are assumed to be concave in $x_i$, $q_{i-1}$, and $\delta_i$. The explanation for the concavity of the production function in $\delta_i$ is derived from the physiology of crop growth. As crop growth proceeds, there is a point in time where each operation, such as cultivation, fertilization, pest control, etc., yields its greatest contribution to final output, given the state of crop growth and previous production activities. Observe, however, that concavity does not impose an algebraic sign on the terms $\partial^2 q_i/\partial x_i \partial \delta_i$. In some types of operations, such as cultivation with a tractor, increasing the interval between operations might increase the marginal productivity of the tractor power by reducing soil compaction; thus, $\partial^2 q_i/\partial x_i \partial \delta_i > 0$. In some other operations, such as pest management, shorter intervals between pesticide applications could result in improved pest control, giving $\partial^2 q_i/\partial x_i \partial \delta_i < 0$. Thus the sign of these cross-derivatives is an empirical question.

Recursively substituting the stage functions $q_i$ into $q_H$ in (2) gives the composite production function,

$$
\begin{aligned}
q_H &= q_H[x_H, q_N[q_{N-1}[\cdots], t_{N-1}, \delta_N, \epsilon_N], t_N, \delta_N, \epsilon_H] \\
&\equiv q^c[{}^H x, {}^N t, {}^N \delta, {}^H \epsilon],
\end{aligned} \tag{3}
$$

where ${}^H x = (x_0, \ldots, x_H)$, and ${}^N t$, ${}^N \delta$, and ${}^H \epsilon$ are defined similarly. As observed by Antle and Hatchett, because intermediate products usually are not observed, the composite function $q^c$ typically is estimated in econometric models.

Various sequential decision rules arise, depending on how the decision maker uses information, and the structure of these decision rules plays a key role in the econometric model, as emphasized in Antle (1983). Two scenarios are considered here. First, the manager could be assumed to update information continuously or with a greater frequency than decisions are made, and to make decisions conditional on that information. For example, as the production process moves through time, the manager could update information on a daily or weekly basis, and take an action when it is judged optimal to do so. An example of this type of behavior is a farmer observing a crop on a periodic basis and applying a pesticide when some indication of pest infestation occurs; the farmer could be basing decisions on personal experience or using a threshold determined by entomologists. Because the econometrician typically does not observe all of the weather conditions, pest populations, and other factors that influence the farmer's decision, this type of decision framework leads to the latent variable models in the econometrics literature. In this type of model, the observed actions take on a limiting value if the exogenous latent variable is below a threshold (e.g., no pesticide is applied if a pest population is below a threshold level), or take a positive value if the latent variable is above a threshold (e.g., a pesticide is applied if more than a threshold level of a pest is observed). The statistical properties of these models can be difficult to ascertain and the associated econometric methods are complex (see Aigner et al.).

Another complication of the analysis of production decision making occurs because information is costly. There are opportunity costs to monitor field conditions, and costs involved in planning and implementing decisions. In view of these econometric and theoretical considerations, the information updating behavior of the farm manager is simplified by the assumption that information is updated when other observable production activities occur. Thus, it is assumed that when the $(i - 1)$th decision is implemented at time $t_{i-1}$, the manager updates information and plans the subsequent action $(x_i)$ and its time of implementation $(t_i = t_{i-1} + \delta_i)$. Because $t_{i-1}$ is known, the choice of $t_i$ is equivalent to the choice of $\delta_i$. With this assumption, the properties of the model with endogenous timing are similar to the Antle–Hatchett model described above, except that the timing decision is endogenous. An important implication of this model is that every decision corresponds to an observable action; hence, there are no latent exogenous variables in the model and all observed values of the endogenous decision variables are positive.

The firm's objective function is assumed to be to maximize expected net returns. Output price $p$ is received at time of harvest $t_H$ with density function $\psi(p \mid t)$. Input prices are assumed, for convenience, to be known. Thus, at time $t_N$, the manager plans the harvest activity by selecting the harvest inputs $x_H$ and the time interval to harvest $\delta_H$ to maximize expected net returns:

$$(4) \quad \begin{aligned} E_N[\pi] &= \int \int (pq_H[x_H, q_N, t_N, \delta_N, \epsilon_H] - w_H x_H - c_N)\psi(p \mid \tau_N + \delta_H)\phi(\epsilon_H \mid {}^N\epsilon)\, dp d\epsilon_H \\ &= E_N[p \mid \delta_H]E_N[q_H \mid x_H, q_N, t_N, \delta_N] - w_H x_H - c_N, \end{aligned}$$

where $c_N$ is factor cost at time $N$. Second-order conditions must be satisfied to assure a maximum. Observe that the concavity of the production function is not sufficient in this case because of the dependence of expected price on time. Thus, it must also be assumed that the behavior of output price is such that expected returns is a globally concave function. Assuming the second-order conditions are met, the harvest decision satisfies

$$(5) \qquad \frac{\partial E_N[\pi]}{\partial x_H} = E_N[p \mid \delta_H] \frac{\partial E_N[q_H \mid \cdot]}{\partial x_H} - w_H = 0$$

and

$$(6) \qquad \frac{\partial E_N[\pi]}{\partial \delta_H} = E_N[p \mid \delta_H] \frac{\partial E_N[q_H \mid \cdot]}{\partial \delta_H} + \frac{\partial E_N[p \mid \delta_H]}{\partial \delta_H} E_N[q_H \mid \cdot] = 0.$$

Note that the input decisions occur before output is realized, and thus a discount factor should be introduced into equation (3). As long as the time period between decisions is relatively short, however, the discount factor is likely to be near one and therefore is not included in the presentation for simplicity.

Equation (5) is the usual first-order condition for optimal input choice to maximize expected net returns. Equation (6) states that the optimal timing of harvest balances an expected price and an expected productivity effect. Expected price may be either increasing or decreasing with time. Recall that expected output is assumed to be concave in $\delta_H$; that is, expected output increases with time up to crop maturity, and then may reach a plateau or decline as quantity or quality decrease. Rearranging (6) shows that, in equilibrium, the expected rate of price change equals minus the expected rate of output change:

$$\frac{\partial E_N[p \mid \delta_H]}{\partial \delta_H} \frac{1}{E_N[p \mid \delta_H]} = -\frac{\partial E_N[q \mid \cdot]}{\partial \delta_H} \frac{1}{E_N[q \mid \cdot]}.$$

Thus, if price is expected to decline, the farmer will harvest where $\partial E_N[q_H \mid \cdot]/\partial \delta_H > 0$.

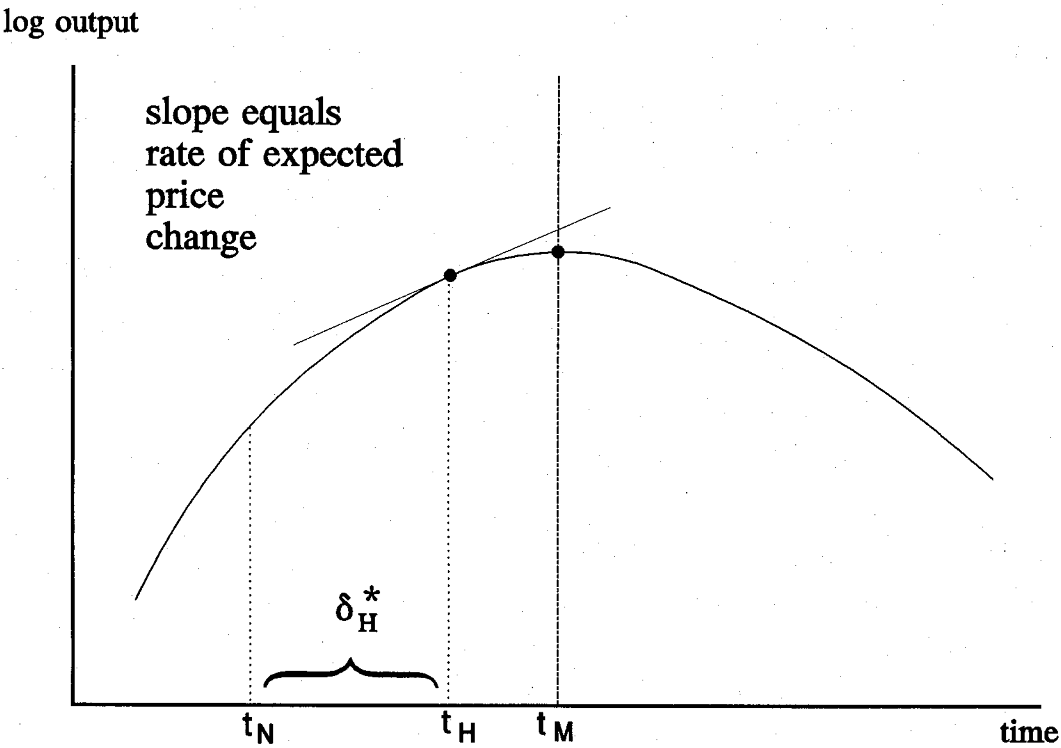


**Figure 2. Harvest timing in relation to expected price change**

As illustrated in figure 2, a declining expected price at time $t_N$ will lead the farmer to choose the time interval to harvest, $\delta_H^*$, such that harvest occurs at time $t_H < t_M$ before the maximum yield is attained. Conversely, when price is expected to be increasing, the farmer will harvest where $\partial E_N[q_H \mid \cdot]/\partial\delta_H < 0$, i.e., to the right of $t_M$ in figure 2. Thus, the harvest time generally should be a decreasing function of the expected harvest price. If a discount rate were included explicitly in the model, it would be subtracted from the left-hand side of this equation, thus demonstrating that the higher the discount rate, the earlier the harvest decision. The system of equations (5) and (6) can be solved for the decision rules:

$$x_H^* = x_H^*(E_N[p], w_H, q_N, t_N) \quad \text{and} \qquad (7)$$
$$\delta_H^* = \delta_H^*(E_N[p], w_H, q_N, t_N).$$

At time $t_{N-1}$, the manager chooses $x_N$ and $\delta_N$ to maximize

$$E_{N-1}[\pi] = E_{N-1}[p \mid t_{N-1} + \delta_N + \delta_H^*]E_{N-1}[q_H \mid x_N, x_H^*, q_{N-1}, t_{N-1}, \delta_N, \delta_H^*]$$
$$- c_{N-1} - w_N x_N - E_{N-1}[w_H x_H^*].$$

The first-order conditions are:

$$E_{N-1}[p \mid \cdot]\frac{\partial E_{N-1}[q_H \mid \cdot]}{\partial x_N} - w_N - w_H\frac{\partial E_{N-1}[x_H^*]}{\partial x_N} = 0 \qquad (8)$$

and

$$\frac{\partial E_{N-1}[p \mid \cdot]}{\partial\delta_N}E_{N-1}[q_H \mid \cdot] + E_{N-1}[p \mid \cdot]\frac{\partial E_{N-1}[q_H \mid \cdot]}{\partial\delta_N} + w_H\frac{\partial E_{N-1}[x_H^*]}{\partial\delta_N} = 0. \qquad (9)$$

Equations (8) and (9) differ from (5) and (6) by the terms representing the impact of decisions at $t_{N-1}$ on expected harvest input $x_H$. It seems plausible that intermediate decisions, such as pesticide use and cultivation, have little or no impact on the quantity or timing of inputs used in harvest; thus, $\partial E_{N-1}[x_H^*]/\partial x_N = 0$ and $\partial E_{N-1}[x_H^*]/\partial \delta_N = 0$. It is also plausible that intermediate input timing would not affect harvest timing and thus not affect the expected price at harvest, in which case $\partial E_{N-1}[p \mid \cdot]/\partial \delta_N = 0$. Under these conditions, equations (8) and (9) imply that intermediate input timing is made to maximize output, i.e., the solution occurs where $\partial E_{N-1}[q_H \mid \cdot]/\partial \delta_N = 0$, and the input quantity $x_N$ satisfies the usual condition that expected value of marginal product equals factor price. Under these assumptions and the assumed concavity of the production function in $x_N$ and $\delta_N$, the comparative static properties of the factor demand function, $x_N^*[E_{N-1}[p], w_N, q_{N-1}, t_{N-1}]$, can be shown to be the same as the neoclassical model, i.e., $\partial x_N^*/\partial E_{N-1}[p] > 0$ and $\partial x_N^*/\partial w_N < 0$. In the case of the optimal time interval, $\delta_N^*[E_{N-1}[p], w_N, q_{N-1}, t_{N-1}]$, comparative static analysis shows that the signs of the price effects depend on the effect of timing on the marginal productivity of $x_N$. In particular, $\partial \delta_N^*/\partial w_N >(<) 0$ as $\partial^2 E_{N-1}[q \mid \cdot]/\partial x_N \partial \delta_N <(>) 0$, with the signs reversed for the output price effect.

Applying the same procedures for $i < N$, let $\delta_*^{i+1} = (\delta_{i+1}^*, \ldots, \delta_H^*)$, etc. It follows that the values of $x_i$ and $\delta_i$ chosen at time $t_{i-1}$ to maximize

$$E_{i-1}[\pi] = E_{i-1}\left[p \mid t_{i-1} + \delta_i + \sum_{j=i+1}^{H} \delta_j^*\right] E_{i-1}[q_H \mid x_i, x_*^{i+1}, q_{i-1}, t_{i-1}, t_*^i, \delta_i, \delta_*^{i+1}]$$

$$- w_i x_i - \sum_{t=i+1}^{H} w_i E_{i-1}[x_i^*]$$

are generally of the form

$$x_{i*} = x_i^*[E_{i-1}[p], w^i, q_{i-1}, t_{i-1}], \tag{10}$$
$$\delta_{i*} = \delta_i^*[E_{i-1}[p], w^i, q_{i-1}, t_{i-1}].$$

Note the dependence of these functions on $w^i = (w_i, \ldots, w_N, w_H)$, because decisions at $t_i$ generally depend on future planned decisions.

## Econometrics of Production Models with Endogenous Timing

The results of the previous section can be summarized as follows. At time $t_i$ of the $i$th production activity, the decision maker is assumed to update information and to plan the quantity and timing of subsequent actions. Application of the dynamic programming algorithm to the problem of maximizing the farmer's objective function yields the system of behavioral equations of the form (10). This section discusses econometric issues that arise in translating this system of theoretical demand functions into an econometric model.

Typically, neither the intermediate-stage production functions in (2) nor the system of equations represented by (10) can be estimated because the intermediate outputs $q_i$, $i < H$, are not observed by the econometrician. Recursively substituting the intermediate-stage functions (2) into (10) yields

$$x_i^* = x_i^r[E_{i-1}[p], w^i, {}^{i-1}x, {}^{i-1}t, {}^{i-1}\delta, {}^{i-1}\epsilon] \quad \text{and} \tag{11}$$
$$\delta_i^* = \delta_i^r[E_{i-1}[p], w^i, {}^{i-1}x, {}^{i-1}t, {}^{i-1}\delta, {}^{i-1}\epsilon],$$

where ${}^{i-1}x = (x_0, \ldots, x_{i-1})$ and other variables are defined similarly. The recursive system of equations, consisting of the composite production function (3) and the system of demand functions (11), is defined in terms of observable variables and is estimable. The composite production function depends on the error terms from all of the production stages. Statistical estimation must account for the joint dependence of output and inputs on the production errors, and for the statistical properties of the errors. Thus, as noted above in the discussion of the model with exogenous timing, an estimate of the production function that does not take this joint dependence into account will be biased. Antle and Hatchett describe a seemingly-unrelated regression estimator and a maximum likelihood estimator that can be used for this model. If the system of factor demand equations (11) is estimated without the production function, then each equation contains errors from previous production stages and exogenous and lagged endogenous variables. Therefore, if ${}^{i-1}x$ is statistically independent of ${}^{i-1}\epsilon$, the factor demand equations can be estimated consistently and efficiently using a suitable generalized least squares estimator. If the lagged inputs on the right-hand side of (11) are correlated with lagged disturbances, then an instrumental variables estimator or a maximum likelihood estimator is required for consistent or efficient estimation.

Econometric estimation of the production model can proceed in several ways. One approach, now standard in the literature, is to parameterize the production function, derive the implied first-order conditions (expressed either as demand functions or as "share" equations), and then estimate the system of equations with across-equation parameter restrictions imposed for statistical efficiency. Several difficulties arise in applying this approach to the dynamic production model represented by the system of equations (3) and (11). First, few functional forms for the dynamic production functions in (2) provide closed-form solutions to the factor demand functions in (11). Antle and Hatchett derive a solution for the dynamic Cobb–Douglas production model under the assumption of exogenous input timing; it is a straightforward, if tedious, exercise to show that a Cobb–Douglas version of (2) can be solved for the demand functions (11) in log-linear form. However, this Cobb–Douglas model is restrictive in its behavioral implications. In addition to the usual restrictions of the log-linear form, such as unitary elasticities of substitution, it implies elastic factor demand functions. Problems also arise in the specification of the time variables $\delta_i$ in the Cobb–Douglas model, because producers may be observed operating where the marginal product of $\delta_i$ is negative [see equation (6) and fig. 2]. It also is possible to solve a quadratic model for explicit factor demand functions, under the restrictive and implausible assumption that the production functions are additively separable in inputs across production stages. The statistical efficiency gained from imposing one of these restrictive functional forms may be an illusion, because the apparent efficiency gain comes at the cost of specification bias. For this reason, Antle and Hatchett suggested an alternative approach, namely, to flexibly approximate the factor demand functions and the production function, without imposing the across-equation restrictions.

A second problem that arises in estimating the model with endogenous timing is that the total number of input decisions is a random variable. Thus, for each production cycle represented in the data (planting to harvest) there is a different number of observed input quantities $x_i$ and intervals $\delta_i$. It is not possible to write the model in the usual form with a prespecified number of parameters unless certain assumptions are made about the constancy of parameters across production stages. For example, if all farms make at least $K < N$ decisions, and the parameters of the functions $q_i$, $i = K + 1, \ldots, N$, in (2) are assumed to be the same, then even though $N$ will vary from farm to farm, the model contains a fixed number of parameters. Under this assumption, it would be possible to parameterize the stage-level production functions and derive the full system of equations consisting of the composite production function (2) and the factor demand functions (11), subject to the qualifications of functional form discussed above.

The approach to econometric specification and estimation pursued in this study is motivated by the philosophy that the objective of econometric research is to extract as much information as possible from the data without imposing untested maintained hypotheses. In view of the specification problems identified above and the limited a priori information available about the structure of the stage-level functions in (2), it is judged most appropriate to utilize a flexible parameterization of the system of demand equations (11) without imposing across-equation restrictions implied by a parameterization of the production functions. For each application event, a system of quantity and timing equations is estimated and subjected to specification tests. Tests for parameter constancy across applications can be performed, and if the parameters are not found to be different, the data across sets of applications can be pooled under the assumption of parameter constancy to increase statistical efficiency.

## An Application to Ecuadorian Potato Production

In this section, the system of dynamic factor demand equations in (11) is specified for the case of fungicide use in potato production in the Carchi Province in northern Ecuador. Potato production in Carchi is concentrated in a highland zone 30 kilometers south of the Colombian border. Only half a degree north of the equator, production occurs in altitudes between 2,800 and 3,400 meters on steeply sloped, deep volcanic soils. There are virtually no changes in day length, little seasonal temperature variation, and limited variation in rainfall. The cropping system is dominated by potatoes and pasture for dairy cattle. Because of the equatorial location and rainfall patterns, there are no distinct planting or harvesting seasons; virtually all recorded planting dates are on different days, evenly distributed through the months of the year. Conditions in Carchi are highly favorable to potato production, with farmers in the sample obtaining average yields of 22 metric tons (MT) per hectare (ha) as compared to a national average of 8 MT/ha and yields of around 30 MT/ha in the United States.

Production data were collected in a farm-level survey conducted in the Carchi region on 40 farms during 1990–92. Because crops are planted and harvested continuously throughout the calendar year, data were collected for parcels, where a parcel is defined as a single crop cycle on a farmer's field. Excluding pasture, a total of 490 parcels were registered, of which 338 were potato. From these, a total of 320 potato parcels were used in the estimation sample. The potato fields not used had incomplete harvest data due to the local practice of selling an unharvested field to third-party harvesters. The 320 parcels in the sample represent 178 different fields.

Detailed parcel-level production data were collected on a monthly basis. Potato production in Ecuador is management intensive, and there are as many as 20 distinct operations during the six-month crop cycle. Post-harvest farmer recall of detailed data on pesticide use is unlikely to be accurate. Thus, the investment in monthly visits was deemed essential to the success of the data collection effort. See Crissman and Espinosa for further details on sampling and data collection procedures.

The late blight fungus (*Phytophthora infestans*) is the principal disease and the tuber-boring Andean weevil (*Premnotrypes vorax*) and several foliage damaging insects are the principal pests affecting production. The control of these three threats requires distinct strategies relying primarily on chemical pesticides.

Late blight can be a devastating disease where, in a susceptible variety, entire fields can be destroyed overnight. Effective control relies on prevention. Most fungicides are contact-type, killing the fungus encountered on the surface of the plant. Manufacturers of these products typically recommend treatment at prescribed intervals depending on the weather. During periods of rainy weather, the frequency of spraying increases as conditions for fungus development are better and the rain washes the fungicide off the foliage.

The data contain 1,881 observations on fungicide applications, where the unit of observation is a day when one or more fungicides were applied. The patterns during the production cycle of the timing of the individual applications are illustrated in figure 3. The data show that most fields were treated with fungicides at least four times. The dispersion in the timing of the applications reveals a wide range of pest management behavior that presumably reflects differing physical and economic conditions faced by farmers. The quantity data reveal that the amounts applied follow the development of the foliage, with average application amounts increasing through the first several sprays and then remaining at about the same level for the remaining sprays. After plant senescence, foliage does not contribute to tuber development and farmers cease to use fungicides.

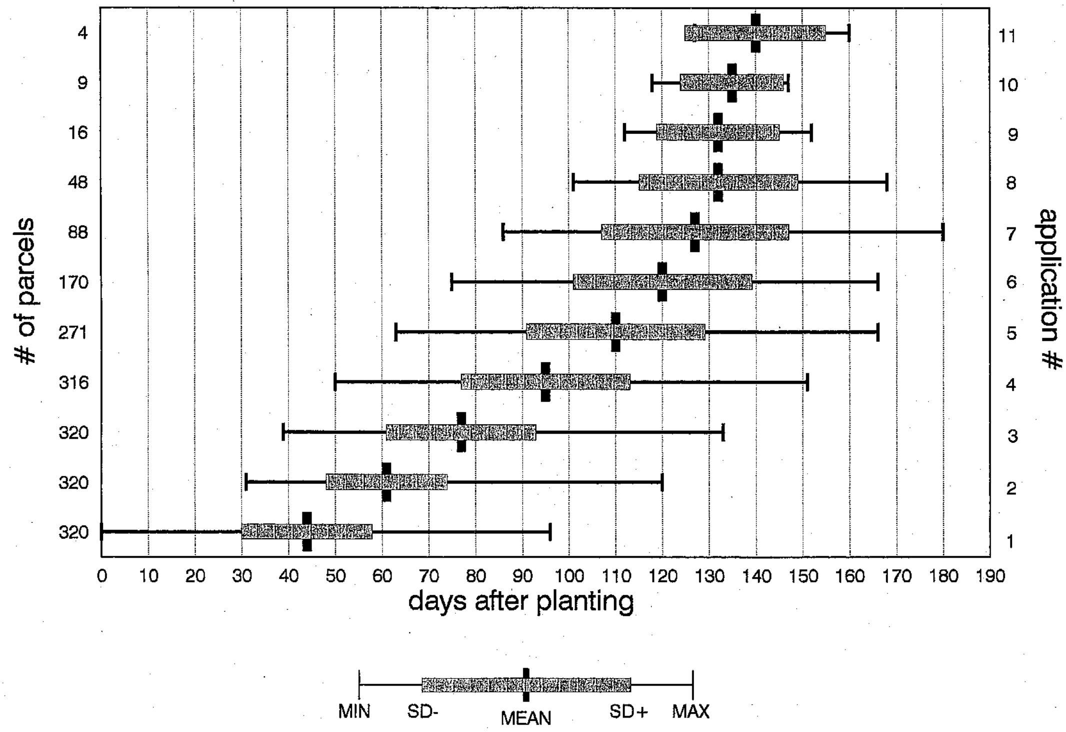


**Figure 3. Timing of fungicide applications**

### *Quality Adjustment of Pesticide and Output Data*

A critical problem in the analysis of pesticide use is that farmers apply many different types of materials to control a given pest, such as late blight or Andean weevil. In the Carchi survey, 27 different insecticides and 41 different fungicides were used. These pesticides are composed of a wide array of organic and inorganic chemicals of differing potencies. Simply aggregating quantities of products applied, or quantities of active ingredients applied, would fail to accurately measure the variation in pest control services embodied in the different materials. Thus, in analyzing pesticide use, production economists face a quality-adjustment problem similar to the one that exists with the measurement of capital stocks and other types of inputs.

So that these materials could be compared in standardized units, a hedonic price model was utilized to quality-adjust quantities and prices of pesticides, following Antle (1988). In this model, pesticide price is assumed to be a function of pesticide quality or effectiveness, as reflected in the application rate and type of pesticide. To help identify the quality component of price, other variables that reflect farmer and crop characteristics unrelated to quality but related to pesticide use also are included in the model.

The fungicide price was regressed on: the application rate (*RATE*), a dummy variable indicating whether the fungicide is a systemic or nonsystemic type (*TYPE*), the variety of the potato (*VDi*), the altitude of the field (*ALT*), the application number (*APPNO*), the days after planting of the application (*DAP*), the size of the field treated (*AREA*), and a trend variable to account for inflation (*TREND*). The results of the log-linear model which fit the data best, with *t*-statistics in parentheses, were:

$$\begin{aligned}\ln(PRICE) = {} & \underset{(3.48)}{35.22} - \underset{(-45.09)}{.44\ln(RATE)} + \underset{(51.75)}{1.77TYPE} + \underset{(2.79)}{.16ALT}\end{aligned}$$

(Continued)

$$
\begin{aligned}
&+ \underset{(1.54)}{.01 APPNO} + \underset{(6.33)}{.003 DAP} - \underset{(-8.15)}{.21 AREA} + \underset{(6.13)}{.04 AREA^2} \\
&- \underset{(-3.12)}{.7 TREND} + \underset{(3.57)}{.0005 TREND^2} + \underset{(2.23)}{.08 VD2} + \underset{(1.78)}{.07 VD3} \\
&+ \underset{(1.96)}{.12 VD4} + \underset{(3.03)}{.13 VD5} + \underset{(1.15)}{.05 VD6} + \underset{(2.09)}{.11 VD7} \\
&N = 3{,}385, \quad R^2 = 0.924, \quad F = 2{,}725.77.
\end{aligned}
$$

According to the interpretation of the application rate as an indicator of quality, the negative sign of the *RATE* coefficient indicates an inverse relationship between application rate and quality, as expected. The *TYPE* coefficient indicates that the systemic fungicides are much more expensive than the nonsystemics. This result corresponds to the fact that much smaller amounts of systemic pesticides are used per standard application as compared to nonsystemics, so the systemics are interpreted as higher quality than the nonsystemics. Setting all variables other than *RATE* and *TYPE* to their sample means to generate a numeraire value, the predicted value of the above equation was then used to generate weights to quality-adjust all fungicides relative to this numeraire unit of measurement. An implicit quality-adjusted price is obtained by dividing the value of each pesticide applied by the quality-adjusted quantity. A similar hedonic procedure was conducted for the two groups of insecticides corresponding to the soil and foliage pests.

Potato quality is a major factor affecting prices received by farmers. Consumer preferences for potatoes are functions of potato variety, as well as a set of quality characteristics such as size, shape, and insect or disease damage. Thus, to standardize potato output for quality, a hedonic model was estimated in which potato price was regressed on dummy variables representing potato variety and potato quality. Varieties are classified as native, local improved (*LOCAL*), and national improved (*NATIONAL*). Potato quality was coded into the data according to a classification system from highest value to lowest value uses, including categories for commercial potatoes shipped to the urban markets (*CLASS*1), seed potatoes (*CLASS*2), potatoes used for home consumption (*CLASS*3), and those for nonhuman consumption (*CLASS*4, 5, 6). The hedonic regression results of the linear model which fit the data best were:

$$
\begin{aligned}
PRICE = &\underset{(104.41)}{5{,}993.85} + \underset{(5.08)}{292.61 LOCAL} - \underset{(-7.31)}{429.55 NATIONAL} \\
&- \underset{(-46.57)}{2{,}155.63 CLASS2} - \underset{(-69.88)}{3{,}773.38 CLASS3} - \underset{(-90.60)}{4{,}834.09 CLASS4} \\
&- \underset{(-29.61)}{5{,}032.12 CLASS5} - \underset{(-25.09)}{4{,}640.04 CLASS6} \\
&N = 2{,}600, \quad R^2 = 0.803, \quad F = 1{,}511.08.
\end{aligned}
$$

The results indicate that the local varieties receive a price premium of about 5% relative to the native varieties, whereas the national varieties receive a 7% discount, presumably because of taste and cooking qualities. Relative to the potatoes shipped to the urban market, those sold as seed in local markets, consumed at home, or for nonhuman consumption were priced substantially lower. This equation treats commercial-grade potatoes of native varieties as the numeraire. Thus, predicted values from this equation, with the variety dummy variables set equal to zero, are interpreted as quality weights corresponding to this numeraire. Multiplying these weights times the quantities of each quality of potato gives a quality-adjusted quantity measured in numeraire units. An implicit quality-adjusted price was obtained by dividing the value of output by the quality-adjusted quantity produced on each field.

As described in the previous section, the dynamic factor demand equations are functions of expected output prices. In principle, it would be desirable to construct a market model to represent price expectations under the assumption of rational expectations. Lacking suitable data for the construction of a market model, a simple model of expected output price was constructed under the assumption that farmers know that nominal output prices can be decomposed into two components: a trend, reflecting general price level inflation which averaged about 50% per annum during the study period; and a seasonal component, reflecting a cyclical pattern of market conditions driven by seasonal variations in production. Thus, the quality-adjusted output price was regressed on a time trend and monthly dummy variables. The estimated equation indicated there are significant trend and seasonal components in the data. The predicted values of the model were used as estimates of expected output prices in the factor demand models.

### *Estimation Results*

The system of factor demand equations (11) for fungicide applications was specified in log-linear form, thus enabling coefficients on all variables except dummy variables to be interpreted as elasticities. The input price vector was specified to include the fungicide price, the price of insecticides applied to treat Andean weevil, the price of other insecticides, and the daily wage for pesticide application and other "management" activities, all normalized by expected output price. Inputs applied at the beginning of the season also should enter the equation. Quantity variables included in the model are field size, fertilizer, field preparation animal labor, and field preparation human labor. The dynamics of the model were represented by the inclusion of lagged dependent variables and a variable indicating the time of the previous application. Preliminary estimates of the model indicated that one lag effectively represented the dynamics, so the second and higher lags were not included in the results presented here.

The data represent time series of each farmer's applications during a single cropping cycle of a potato field. To solve the problem of a random number of total applications across fields, the seventh and higher numbered applications were assumed to have the same parameters and were pooled for each field. The error structure of the factor demand equations could contain serial correlation due to weather events that span more than one application. However, because the time series is only seven observations long for each field, there are not enough degrees of freedom to estimate a different autoregressive process for each field. Moreover, beause fields may be planted at any time during the year and applications occur at widely varying intervals, there is little reason to believe that different fields exhibit the same autoregressive processes; therefore, it would be unreasonable to pool the data from different fields to estimate the error process. Consequently, an autoregressive error process was not estimated, although it is recognized in the design of the estimation procedures that the errors may be correlated over time.

It is also possible that the error covariance matrix may exhibit heteroskedasticity. This hypothesis was tested by applying the method of Antle (1983) to test whether the variances of the quantity and timing equations are statistically significant functions of the exogenous variables. The null hypothesis of homoskedasticity could not be rejected for any of the equations, so heteroskedastic corrections were not made.

The quantity and timing equations form a simultaneous system with lagged endogenous variables. As noted above, serial correlation in the errors is possible, in which case the lagged endogenous variables would be correlated with the error terms of the equations. Therefore, the choice of estimation method should consider the presence of endogenous variables as regressors. Hausman tests were used to compare ordinary least squares (OLS) and two-stage least squares (2SLS) estimates for each equation (quantity and timing) for each application. The OLS estimates were not found to be significantly different from 2SLS for any of the quantity equations and for five of the seven timing equations. In view of the trade-off between efficiency and bias in using OLS or 2SLS estimates, and because only a limited number of excluded exogenous variables were available for use as instruments for 2SLS estimation, it was judged that OLS estimation was the preferred method. Therefore, OLS estimation was used to produce the results presented in tables 1 and 2.

Standard $F$-statistics were computed to test the hypothesis that the parameters of equations for individual applications are equal across applications 1 through $N$. For pooling all applications, the test statistic for the quantity equations was $F(13,1790) = 41.22$ and the statistic for the timing equations was $F(14,1783) = 18.71$. These statistics both exceed the critical value of approximately 2.1, indicating clear rejection of the hypothesis that the parameters of all applications are equal for either quantity or timing equations. Next, the hypothesis of equal parameters was tested for pairs of applications (1 and 2, 2 and 3, etc.). The only pairs for which parameter equality was not rejected were (4, 5) and (5, 6). Finally, groups of three applications were tested (1, 2, and 3; 2, 3, and 4; etc.). The only case for which parameter equality was not rejected was for the quantity equation with the combination (4, 5, 6). Therefore, it was concluded that it was not suitable to pool the applications. This finding also demonstrates that aggregating the data over time would be inappropriate.

The parameter estimates show several important features of the model. First, the quantity equations (table 1) generally fit well considering that the data are cross-sectional, with $R^2$ statistics in the 0.88 to 0.92 range. In contrast, the timing equations (table 2) explain between 16 and 31% of the variation in the timing intervals between applications. These results appear to be due to the preventative character of late blight control, and to the fact that farmers lack accurate methods to predict late blight infestations. Thus, the timing of treatments is likely to be based more on a fixed schedule of applications, with the schedule based on farmers' experience, rather than on a sequential updating scheme. Considering the potentially catastrophic nature of late blight infestations, the timing of applications also is less likely to be responsive to economic variables than other pest control decisions. This situation can be contrasted with an integrated pest management technology that uses weather data and measures of pest incidence to time treatments in relation to an economic threshold. Both environmental conditions and economic variables would be expected to play a more important role in explaining the timing of input decisions with this type of pest management.

Second, despite the tendency for the timing equations to fit the data less well than the quantity equations, the results demonstrate that both the quantity and timing of fungicide applications are significant functions of prices. The own-price elasticity of the quantity demanded is close to unity for all applications. The own-price elasticity of the timing decision is significant for the first four applications, and ranges from a value of .55 for the first application to .17 for the fourth. As hypothesized in the discussion of the comparative statics of the model, the sign of this timing elasticity is positive, indicating that a higher price leads farmers to spray less frequently, *ceteris paribus*. The insecticide price coefficients are mostly insignificant, indicating there is not a strong interrelationship between insecticide and fungicide use. The labor wage coefficient is positive in the quantity equations and negative in the timing equations, indicating that labor generally substitutes for pesticides.

Third, the results indicate that fungicide timing generally has a statistically significant effect on fungicide quantity, and vice versa. The positive coefficient on the time between applications in the quantity equation indicates that as frequency of application declines, quantity increases. Similarly, the positive coefficient of the quantity variable in the timing equation indicates that as quantity increases, frequency of application declines.

The results also show dynamic relationships across applications. The positive coefficient of the lagged endogenous quantity variable corresponds to the observed pattern of increasing rates of application as the foliage develops and the crop matures. The positive coefficient on the lagged endogenous variable in the timing equations of the later applications indicates that, after the third application, the length of time between applications tends to be positively related across applications. This phenomenon, as well as the dynamics of the quantity equation, could be explained in part by field characteristics that relate to pest incidence and unobserved farmer characteristics such as risk attitudes. For example, it is clear from the data that some farmers generally treat more times and apply higher rates than other farmers, regardless of pest incidence. The dynamics of the early

**Table 1. OLS Estimates of Log-Linear Fungicide Quantity Equations, Ecuadorian Potato Production**

| Variable | Equation for Application Number | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | $7-N$ | $1-N$ |
| Intercept | −1.388 | −2.425 | −2.697 | −.403 | .959 | 3.284 | 1.777 | −1.176 |
| | (−.577) | (−.907) | (−1.429) | (−.140) | (.484) | (1.553) | (.740) | (−1.219) |
| Fungicide Price | −1.064 | −.965 | −.946 | −1.015 | −1.023 | −.994 | −1.018 | −.979 |
| | (−28.610) | (−23.714) | (−29.134) | (−28.672) | (−27.604) | (−24.462) | (−25.106) | (−69.716) |
| Soil Pest Insecticide | .116 | .257 | .216 | −.031 | −.261 | −.394 | .198 | .060 |
| Price | (.465) | (.928) | (1.138) | (−.102) | (−1.240) | (−1.682) | (.766) | (.592) |
| Foliage Pest Insecticide | −.014 | .060 | .013 | −.017 | .033 | .012 | −.022 | .027 |
| Price | (−.564) | (2.291) | (.491) | (−.603) | (1.036) | (.348) | (−.536) | (2.250) |
| Labor Wage | .744 | .744 | .757 | .845 | 1.053 | .897 | .606 | .805 |
| | (6.400) | (6.056) | (7.383) | (8.030) | (8.996) | (7.044) | (4.629) | (16.605) |
| Area | .393 | .283 | .309 | .437 | .361 | .429 | .499 | .351 |
| | (4.396) | (2.995) | (4.063) | (5.621) | (4.146) | (5.011) | (5.655) | (9.753) |
| Fertilizer Quantity | .401 | .307 | .303 | .345 | .333 | .320 | .295 | .390 |
| | (5.332) | (3.780) | (4.584) | (5.139) | (4.385) | (3.975) | (3.168) | (12.574) |
| Land Preparation Labor | .011 | .017 | .006 | .003 | .012 | .006 | .011 | .008 |
| | (1.643) | (2.407) | (1.087) | (.501) | (1.808) | (.890) | (1.517) | (2.904) |
| Land Preparation | −.001 | .010 | −.005 | −.012 | .001 | −.008 | .025 | .003 |
| Animal Power | (−.087) | (1.005) | (−.685) | (−1.464) | (.110) | (−.878) | (3.491) | (.944) |
| Lagged Fungicide | | .180 | .193 | .116 | .099 | .149 | −.001 | .121 |
| Quantity | | (5.233) | (7.363) | (3.909) | (3.126) | (4.249) | (−.036) | (33.022) |
| Fungicide Timing | .221 | −.074 | .239 | .310 | .131 | .074 | −.083 | .217 |
| | (5.211) | (−1.029) | (3.394) | (4.109) | (1.611) | (.754) | (−.932) | (8.440) |
| Sample Size | 320 | 320 | 320 | 316 | 271 | 170 | 165 | 1,881 |
| ESS | 81.561 | 86.177 | 58.429 | 58.638 | 52.355 | 23.124 | 19.493 | 487.261 |
| $R^2$ | .884 | .886 | .912 | .920 | .901 | .934 | .919 | .891 |
| $F$ | 263.268 | 240.018 | 321.882 | 350.505 | 237.659 | 224.742 | 174.353 | 1,531.640 |

Note: $t$-statistics are in parentheses.

**Table 2. OLS Estimates of Log-Linear Fungicide Timing Equations, Ecuadorian Potato Production**

| | Equation for Application Number | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 − N | 1 − N |
| Intercept | −15.963 | −5.713 | −4.871 | −1.488 | 9.902 | −14.046 | −4.784 | −6.507 |
| | (−1.385) | (−.882) | (−.807) | (−.249) | (1.578) | (−2.110) | (−.703) | (−2.152) |
| Fungicide Price | .555 | .243 | .262 | .168 | .067 | −.049 | −.023 | .264 |
| | (6.595) | (4.844) | (5.554) | (3.464) | (1.239) | (−.761) | (−.374) | (11.203) |
| Soil Pest Insecticide Price | 1.140 | .472 | .203 | .199 | −.014 | −.051 | −.030 | .413 |
| | (3.622) | (2.468) | (1.349) | (.905) | (−.089) | (−.284) | (−.146) | (4.956) |
| Foliage Pest Insecticide Price | −.020 | .011 | −.020 | .038 | .020 | −.048 | .036 | −.001 |
| | (−.648) | (.587) | (−.945) | (1.738) | (.808) | (−1.709) | (1.060) | (−.123) |
| Labor Wage | −.188 | −.172 | −.225 | −.126 | −.050 | .065 | .010 | −.185 |
| | (−1.184) | (−1.920) | (−2.610) | (−1.506) | (−.506) | (.580) | (.090) | (−4.186) |
| Fertilizer Quantity | −.278 | −.132 | −.155 | −.173 | −.062 | .031 | −.034 | −.175 |
| | (−4.348) | (−3.562) | (−4.359) | (−4.835) | (−1.579) | (.627) | (−.616) | (−9.642) |
| Lagged Application Days after Planting | | −.318 | .103 | .088 | −.048 | .376 | −.081 | −.289 |
| | | (−9.970) | (1.021) | (.776) | (−.338) | (2.340) | (−.492) | (−32.047) |
| Lagged Fungicide Timing | | | −.012 | .161 | .294 | .174 | .485 | .072 |
| | | | (−.253) | (2.724) | (4.030) | (2.321) | (5.745) | (6.500) |
| Fungicide Quantity | .336 | .170 | .163 | .143 | .083 | −.059 | .012 | .183 |
| | (4.890) | (4.252) | (4.070) | (3.687) | (1.903) | (−1.086) | (.199) | (9.274) |
| Zone 1 | .0002 | −.285 | −.237 | −.097 | −.375 | −.255 | .207 | −.188 |
| | (−.001) | (−2.414) | (−2.141) | (−.923) | (−2.974) | (−1.289) | (.704) | (−3.182) |
| Zone 2 | −.148 | −.257 | −.112 | −.049 | −.226 | −.245 | .068 | −.158 |
| | (−.722) | (−2.238) | (−1.047) | (−.484) | (−1.902) | (−1.351) | (.231) | (−2.807) |
| Zone 3 | −.235 | −.267 | −.183 | −.066 | −.244 | −.428 | .229 | −.206 |
| | (−1.509) | (−3.055) | (−2.246) | (−.850) | (−2.554) | (−2.473) | (.788) | (−4.659) |
| Altitude | 1.133 | .735 | .824 | .280 | −.921 | 1.913 | .834 | .908 |
| | (.834) | (.974) | (1.151) | (.413) | (−1.222) | (2.354) | (1.031) | (2.547) |
| Sample Size | 320 | 320 | 320 | 316 | 271 | 170 | 165 | 1,881 |
| ESS | 135.099 | 41.306 | 35.468 | 30.723 | 28.239 | 13.186 | 11.975 | 336.841 |
| $R^2$ | .219 | .287 | .199 | .212 | .163 | .198 | .314 | .445 |
| $F$ | 8.681 | 11.254 | 6.354 | 6.802 | 4.193 | 3.226 | 5.806 | 124.719 |

Note: $t$-statistics are in parentheses.

applications seem less systematic. The negative and significant coefficient of the time variable in the timing equation for application 2 contrasts with the positive and significant coefficient for application 6. This outcome corresponds to the changing pattern seen in figure 3, where the intervals between applications are longer on average and more variable in the early applications than the intervals between later applications.

The other input quantities (area, fertilizer, land preparation labor, and animal power) are generally positively and significantly related to fungicide quantity, as expected. The fertilizer quantity has a negative and significant effect on the time interval between applications. This effect is explained by the relationship between fertilizer and foliage development. Fertilizer use stimulates foliage development, which is positively related to tuber yield. Late blight attacks the foliage, so it follows that farmers who apply larger quantities of fertilizer per hectare also will have a greater incentive to use fungicide to protect their investment in the crop. The data show that fertilizer's share in variable production cost is 20%, the largest of any input.

Finally, parcels in the numeraire zone are generally at higher altitudes and more humid, and thus more conducive to late blight than parcels in other agro-ecological zones represented in the sample. The coefficients of the zone dummy variables and the altitude variable in the timing equations confirm this.

## Conclusions

In this article, a model was developed in which the quantity and timing of input and harvest decisions are endogenous. The model was estimated for fungicide input decisions in Ecuadorian potato production. This approach has numerous advantages over static models in which inputs are aggregated over time or models in which input decisions are sequential but the number and timing of decisions are exogenous. Most importantly, the endogenous timing model allows all of the information about input and harvest behavior to be utilized, and it provides a basis for linking econometric production analysis to the time-specific analyses in other scientific disciplines used to assess the environmental or human health impacts of agricultural production practices.

The Ecuadorian case study of fungicide use on potatoes was conducted with a unique data set containing detailed information on both quantity and timing of input use. The results showed that both quantity and timing of chemical use were responsive to economic variables. It also was found that the demand equations' parameters were not constant across applications during the growing season, and that there was a systematic pattern in these differences. Therefore, the assumption of constant parameters could lead to biased predictions of responses to changes in economic and technological variables.

To make this modeling approach feasible, data must be collected in such a way that both the quantity and timing of input decisions are recorded. It could be argued that collecting production data in this way is more costly than conventional survey methods that do not record when input decisions are made. However, the experience of the authors suggests that in cases where the timing of input decisions is an important part of the production process, the only way to ensure the quality of the data is to collect data on an ongoing basis throughout the growing season. This can be accomplished either through periodic farm visits to collect intermediate input data, as was done in this study, or by obtaining agreements with farmers in advance to keep records during the season.

Several extensions of the model presented in this article could be explored in future research. The key behavioral assumption made in this study, namely that farmers sequentially plan subsequent decisions when the previous one is implemented, needs to be tested. This test would involve formulating and estimating the more complex limited-dependent variable model that results from the assumption that information is updated more frequently than when observable production activities take place. Another issue that could be investigated concerns the fact that sequential production processes generally involve multiple, jointly-dependent intermediate inputs. For example, in the case of

Ecuadorian potato production, both insecticides and fungicides are used, and the use of one may affect crop growth and thus the use of the other. The issue of the timing of harvest decisions also could be investigated, as in the recent study by Ramos. Because yield reaches a plateau as the crop matures and then may decline, the question of appropriate functional forms for models with harvest timing decisions needs to be investigated. Harvest timing decisions should depend critically on price expectations, and more sophisticated price expectations models may need to be incorporated into the econometric analysis.

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## References

Aigner, D. J., C. Hsiao, A. Kapteyn, and T. Wansbeek. "Latent Variable Models in Econometrics." In *Handbook of Econometrics,* Vol. 1, eds. Z. Griliches and M. D. Intriligator. Amsterdam: North Holland Publishing Co., 1983.

Antle, J. M. *Pesticide Policy, Production Risk, and Producer Welfare: An Econometric Approach to Applied Welfare Economics.* Washington DC: Resources for the Future, 1988.

———. "Sequential Decision Making in Production Models." *Amer. J. Agr. Econ.* 65(1983):282–90.

Antle, J. M., and S. M. Capalbo. "Physical and Economic Model Integration for the Measurement of the Environmental Impacts of Agricultural Chemical Use." *Northeast. J. Agr. and Resour. Econ.* 20(1991):68–82.

Antle, J. M., and S. A. Hatchett. "Dynamic Input Decisions in Econometric Production Models." *Amer. J. Agr. Econ.* 68(1986):939–49.

Antle, J. M., and P. Pingali. "Pesticides, Productivity, and Farmer Health: A Philippine Case Study." *Amer. J. Agr. Econ.* 76(August 1994): in press.

Crissman, C. C., and P. Espinosa. "Agricultural Chemical Use and Sustainability of Andean Potato Production: Project Design and Pesticide Use in Potato Production in Ecuador." Paper presented at conference, "Measuring the Health and Environmental Effects of Pesticides," Bellagio, Italy, 30 March 1992.

King, R. P., D. W. Lybecker, A. Regmi, and S. M. Swinton. "Bioeconomic Models of Crop Production Systems: Design, Development, and Use." *Rev. Agr. Econ.* 15(May 1993):389–401.

Mjelde, J. W., B. L. Dixon, and S. T. Sonka. "Estimating the Value of Sequential Updating Solutions for Intrayear Crop Management." *West J. Agr. Econ.* 14(1989):1–8.

Mundlak, Y., and R. Hellinghausen. "The Intercountry Agricultural Production Function: Another View." *Amer. J. Agr. Econ.* 64(1982):664–72.

Opaluch, J. J., and K. Segerson. "Aggregate Analysis of Site-Specific Pollution Problems: The Case of Groundwater Contamination from Agriculture." *Northeast. J. Agr. and Resour. Econ.* 20(1991):83–97.

Pudney, S. *Modeling Individual Choice: The Econometrics of Corners, Kinks, and Holes.* New York: Basil Blackwell, 1989.

Ramos, M. G. P. "Pesticide Inputs, Harvest Timing, and Functional Forms." Unpub. M.S. thesis, Montana State University, Bozeman, April 1993.

Skoufias, E. "Seasonal Labor Utilization in Agriculture: Theory and Evidence from Agricultural Households in India." *Amer. J. Agr. Econ.* 75(1993):20–32.

Wagenet, R. J., and P. S. C. Rao. "Modeling Pesticide Fate in Soils." In *Pesticides in the Soil Environment: Processes, Impacts, and Modeling,* Soil Sci. Book Ser. No. 2, eds., H. H. Cheng, R. E. Green, W. Spencer, and G. W. Bailey. Madison WI: American Society of Agronomy, 1990.