Combining Economic and Biological Data to Estimate the Impact of Pollution on Crop Production

Bruce L. Dixon, Philip Garcia, Richard M. Adams and James W. Mjelde

Duality methods utilizing a profit function framework are employed to estimate the output elasticity of ambient ozone levels on cash grain farms in Illinois. While duality methods have been recommended as a cure to many of the statistical problems of direct estimation of production functions, multicollinearity may still be a problem. A method for utilizing stochastic information on parameters of a seemingly unrelated system of equations, which is implied by profit function estimation, is developed and applied to measuring the impact of ozone. Such an approach may be necessary in measuring other environmental effects because of a lack of regressor variability.

Considerable research effort is expended to estimate the impact of ambient pollutants on crop production. This, in part, has been motivated by the need to establish federal air quality standards as mandated in the Clean Air Act. See, for example, Heck *et al.* (1982, 1983). In many of these studies, dose response functions estimated from experimental data are frequently used to predict the physical damage to crops from various pollutants. If benefit-cost information is needed on alternative levels of pollution control, these predicted biological damages can then be entered into economic models to simulate producer and consumer response given the impact of specific pollutants on crops. This two-step procedure has been used in a number of bioeconomic assessments of air pollutants (e.g., Adams *et al.*, Adams and McCarl).

Estimation of production functions with the level of ambient pollutants entered as inputs is an alternative to dose response function estimation for the purposes of directly modeling the economic effect of pollutants. The direct estimation of production functions in this context has several serious statistical problems as outlined in Leung *et al.*, and Adams *et al.* In addition, there is likely to be insufficient variability in the regressors to identify the impact of environmental variables whose effects are not, on the average, readily apparent. Estimation of dose response functions is not likely to be plagued by such problems because the plant scientist can control the levels of all other important independent variables.

An alternative procedure for overcoming some of the practical difficulties asso-

Bruce L. Dixon and Philip Garcia are Associate Professors of Agricultural Economics at the Universities of Arkansas at Fayetteville and Illinois at Urbana-Champaign, respectively, and James W. Mjelde is a research assistant in Agricultural Economics at the University of Illinois at Urbana-Champaign. Richard M. Adams is an Associate Professor of Agricultural Economics at Oregon State University in Corvallis.

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ciated with both approaches is the use of duality concepts grounded in microeconomic theory to estimate a profit function. While avoiding many of the problems associated with direct estimation of the production function, the problem of insufficient variability of independent variables is likely to remain. A commonly prescribed cure is to obtain more information. The most straightforward way to do this is to obtain additional sample observations. However, this is usually costly (particularly with experimental data) and frequently impossible. An alternative is to obtain coefficient estimates from other studies which pertain to the model being estimated and incorporate this information into the estimation process.

The purpose of this paper is to demonstrate how economic and nonsample biological data can be integrated into the estimation of profit functions to obtain a more robust estimate of the impact of pollution on crop production. This procedure is applied by using duality concepts to estimate a production function that gives the impact of ambient ozone levels on the output of cash grain farms in Illinois. As observed in Heck *et al.* (1982), ozone is cited as the primary pollutant in terms of physical damage to plants. The estimation method described is of sufficient generality to be used in most applications of estimating the parameters of a seemingly unrelated system where stochastic parameter information is available.

Methodology

Adams and Crocker advise using duality theory to determine the output response of economic agents to the level of ambient pollutants. In production studies either a profit function or cost function may be estimated. In cost function analysis, output level is an exogenous variable. Short-run profit functions are specified as having only input and output prices and fixed inputs in their domain which can all be reasonably assumed to be exogenous for agricultural firms. For most farms in the United States, output levels are not imposed externally. For this reason, a profit function approach is used here.

Biological results derived under experimental conditions show a negative impact of ozone on crop yields, Heck *et al.* (1983). One objective of this study is to estimate the impact of ozone on output, all other inputs constant, with data generated by commercial producers. To derive this impact, a production function is derived from the profit function. Since it is not always possible to determine the underlying technology from a profit function (McFadden, p. 81), the Cobb-Douglas profit function is used because it implies a known production function, the Cobb-Douglas, whose parameters can be readily obtained from the estimated profit function parameters. More justification of the Cobb-Douglas specification of the profit function is given later.

The general approach for estimating a profit function is to estimate simultaneously the profit function and the derived demand equations or some transformation of the derived demands. Since the approach here uses the Cobb-Douglas function, the derived demand equations are transformed to be what are labelled as share equations. For purposes of estimation, additive error terms are attached to each equation. As Yotopoulos and Lau acknowledge, this is an ad hoc practice. However, error terms on the profit and share equations can be justified in terms of inevitable misspecification of the profit function and, as suggested by Yotopoulos and Lau, to partially compensate for the fact that individual farmers most likely have different output price expectations which are unobservable. Since all the independent variables in the profit function and share (demand) equations are considered predetermined, but the error terms of the share equations and the profit function are likely correlated, the customary approach is estimation of the parameters in a seemingly unrelated framework. In estimating the system of equations, any parameter common to the profit function and share equations is restricted to have a unique value which is required by theory for a profit maximizing firm.

Even though all of the variables which serve as regressors can readily be assumed to be independent variables, the problem of the independent variables being strongly correlated with each other may still exist. This may pertain particularly to agricultural applications in which the observational unit is a farm. For farms within an essentially homogeneous region, the prices of outputs and inputs are likely to be quite similar, increasing the problem of multicollinearity. This is more likely if all the observations are taken at one point in time, i.e., one crop year. While using additional years is an obvious solution, it is costly and the necessary data frequently are not available. Moreover, natural factors such as temperature variation and rainfall might not show a great deal of variability within a given year so that disentangling a particular environmental effect can be difficult. In a case where additional observations are not available, a desirable alternative is to incorporate information from other sources.

In contemporary econometric techniques, nonsample information can be incorporated into the estimation process using exact restrictions or stochastic information on regression coefficients. Mittlehammer *et al.* discuss the benefits of stochastic information in regression. For this study, nonsample information is available in both the form of exact linear restrictions on some parameters (due to profit maximization) and stochastic information about one of the parameters. While the use of exact linear restrictions on a system of seemingly unrelated equations is straightforward, the use of stochastic information has not been widely treated. Almost all empirical and theoretical work on stochastic restrictions has been applied to single equation models. As shown below, assuming the stochastic information to be exact is an unnecessary simplification. To capture the efficiency gains of using a seemingly unrelated system of equations for estimating the parameters of a profit function, it is necessary to apply stochastic information to a system of equations. This can be done by utilizing the Theil and Goldberger mixed estimation technique.

To see how the Theil and Goldberger mixed estimator can be applied to multiple equations, first consider how it is used in single equation models. Assume the vector of unknown parameters to be estimated, β, is related to the sample observations, y, a T $\times$ 1 vector where T is the number of observations, as:

$$y = X\beta + e \qquad e \sim (0\ \Sigma) \tag{1}$$

where X is a T $\times$ k matrix of regressors and e is a T $\times$ 1 vector of error terms with covariance matrix Σ. Let the nonsample information, sometimes referred to as prior information, be expressed as:

$$r = R\beta + v \qquad v \sim (0, \Omega) \tag{2}$$

where r is m $\times$ 1, R is m $\times$ k and v is m $\times$ 1. The precise structure of the matrices r and R is indicated by the nature of the prior information. Uncertainty about the accuracy of the prior information is represented by the magnitude of the covariance matrix of v, Ω. The larger Ω is, the less precise the nonsample information.

Estimation of the vector β combines the information in (1) and (2) via generalized least squares (GLS), essentially treating the information in (2) as m additional observations. To get the standard form of the mixed estimator, it is assumed the error vectors e and v are uncorrelated with each other. Given this assumption the mixed estimator of β, β_m, is

$$\beta_m = (X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}(X'\Sigma^{-1}y + R'\Omega^{-1}r). \tag{3}$$

The covariance matrix of β_m is

$$\text{Cov}(\beta_m) = (X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}. \tag{4}$$

For most empirical work Σ must be estimated and this is straightforward as discussed in Theil (1963) when Σ is a scalar covariance matrix. The estimate of Σ replaces Σ in (3) and (4) and this procedure gives an approximate mixed estimator with an approximate covariance matrix. When Σ is not known up to a scalar of proportionality, there appears to be little empirical or theoretical work on how to obtain an approximation of the mixed estimator. This problem is of particular concern for estimating profit functions because use of the seemingly unrelated framework implies $\Sigma \neq \sigma^2 I$.

To see this problem more clearly and to derive a reasonable solution, consider the model implied by estimating a profit function. For every firm in the sample, assuming only a cross section of data, there is an observation of its profit and an observation on each of the demands for the p variable inputs. Each firm thus generates p + 1 observations. Let the first p + 1 observations in y in (1) correspond to the observations on the first firm. Thus y is $T(p + 1) \times 1$. Correspondingly, the X matrix is $T(p + 1) \times K$ where K is the total number of unique parameters to be estimated.[1] Thus Σ in (1) has the structure:

$$\Sigma = \phi \times I_T \qquad (5)$$

where $\times$ denotes the Kronecker product and ϕ is of dimension $(p + 1) \times (p + 1)$. By ordering the data in this way, (1) is now a system of seemingly unrelated equations. Using maximum likelihood techniques a consistent estimator of Σ, $\tilde{\Sigma}$, can be obtained and substituted for Σ in (3) and (4).

Sampling properties or Monte Carlo evidence have not been developed for the above procedure although there is a precedent for using a consistent estimator for Σ. First, Theil (1971) suggests using the unbiased estimate of σ^2 when $\Sigma = \sigma^2 V$ and V is known. Second, Zellner argues for Bayesian analysis that in large samples a consistent estimate of Σ, $\tilde{\Sigma}$, should be very close to the true value of Σ so that assuming $\tilde{\Sigma}$ equals Σ should produce reasonable results. Although Zellner makes this argument with respect to deriving the posterior mean of β in a Bayesian framework with diffuse prior information about β, it seems reasonable for use with the mixed estimator and this is the method employed in the empirical section of this paper.

Theil (1971) has developed a test of the compatibility of prior information and the sample data. Essentially mixed estimation combines two independent estimates of the vector $R\beta$. These are r and $R\tilde{\beta}$ where $\tilde{\beta}$ is the generalized least squares (GLS) estimator of β in (1). Thus, Theil (1971) proposes the following test statistic, assuming e and v to be normally distributed,

$$u = (r - R\tilde{\beta})'(RSR' + \Omega)^{-1}(r - R\tilde{\beta}) \qquad (6)$$

where S is the covariance matrix of $\tilde{\beta}$. The test statistic is distributed approximately as chi-square with m degrees of freedom.[2]

In applied econometric research it is often of interest to know how sensitive the

[1] In the model estimated shortly, which is a Cobb-Douglas profit function as in Lau and Yotopoulos, all the parameters in the share equations also appear in the profit function. Hence, the restrictions that these parameters be equal can be invoked by limiting the coefficient vector in (1), β, to have only unique parameters. This makes the actual mechanics of computing the estimates easier since the dimension of β is lower. For example, suppose the profit function is given as $\ln \Pi = \alpha_0 + \alpha_1 \ln r$ where Π is profit and r is the variable input price. Then the share equation is

$$\frac{-xr}{\Pi} = \alpha_1$$

where x is the quantity of the variable input. Thus β in (1) would be 2×1 and the first two rows of X would be

$$\begin{bmatrix} 1 & \ln x_1 \\ 0 & 1 \end{bmatrix}.$$

[2] Theil gives this test as being exactly chi-square but it is considered approximate here because Σ is not known with certainty.

estimated coefficients are in the mixed estimator to small variations in the prior information. An alternative form of the mixed estimator in Judge, Yancey and Bock or Havenner and Craine shows the relationship analytically. Havenner and Craine show that

$$\beta_m = \tilde{\beta} + PR\Omega^{-1}(R - R\tilde{\beta}) \tag{7}$$

where P is equal to the covariance matrix of β_m given in (4). The matrix $PR\Omega^{-1}$ gives the factors by which elements of $\tilde{\beta}$, the GLS estimator of β based only on the sample data, will be changed by the nonsample information. Thus elements of $PR\Omega^{-1}$ near zero indicate insensitivity to prior information. Hence, if the elements of the i^{th} row of $PR\Omega^{-1}$ are substantially different from zero, then the i^{th} element of β_m is strongly influenced by the nonsample information. Thus in evaluating the results, $PR\Omega^{-1}$ can be used to determine the sensitivity of individual components of β_m to variations in r.

Specification of the Empirical Model

In a prior study Garcia, Sonka and Yoo use a profit function of the Cobb-Douglas form for Illinois cash grain farmers to examine questions about the impact of farm size on efficiency. In a different study, Mjelde *et al.* utilize the translog function, with all but one of the interaction coefficients restricted to be zero, to estimate a profit function using the same data as the present study. However, since a goal of this study is to estimate the underlying technology, the Cobb-Douglas form of the profit function is used since it also gives quite plausible results as discussed below.[3] Algebraically the Cobb-Douglas production function is specified as:

$$y = A \prod_{j=1}^{m} x_j^{\alpha_j} \prod_{j=1}^{n} z_j^{\phi_j} \tag{8}$$

where α_j and ϕ_j are output elasticities of variable inputs, x_j and fixed inputs z_j, respectively. The profit function corresponding to (8) is:

$$\Pi^* = A^{(1-\mu)^{-1}}(1 - \mu)\left[\prod_{j=1}^{m}\left(\frac{c_j'}{\alpha_j}\right)^{-\alpha_j(1-\mu)^{-1}}\right]\left[\prod_{j=1}^{m} z_j^{\phi_j(1-\mu)^{-1}}\right] \tag{9}$$

where the parameter μ is the sum of the α_j, and c_j' is the price of x_j divided by output price. By taking logarithms the estimating form of the profit function is:

$$\ln \prod{}^* = \ln A^* + \sum_{j=1}^{m} a_j^* \ln c_j' + \sum_{j=1}^{n} \phi_j^* \ln z_i + e_1. \tag{10}$$

To compute the parameters of the production function given the estimates of the profit function parameters in (8) is straightforward and discussed in Lau and Yotopoulos. The estimating equations for the derived demand functions for the Cobb-Douglas profit function are:

$$-c_j' x_j / \Pi^* = \alpha_j^* + e_{j+1}. \tag{11}$$

Estimates of the α_j^* and ϕ_j^* are obtained by considering (10) and the p equations indicated by (11) as a system of seemingly unrelated regressions.

The Cobb-Douglas production technology is one of many possible technologies. It has been used frequently in agricultural studies although it has been recognized as somewhat restrictive. The Cobb-Douglas profit function can be viewed as a first order Taylor series approximation (in the logarithms of the variables) to the true underlying profit function. This is similar to the justification given for the translog function which is frequently used as an approximating form for a profit function except that it is a second order approximation. Thus, instead of assuming the Cobb-Douglas production technology is the technology for the population, it is assumed in this study to be a reasonable approximation.

[3] The authors are not aware of any studies deriving the elasticities of production of the technology underlying the translog profit function.

Model Specification

As described in Mjelde *et al.*, (9) is a unit output price profit function specified to be a function of normalized wages of hired labor, W, and the normalized indexed price of the other variable inputs that is labelled CE for the price of cash expenditures.[4] The fixed inputs are tillable acres per farm, AC, value of non-land capital for each farm, IN, and a soil productivity index, PR given in Fehrenbacher *et al.* Three other variables are entered to represent the effect of the weather and the environment. Ozone, OZ, is measured in parts per billion and July rainfall, R, and July mean temperature, TEM, are used to represent the effect of weather on crop yields. Rainfall is measured in inches and temperature in Fahrenheit. Ozone data are by county. Rainfall and temperature are by crop reporting district.

The ozone data are part of the United States Environmental Protection Agency (USEPA) SAROAD data set with modifications to reflect rural concentrations. Specifically, the ozone data are reported for the growing season in Illinois (May 1 through September 30) for the years 1978–81. The data are the mean of the hourly readings in parts per billion from 9:00 a.m. to 4:00 p.m. averaged over these five months. This is the standard dose measure being used in all National Crop Loss Assessment Network studies. The ozone concentration levels are measured for the seven-hour, mid-day period when plant physiological processes (stomatal activity) are greatest. It is during this period that ozone is believed to be most injurious to plants.

[4] Wages, W, are computed for each farm for each year as a function of the total wage bill for the farm divided by the number of months of labor. The operator wage is equal to the average wage rate for all hired labor in the sample in a given year. The index of cash expenditures, CE, is formed by an index of representative inputs to give an index of variable input prices except labor for each year. The variable CE is the same for all farms in a given year but varies over years.

Sample Selection and Characteristics

Individual farm data are used in the study. Data are collected on an annual basis by the Illinois Association of Farm Business Farm Management (FBFM). The data base is not truly a random sample because participation in the program is voluntary. However, it is the subjective opinion of many familiar with the FBFM membership and agriculture in Illinois that the FBFM data are representative of commercial agriculture in Illinois.

Farms included in the sample are primarily cash grain farms with little or no livestock activity and at least 95 percent of tillable acres in corn, soybeans or wheat. The observations for the sample are from 1978 through 1981. A total of 229 farms are included in the sample. Since there are four observations on each farm, one for each year, the total number of observations is 916. Greater detail about the sample and variables is reported in Dixon *et al.*

Given the variables above, the profit function and share equations to be estimated can be written as:

$$\begin{aligned}\ln \Pi^* = \alpha_0 &+ \alpha_1^* \ln W + \alpha_2^* \ln CE \\ &+ \phi_1^* \ln AC + \phi_2^* \ln IN \\ &+ \phi_3^* \ln PR + \phi_4^* \ln OZ \\ &+ \phi_5^* \ln R\ \phi_6^* \ln TEM + e_1 \qquad (12)\end{aligned}$$

$$-TWB/\Pi^* = \alpha_1^* + e_2 \qquad (13)$$

$$-TCE/\Pi^* = + \alpha_2^* + e_3. \qquad (14)$$

The coefficients of the variable input prices α_1^* and α_2^* should be negative so that the profit function has the property of monotonicity. All the ϕ_i^* coefficients should be positive except ϕ_4^* and ϕ_6^*. Biological evidence (Heck *et al.*, 1983) has indicated that increased ambient ozone concentrations make yields decline. A past study of Illinois agriculture, Huff and Neill, indicates that increases in temperature during the growing season generally have a deleterious effect on corn and soybeans which constitute over 98 percent of the acres planted in our sample.

Utilizing the study by Huff and Neill, it is possible to obtain a prior estimate of the coefficient ϕ_6^*. The details on the derivation of this estimate are involved and given fully in Dixon *et al.* Essentially, Huff and Neill estimated separate regression equations for corn and soybean yields using temperature and rainfall as explanatory variables for variations in yields over time for four regions in Illinois. The coefficients for each region are weighted by the number of farms in our sample in the respective regions and averaged to give one coefficient for each crop for the state. These coefficients are then converted to yield elasticities using mean yields and temperatures for the sample farms. Then these yield elasticities are converted into changes in average revenue for temperature fluctuations. These coefficients are used in this study to compute the decline in gross revenues for farms during the sample period. These revenue declines are then converted into elasticities of profit for a change in temperature. The resulting estimate for ϕ_6^* is -1.645 with a variance of .176. The estimate of the variance is constructed so that, if anything, it is an overestimate of the true prior variance.[5]

Similar types of nonsample estimates could have been developed for rainfall and ozone. However, this was not done because a major objective of the study was to identify the effect of ozone independently of the results of other ozone studies. Additionally, the estimate of the coefficient of ln R seemed reasonable in preliminary estimation suggesting that multicollinearity did not appear to be a problem with respect to rainfall.

Results of Estimation

To show the effect of the prior information, equations (12)–(14) are first estimated without the prior information. The specific estimation technique used is iterative maximum likelihood which means that it is assumed the error terms of the equations in (12)–(14) are multivariate normal.[6] The estimated profit function is:

$$\begin{aligned} \ln \Pi^* = 9.58 &- \underset{(-15.0)}{.599 \ln W} - \underset{(-13.9)}{1.90 \ln CE} \\ &+ \underset{(20.6)}{1.32 \ln AC} - \underset{(-1.30)}{.0620 \ln IN} \\ &+ \underset{(4.62)}{.704 \ln PR} - \underset{(-.508)}{.151 \ln OZ} \\ &+ \underset{(4.28)}{.201 \ln R} - \underset{(-4.60)}{4.03 \ln TEM} \end{aligned} \tag{15}$$

$R^2 = .513.$

The numbers in parentheses are the ratios of the estimated coefficient to its estimated asymptotic standard error and R^2 is the coefficient of determination for the profit function.

The signs of all the coefficients in (15) are as prior theory indicates except the sign of ln IN is negative. This is probably due to the difficulty in measuring capital stocks accurately and it is a problem which frequently arises in farm level production estimates. The coefficient of determination, .513, is reasonable for cross sectional data. A disturbing aspect of (15) is that the coefficient of ln TEM is substantially higher than the prior value computed ear-

[5] Some statistics based on the sample data are used in transforming the estimates in Huff and Neill to use in the profit function. For example, the percent of revenue which is profit is used. However, the Huff and Neill estimates are based on data outside the period of our sample. Hence, it is our assumption that any correlation implied by using sample statistics is of such minor importance that it can be ignored.

[6] The independent variables are divided by their geometric mean prior to the logarithmic transformation since (16) is considered a first order linear approximation.

lier. Furthermore, the coefficient of ln OZ is not statistically significant, which is contrary to what is expected on the basis of experimental data about the effect of ozone on corn and soybeans.

Ozone is created through a photochemical reaction, suggesting that ozone levels and temperatures should be correlated. For the sample, the correlation coefficient between ln OZ and ln TEM is .583. This linear relationship between these two variables might make it difficult to distinguish between their individual effects. Moreover, the collinearity could obscure the effect of ozone. Hence, the model is reestimated using the nonsample information on the coefficient of ln TEM. The resulting profit function is:

$$\begin{aligned}\ln \Pi^* = 9.58 &- \underset{(-14.9)}{.590} \ln W - \underset{(-13.8)}{1.88} \ln CE \\ &+ \underset{(20.5)}{1.30} \ln AC - \underset{(-1.22)}{.0582} \ln IN \\ &+ \underset{(4.88)}{.739} \ln PR - \underset{(-1.68)}{.456} \ln OZ \\ &+ \underset{(6.35)}{.258} \ln R - \underset{(-5.52)}{2.09} \ln TEM \qquad (16)\end{aligned}$$

$R^2 = .510.$

Two immediate impacts of the nonsample information stand out by comparing (15) with (16). First, only the coefficients of ln OZ and ln TEM are changed substantially by the nonsample information. Second, the coefficients of the environmental variables are more statistically significant and the coefficient of ln OZ has now become significant at the 95 percent level for a one-sided test. This is in concurrence with the prior findings of biological experiments about the effects of ozone. In addition, given that the variance of the prior is likely overestimated, the significance of ln OZ is probably underestimated.

The model in (16) satisfies monotonicity because both α_1^* and α_2^* are negative and statistically significant. Also, the function is convex in variable inputs since the appropriate Hessian involving the α_j^* is positive definite. In comparison with the translog model estimated by Mjelde *et al.*, the coefficient of determination is lower (.510 to .659) but all linear coefficients in the two models have the same sign for each variable. None of the coefficients in (16) varies from its counterpart in the translog model by more than 43.8 percent and only three vary by more than 11 percent.[7] In the translog model the coefficient of ln OZ is .408 compared with .456 in (16), suggesting that .456 may be an overestimate.

The sensitivity of the estimates to variations in r can be measured by examining $PR\Omega^{-1}$ in (7). For the results in (16), using $\tilde{\Sigma}$ instead of Σ for P,

$$PR\Omega^{-1} = 10^{-2}(.00955,.376,.790,-.553,\ .519,.150,-12.8,2.40,81.2) \qquad (17)$$

What (17) clearly displays is that variations in r would affect the coefficients of ln OZ and ln TEM much more substantially than any of the other coefficients. This is true because the seventh and ninth components of (17) correspond to ln OZ and ln TEM, respectively. Moreover, the sign of the seventh component is negative whereas the ninth component is positive, indicating that as the coefficient of ln TEM increases due to prior information, that of ln OZ decreases. Such a relationship is typical of collinear variables and earlier results indicate that ln OZ and ln TEM are collinear.

The test statistic for the compatibility of the sample and prior information, u in (6), has a value of 6.03. The critical value for chi-square with one degree of freedom at the .05 level is 3.84 and 6.63 at the .01 level. Thus, it would appear the two sources of information are barely compatible. However, the lack of compatibility is probably more due to the functional form of the profit function than a true, under-

[7] The coefficients of ln PR, ln R and ln TEM vary by 43.8, 32.6, and 21.5 percent respectively.

lying difference. When the more complex approximation in Mjelde *et al.* is fitted to the data, the coefficient of ln TEM is not significantly different from the prior estimate at the .1 level. Using the prior information in (16) is justified because it incorporates both nonsample information and serves as a means of correcting for a likely specification error in the model. Given the above aspects and the fact that all of the coefficients have the expected signs and significance (except ln IN), the model in (16) is judged a good approximation of the true profit function.

Implications of the Results

The output elasticities for the inputs, ϕ_4, ϕ_5, and ϕ_6, derived from the profit function (16), are

$$\tilde{\phi}_4 = -.131$$
$$\tilde{\phi}_5 = .0744$$
$$\tilde{\phi}_6 = -.602$$

A 25 percent increase in ozone concentration would lead to a 3.3 percent decrease in output where output must be interpreted as a combination of corn, beans and wheat, although wheat is a very minor component. Results in Heck *et al.* (1983), for dose response functions based on data generated by experiments at the Argonne National Laboratory are in general agreement with this estimate. For the Corsoy soybean type a 25 percent increase in ozone levels (from 40 parts per billion to 50 parts per billion) would elicit an 11.7 percent decrease in output. For the two Argonne corn varieties, the percentage declines are .6 percent and 1.4 percent. Figuring corn and beans to be roughly equal (corn does contribute more toward gross revenue in our sample), the estimate of 3.3 percent is reasonable because it lies above the corn estimate and below both soybean observations.

The fact that 3.3 percent is lower than an average of the experimental data is not surprising. The experimental results in Heck *et al.* (1983) were derived under favorable growing conditions.[8] The contrasts in yields most likely reflect the differences between using experimental and field conditions for measuring the impact of variations in a specific input.

Conclusions

The Theil and Goldberger mixed estimator is applied to a system of seemingly unrelated equations to measure the impact of a pollutant, ozone, on cash grain farms in Illinois. Using duality concepts, a system comprised of a profit function and input demands is specified. As with production functions, estimation of profit function parameters using individual producer data is likely to provide some imprecise estimates because of insufficient variability of regressors. Using nonsample information on the effect of temperature on profits, the impact of ozone is more clearly estimated, shown to be statistically significant and is in general agreement with biological science results. Results of this research suggest that combining economic theory and data with biological data through the mixed estimation technique is a useful procedure for the measurement of the impact of pollutants on agriculture.

References

Adams, R. M., T. D. Crocker, and N. Thanvibulchai. "An Economic Assessment of Air Pollution Damages to Selected Annual Crops in Southern California." *Journal of Environmental Economics and Management*, 9(1982): 42–58.

Adams, R. M. and T. D. Crocker. "Economically Relevant Response Estimation and the Value of

[8] In the Heck *et al.* data, corn yields were in excess of 170 bushels per acre and soybeans averaged 39.3 bushels per acre. In our sample, corn and soybeans averaged 94.0 and 38.3 bushels per acre, respectively, for the same year, 1981, as the Heck *et al.* experiments.

Information: The Case of Acid Deposition." *In Economic Perspectives on Acid Deposition*, T. D. Crocker, ed. Ann Arbor Science, Ann Arbor, 1983.

Adams, R. M. and B. A. McCarl. "Assessing the Benefits of Alternative Oxidant Standards on Agriculture: The Role of Response Information." Submitted to the *Journal of Environmental Economics and Management.*

Dixon, B. L., P. Garcia, J. Mjelde, and R. M. Adams. "Estimation of the Economic Cost of Ozone on Illinois Cash Grain Farms Using a Duality Approach." Final Report to USEPA, Corvallis Environmental Research Laboratory, 1983.

Fehrenbacher, J. B., I. J. Jason, J. D. Alexander, and B. W. Ray. *Soil Productivity in Illinois*. University of Illinois Extension Circular 1156, April 1978.

Garcia, P., S. T. Sonka, and Man Sik Yoo. "Farm Size, Tenure, and Economic Efficiency in a Sample of Illinois Grain Farms." *American Journal of Agricultural Economics*, 64(1982): 119–124.

Havenner, A. and R. Craine. "Estimation Analogies in Control." *Journal of the American Statistical Association*, 76(1981): 850–859.

Heck, W. W., O. C. Taylor, R. M. Adams, J. Bingham, J. Miller, E. Peterson, and L. Weinstein. "Assessment of Crop Loss From Ozone." *Journal of the Air Pollution Control Association*, 32(1982): 353–361.

Heck, W. W., R. M. Adams, W. W. Cure, A. S. Heagle, H. E. Heggestad, R. J. Kohut, L. W. Kress, J. O. Rawlings, and O. C. Taylor. "A Reassessment of Crop Loss from Ozone." *Environmental Science and Technology*, 17(1983): 573–581.

Huff, Floyd A. and James C. Neill. "Assessment of Effects and Predictability of Climate Fluctuations as Related to Agricultural Production." Final Report-Phase 1 to the National Science Foundation, University of Illinois State Water Survey Division, 1980.

Judge, G. G., T. A. Yancey, and M. E. Bock. "Properties of Estimation After Preliminary Tests of Significance When Stochastic Restrictions Are Used in Regression." *Journal of Econometrics*, 1(1973): 29–47.

Lau, L. J. and P. A. Yotopoulos. "Profit, Supply, and Factor Demand Function." *American Journal of Agricultural Economics*, 54(1972): 11–18.

Leung, S., W. Reed, S. Cauchois, and R. Howitt. *Methodologies for Valuation of Agricultural Crop Yield Changes: A Review*. USEPA-600/5-78-018, Corvallis, Oregon, August 1978.

McFadden, D. "Duality of Production, Cost and Profit Functions." In *Production Economics: A Dual Approach to Theory and Applications*, Vol. I, 3–109, M. Fuss and D. McFadden, eds. North-Holland, Amsterdam, 1978.

Mittlehammer, R. C., D. L. Young, D. Tasanasanta, and J. T. Donnelly. "Mitigating the Effects of Multicollinearity Using Exact and Stochastic Restrictions: The Case of an Aggregate Agricultural Production Function." *American Journal of Agricultural Economics*, 62(1980): 199–210.

Mjelde, J. W., R. M. Adams, B. L. Dixon, and Philip Garcia. "Using Farmers' Actions to Measure Crop Loss Due to Air Pollution." *Journal of the Air Pollution Control Association*, 34(1984): 360–364.

Theil, H. "On the Use of Incomplete Prior Information in Regression Analysis." *Journal of the American Statistical Association*, 27(1963): 401–414.

Theil, H. *Principles of Econometrics*. John Wiley & Sons, Inc., New York, 1971.

Theil, H. and A. S. Goldberger. "On Pure and Mixed Statistical Estimation in Economics." *International Economics Review*, 2(1960): 65–78.

Yotopoulos, P. A. and Lau, L. J. "A Test for Relative Economic Efficiency: Some Further Results." *American Economic Review*, 63(1973): 214–223.

Zellner, A. *An Introduction to Bayesian Inference in Econometrics*. John Wiley & Sons, Inc., New York, 1971.