Pesticide Productivity: What are the Trends?

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Abstract

Obtaining estimates of pesticide productivity is an economic response to the growing public concern about the steady increase of pesticide use in the United States. This type of research indicates the cost of limiting pesticide use in terms of foregone output. Previous empirical studies give a "snap-shot", or "average", look at pesticide productivity. This research effort employs a random coefficient model to determine the trend of the marginal value product of pesticides in agriculture in the United States. Results show a distinct downward trend in two states, Iowa and Texas. California, however, shows no evidence of a downward trend.

Key words: pesticide productivity, marginal value product, random coefficients

Introduction

Pesticide use has been increasing steadily in the United States. In 1935, just prior to the discovery of DDT, about 50 million pounds of pesticides were applied (Prokopy). Approximately 55 thousand pesticide products were formulated from about 600 active ingredients in 1986 (U.S. General Accounting Office). In 1991, corn and soybeans alone received 210.4 million pounds and 63.5 million pounds of pesticides, respectively (United States Department of Agriculture 1992).

Public concern over pesticide use has increased due to the possible external effects of pesticides, including negative public health effects through groundwater and surface water contamination, negative environmental impacts, reduced farm worker safety, and increased pest resistance. A natural response of economists is to conduct research on the productivity of pesticides. This type of research provides useful information, such as indicating the cost of limiting pesticide use in terms of foregone output (Campbell).

Headley produced the first study of pesticide productivity using cross-sectional (state) data from a single year, 1963. He concluded that the marginal value product (*MVP*) of pesticides exceeded its marginal factor cost (*MFC*) $4.00 to $1.00. Other studies give similar results, indicating a general range of $3 to $6 for pesticide *MVP*. This suggests that pesticides are under used (Campbell, Carlson, Pimentel et al., Lichtenberg and Zilberman, Carrasco-Tauber and Moffit).

These empirical studies determine the pesticide *MVP*, but they do not show changes in *MVP* over time. Studies using cross-sectional data for a single year, or a few select years, give a "snap-shot" look at the *MVP* of pesticides. Studies that use a substantial time-series only serve to give an "average" estimate of the pesticide *MVP* over the time-series. Roth, Martin, and Brandt show that estimates of pesticide *MVP* from cross-sectional studies using state data for a single year are sensitive to the year chosen, suggesting the possibility of a time-trend in pesticide productivity. Increasing pest resistance would cause the *MVP* of

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pesticides to decrease over time (Osteen and Suguiyama; Carlson). Other factors, such as technological breakthroughs that increase efficacy, may cause the productivity of pesticides to increase over time. The purpose of the research reported in this paper is to determine the trend of the marginal value product of pesticides in agriculture in the United States.

Theory

Random coefficient models allow each observation of an independent variable to have a unique slope coefficient. This can be useful for evaluating the time trend in a coefficient such as the marginal value product of pesticides. One type of random coefficient model takes the form:

$$y_t = \beta_{t1} + \sum_{k=2}^{K} \beta_{tk} x_{tk} \qquad t = 1, ..., T \qquad (1)$$

where t is the individual observation; cross-section, time-series, or a combination of both, and T is the total number of observations (Hildreth and Houck, Judge et al. 1988).

Each β_{tk} is a random coefficient, so that

$$\beta_{tk} = \bar{\beta}_k + \mu_{tk} \qquad k = 1, ..., K \qquad (2)$$

where K is the number of independent variables, $\bar{\beta}_k$ is a nonstochastic mean response coefficient, and μ_{tk} is a random disturbance with

$$\begin{aligned} E[\mu_{tk}] &= 0 \\ var(\mu_{tk}) &= \alpha_k^2 \\ cov(\mu_{tk},\mu_{sl}) &= \begin{cases} 0, & t \neq s \\ \alpha_{kl}, & t = s \end{cases} \end{aligned} \qquad (3)$$

Let β_t be the $(K \times 1)$ vector of random coefficients from equation (2), so that T of these vectors exist. Rather than estimating β_t, it is more accurate to say that β_t is predicted. "Predicted" is preferred to "estimated" because the β_{tk}'s are random variables drawn from a probability distribution. In order to predict β_t, two things must be estimated: the mean response vector $\bar{\beta} = (\bar{\beta}_1, ..., \bar{\beta}_K)'$, and the covariance matrix of the disturbance vector v_t, $E(v_t v_t') = \Sigma$. v_t contains the elements $(\mu_{t1}, ..., \mu_{tK})'$ from equation (2), and is a $(K \times 1)$ vector where T of these vectors exist. The covariance matrix Σ is a $K \times K$ matrix with individual elements from equation (3) of α_{kl}, $k,l = 1, ..., K$ (Judge et al. 1988).

The estimated generalized least squares (EGLS) estimator of $\bar{\beta}$ is given by

$$\hat{\bar{\beta}} = (\mathbf{X}'\hat{\Phi}^{-1}\mathbf{X})^{-1}\mathbf{X}'\hat{\Phi}^{-1}\mathbf{y} \qquad (4)$$

with covariance matrix of

$$cov\left(\hat{\bar{\beta}}\right) = (\mathbf{X}'\hat{\Phi}^{-1}\mathbf{X})^{-1} \qquad (5)$$

where $\hat{\Phi}$ is a diagonal matrix with estimated elements $\hat{\sigma}_1^2, \hat{\sigma}_2^2, ..., \hat{\sigma}_T^2$. After obtaining the estimated covariance matrix $\hat{\Sigma}$, with the method shown below, the elements of $\hat{\Phi}$ are given by $\hat{\sigma}_t^2 = \mathbf{x}_t' \hat{\Sigma} \mathbf{x}_t$, where $\mathbf{x}_t' = (1, x_{t2}, x_{t3}, ..., x_{tK})$ is the tth row vector of $\mathbf{X}$. $\hat{\Phi}$ is analogous to the variance-covariance matrix for the EGLS model when σ_t^2 is assumed to be a function of a set of explanatory variables (Judge et al. 1988).

In order to obtain the estimate $\hat{\Sigma}$, let $N = K(K + 1)/2$, and α be an $(N \times 1)$ vector containing the distinct elements of Σ. For example, if $K = 3$, then $\alpha' = (\alpha_1^2, \alpha_{12}, \alpha_{13}, \alpha_2^2, \alpha_{23}, \alpha_3^2)$. Let $\mathbf{X}$ be defined as above, the matrix of independent variables, and let $\mathbf{Z}$ be defined as a $(T \times N)$ matrix with tth row vector of $\mathbf{z}_t' = (1, z_{t2}, z_{t3}, ..., z_{tN})$. $\mathbf{z}_t'$ is found by calculating $\mathbf{x}_t' \otimes \mathbf{x}_t'$ and combining identical elements. Using the example of $K = 3$, $\mathbf{z}_t' = (1, 2x_{t2}, 2x_{t3}, x_{t2}^2, 2x_{t2}x_{t3}, x_{t3}^2)$. Based upon this,

$$E(\hat{\mathbf{e}}^2) = \mathbf{F}\alpha \qquad (6)$$

where $\hat{\mathbf{e}}^2$ is a vector containing the squares of the least squares residuals from the model $\mathbf{y} = \mathbf{X}\beta + \mathbf{e}$. $\mathbf{F} = \dot{\mathbf{M}}\mathbf{Z}$, where $\dot{M}$ contains the squares of the elements of $\mathbf{M} = \mathbf{I}_K - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ (Hildreth and Houck, Judge et al. 1985).

It is evident from equation (6) that the least squares estimate of α, and therefore of Σ, is $\hat{\alpha} = (\mathbf{F}'\mathbf{F})^{-1}\mathbf{F}'\hat{\mathbf{e}}^2$. This estimate is unbiased, but unfortunately, it is not guaranteed to produce a $\hat{\Sigma}$ that is positive semidefinite. This is an essential property for any variance-covariance matrix. Froehlich and Dent and Hildreth show through Monte Carlo studies that it is better to impose these properties when estimating Σ. This can be done through nonlinear programming with nonlinear inequality constraints (Judge et al. 1985). The estimated $\hat{\alpha}$ is the solution to the problem

$$\underset{\alpha}{Minimize} \quad (\hat{\mathbf{e}}^2 - \mathbf{F}\alpha)'(\hat{\mathbf{e}}^2 - \mathbf{F}\alpha) \qquad (7)$$
$$subject\ to \quad |\mathbf{A}_i| \geq 0, \qquad i = 1, ..., K$$

where $|\mathbf{A}_i|$ is the determinant of the ith principal minor of $\hat{\Sigma}$. Using this method, $\hat{\alpha}$ is essentially the restricted least squares estimate of α.

Finally, an appropriate predictor of the disturbance vector $v_t = (\mu_{t1}, ..., \mu_{tK})'$ must be found. Equation (8) gives such a predictor (Griffiths).

$$\hat{v}_t = \hat{\Sigma}\mathbf{x}_t\left(\mathbf{x}_t'\hat{\Sigma}\mathbf{x}_t\right)^{-1}\left(y_t - \mathbf{x}_t'\hat{\beta}\right) \qquad (8)$$

Combining equations (2), (4), and (8), the prediction of β_t becomes

$$\hat{\beta}_t = \hat{\beta} + \hat{v}_t \qquad (9)$$

Before predicting β_t in a random coefficient modelling framework, a good question to ask is whether or not the coefficients are random. Since this type of model is based upon heteroskedastic error terms, a Breusch-Pagan type test is appropriate to use in testing for randomness in the coefficients (Judge et al. 1988, Judge et al. 1985). The implementation of this test is described below.

Data Description and Procedure

All data on agricultural output and inputs are from the United States Department of Agriculture, Economic Research Service for the years 1949-1991. Specifically, the data correspond to Table 4--Farm Income Indicators in recent versions of Economic Indicators of the Farm Sector, State Financial Summary, USDA-ERS. All variables are reported by state. In order to keep the size of the data set manageable for matrix manipulations, the top ten ranking states in cash receipts were used to estimate the model. These states are California, Florida, Illinois, Indiana, Iowa, Kansas, Minnesota, Nebraska, Texas, and Washington. Forty-three time periods and ten states yield 430 observations. After model estimation, the trend of pesticide *MVP* can be compared across states for the time period 1949-1991.

Aggregate output, the dependent variable, is the market value of all crops sold plus government payments and the value of home consumption, divided by the Index of Prices Received by Farmers, base year equal to 1991 (Agricultural Prices, USDA-NASS). This leaves aggregate output as a value in constant 1991 dollars. The inputs are seed, fertilizer and lime, pesticides, fuel and oil, electricity, repair and maintenance, miscellaneous (includes machine hire and custom work, marketing, storage, transportation, and other miscellaneous expenses), non-real estate interest, and hired labor (includes contract labor, wages, Social Security payments, and labor perquisites). The inputs are not adjusted for the amount spent on livestock enterprises, which may result in a bias in the parameters. All of the independent variables are deflated to the base year of 1991 by the Index of Prices Paid by Farmers (Agricultural Prices, USDA-NASS), leaving inputs as a value measured in constant 1991 dollars.

The nonlinear constraints of equation (7) make it necessary to have a small number of coefficients in the model. This requires a small K, the number of independent variables, and a relatively simple functional form to represent production technology. In order to reduce K to a reasonable number, the independent variables are grouped into three categories: pesticides, other material inputs (seed, fertilizer and lime, and hired labor), and machinery costs (miscellaneous, electricity, fuel and oil, repair and maintenance, and non-real estate interest). These three independent variables, along with a constant term, make $K = 4$.

Assuming that aggregate technology in agriculture takes a Cobb-Douglas form, and transforming all variables to natural logs, the production function becomes linear and compliant with the conditions mentioned in the paragraph above. A major limitation of the Cobb-Douglas function is constant elasticities of production for each observation, and therefore constant marginal value products for a given level of production and output price. This assumption is relaxed in the random coefficients framework by regarding the coefficients as a random drawing from a probability distribution with mean $\bar{\beta}$ and covariance matrix Σ (Griffiths et al.).

Although the input aggregation discussed above and the specification of Cobb-Douglas technology enable model estimation, these assumptions impose certain relationships on the data. For example, an input within an aggregate variable is assumed to be a perfect substitute for any other input within the same aggregate variable. Also, aggregate variables are assumed to be technically complementary in the Cobb-Douglas specification. This implies that inputs within an aggregate variable are technically complementary with inputs in another aggregate variable.

The elasticity of production for input i at observation t, ε_{pti}, is β_{ti}. This is the percentage change in the value of output associated with a one percent change in the amount spent on input i. Since outputs and inputs are measured in dollar units, the marginal value product of input i at observation t is $\partial y_t/\partial x_{ti} = \beta_{ti}(y_t/x_{ti})$. The *MVP* has units of dollars of output produced per dollar spent on input i, measured in constant 1991 dollars.

The null and alternative hypotheses for the Breusch-Pagan type test are H_0: $\sigma_t^2 = \sigma^2$ and H_1: $\sigma_t^2 = \mathbf{z}_t'\gamma$, respectively. $\mathbf{z}_t$' is defined as above and γ is an N x 1 vector of unknown coefficients. This test is implemented by regressing $\hat{\mathbf{e}}^2$, the vector containing the squares of the residuals from a least squares regression in equation (1), on $\mathbf{Z}$, the (T x N) matrix with $\mathbf{z}_t$' as the tth row, and testing for the joint significance of all slope coefficients. This is done using a Wald χ^2 statistic, which has degrees of freedom equal to the number of restrictions. All matrix manipulations and hypothesis tests are done using the *SHAZAM* econometrics package (White), and the nonlinear optimization from equation (7) is accomplished using *GAMS* (Brooke et al.).

Results

Table 1 reports the EGLS estimates of $\bar{\beta}$, the mean response vector, from equation (4). All coefficients have the expected sign, and all are highly significant. The Wald χ^2 test for randomness in the coefficients has nine degrees of freedom and a test statistic value of 64.024. The critical value for a five percent confidence level is 16.919. Therefore, the null hypothesis of non-random coefficients is strongly rejected at the five percent level.

Table 2 reports the production elasticities and marginal value products of pesticides. The production elasticities are based on equation (9), and the marginal value products follow directly from the method outlined in the data description and procedure section. Pesticide *MVP* reflects dollars of output produced per dollar spent on pesticides, in constant 1991 dollars.

The results are reported for three states: California, Iowa, and Texas. These states were selected because they have consistently been the top three ranking states in cash receipts from agricultural sales (U.S.D.A. Economic Indicators of the Farm Sector, State Financial Summary). Only the odd years are reported for the time period 1949-1991. This limits the results to a reasonable amount, and is sufficient to accomplish the original intent: determine the time trend of pesticide *MVP*.

The states of Iowa and Texas reflect a definite downward trend in pesticide *MVP*. The pesticide *MVP* in Iowa drops from \$32.79 in 1949 to \$3.19 in 1991, with a low of \$1.85 in 1979. The pesticide *MVP* for Texas declines from \$15.87 in 1949 to \$3.32 in 1991, with a low of \$2.86 in 1971. The pesticide *MVP* for California, however, shows no discernable trend. Except for the years 1949 and 1951, the *MVP* holds steady between the approximate range of \$3 to \$9 over the entire period.

Conclusions

Pesticide use has increased steadily in the United States, along with concerns about the negative impacts of pesticides. This situation calls for economic analysis of the value of pesticides in

Table 1. Estimates and T-Ratios of Mean Response Coefficients from a Hildreth-Houck Random Coefficient Model for United States Agriculture 1949-1991

Variable	Coefficient Estimate [a]	*t* Ratio
Constant	2.0970	17.851
Other Material Inputs	0.3305	18.363
Pesticides	0.2348	20.865
Machinery Costs	0.3376	16.209

[a] All coefficient estimates are highly significant at the five percent level.

Table 2. Estimated Random Production Elasticities (ε_p) and Marginal Value Products (*MVP*) of Pesticides for California, Iowa, and Texas, 1949-1951, Odd Years Only

	California		Iowa		Texas	
Year	ε_p	*MVP* [a]	ε_p	*MVP* [a]	ε_p	*MVP* [a]
1949	0.0356	0.85	0.2340	32.79	0.1756	15.87
1951	0.0597	1.43	0.4039	26.00	0.2541	13.62
1953	0.2727	9.36	0.2413	30.62	0.2018	17.16
1955	0.3098	9.01	0.2631	22.19	0.1842	15.62
1957	0.2719	8.33	0.3095	19.80	0.1903	18.85
1959	0.2365	6.02	0.3523	13.98	0.1711	13.76
1961	0.2151	5.69	0.2757	11.72	0.2176	11.19
1963	0.2702	8.19	0.2491	10.71	0.2339	8.74
1965	0.2686	8.29	0.2407	7.01	0.2330	6.65
1967	0.2220	4.41	0.1825	2.87	0.2163	4.35
1969	0.2053	3.32	0.1974	3.10	0.2040	3.82
1971	0.2223	3.48	0.1922	2.86	0.1840	2.86
1973	0.2346	3.89	0.2582	4.82	0.2359	4.77
1975	0.2632	5.22	0.1462	2.22	0.2080	3.84
1977	0.3491	8.92	0.1785	2.75	0.2303	5.15
1979	0.2585	4.66	0.1665	1.85	0.2126	3.49
1981	0.2847	5.25	0.2126	2.82	0.2253	4.01
1983	0.2870	5.82	0.2450	3.93	0.2304	5.33
1985	0.3240	6.72	0.2744	4.69	0.2354	4.83
1987	0.3788	8.70	0.3232	6.29	0.2369	4.36
1989	0.3491	7.03	0.2386	2.96	0.2365	4.02
1991	0.3300	5.96	0.2570	3.19	0.2240	3.32

[a] Marginal value product of pesticides in dollars per dollar spent on pesticides, constant 1991 dollars.

use. This paper provides such an analysis, and extends beyond other research by determining the trend of the marginal value product of pesticides over time. A random coefficient model is outlined and used with data from ten states and 43 years (1949-1991) to accomplish this.

A distinct downward trend in pesticide *MVP* is shown in two states, Iowa and Texas. California, however, shows no evidence of a downward trend. Pesticide *MVP* in this state fluctuates in a steady range of \$3 to \$9 over the entire time period. These results give economic justification for the observed growing aggregate demand for pesticides: the benefits exceed the costs. One limitation to this study, though, is that the cost of possible negative externalities is not considered (e.g. non-point source pollution, increased pest resistance, reduced farm worker safety). Although entrepreneurial farm managers have a strong economic incentive to increase pesticide use at the present, the trend in pesticide *MVP* indicates a change may be coming, at least in some production areas. As the dollar value of output per dollar spent on pesticides approaches one, the intensity of aggregate demand for pesticides should decrease.

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