Regulating Pesticides in Greek Agriculture

Katerina Melfou[1]

[1] Technological Education Institute of Western Macedonia, Department of Agricultural Products Marketing and Quality Control, Florina, Greece

Regulating Pesticides in Greek Agriculture

Katerina Melfou

Technological Education Institute of Western Macedonia, Department of Agricultural Products
Marketing and Quality Control, Florina, Greece

Abstract

The objective of this paper is to estimate the short run and long run own- price elasticity of pesticide demand in Greece in a profit maximization context. A single equation approach is adopted and the dynamic aspects of pesticide demand are captured by the use of cointegration techniques. The policy implications of the empirical findings concern the price responsiveness of pesticide demand in Greece to potential changes in pesticide price due to the imposition of an environmental tax on that polluting input. The estimated short run elasticity of pesticide demand is -0.8 whereas the long run estimate is slightly larger, approximately -0.9. The short run pesticide elasticity with respect to output price is 1.58 and the long run 1.75 both highly elastic estimates. The reduction of output prices may thus be expected to bring about a larger reduction in pesticide use than the imposition of a tax on that input.

Key words: pesticide demand, cointegration, error correction model.

Introduction

Intensive agriculture makes increasing demands to the resource base both in quantitative and qualitative terms which have led to the generation of numerous externalities. Along with rising agricultural output we also observe frequent incidences of polluted aquifers due to agrochemicals, or reduced biodiversity in ecosystems adjacent to intensively cultivated land. More specifically, pesticide runoff reduces the quality of drinking water and adversely affects aquatic habitats thus putting pressure on a number of activities commercial and recreational which depend on the use of water resources. The need to regulate the use of pesticides lies also on their undesirable effects on the health of farmers and farm workers and on the health of consumers due to potential pesticide residues on agricultural produce.

The environmental pressures resulting from the current level of pesticide use constitute an even more complex problem because pesticides have a low rate of degradation and their detrimental effect becomes apparent with some delay. To make things worse, analytical methods for environmental monitoring of pesticides are only available for about 50% of approved substances so there is considerable uncertainty about the true levels (Defra, 2004).

The environmental damage from pesticide use differs according to the precise type of chemical that is applied, the application rate and the location specific environmental conditions. Hence, it is not a straightforward undertaking to quantify the associated external costs and determine a socially optimum tax on pesticides. In such cases of non-point source pollution it is not an easy task to implement an emission based pollution tax, rather it may more realistic to consider a tax on the polluting input.

Hence, the price responsiveness of pesticide demand to potential changes in pesticide price due to the imposition of an environmental tax on that polluting input needs to be looked at. The objective of this paper is to estimate the short run and long run own- price elasticity of pesticide demand in Greece.

The annual consumption of pesticides in Greece approximates the 16.000 tons which correspond to 10.000 tons of active ingredients, bringing average consumption to 250 gr/stremma (Papanagiotou, 1997). Pesticide consumption, in terms of its value in constant prices, exhibits an increasing trend since 1973 with an upward shift occurring in the late 1980's. This trend showed a break in the years between 1993 and 1995 and then was reversed in 1996 (figure 1).

The same pattern is followed by the figure depicting the value of pesticide imports which reflects the fact that a large part of the quantities consumed in the country are imported (figure 2).
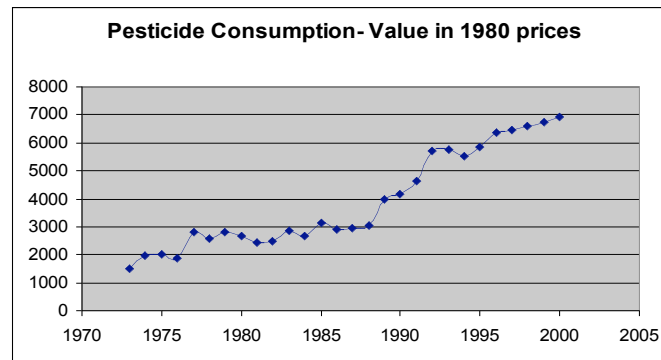
Source of data: National Accounts

Figure 1. Pesticide consumption in Greece

427

The bulk of imports come from the EU whereas about 25% is imported from third countries. Most of the active ingredients are imported and are then processed into their final form, ready for consumption, by the home chemical industry (Papanagiotou and Evgeniou, 1998). The relative share of the various categories of pesticides imported is shown in Figure 3.

Pesticides- Imports (000$)
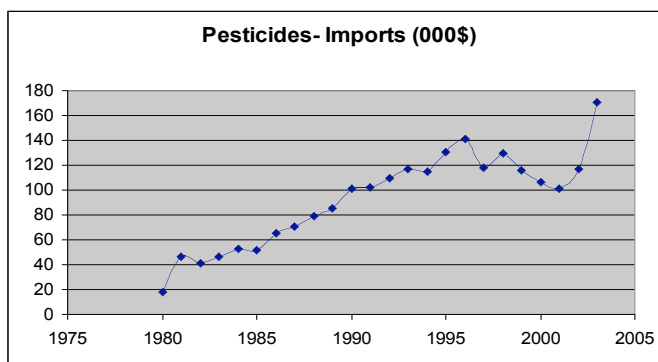
Source of data: FAOSTAT

Figure 2. Value of pesticide imports

Pesticides imports by category
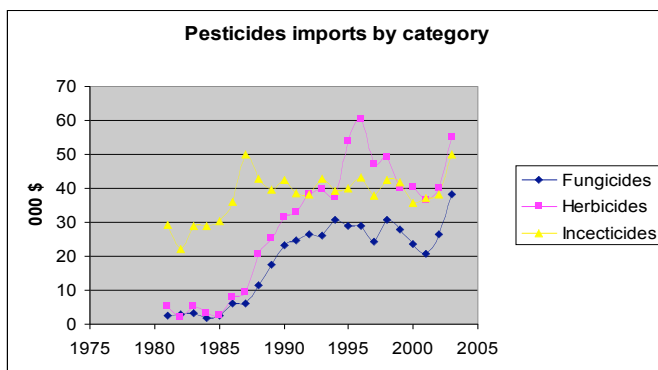
Source of data: FAOSTAT

Figure 3. Pesticide imports by category

428

Input Demand

A number of studies have dealt with the issue of pesticide demand in various European countries. In a Danish study an ad-hoc econometric model is used to investigate the observed behaviour of farmers with annual data on price and pesticide use (Dubgaard, 1991). The average number of treatments per hectare is taken to be a function of pesticide price index and time. The price elasticities of herbicides and fungicides in Denmark, grouped together, are estimated at -0.69 and of insecticides at -0.81, both figures being long run estimates.

Oskam et al. (1992) look into the price sensitivity of fertilizer and pesticide use in Dutch arable farming with data from a stratified sample of arable farms, according to the amount of activity reserved for these crops. It is a structural model based on the profit function estimated with SUR and elasticities are derived from the demand equations. The results point to a price elasticity of pesticides in Dutch arable farming of about -0.21 in the short run and -0.22 in the long run. Similar results are found when this model is applied to the Dutch horticultural sector with the short run and long run elasticities calculated at -0.25 and -0.29 respectively. Lansink and Peerlings (1997) in a paper examining the effects of a regulatory levy on pesticide use in Dutch arable farming point to a price elasticity figure of -0.48. Most empirical studies in the Netherlands indicate price elasticities of pesticide demand within the range -0.2 to -0.5 (Oskam, 1997).

Fairly low elasticity is reported for Greece -0.276 with the use of an ad-hoc specification for the agricultural sector for the period 1961-1990, (Papanagiotou,1994) The response of pesticide consumption with respect to output price is also found to be very inelastic with an estimate of -0.281.

Remarkably higher are the estimates for the UK agriculture (Russel et al. 1997) indicating a slightly elastic response of pesticide demand to a change in their price. Under the assumptions that farmers maximize profits in the short run subject to constraints in land use and face a Constant Elasticity of Substitution technology, two alternative runs of the model based on alternative assumptions for the set aside scheme produced elasticity figures of -1.09 and -1.12.

Burrell (1989) stresses the problems concerning the econometric estimation of input demand functions. If they rely on dual cost or profit functions, cross equation restrictions implied by duality theory do not often hold globally in empirical studies of the agricultural sector. If on the other hand they use reduced form equations they may be subject to spurious regressions.

The methods adopted in the previous studies, either based on structural models or on ad hoc single equation specifications are static models, which assume that adjustments of input demand toward equilibrium are instantaneous. They do not take into account the dynamic aspects of pesticide demand. The developments on cointegration and error correction models have been applied to fertilizer demand functions of corn by Denbaly and Vroomen (1993) for the US agriculture. As they point out, static models do not allow quantity demanded to diverge from long run equilibrium levels which in any case are not really observable. The observed data reflect the motion involved in a dynamic process of convergence toward equilibrium.

Rayner and Cooper (1994) construct time series models of demand for nitrogenous fertilizers in the UK and examine in detail the time properties of the data in order to estimate short run and long run price elasticities.

Mergos and Stoforos (1997) analyze fertilizer demand in Greece by means of an error correction model. They also make the point that single equation demand estimation does not have to be ad hoc. A single equation demand function is specified and estimated that is grounded to duality theory. Having duality as the starting point they assume that producer behaviour is best modeled by a profit function that has the Generalized Quadratic functional form.

A similar approach is taken in this paper in order to obtain the pesticide elasticities (Chambers, 1988). Producers are assumed to maximize profits hence:

$$\prod = \max (P*Y - R*X) \tag{1}$$

Subject to the transformation function:

$$F(Y, X; Z) = 0 \tag{2}$$

Where P is the vector of output prices, R the vector of input prices and Y and X are the vectors of output and input quantities, respectively.

The normalized profit function for the multi-output, multi-input firm is given by:

$$\pi = G(p, q) = \text{Sup}\{p*y + q*x - F(y, x)\} \tag{3}$$

where p and q are the normalized prices of y and x with the price of intermediate inputs (excluding pesticides) as the numeraire. According to duality theory input demand functions can be obtained using Hotelling's Lemma. Thus the pesticide demand function takes the following form:

$$Q_{PE} = f(p_1, p_2, p_3, p_4, D81) \tag{4}$$

where Q_{PE} is the quantity of pesticides demanded, p_1 is the price of pesticides, p_2 the price of crop output, p_3 the price of labour and $p4$ the price of capital. D81is a dummy variable for Greek accession to the EC.

Methodology

Non-stationary variables and the classical model

It is not appropriate to apply classical regression techniques to variables that exhibit consistent trends over time. When time series are non-stationary other methods should be used in order to analyze their relationship (Hallam and Zanoli 1993, Thomas 1997, Kennedy 2003).

A time series is stationary if its mean, variance and co-variances remain constant over time. If any of the above is violated the series is non-stationary and the use of the classical regression model may lead to spurious regressions. If at least one of the regressors exhibits a clear trend and is therefore non-stationary, it is very probable that the dependent variable will display a similar trend. The result would be to obtain artificially significant regression coefficients and very high R^2 even if the trending variables are totally unrelated. Another indication of a spurious regression is a relatively low Durbin-Watson statistic combined with a good R^2.

One way that has been used to overcome the problem is to take first differences of the variables and hence work with their rate of change. However, important information regarding the levels of the variables is lost in that way and the focus stays only on the short run relationships. A change in the dependent variable during period t does not depend only on the change in the explanatory variables during period t but also depends on the relationship between the dependent and explanatory variables at the end of the previous period. That is, it will depend on the extent of any disequilibrium between them during period (t-1). If we solely use the differenced variables this information is ignored. The error correction model offers the possibility to handle non-stationary variables and maintain the information contained in the levels of variables.

In order to be able to use the ECM all the series must be cointegrated that is there must be a linear combination of Y and X that is stationary even though the individual variables are not. Before proceeding to test for cointegration we must test whether the variables of interest are stationary or not.

Tests for stationarity

A series is considered to be weakly or covariance stationary if the mean and autocovariances of the series do not depend on time. Any series that is not stationary is said to be non-stationary.

An example of a non-stationary series is the random walk:

$$Y_t = Y_{t-1} + \varepsilon_t \tag{5}$$

where ε_t is a stationary random disturbance term. The random walk is a difference stationary series since the first difference of Y is stationary.

A difference stationary series is said to be integrated and is denoted as I (d) where d is the order of integration. The order of integration is the number of unit roots contained in the series, or the number of differencing operations it takes to make the series stationary. There is one unit root in the random walk so it is an I (1) series. Similarly, a stationary series is I (0).

The formal method to test the stationarity of a series is the unit root tests and the Dickey-Fuller and Augmented Dickey and Fuller tests are widely applied. The objective of the tests developed by Dickey and Fuller is to determine if, in the following time series model

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 t + \varepsilon \tag{6}$$

The parameter b_1 is equal to one and therefore the series Y contains a unit root, or less than one in which case it is a stationary series. At the same time it can be determined whether the drift term b_0 and the time trend term b_2 are different from zero.

Three different regressions can be used to test the presence of a unit root

$\Delta Y_t = \beta Y_{t-1} + \varepsilon_t$ \qquad Tests whether Y is a pure random walk

$\Delta Y_t = b_0 + \beta Y_{t-1} + \varepsilon_t$ \qquad Tests whether Y is a random walk with drift

$\Delta Y_t = b_0 + \beta Y_{t-1} + b_2 t + \varepsilon_t$ \quad Tests whether Y is a random walk with drift and deterministic trend

The difference between the three regressions concerns the presence of deterministic elements b_0 and $b_2 t$.

The augmented version of the Dickey-Fuller test includes additional differenced terms as regressors and the presence of unit roots is tested for by the following general equation:

$$\Delta Y_t = b_0 + \beta Y_{t-1} + b_2 t + \sum \gamma\gamma Y_{t-j} + \varepsilon_t \tag{7}$$

with j=1....k If k=0 the augmented version test reverts back to the Dickey-Fuller test.

If a number of economic variables have been tested for unit roots and have been found to be integrated of order one I(1), the question remains of whether they are cointegrated variables, which rephrased is effectively asking whether there is a long run economic relationship between them.

Cointegration

More generally, in the regression model,

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + ... + \beta_k X_{kt} + e_t \tag{8}$$

If there exists a relationship between a set of variables, Y_t, X_{1t}, X_{2t}, …, X_{kt}, the error terms can be thought of as measuring the deviations between the components of this model:

$$e_t = Y_t - \beta_0 - \beta_1 X_{1t} - \beta_2 X_{2t} - .... - \beta_p X_{pt} \tag{9}$$

In the short run the divergence between the components will fluctuate, but if the model is really capturing a true relationship there will be a limit to the divergence. Consequently, although the time series are non-stationary (eg. I(1)), e_t will be stationary I(0). When two or more non-stationary time series are connected in such a way, then these series are said to be cointegrated. In order to determine whether this is, so the Dickey-Fuller and Augmented Dickey-

Fuller tests can be applied to the residuals of the OLS estimates of the cointegrating long run relationship. If these residuals are stationary then the OLS regression can be considered as the true long run relationship between the variables. However, because these residuals have been produced by OLS which makes them as small as possible the DF and ADF tests for unit roots are biased towards finding cointegration. This problem is dealt with by using special critical values (MacKinnon, 1991). Another test that is being used is the cointegrating regression Durbin-Watson test (CRDW) which assumes that the disequilibrium errors and their estimates- the observed residuals- can be modeled as a first-order process.

If the variables are cointegrated the coefficient on the error correction term in the estimates of the error correction model is expected to be significantly different from zero, as a consequence of the Granger Representation Theorem, which states that there is an error correction representation for every cointegration relationship.

Error correction models

If we take the simple case of two variables Y and X and assume only first order lags the Error Correction Model (ECM) takes the following form:

$$\Delta Y_t = b_1 \Delta X_t - \lambda (Y_{t-1} - \beta_0 - \beta_1 X_{t-1}) + \varepsilon_t \tag{10}$$

where ε is a disturbance term with zero mean, constant variance and zero covariance.

The principle behind this model is that there often exists a long run equilibrium relationship between two economic variables. The long run equilibrium between Y and X is

$$Y_t = \beta_{0+} \beta_1 X_{t-1} \tag{11}$$

In the short run, however, there may be disequilibrium. With the error correction mechanism, a proportion of the disequilibrium is corrected in the next period. The error correction process is thus a means to reconcile short-run and long run behavior. The term in parenthesis can be regarded as the disequilibrium error from period (t-1) and its interpretation is that the current change in Y depends on the change in X and on the extent of disequilibrium in the previous period. The value of Y is being corrected for any previous error. The extent to which any error in period (t-1) is compensated for in period t depends on the size of the parameter λ. Since λ takes values between zero and one only a fraction of the disequilibrium is made up for in the current period. The absolute value of λ decides how quickly the equilibrium is restored.

In the error correction model, the right hand side contains the short-run dynamic parameter b_1 as well as the long-run parameter β_1. The parameter β_1 appears in the equilibrium relationship and measures the long run effect of X on Y. The short-run effect on Y of changes in X is measured by b_1.

When there is a single cointegrating equation an appropriate method of estimation for the ECM is the Engle-Granger two-step procedure (Engle-Granger 1987). In the first stage the long run parameters are estimated and this is achieved by estimating the cointegrating equation

(11). If Y and X are in fact cointegrated then the OLS estimators of the long run parameters β_0 and β_1 will be consistent.

In the second stage the residuals obtained from the cointegrating regression are used as estimates of the true disequilibrium errors. Hence the second step is to run a regression using first differenced variables, adding the lagged value of these residuals in order to capture the error correction term. The number of lags on the differenced variables can be determined by experiment, dropping if necessary after an F-test those lags with insignificant coefficients. At this stage the estimates of λ and all the short run parameters is also obtained. It is possible to include the first differences of other I (1) variables that have not been used in the long run relationship if it is thought that they affect the dependent variable Y in the short run. Since all the differenced variables in the second stage are stationary OLS can be used for estimation. Engle and Granger have shown that the estimates of the short run parameters obtained in this way are consistent and asymptotically efficient as if the true disequilibrium errors have been used instead of their estimates, the residuals. In addition the estimated standard errors are consistent estimators of the true standard errors.

The multivariate model

If there are more than two variables in the model, it is possible that there may be multiple cointegrating relationships, the maximum number in theory being equal to p-1. If I (1) variables are linked by more than one cointegrating vector it is more appropriate to use the Johansen maximum likelihood procedure to test for cointegration (Johansen and Juselius, 1990). The reason is that the OLS estimation of the cointegrating regression does not produce consistent estimates of any of the cointegrating vectors.

The Johansen method determines the number of cointegrating vectors and gives estimates of these vectors along with estimates of the adjustment matrix. It proceeds by testing the hypothesis that there are no cointegrating vectors r=0. If this hypothesis is rejected it is possible to test the hypothesis that there is at most one cointegrating vector r≤1. If this hypothesis is also rejected, then the hypothesis r≤2 may be tested and so on until a hypothesis can not be rejected. The Johansen method then gives estimates of all the existing cointegrating vectors in the multivariate model.

Empirical analysis

In this section an error correction model of pesticide demand in Greece is estimated by the Engle-Granger two-step procedure using yearly data for the period 1973-2000. The source of data is the Economic Accounts for Agriculture and the National Statistical Service of Greece. The variables used in this model are normalized price indices of pesticides, crop output, labour and capital. Output price is taken to be producers' expected price hence lagged output price is

used as a proxy for current output price. A dummy variable D81 is also used to reflect the country's accession to the EC in 1981. Δ corresponds to the difference operator and ECT are the estimated residuals from the cointegrating equation.

$$\Delta(LPE) = \alpha * \Delta(LPE(-1)) + \beta_1 * \Delta(LP1) + \beta_2 * \Delta(LP2(-1)) + \beta_3 * \Delta(LP3) + \beta_4 * \Delta(LP4) - -\gamma * ECT(-1) + \delta * D81 + e \qquad (12)$$

With the purpose of proceeding with the error correction model the time series properties of the data is investigated with the DF and ADF tests for the variables in the equation.

Table 1. Dickey-Fuller and Augmented Dickey-Fuller tests for order of integration in the levels of variables

	DF	ADF
LPE	-1.298	-0.596 (1)
LP1	-1.937	-1.470 (1)
LP2	-3.012	-2.242 (1)
LP3	-1.301	-1.934 (1)
LP4	-2.993	-2.191 (1)

The 1%, 5% and 10% critical values for the DF test in the levels of variables are -3.6959, -2.975 and -2.6265 and the corresponding critical values for the ADF test are -3,71, -2.98 and -2.63

Table 2. Dickey-Fuller and Augmented Dickey-Fuller tests for order of integration in the differenced variables

	DF	ADF
LPE	-7.14	-4.29 (1)
LP1	-3.41	-3.35 (1)
LP2	-3.58	-3.52 (1)
LP3	-8.12	-4.35 (1)
LP4	-3.31	-3.36 (1)

The 1%, 5% and 10% critical values for the DF test in the differenced variables are -4.3552, -3.5943 and -3.2321 and the corresponding critical values for the ADF test are -4,3738, -3.603 and -3.2367.

The levels of all variables are non-stationary I (1) processes and the possibility of a long run relationship between the variables must be investigated with cointegration analysis.

Table 3. Maximum Likelihood Test for Cointegration

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.683457	82.92273	76.07	84.45	None *
0.566803	53.01503	53.12	60.16	At most 1
0.427214	31.26440	34.91	41.07	At most 2
0.352873	16.77608	19.96	24.60	At most 3
0.189433	5.460545	9.24	12.97	At most 4

The Johansen-Juselius maximum likelihood test examines the presence of different numbers of cointegrating equations. In this case, the maximum eigenvalue test rejects the hypothesis of no cointegrating vectors at the 95% significance level and indicates the presence of one cointegrating equation. The maximum eigenvalue test statistic is estimated at 82.92 against a critical value of 76.07 at the 5% significance level. The test statistic rejects the hypothesis of more than one cointegrating vector at the 95% level given that the maximum eigenvalue test statistic is estimated at 53.01 against a critical value of 53.12.

According to the second stage of the Engle-Granger two-step procedure the estimated residuals from the cointegrating equation are used in the estimation of the following error correction model. The letter Δ indicates differenced variables and ECT is the residual from a cointegrating regression of LPE on the relative prices LP1, LP2, LP3 and LP4. Numbers in parentheses are t-statistics.

$$\Delta(LPE) = -0.80 * \Delta(LP1) + 1.58 * \Delta(LP2(-1)) - 0.11 * \Delta(LP3) - 0.50 * \Delta(LP4) -$$
$$(-4.80) \qquad (6.54) \qquad (-0.65) \qquad (-1.85)$$

$$- 0.90 * ECT(-1) - 0.03 * \Delta(LPE(-1)) + 0.04 * D81 \qquad\qquad (13)$$
$$(-3.49) \qquad (-0.24) \qquad (1.52)$$

The coefficient in the error correction term is negative and statistically significant with a large value which means that pesticide demand adjusts rapidly to long run equilibrium levels. About 90 % of the adjustment is completed within one year. The signs and magnitudes of the estimated coefficients, at least for those statistically significant, are reasonable in terms of what might be expected from economic theory with a reservation for the rather large lagged output coefficient.

The R-squared=0.75 shows an acceptable goodness of fit. The Durbin-Watson test statistic is 1.84 and a further Lagrange multiplier test was performed for first and second order serial correlation giving $x^2_1 = 0.34$ and $x^2_2 = 1.44$. Tests for first and second order ARCH residuals

yielded values $x^2_1=0.52$ and $x^2_2=0.55$ respectively. These values are below the relevant critical values and so we may not reject the null hypotheses of no first order or second order autoregressive conditional heteroscedasticity. The RESET test for functional misspecification gave a value of 3.3 with a critical value $F^1_{16}=4.49$ (0,05) and therefore fails to reject the null hypothesis of a correct specification. The Jarque-Bera test for normality in the residuals yields $x^2_2=0.29$ well below the critical value $x^2_{0.05}=5.991$

Overall the estimated equation satisfies the econometric criteria regarding serial correlation, autoregressive conditional heteroscedasticity, functional misspecification, and normality of the obtained residuals.

The estimated short run elasticity of pesticide demand is -0.8 whereas the long run estimate is slightly larger, approximately -0.9. The short run pesticide elasticity with respect to output price is 1.58 and the long run 1.75 both thought to be fairly inflated estimates. These figures are reported with the reservations that a larger sample combined with a disaggregated approach that will examine separate demand functions for an admittedly heterogeneous input, might improve the performance of the model. The estimates from other countries vary a great deal, but when these results are compared with the elasticities reported for Greece, there is appreciable difference in the estimated figures which may possibly be attributed to the difference in methodology applied.

Concluding Remarks

This paper examines pesticide demand in Greece for the period 1973-2000 by means of an error correction model. The time series are tested for stationarity and a cointegrating relationship is found which allowed the formulation of an ECM. The own price elasticity is fairly large, pointing to an 8% reduction in the use of pesticides following a price increase by 10%. However, if this elasticity estimate is compared with the elasticity with respect to output price, pesticide demand appears to respond more to changes in the price of crop output than to changes in their own price. A 10% reduction in the price of output is expected to reduce pesticide use by approximately 15%. Hence the reduction of output prices may be expected to bring forth a larger reduction in the use of pesticides than the imposition of a tax on that input.

In view of the heterogeneity of that input, it would be worthwhile to divide the separate categories namely, fungicides, insecticides and herbicides and examine them in turn. More so because the relative use of each sub-category differs in various countries according to the specific climatic conditions and the agro-ecosystem's characteristics, information that is lost in aggregation. Besides it may be more effective to consider targeted measures, which may be overall more successful in reducing the accumulation of active ingredients in the environment given that their relative concentration and toxicity is not the same in all the categories of pesticides.

References

Burrell A. (1989): "The demand for fertilizer in the UK", *Journal of Agricultural Economics*, 40: 1-20.

Chambers R.G. (1988): *Applied Production Analysis: A Dual Approach*, Cambridge University Press.

Department for Environment, Food & Rural Affairs (2004): *Design of a Tax or Charge Scheme for Pesticides*, http://www.defra.gov.uk/environment.

Denbaly M., Vroomen H. (1993): "Dynamic Fertilizer Nutrient Demands for Corn: A Cointegrated and Error-Correcting System", *American Journal of Agricultural Economics*, 75: 203-209.

Dickey D.A., Fuller W.A. (1979): "Distribution of the estimators for autoregressive time series with a unit root", *Journal of the American Statistical Association*, 74: 427-31.

Dubgaard A. (1991): "Pesticide Regulation in Denmark", in Hanley N. (ed.): *Farming and the Countryside: An Economic Analysis of External Costs and Benefits*, CAB International, United Kingdom.

Engle R.F., Granger C. (1987): "Cointegration and error correction: Interpretation, estimation and testing", *Econometrica*, 66: 251-276.

Hallam D., Zanoli R. (1993): "Error Correction Models and Agricultural Supply Response", *European Review of Agricultural Economics*, 20: 151-166.

Johansen S., Juselius K. (1990): "Maximum Likelihood Estimation and Inference on Cointegration with Applications to the Demand for Money", *Oxford Bulletin of Economics and Statistics*, 52: 169-210.

Kennedy P. (2003): *A Guide to Econometrics*, The MIT Press Cambridge, Massachusetts.

Mergos G.J., Stoforos Ch.E. (1997): "Fertilizer demand in Greece", *Agricultural Economics*, 16: 227-235.

Oskam A. (1997): "The Economics of Pesticides: an Overview of the Issues", in Oskam A.J. and Viftigschild R.A.N. (eds.): *Policy Measures to Control Environmental Impacts from Agriculture*, Proceedings and Discussions from a Workshop on Pesticides, Wageningen, August 24-27, 1995, Wageningen Agricultural University, Netherlands, May 1997.

Oskam A.J., Van Zeijts H., Thijssen G.J., Wossink G.A.A. and Vijftigschild R. (1992): "Pesticide Use and Pesticide Policy in the Netherlands. An Economic Analysis of Regulatory Levies in Agriculture", *Wageningen Economic Studies 26*, Wageningen Agricultural University, Wageningen, Netherlands.

Oude Lansink A., Peerlings J. (1997): "Farm-specific impacts of policy changes on pesticide use in Dutch arable farms", in Oskam A.J. and Viftigschild R.A.N. (eds.): *Policy Measures to Control Environmental Impacts from Agriculture*, Proceedings and Discussions from a Workshop on Pesticides, Wageningen, August 24-27, 1995, Wageningen Agricultural University, Netherlands, May 1997.

Papanagiotou E. (1997): "The Potential for a Substantial reduction of Pesticide Application in Greek Agriculture", in Oskam A.J. and Viftigschild R.A.N. (eds.): *Policy Measures to Control Environmental Impacts from Agriculture*, Proceedings and Discussions from a Workshop on Pesticides, Wageningen, August 24-27, 1995, Wageningen Agricultural University, Netherlands, May 1997.

Papanagiotou E., Evgeniou K. (1998): *Policy and use of pesticides in Greece*, Proceedings from the 5th Conference of Agricultural Economics, Athens December 11-13, 1998 (in Greek), publ. Stamoulis.

Rayner A.J., Cooper D.N. (1994): "Cointegration Analysis and the UK Demand for Nitrogen Fertilizer", *Applied Economics*, 26: 1049-1054.

Rendleman C.M. (1993): "Estimation of Aggregate U.S. Demands for Fertilizer, Pesticides, and other Inputs: A Model for Policy Analysis", U.S. Department of Agriculture, *Technical Bulletin*, 1813: 1-29.

Russel N.P., Smith V.H., Goodwin B.K. (1997): "The Effects of CAP Reform on the Demand for Crop Protection in the UK", in Oskam A.J. and Viftigschild R.A.N. (eds.): *Policy Measures to Control Environmental Impacts from Agriculture*, Proceedings and Discussions from a Workshop on Pesticides, Wageningen, August 24-27, 1995, Wageningen Agricultural University, Netherlands, May 1997.

Thomas R.L. (1997): *Modern Econometrics*, Addison-Wesley Longman.