Estimating Population Dynamics without Population Data

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Abstract

We develop a biologically correct cost system for production systems facing invasive pests that allows the estimation of population dynamics without a priori knowledge of their true values. We apply that model to a data set for olive producers in Crete and derive from it predictions about the underlying populations dynamics. Those dynamics are compared to information on population dynamics obtained from pest sampling with extremely favorable results.

Keywords: separabale technologies, pest population, damage control, olive farms, Greece

1 Introduction

Accurate representation of supply-response relationships is essential to the scientific management of natural-resource industries. An important challenge to modelling supply-response in many of those industries is lack of population data for the biological entity that affects output. For example, the population of invasive pests is an important determinant of both pest damage and crop harvest (Lichtenberg and Zilberman, 1986; Babcock, Lichtenberg, and Zilberman, 1992; Underwood and Caputo, 1996; Bulte and Rondeau, 2007; Coburn *et al.*, 2011). But data on pest populations are typically unavailable in many practical instances. This creates a dilemma. Use models that ignore this basic biological component of the technology. Or, maintain biologically correct models that cannot be estimated without extreme assumptions on population behavior.

This paper, following Chambers and Strand (1999), proposes a potential solution. The key observation is that the separability properties of many biologically-grounded models of the underlying production processes, when combined with information on rational producer supply response, can be used to circumvent this obstacle. While biologists have focused on the development of accurate yield-response relationships, economists instead have concentrated on developing estimable production systems. Natural synergies should emerge from combining these efforts into a common

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*University of Maryland, USA and University of Crete, Greece, respectively. This research has received funding from the European Community's Seventh Framework Programme [FP 7/2008-2011] under Grand Agreement Number 212120. Corresponding author: V. Tzouvelekas, Dept of Economics, University of Crete, University Campus, 74100 Rethymno, Greece, e-mail: vangelis@econ.soc.uoc.gr, Ph.: +302831077417 framework. We show how biological models can be combined with information on supply response to make inferences on population dynamics and to estimate correctly specified biological production response behavior *even in the absence of direct observations on underlying population variables.*

The intuition is unabashedly simple: if a yield-response relationship is correctly specified, then once other factors affecting production levels (for example, input use) are properly controlled for, yield effectively indexes of the underlying biological population. We use agricultural data to illustrate and evaluate our procedures. And so, for concreteness sake, the conceptual treatment is for an agricultural producer facing an invasive pest species. But because the basic principle behind our approach is so simple, the procedures outlined here can be readily extended, after suitable adaptation, to a host of other applications. If biological populations truly affect supply response, information on supply (as well as derived demands) should mirror that effect and thus provide an avenue for recapturing information on the underlying population.

In what follows, we first specify the production model and the producer's objective function. Then we briefly characterize optimal producer behavior to establish a direct link between population variables and observable economic phenomena such as prices, supply, and derived demand. We then follow with a parametric specification of pest damage to crops and show how that choice yields a variable cost function, consistent with biological behavior, that is estimable without direct knowledge on pest population. It also yields a procedure for approximating pest-population dynamics. An empirical specification and description of the data is followed by an empirical application of our ideas. That empirical application takes advantage of a unique characteristic of our data set, direct observations on population variables. Those data are *not* used in estimation, but they allow us to compare the population dynamics our procedure yields with actual population dynamics. Once our empirical results are presented, we then discuss related literature. In particular, we compare our empirical results with those from an alternative approach that is grounded in the biological literature but that is applied to our data set. The paper then concludes.

2 The Model

2.1 Structure of Production and Producer Objective

Production of a single crop, y, in period t is characterized by

$$y = g(b, z) f(x, K, t)$$

where $x \in \mathbb{R}_+^J$ represents variable productive inputs, $K \in \mathbb{R}_+^K$ quasi-fixed productive inputs, $b \in \mathbb{R}_+$ the pest population, $z \in \mathbb{R}_+$ a damage-control or abating input, $f(x, K, t)$ is (maximal) potential supply in the absence of pests, and $g(b, z)$, $g : \mathbb{R}_+^2 \to (0, 1]$, represents the percentage of maximal potential output that is realized in the presence of pest population b when the damage-control input is applied at level z.

The producer's short-run problem is to choose variable productive and damage control inputs (x, z) to maximize profit. Notationally,

$$\max_{x,z} \left\{ pg(b,z)\, f(x,K,t) - w'x - v'z \right\} \tag{1}$$

where $p \in \mathbb{R}_{++}$ is output price, $w \in \mathbb{R}^{J}_{++}$ is a vector of variable productive input prices, and $v \in \mathbb{R}_{++}$ is the damage-control input price.

We rewrite this problem as

$$\begin{aligned} \max_{x,z} \left\{ pg(b,z)\, f(x,K,t) - w'x - v'z \right\} &= \max_{y,x,z} \left\{ py - w'x - v'z : y = g(b,z)\, f(x,K,t) \right\} \\ &= \max_{y,x,z} \left\{ py - w'x - v'z : \frac{y}{g(b,z)} = f(x,K,t) \right\} \\ &= \max_{y,z} \left\{ py - c\left(w, \frac{y}{g(b,z)}, K, t \right) - v'z \right\}. \end{aligned} \tag{2}$$

Here

$$c(w,f,K,t) := \min_{x} \left\{ w'x : f = f(x,K,t) \right\}$$

is minimum variable-cost associated with the productive inputs, x, producing f in the absence of pests. The first-order conditions for an interior solution to (**??**) require:

$$\begin{aligned} pg(b,z) &= c_f\left(w, \frac{y}{g(b,z)}, K, t \right), \\ c_f\left(w, \frac{y}{g(b,z)}, K, t \right) \frac{y g_z(b,z)}{g(b,z)^2} &= v, \end{aligned}$$

where $c_f\left(w, \frac{y}{g(b,z)}, K, t \right)$ denotes the partial derivative of $c(w,f,K,t)$ with respect to f. Solving gives:

$$py \frac{g_z(b,z)}{g(b,z)} = v. \tag{3}$$

Expression (**??**) can also be obtained directly as a first-order condition for (**??**). The solution to these first-order conditions yields: optimal product supply, $y(p,w,K,t,v,b)$, and optimal derived demands for x and z, $x(p,w,K,t,v,b)$ and $z(p,w,K,t,v,b)$, respectively.

2.2 The Damage-Control Specification and Population Dynamics

The choice of a parametric specification for $g(b,z)$ has been widely discussed (Lichtenberg and Zilberman, 1986; Babcock *et al.*, 1992; Carasco-Tauber and Moffit, 1992; Fox and Weersink, 1995; Carpentier and Weaver, 1997; Hennessy, 1997; Oude Lansink and Carpentier, 2001). We follow Lichtenberg and Zilberman (1986) and Fox and Weersink (1995) and formulate $g(b,z)$ as comprising two components, control and damage:

$$g\left(b,z\right)=\exp\left(-\lambda b\exp\left(-\delta_z z\right)\right),\tag{4}$$

where λ and δ_z are parameters. In this specification, $C:=\exp\left(-\delta_z z\right)$ represents the control component of the technology, and $\exp\left(-\lambda bC\right)$ the damage-component given control at level C.

Choosing a parametric specification for $g\left(b,z\right)$ establishes via (**??**) a direct (and typically invertible) link between the underlying pest population, b, and $y\left(p,w,K,t,v,b\right)$. That link yields a closed-form solution for the pest population (up to proportional transformation), b. Mathematically, this simply reflects some version of the implicit-function theorem. From that perspective, the insight is not terribly sophisticated. Economically, the intuition is that once the presence of other conditioning factors is taken into account, realized output is an index of b expressed in units of the produced output. Effectively, observed output represents a monotonic transformation of the population and thus provides an ordinal measure of it. The effect of the conditioning factors (x,z,K) is accounted for by the assumption of rational economic behavior, and cardinal identification is permitted by knowledge of the parametric structure. Hence, the approach is a simple, but practical, melding of biological information with economic theory.

Using (**??**) in (**??**) and rearranging gives

$$\lambda b=\frac{v}{\delta_z py\left(p,w,K,t,v,b\right)\exp\left(-\delta_z z\left(p,w,K,t,v,b\right)\right)}.\tag{5}$$

Given information on p, $y\left(p,w,K,t,v,b\right),z\left(p,w,K,t,v,b\right)$, v, and the parameter δ_z, λb can be calculated from (**??**). Substituting (**??**) into (**??**) gives

$$g\left(b,z\left(p,w,v,b\right)\right)=\exp\left(-\frac{v}{\delta_z py\left(p,w,K,t,v,b\right)}\right)\tag{6}$$

Conditional on the assumption of profit maximization, a strategy for inferring λb is now apparent. From (**??**), given observations on supply response and price, the essential problem is to obtain an estimate for δ_z, which is the parameter determining the effectiveness of pesticides in controlling pests. Optimal variable input cost (conditioned on z and y) for the variable productive inputs equals $c\left(w,\frac{y}{g(b,z)},K,t\right)$, which depends upon b. Substituting from (**??**) gives

$$c\left(w,\frac{y\left(p,w,K,t,v,b\right)}{g\left(b,z\left(p,w,K,t,v,b\right)\right)},K,t\right)=c\left(w,\frac{y}{\exp\left(-\frac{v}{\delta_z py(p,w,K,t,v,b)}\right)},K,t\right).$$

Therefore, once a parametric specification for $c\left(w,f,K,t\right)$ is chosen, substituting $\frac{y}{\exp\left(-\frac{v}{\delta_z py(p,w,K,t,v,b)}\right)}$ for f in that form, gives an expression for variable-productive input cost that can be combined with information on w, p,K, and $y\left(p,w,K,t,v,b\right)$ to estimate both the parameters of $c\left(w,f,K,t\right)$ and δ_z. Once that information is obtained, the estimate of δ_z can be used with (**??**) to approximate λb.

3 Data and the Practical Problem

Our data are from survey of 50 olive-growers during the 1999-04 cropping period that was conducted by extension personnel of the Greek National Agricultural Foundation. The survey was designed to examine empirically the effectiveness of six-pesticide ingredients against the olive-fruit fly *Bactocera Oleae* (*Gmellin*) in the Western part of Crete, Greece. The olive-fruit fly is the only serious pest towards olives, and it significantly threatens olive-oil production in most olive growing areas (Burrack and Zalom, 2008).[1] Worldwide olive trees number about 800 million and occupy a surface area of approximately 10 million hectares. They produce about 1.6 million metric tonnes per annum of olive-oil. The losses attributed to the olive-fly have been set as high as 15-20 per cent of production, which equates to roughly $800 million annually. This estimated damage occurs despite annual expenditures (worldwide) of approximately $100 million annually to combat the olive-fruit fly. About 50 per cent of that expenditure corresponds to chemical pesticides (Guerbaa, 1987; Kiritsakis, 1990).

The olive-fruit fly survives best in cooler coastal climates, but they are also found in hot, dry regions of Greece, Italy, Spain, Mexico, and California. The optimum temperature for larval development is between 20 and 30°C. Temperatures above 40°C are detrimental to adult flies and to maggots in the fruit. However, because the flies are very mobile they have the ability to seek out cooler areas of the orchard and trees. Reports of fly movement range from 600 ft in the presence of an olive host to as much as 2.5 miles to find hosts. During rainy winter weather, the number of flies usually drops off significantly, but stings and damage can still continue.

The biological cycle of *Bactocera Oleae* is closely linked to the microclimate and the state of the olives (Wang *et al.*, 2009). Within a year, there are generally three to five generations, but in many years there can be a sixth generation, which grows in the spring on the olive tree. The population size varies throughout the year, but there are two peaks: one at the end of spring (April to May), at the development of the winter generation of adults. The second, more intense peak, occurs in early autumn (late August to early October) when the olives are most vulnerable, the temperatures drop slightly and the climate becomes more humid. The olive-fruit fly causes damage to both quantity and quality of fruit produced. From a quantity point of view the damage is caused by the removal of the significant proportion of the pulp. This, in turn, results in a reduction in yield. Part of the lost production is due to premature falling of the attacked fruit. For table olives, however, the damage also extends to the sterile punctures which cause the variation in production. There is also a significant deterioration in the quality of the oil extracted from olives with a high percentage of attacks by the olive-fruit fly. The olive-oil obtained from infected olives has a high acidity level (expressed as oleic acid, from 2 to 10 percent depending on the level of pest infestation) and a lower shelf life.

For our empirical model, output is measured in kilograms and consists of olive-oil quantities

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[1] In fact, olives are the only breeding host plants.

sold off the farm, quantities consumed by the farm household during the crop year, and the portion of output kept by olive mills as a fee for extraction services.[2] Farmers use a mixture of fertilizers including nitrate, phosphorous, and potassium. These different fertilizers were aggregated into a single aggregate *Tornqvist* fertilizer index with the cost shares of each type of fertilizer defining the relevant weights. Intermediate inputs consist of goods and materials used during the crop year, whether purchased off-farm or withdrawn from beginning inventories. These include fuel and electric power, storage expenses, and irrigation measured in Euros. The price of hired labor was computed as the average hourly wage including social security and taxes paid by farmers. The computed hourly wage varies across farms as the demand for hired workers differs significantly during harvesting season (harvesting season usually starts from the late October until the end of January with significant fluctuations depending on the maturity stage and pest infestation among farms). Family labor devoted to productive activities was treated as a quasi-fixed input and is measured in hours worked on-farm. Capital stock was computed using the *perpetual-inventory* method as described by Ball *et al.*, (1993) and data on depreciation rates obtained from the Greek Ministry of Agriculture for different farming equipment.

The survey contains farm-level information on six different pesticide ingredients, which are applied approximately every two weeks depending on the pest population levels observed in the olive fields. These consist of data on expenditures and quantities used measured in litres. We use these data to construct an aggregate pesticides input quantity and price index using again *Tornqvist* procedures with cost shares of each ingredient to total pesticides expenditures being the relevant weights. Finally, information on the pest population was obtained by means of chemical traps (*i.e.*, *McPhail* traps) that are installed (for our sample) on every 500 square meters of the farm's plot. Our information on pest population was derived by following the standard practice of olive growers and biologists of using the number of olive flies captured in these traps to proxy the whole pest population in each plot. The number of pests were converted to biomass equivalent using the empirical study by Genc (2008) (see Table **??**).

Adult olive fruit fly populations are typically monitored using yellow sticky traps that are baited with sex pheromone and ammonium bicarbonate. The sex pheromone is attractive to male flies while the ammonium bicarbonate is primarily attractive to females. Both sexes are attracted to the trap's yellow colour. Thus, the population numbers used in our empirical analysis are not biased with respect to fly gender and can be expected to reflect, as closely as possible, the actual pest situation in each olive orchard. Trap catches may vary in response to numerous variables, including temperature, humidity, physiological status of the fly and, of course, population size (Economopoulos, 1979). Nevertheless, monitoring populations using sticky traps is commonly used in timing pesticide applications and is generally believed to produce a close approximation to actualy olive-fruit fly populations. This practice is particularly wide-spread in Europe, where

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[2] Output is measured in quantities of olive-oil produced and therefore it does not take into account the quality effects of pest infestation. Our model though can be extended to that direction using Babcock *et al.*, (1992) modelling approach in a straightforward manner.

pesticide applications are routinely made on the basis of threshold trap counts (Haniotakis *et al.*, 1986).

Summary statistics for all variables used in the empirical analysis are presented in Table **??**. Finally, prior to econometric estimation, and to avoid problems associated with units of measurement, all variables were converted into indices, with the basis of normalization being the representative olive-oil farm. The representative farm was the one with smallest deviation of all variables from the sample means.

4 Empirical Model and Econometric Estimation

In our empirical application, the variable cost function takes the following flexible, transcendental logarithmic (*translog*) form:

$$\begin{aligned} lnc_{it}\left(w_{it}, f_{it}, K_{it}, t\right) &= \alpha_0 + \alpha^y lnf_{it} + \sum_j \alpha_j^w lnw_{jit} + \sum_k \alpha_k^q lnK_{kit} + \sum_j \alpha_j^{yw} lnf_{it} lnw_{jit} \\ &+ \alpha^t t + \sum_k \alpha_k^{yq} lnf_{it} lnK_{it} + \alpha^{yt} lnf_{it} t + \sum_j \sum_k \alpha_{jk}^{wq} lnw_{jit} lnK_{kit} \\ &+ \sum_j \alpha_j^{wt} lnw_{jit} t + 0.5 \Bigg[\alpha^{yy} lnf_{it}^2 + \sum_j \sum_h \alpha_{jh}^{ww} lnw_{jit} lnw_{hit} \\ &+ \sum_k \sum_l \alpha_{kl}^{qq} lnK_{kit} lnK_{lit} + \alpha^{tt} t^2 \Bigg] + \sum_k \alpha_k^{qt} lnK_{it} t + \varepsilon_{0it} \end{aligned} \tag{7}$$

Here i subscripts correspond to the i^{th} farm and t subscripts to the t^{th} year, w_{jit} is the price for the j^{th} variable input, K_{kit} is the k^{th} quasi-fixed input used in farm production and, t is a time index capturing changes in farming technology. This translog cost function is converted to estimable form by using (**??**) and making the following substitution:

$$lnf_{it} = lny_{it} + \frac{v_{it}}{\delta_z p_{it} y_{it}}$$

where v_{it} is the price of pesticide materials, p_{it} the output price, and y_{it} is realized output. Symmetry and linear homogeneity in variable-input prices imply the following parameter restrictions on our cost function: $\alpha_{jh}^{ww} = \alpha_{hj}^{ww}$, $\alpha_{kl}^{qq} = \alpha_{lk}^{qq}$, $\sum_j \alpha_j^w = 1$, $\sum_h \alpha_{jh}^{ww} = 0 \ \forall j$, $\sum_j \alpha_j^{yw} = 0$, $\sum_j \alpha_{jk}^{wq} = 0 \ \forall k$ and $\sum_j \alpha_j^{wt} = 0$. By *Shephard's* lemma, the variable-input cost share for input j is given from the following expression:

$$S_{jit} = \alpha_j^w + \alpha_j^{yw} \left(lny_{it} + \frac{v_{it}}{\delta p_{it} y_{it}} \right) + \sum_h \alpha_{jh}^{ww} lnw_{hit} + \alpha_j^{wt} t + \sum_k \alpha_{jk}^{wq} lnK_{kit} + \varepsilon_{jit} \tag{8}$$

where $S_{jit} = (w_{jit} x_{jit})/c_{it}$ denotes the share of the j^{th} variable-input in total cost of farm production.

The system of variable-input cost shares was estimated together with the cost function using the random effects model suggested by Bjørn *et al.* (2003) and Bjørn (2004) adapted to a balanced panel data setting.[3] Assuming that farm heterogeneity is captured by the constant terms in both the cost function and cost share equations, the random terms in (**??**) and (**??**) can be expressed, respectively, as:

$$\varepsilon_{0it} = \sum_j u_{ji} lnw_{jit} + u_{0i} + e_{0it} \quad \text{and} \quad \varepsilon_{jit} = u_{ji} + e_{jit}$$

where u_i and e_{it} are independently and identically distributed random terms, *i.e.*, $u_i \sim N(0, \mathbf{\Sigma}_u)$ and $e_{it} \sim N(0, \mathbf{\Sigma}_e)$. Further it is assumed that u_i and e_{it} are mutually uncorrelated and unrelated with variable-input prices, quasi-fixed inputs, and t. In this framework the random coefficient structure implies: $\alpha_{0i} = \alpha_0 + u_{0i}$ and $\alpha^w_{ji} = \alpha^w_j + u_{ji}, \forall j$. Under these assumptions Bjørn (2004) showed that the variance-covariance matrix of ε_{it} is given by:

$$\mathbf{\Sigma}_\varepsilon = \mathbf{x}_{it} \mathbf{\Sigma}_u \mathbf{x}'_{it} + \mathbf{I}_t \otimes \mathbf{\Sigma}_e$$

where $\mathbf{x}_{it}$ is the augmented matrix of constants and variable-input prices and, $\mathbf{I}_t$ is the t dimensional identity matrix. Parameter estimates of the above system are obtained in three steps (see Bjørn *et al.* (2003), Bjørn (2004)) when both variance-covariance matrices are unknown.

First, the system is estimated as a simple SUR model and the residuals from each equation (*i.e.*, cost function and variable-input cost shares) are used to calculate the unknown variance-covariance matrices, $\mathbf{\Sigma}_u$ and $\mathbf{\Sigma}_e$, from the following:

$$\mathbf{\Sigma}_e = \frac{\mathbf{W}_e}{N(T-1)} \quad \text{and} \quad \mathbf{\Sigma}_u = \frac{\mathbf{B}_e - \left(\frac{N-1}{N(T-1)}\right) \mathbf{W}_e}{T(N-1)}$$

where $\mathbf{W}_e = \sum_i \sum_t (\varepsilon^s_{it} - \bar{\varepsilon}^s_i)(\varepsilon^s_{it} - \bar{\varepsilon}^s_i)'$ and $\mathbf{B}_e = \sum_i (\bar{\varepsilon}^s_i - \bar{\varepsilon}^s)(\bar{\varepsilon}^s_i - \bar{\varepsilon}^s)'$ with ε^s_{it} being the obtained residuals from the first step and $\bar{\varepsilon}^s_i = (1/T) \sum_t \varepsilon^s_{it} \ \forall i$, $\bar{\varepsilon}^s = (1/N) \sum_i \bar{\varepsilon}^s_i$.

In the second step, parameter estimates are obtained by maximizing the following likelihood function with respect to the parameter vector α (Bjørn, 2004) :

$$\mathscr{L} = -\frac{GN}{2} ln(2\pi) - \frac{1}{2} \sum_i \sum_t ln \left| \mathbf{\Sigma}_\varepsilon \right| - \frac{1}{2} \sum_i \sum_t \left(\mathbf{y}_{it} - \mathbf{x}_{it} \alpha \right) \mathbf{\Sigma}^{-1}_\varepsilon \left(\mathbf{y}_{it} - \mathbf{x}_{it} \alpha \right)'$$

where G is the number of equations in the translog cost system above and $\mathbf{y}_{it}$, $\mathbf{x}_{it}$ are the stacked matrices over all equations of the dependent and independent variables, respectively. For given $\mathbf{\Sigma}_u$ and $\mathbf{\Sigma}_e$ this is identical with the GLS estimation of the system.

In the third step, using the estimates of the parameter vector α, the likelihood function above is again maximized with respect to $\mathbf{\Sigma}_u$ and $\mathbf{\Sigma}_e$ to obtain estimates of the two covariance matrices. The whole process is repeated again from the second step until parameter estimates of the translog

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[3] We are indebted to a reviewer of an earlier version of this paper for suggesting this estimation procedure.

cost system converges. Oberhofer and Kmenta (1974) and Breusch (1987) have shown that this sequential procedure ensures that convergence is achieved, even if the likelihood function is not globally concave. After convergence, the best linear unbiased predictor of the random coefficients is given by (Bjørn *et al.*, 2003):

$$\hat{\alpha}_i = \hat{\alpha} + \hat{\mathbf{\Sigma}}_u x'_{it} \left(\mathbf{x}_{it}\hat{\mathbf{\Sigma}}_u \mathbf{x}'_{it} + I_t \otimes \hat{\mathbf{\Sigma}}_e\right)^{-1} (\mathbf{y}_{it} - \mathbf{x}_{it}\hat{\alpha}) \tag{9}$$

where ˆ indicates the corresponding GLS estimates of the expected coefficient vector and variance-covariance matrices obtained from the above procedure.

5 Empirical Results

Although our variable-cost function specification treats farm output as predetermined, econometrically it is endogenous. To accommodate this endogeneity, before the GLS estimation of the translog cost system, we ran a first-stage OLS regression of realized output against variable input and output prices as well as two environmental variables (humidity rates and air temperature), the altitude of farm location, and two farm-specific characteristics (average household education level and number of extension visits on-farm). High temperature and humidity levels[4] create favorable micro-climatic conditions for pest occurrence and their reproduction. Moreover, more educated farmers can more easily digest technical information and read bulletins or manuals related with the appropriate application of pesticide materials on-farm. At the same time, extension agents can provide to the farmers useful information on the levels of pest infestation and the maturity stage of pests during their biological cycle. After running the OLS regression, the predicted values of realized output were used in the econometric estimation of the cost system as explained in the previous section.

The GLS parameter estimates of the conditional translog cost system are reported in Table **??**. Consistent standard errors for these estimated parameters that are robust to heteroscedasticity and serial correlation were obtained using the stationary bootstrapping technique of Politis and Romano (1994). Specifically, farms in the dataset were grouped randomly in a number of blocks of five farms and reestimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors. Most of the estimated parameters are statistically different from zero at standard confidence levels. We note, in particular, that δ_z, the parameter determining the effectiveness of pesticides, appears to have been very precisely estimated and that it appears significantly different zero (the corresponding t-ratio is 6.049, well above the critical value at the 5 per cent significance level).

To assess the econometric performance of our estimated translog cost system, we conducted a series of statistical tests. First, we used the *Hausman* test to examine statistically whether output

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[4] It should be noted here that humidity rates are not related with irrigation application by olive farmers and mostly reflect the microclimatic conditions in olive orchards. Olive trees are usually irrigated 5 to 6 times during the summer period and therefore irrigation practices are not related directly with pest infestation.

is endogenous or not in the econometric estimation of the translog cost system. The result strongly supports our treatment of it as endogenous.[5] Next, an application of *Sargan's* test validates our choice of instruments in the first-stage as it rejects the hypothesis that the error term is uncorrelated with the instruments (the test statistic is 18.5 well above the corresponding critical value of the *chi*-squared distribution at the 5% significance level with 4 degrees of freedom). We also checked for the presence of serial correlation. Although the time-span in our data is only six years, we followed Wooldridge's (2002) approach of regressing the estimated residuals from each equation in the translog cost system against their one-period lagged value. In each case, the estimated coefficient of the lagged residuals was not statistically significant different from zero suggesting that serial correlation is not a problem. Finally, the *Hausman* specification test suggests that individual farm effects are uncorrelated with the other regressors in the translog cost system validating our choice of the random coefficient model.[6]

Tables **??** and **??** report the estimated variance-covariance matrix of the random coefficients and variable-input demand elasticities evaluated at sample means, respectively. The estimated variance-covariance matrix is positive definite (at sample means) as the calculated eigenvalues of the matrix are positive. Furthermore, all estimated own-price elasticities are negative, as required by theory, and less than one indicating rather inelastic own-price responses for hired labor, chemical fertilizers and intermediate inputs.[7] All estimated cross-price effects are positive suggesting that hired labor, fertilizers and intermediate inputs are substitutes in olive-oil production. The magnitudes of these point elasticity estimates all appear plausible and are consistent with existing results on input-demand elasticities (see Table **??**).

We now turn to the main focus of our analysis, inferring information on the underlying population of olive-fruit fly. From (**??**), one can obtain point estimates of the compound term, λb_{it}, for each observation (*i.e.*, farm or period) as

$$\lambda b_{it} = \frac{v_{it}}{\hat{\delta}_z p_{it} y_{it} \exp\left(-\hat{\delta}_z z_{it}\right)},$$

whence

$$\frac{b_{it}}{b_{it-1}} = \frac{v_{it}}{v_{it-1}} \frac{p_{it-1} y_{it-1} \exp\left(-\hat{\delta}_z z_{it-1}\right)}{p_{it} y_{it} \exp\left(-\hat{\delta}_z z_{it}\right)}$$

where $\hat{\delta}_z$ represents the estimate of δ_z reported in Table **??**. Point estimates of pest-population growth rates for each olive farm in the sample can now be obtained by taking natural logarithms

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[5] The *Hausman* test involves a simple F-test that the residuals of the first-stage OLS regression are jointly equal to zero in the econometric estimation of the translog cost system. In our case the test statistic was 13.45 well above the corresponding critical value at the 0.05 significance level with (7,293) degrees of freedom.

[6] Fixed-effects estimation of the model was done by maximizing the likelihood function including simple farm-specific dummies in both the cost function and the cost share equations.

[7] Given that the cost shares depend on the random coefficients, in calculating the variable-input demand elasticities reported in Table **??** we use their estimated expectations provided by (**??**).

of the above expression, *i.e.*, $\dot{b}_{it} = lnb_{it} - lnb_{it-1}$.

Table **??** reports the resulting estimates of annual average olive-fly population growth rates for the period 1999 to 2004 along with the actual growth rates computed from our sample estimates of olive-fly population. According to both the survey data and our estimates, olive-fruit fly infestation has grown over the sample period, but its growth has been quite erratic. With the exception of the first year, the agreement between our estimate of the olive-fly population growth rate and the actual growth rate is quite close. In each year that the actual pest population grew our estimate also indicates growth, and in each year that the pest population fell our estimate also indicates a decline. The correlation coefficient between the two distributions is 0.908. The calculated *Kolmogorov-Smirnov* test statistic, which examines whether the two empirical distributions differ, is well above its critical value at the 5 per cent significance level. That result supports the hypothesis that the actual and estimated olive-fly growth rates are drawn from the same distribution (see last row in Table **??**). Figure **??** presents the point estimates of these average growth rates visually. Their associated 95 per cent confidence intervals, constructed by using the bootstrapping methods of Politis and Romano (1994) technique and the observed olive-fly population growth rates, are also depicted on common axes. Only the observed growth rate for 2000-01 falls outside the interval estimate derived from our model.

Table **??** reports average observed olive-fly population levels converted to biomass equivalent (6.8 mg per adult weight), average observed pesticide application rates, average observed olive-fly population growth rates, and average estimated olive-fly population growth rates at different times over the same crop year. Values in Table **??** were calculated as the average values over olive farms for the six-years of the survey. They refer to specific days that olive-fly measures were taken by the extension agents from the yellow sticky traps on the field. In total there are twelve different data points covering the whole cycle of olive-fly reproduction during cropping seasons, May to October.[8] The observed olive-fly population measures reported in the first column,exhibit the two peaks observed every cropping season (late spring and early autumn) as expected. Growth rates decline from May until the end of July, following then an increasing trend until the last measure taken in the 1st of October.

Figure **??** presents our point estimates of these same growth rates, their bootstrapped 95 per cent confidence intervals, and the actual observed values on a common axes. It illustrates that, apart from the intertemporal population growth rates, the seasonal pattern of olive-fly infestation in olive orchards in our sample is well captured by our procedures as all observed values fall within our interval estimates. In late spring and early autumn pest infestation rates are higher due to the prevailing low temperatures and high humidity rates. The same pattern is followed by pesticide application rates as farmers respond to increased infestation levels. Although the absolute figures exhibit some variations around the true values, our model predicts directional change accurately in all instances. Our point estimates under-predict slightly the early stages of larval development (May,

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[8] During winter season chemical traps are removed from the olive orchards.

June and August) and over-predict the late stages of its maturity (July, September and October). But overall the fit is close. The correlation coefficient between observed and estimated growth rates is quite high, 0.942. This high correlation value is further confirmed by the corresponding *Kolmogorov-Smirnov* test statistic that indicates no statistically significant differences between the two empirical distributions, *i.e.*, observed and estimated growth rates (see the last row of Table **??**).

Finally, Table **??** reports averages of estimated values for output realization (*i.e.*, $g(b,z)$), estimated olive-fly population growth rates, and observed olive-fly population growth rates for each one of the fifty olive farms in the sample. The average farm realizes approximately 82.5 per cent of maximum potential output so that average pest damage is 17 to 18 per cent. The lowest value is 34.2 per cent and the highest 99.9 per cent. Besides some notable differences in the magnitude of change in some olive farms, in every instance, our model predicts accurately the direction of average olive-fly population growth. The average predicted olive-fly population growth was found to be 0.40 percent as compared to the observed value of 0.29 per cent. As Figure **??** illustrates, in some instances, the difference between estimated and observed growth rates is negligible. The correlation coefficient between the observed and the estimated series is 0.982. Again the *Kolmogorov-Smirnov* test statistic is well above the corresponding critical value indicating no statistically significant differences among the two empirical distributions (see Table **??**).

6 Discussion and Related Literature

We have developed a framework that integrates information from biological yield response relationships into economic production models to make inferences on pest population dynamics in the absence of actual observations on the underlying pest population while also estimating supply-response models. Although our empirical analysis focuses on a specific pest-host relationship (*i.e.*, olive-fruit fly), our analyses can be extended to a broader class of environmental and resource problems by making suitable adjustments to accommodate the biological relationships underlying the specific production process being studied. As long as an identifiable relationship exists between the biological population and production, observations on supply data (both input demands and supply), which are conditional on the biological population, must have that information embedded in them. So, even if the population data are not directly available, knowledge of the underlying biological relationship permits making inferences on the underlying pest population.

Models that ignore that linkage ignore an important source of information on the associated production system. The result is a less-efficient approximation. Ideally, the more biological information available on the population's demographics and how those factors interact with observable supply behavior that can be incorporated in the modelling process, the more precise the resulting model. Economists routinely rely on relatively simplistic production structures precisely because they lack such structural information. The choice is not between using purely biological approaches to estimating population dynamics and using a purely economic approach. Rather the challenge is to combine economic and biological approaches in a truly synergistic fashion.

Cobourn *et al.* (2011) have suggested that modellers frequently misrepresent causality in the damage relationship. This is due to conflating the role that the pest population plays in the damage relationship with the role that it plays on pest reproduction. Frequently, the cause is a lack of appropriate data. For example, empirical models may link the adult pest population to yield losses, even though in many cases (like olive-fruit fly in our case study and in theirs) adult pest populations are only indirectly responsible for the crop damage. Such problems become more intense the more complex the predator-prey interactions and in multi-species pest populations. Their solution is to incorporate information beyond the pest population into the damage relationship (what they refer to as host characteristics). We lack such information for our data set. However, our procedure can be augmented to incorporate that type of empirical information, when available, to refine our analysis even further. It can also be applied to more complex biological relationships for longer-lived species in heterogeneous or non sedentary pest populations.

What our model cannot do is to make out-of-sample predictions and to define biological reference points. To do so, one must specify a full biological model specific to the pest population under study. For the olive-fruit fly, a series of alternative biological models of its spatial or temporal population dynamics have been developed following procedures introduced in the seminal paper of Comins and Fletcher (1988) (see, for example, Yonow *et al.*, (2004), Gutierrez *et al.*, (2009), Castrignano *et al.*, (2012) and the references cited therein). These models are typically highly structural and require detailed data on the microclimatic conditions in the field to ensure accurate prediction of olive-fly population dynamics. Some use huge simulation tools demanding experimental data for pest reproduction. This effectively prohibits their practical application in studies such as the current one where only limited information is available.

To illustrate the problems of fitting such models with limited data, as well as to provide a basis for comparison with our model, we have fit the Gutierrez *et al.*, (2009) biological model for olive-fly reproduction. Their model is able to compute many aspects of the structural dynamics of olive flies and olive production (that is, olive-tree development, seasonal yield and olive-fly reproduction).[9] Our interest is in olive-fly reproduction during the May-October season for which the necessary data were available from secondary sources. All biological processes in the Gutierrez *et al.*, (2009) model, are driven by climatic conditions making the model independent of time and place (this is important for our case study because detailed data from olive growers in the sample were not available).

Entomologists from National Agricultural Research Foundation of Greece (NAgREF) provided us with the necessary data on olive-fly phenology and assisted us in running the simulation tool in their premises. We maintained the same non-linear olive-fly development rate model of Gutier-

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[9] More details on the development of this particular model of olive-fly population dynamics can be found in Gutierrez (1996).

rez *et al.*, (2009) as well as those for egg-larval and pupal stages development which were fitted using experimental data provided from NAgREF and the prevailing climatic conditions (that is, temperature and humidity rates) obtained from the local meteorological stations. As our survey was completed many years ago, it was not possible to get the exact climatic conditions (that is, temperature, humidity rates) on each plot in the sample. Hence, we used historical data from the network of local meteorological stations in the island.

The resulting average values of olive-fly population growth rates for each one of the farms in our sample are presented in Table **??**. Their model was able to predict accurately within season population dynamics of olive-fly suggesting four summer generations and a partial one occurring after harvesting. However, it was not able to predict between seasons pest population changes and as a result individual pest infestation levels for olive growers in our sample were not predicted accurately. As depicted in Table **??** for the majority of olive growers, both the direction and the magnitude of change is not captured by the fitted biological model. On the average, it predicted a 2.30 per cent olive-fly population growth which is considerably higher than the observed value of 0.29 per cent. The correlation coefficient between fitted and observed is very low (only 36.87 per cent) and statistically insignificant. The computed *Kolmogorov-Smirnov* test statistic also suggests statistically significant differences among the two empirical distributions (see the last row in Table **??**).

This poor performance of the fitted biological model in this setting is not due to any theoretical flaws in the model. In fact, this model has been successfully applied in many olive-oil producing regions around the globe. Rather its poor performance here is due to its reliance on accurate data for olive-fly phenology that were not available for our sample of olive growers. Biologically grounded models can be very accurate when reliable and consistent data are available. But they can be very inaccurate when those data are missing. Our approach, which relies observable economic data and makes inferences based on rational producer behavior has shown to be quite accurate in such a setting. Its accuracy can only be enhanced when it is combined with even more precise information on olive-fly phenology that are necessary to the successful implementation of biological models.

7 Concluding Remarks

We developed a biologically correct cost system for production systems facing invasive pests that allows the estimation of population dynamics without *a priori* knowledge of their true values. We applied that model to a data set for olive producers in Crete, Greece and derived from it estimates of the underlying population dynamics. Those dynamics were compared to information on population dynamics obtained from pest sampling with extremely favorable results.

These results suggest that our method offers an appealing alternative in modelling supply response systems that depend upon unobserved population variables. Obviously, the empirical findings cannot be extrapolated beyond the current application. But the basic theoretical procedure for using information from biological models can easily be extended to other applications. That procedure essentially marries economic analysis with prior biological information. Biologists have expended considerable effort in developing biologically plausible specifications of the interactions between populations and yield response. Similarly, economists have expended generations of effort in developing and estimating production systems. It seems natural that synergies should arise from combining these efforts.

From a production perspective, biological specifications often define natural separable structures that can be exploited in analytic and econometric modelling. Incorporating this biological information into our models potentially improves modelling efficiency. But there is another natural by-product: it should also enhance our ability of economists to communicate economic analysis to other disciplines. Our results suggest that other studies on natural-resource industries could benefit by incorporating biologically correct models to provide more accurate supply-response modelling.

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Tables and Figures

Table 1: Summary Statistics of the Variables

Variable	Mean	Maximum	Minimum
Olive-Oil			
- Quantity (kgs)	21,051	111,168	1,658
- Price (euros)	2.62	3.62	1.63
Labor			
- Quantity (hrs)	578	2,985	48
- Price (euros)	20.33	29.85	13.79
Fertilizers			
- Quantity (kgs)	16,037	87,266	846
- Price (euros)	0.236	0.350	0.113
Intermediate Inputs			
- Total Cost (euros)	2,813	13,587	350
- Price (euros)	3.19	4.41	1.85
Capital (euros)	25,214	142,543	2,341
Education (years)	8	16	2
Extension Visits (no)	8	37	1
Temperature (°C)	24.91	37.32	12.38
Humidity (percentage)	0.43	0.88	0.20
Altitude (meters)	316	995	6

Table 2: Parameter Estimates of the Translog Cost Function

Parameter	Estimate	StdError	Parameter	Estimate	StdError
α_0	0.9796	(0.2341)			
α_L^w	0.3572	(0.0087)	α_{LC}^{wq}	0.0141	(0.0074)
α_F^w	0.1533	(0.0068)	α_{LH}^{wq}	-0.0029	(0.0089)
α_I^w	0.4895	(0.0932)	α_{FC}^{wq}	0.0207	(0.0059)
α_C^q	-0.3358	(0.0237)	α_{FH}^{wq}	-0.0036	(0.0071)
α_H^q	-0.0812	(0.0284)	α_{IC}^{wq}	-0.0348	(0.0036)
α^y	0.9584	(0.1022)	α_{IH}^{wq}	0.0066	(0.0023)
α^t	-0.0328	(0.0124)	α_L^{yw}	-0.0092	(0.0393)
α_{LL}^{ww}	-0.1879	(0.1078)	α_F^{yw}	0.0728	(0.0315)
α_{FF}^{ww}	-0.0736	(0.0124)	α_I^{yw}	-0.0635	(0.0231)
α_{II}^{ww}	-0.2345	(0.1053)	α_L^{wt}	0.0016	(0.0095)
α_{LF}^{ww}	0.0135	(0.0221)	α_F^{wt}	0.0154	(0.0074)
α_{LI}^{ww}	0.1744	(0.1324)	α_I^{wt}	-0.0170	(0.0143)
α_{FI}^{ww}	0.0601	(0.0266)	α_C^{yq}	-0.1079	(0.0275)
α^{tt}	0.0861	(0.0572)	α_H^{yq}	0.1642	(0.1124)
α_{CC}^{qq}	-0.1810	(0.0605)	α_C^{qt}	-0.0217	(0.0269)
α_{HH}^{qq}	0.0146	(0.0098)	α_H^{qt}	0.0415	(0.0212)
α_{CH}^{qq}	0.0941	(0.0518)	α^{yt}	-0.1790	(0.0924)
α^{yy}	0.2854	(0.0875)	δ_z	-0.6128	(0.1013)
LnL			189.321		

where, L stands for labor, F for fertilizers, I for intermediate inputs, C for capital, H for household labor, Z for pesticides and Y for output (*i.e.*, olive-oil). α_0, α_L^w, α_F^w and α_I^w are the mean expectations of α_{0i}, α_{Li}^w, α_{Fi}^w and α_{Ii}^w, respectively. In parentheses are the corresponding standard errors obtained using block resampling techniques (Politis and Romano 1994).

Table 3: Variance-Covariance Matrix of the Random Coefficients

	Constant (α_{0i})	Labor (α_{Li}^w)	Fertilizers (α_{Fi}^w)
Constant (α_{0i})	12.3424	-	-
Labor (α_{Li}^w)	-2.1442	1.0524	-
Fertilizers (α_{Fi}^w)	-1.7462	0.8732	2.1382

All entries are multiplied by 100.

Table 4: Variable Input Demand Elasticities

Variable-Input Demands	w_L	w_F	w_I
Labor (L)	-0.9244	0.3831	0.5414
	(0.1764)	(0.0887)	(0.1143)
Fertilizers (F)	0.1626	-0.8183	0.6557
	(0.0514)	(0.1443)	(0.1298)
Intermediate Inputs (I)	0.2092	0.5440	-0.7532
	(0.0512)	(0.1125)	(0.1873)

Elasticities are computed at the mean values of all exogenous variables and mean random coefficient estimates. In parentheses are the corresponding standard errors obtained using block resampling techniques (Politis and Romano 1994).

Table 5: Estimated and Observed Pest Population Growth

Pest Population Growth	1999-00	2000-01	2001-02	2002-03	2003-04	Mean	rho
Observed	6.03	-8.69	7.85	-3.27	-0.27	0.29	91.31
Estimated	1.90	-5.84	9.71	-1.39	-2.39	0.40	
Kolmogorov-Smirnov test-statistic: 0.3219				Critical value (α=0.05, n=300): 0.1110			

Table 6: Pest Biomass, Pesticide Materials and Pest Population Growth During the Cropping Season

Date	Pest Biomass (6.8 mg of adult weight)	Pesticide Materials (in grams)	Pest Population Growth	
			Observed	Estimated
May 15th	929.9	278	-	-
June 1st	813.0	254	-13.9	-9.8
June 15th	624.5	214	-26.4	-22.7
July 1st	349.9	169	-57.9	-63.1
July 10th	161.9	76	-77.1	-84.0
July 20th	75.0	31	-77.0	-84.6
August 1st	108.4	22	36.9	33.1
August 10th	279.5	48	94.7	84.2
August 20th	591.9	98	75.0	83.4
September 1st	754.3	182	24.2	33.5
September 15th	871.2	244	14.1	17.3
October 1st	950.1	280	8.7	11.2
Mean	542.4	158	0.26	0.41
rho	88.5		96.3	
Kolmogorov-Smirnov test-statistic: 0.1432		Critical value (α=0.05, n=600): 0.0785		

Figure 1: Observed and Estimated Pest Population Growth: Average Values of the 2000-2004 Period

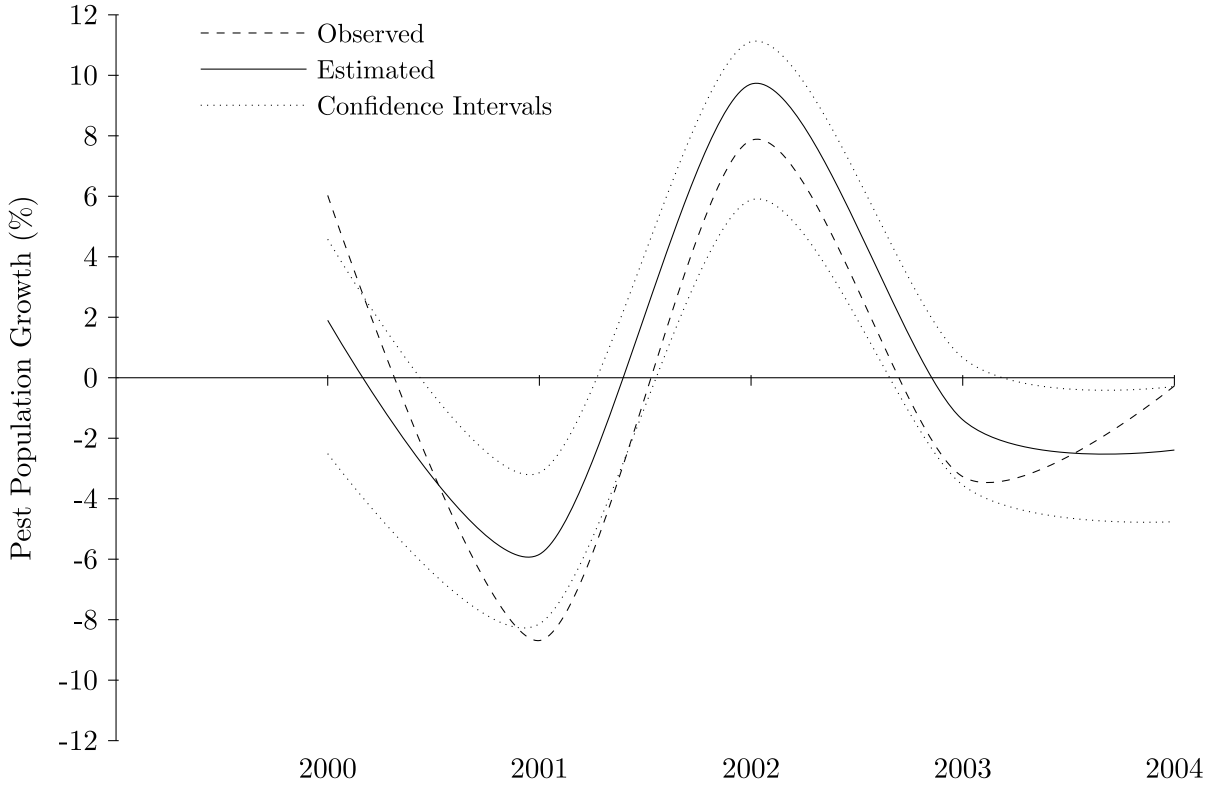

Figure 2: Observed and Estimated Pest Population Growth: Average Values of the Cropping Season

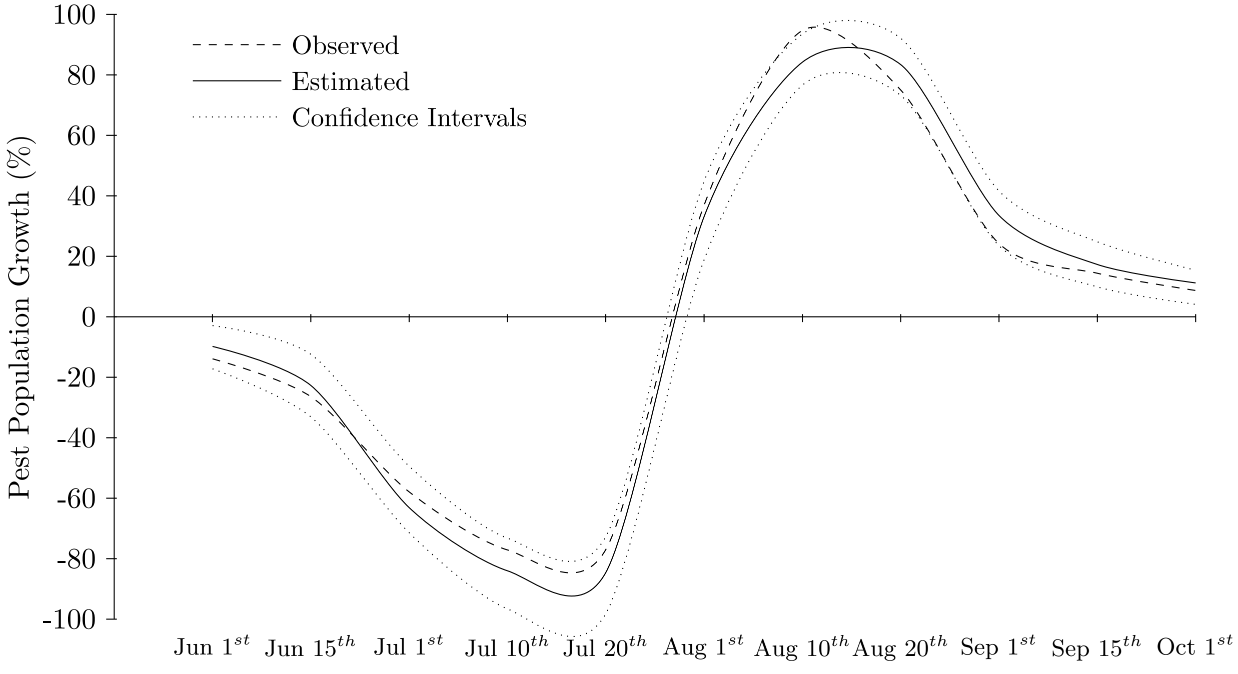

Figure 3: Observed and Estimated Pest Population Growth: Average Farm Values

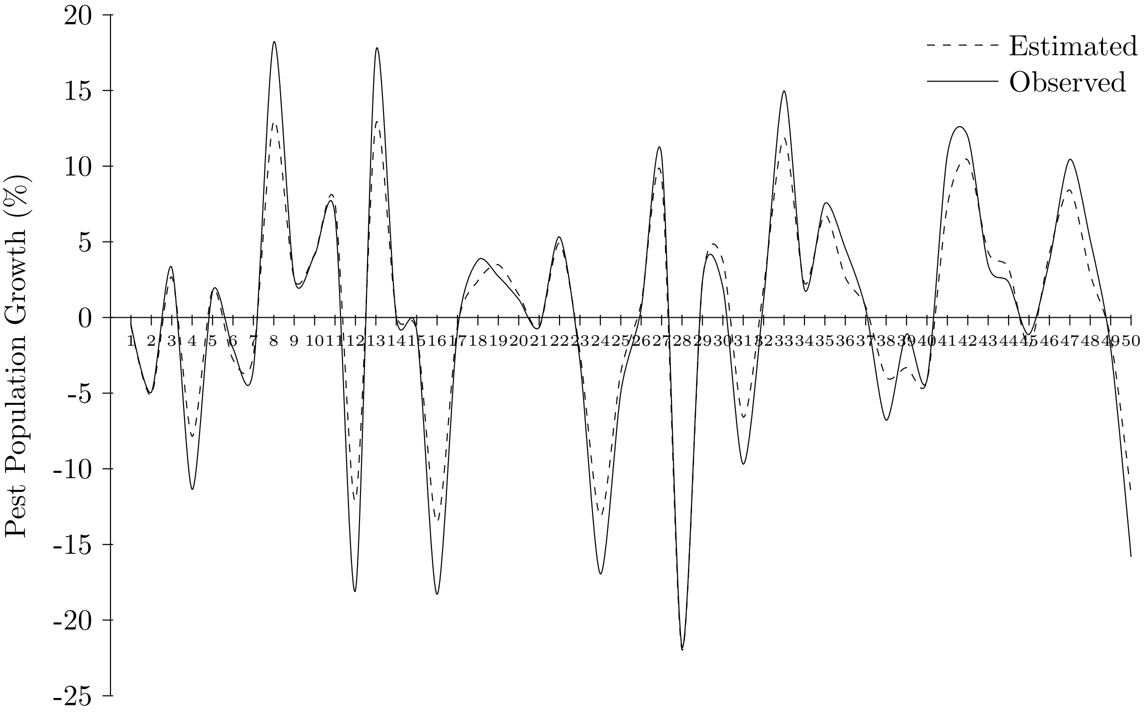

Table 7: Average Farm Values of Output Realization and Pest Population Growth

Farm	Output	Pest Population Growth			Farm	Output	Pest Population Growth		
No	Realization	(1)	(2)	(3)	No	Realization	(1)	(2)	(3)
1	94.78	-0.43	-0.53	3.14	26	52.44	0.58	0.95	-4.56
2	53.12	-4.94	-5.11	-0.34	27	95.68	10.73	9.24	23.45
3	48.74	3.31	2.67	8.98	28	34.15	-21.76	-21.95	-43.23
4	93.33	-11.36	-7.85	9.34	29	71.07	2.41	2.34	14.53
5	91.85	1.73	1.83	-7.63	30	69.80	2.01	3.76	-4.56
6	59.08	-2.04	-2.78	-6.53	31	98.70	-9.69	-6.58	6.34
7	99.78	-3.41	-2.51	-15.34	32	36.52	1.19	2.01	-6.75
8	99.43	18.20	12.98	4.54	33	98.81	14.97	11.86	30.21
9	96.28	2.60	2.57	8.96	34	81.02	1.84	2.27	-8.76
10	96.00	4.12	4.18	11.32	35	71.60	7.54	6.78	21.23
11	99.40	6.75	7.54	-4.32	36	98.09	4.57	2.65	14.35
12	77.28	-18.04	-12.10	-31.23	37	62.79	0.56	0.71	-7.65
13	89.56	17.58	12.78	21.32	38	99.46	-6.78	-3.93	-17.65
14	69.79	0.03	0.28	-2.34	39	99.81	-1.10	-3.32	4.35
15	99.46	-0.87	-0.93	-8.54	40	92.86	-4.14	-4.20	8.79
16	81.19	-18.29	-13.53	-2.94	41	75.49	10.75	7.40	-3.42
17	79.98	-0.84	-0.56	4.56	42	99.99	11.96	10.40	0.09
18	99.81	3.78	2.42	9.77	43	99.98	3.47	4.32	23.45
19	90.07	2.72	3.48	8.96	44	82.88	2.33	3.24	-11.23
20	99.99	1.20	1.51	10.34	45	99.99	-1.12	-1.93	8.65
21	80.97	-0.65	-0.67	6.54	46	72.18	3.73	4.23	15.43
22	99.96	5.32	4.91	12.83	47	50.81	10.45	8.42	1.21
23	83.31	-2.89	-2.31	7.65	48	92.61	5.13	2.85	13.45
24	26.67	-16.94	-13.13	-2.34	49	87.71	-1.99	-1.37	-12.65
25	96.66	-4.96	-3.63	3.45	50	92.36	-15.82	-11.68	-0.16
Mean Values						82.47	0.29	0.40	2.31
Correlation Coefficient (rho):								96.31	36.87
Kolmogorov-Smirnov test-statistic (CV α=0.05, n=50: 0.2720):								0.3073	0.1983

(1) observed values, (2) estimated values from our supply-response model, (3) estimated values from Gutierrez *et al.*, (2009) biological model.