Ozone Externalities on Crop Production: Insights from UK Farm Level Data

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***Abstract**: Tropospheric ozone is an air pollutant thought to reduce crop yields across Europe. Much experimental scientific work has been completed or is currently underway to quantify yield effects at ambient ozone levels. In this research, we seek to directly evaluate whether such effects are observed at the farm level. We use both primal (production function) as well as dual (profit function) methods, with ozone as a fixed input, to explore the extent to which output and profits are affected by ozone in the UK. A panel dataset on UK farms is intersected with spatial data on ozone, and panel data production and profit function estimation methods are used. The production function does predict a statistically significant negative effect of ozone on wheat yields at the farm level. However, this elasticity is small, and indicates that ozone is unlikely to result in the imposition of substantial external costs on wheat production. The profit function implications regarding ozone are less clear. Although the estimates indicate that ozone depresses wheat farm profits and wheat supply, the elasticities are statistically insignificant, and few definite conclusions can be drawn. We conclude that the farm-level evidence does not show a substantial ozone effect in the UK, and that it may be wise to interpret economic valuations based upon experimental results with some caution*

Keywords: Ozone, wheat, crop production, production function, profit function.

JEL Classification: Q4, P2.

1. Introduction

Tropospheric (ground level) ozone is a pollutant produced by the interaction of solar radiation with the oxides of nitrogen (NO_x) and Volatile Organic Compounds (VOC). Although the precursor NO_x and VOC are also produced by natural processes, combustion in industrial production and motor vehicle operation has contributed significantly to elevated ozone concentrations throughout the industrialised west. Ozone has been known to impose an externality on crop production for the last 30 years, but it is only for the last decade that its impact has become a major concern in Europe. It is now established that ozone at ambient European concentrations can cause a range of negative effects including visible leaf injury, yield reductions and altered sensitivity to biotic and abiotic stresses (Jäger et al., 1993). Scientific research commissioned under the United Nations Economic Commission for Europe (UNECE) has established critical levels of ozone concentration, beyond which crop yields may be affected. This level is currently exceeded in 91% of UK arable crop area (PORG, 1997). Higher temperatures generally result in elevated ozone levels, and thus crop production in most of the rest of Europe is also susceptible to ozone. Wheat, potatoes and sugar-beet are among the important crops in Europe that suffer this externality.

The ozone-yield relationship has been extensively studied in the US (reviewed in Heck, 1989). In Europe, the biological research in this area has concentrated on establishing dose-response relationships for various crops using experimental methods, and establishing and refining critical levels beyond which crop yields are likely to be affected. Rather than use direct (mean) ozone concentrations, this 'Level 1' research worked with the 'AOT40' concept, *i.e.*, the cumulative ozone exposure over a threshold of 40 parts per billion, over a fixed growing season. Recognising that dose-response can be modified by several factors such as pests, rainfall, etc, 'Level II' research efforts have been underway to fine-tune critical levels based on such modifying factors that may be encountered (Karlsson, *et. al*, 2003).

Some economic evaluation of ozone external cost for European crop production has also been carried out. For example, Van der Eerden (1988) analysed the effects of air pollutants, including ozone, on economic surplus values for a number of crops in the Netherlands. Kuik, *et. al.* (2000) also analysed the Dutch case, by using a spatial economic model of the country's agricultural sector. Holland *et. al.* (2002) valued ozone reduction scenarios compared to the baseline for the whole of Europe. In all these cases, and in several other studies in Europe, the basis for conducting the valuation/simulation has been data established by exposure-response studies, *i.e.*, experimental data. The computed external cost of ozone has been considerable – for example, Holland *et. al.* (2002) computed external costs from ozone in 1990 at £4.3 billion for Europe.

Consider two factors. Firstly, external costs imposed by ozone will significantly depend on what transpires in farmer's fields in actual production conditions, with farmers varying a range of inputs, and facing a range of external shocks caused by weather, pests, *etc*. Secondly, findings from even the most sophisticated experimental research may not translate into farm-level reality. Given these factors, a question that naturally arises is: can we find statistical evidence based on farm-level data that ozone affects yields and profits? This paper investigates this issue. Specifically, we adopt parallel primal (production) function as well as dual (profit function) methods to explore the effects of ozone on farm level outcomes. Primal methods have the advantage of avoiding imposition of restrictive behavioural assumptions. Dual methods avoid thorny endogeneity issues and provide more efficient estimates if imposed behavioural assumptions hold. We choose to implement both methods so that the set of results available to make an informed judgement is larger.

The implementation is based on data on wheat farms in England & Wales and uses panel data and GMM methods to simply test the hypothesis that ozone significantly affects farm outputs and/or profits, conditional on observed modifying variables and random error.

This approach of sidestepping the biological route in establishing the impacts of ozone on farm outcomes has been used before in Garcia, *et. al.* (1986) for the US, and Young and Aidun (1993) for Canada. To our knowledge, this is the first application using European data. Obviously, direct estimation at the farm level cannot replace the detailed *understanding* of biological and physical processes provided by experimental science. However, farm level estimates such as this can have *confirmatory* value, especially at the level (whole farm) at which losses ultimately matter, but are seldom explored in experimental work.

2. Data

The farm level balanced panel data used here pertain to 116 cereal farms growing winter wheat in England and Wales over 6 years, 1993-98. The data are taken from the survey information collected from the study of the economics of cereal production conducted for the Department of Environment and Rural Affairs, U.K., as part of their studies in agricultural economics. Farms may produce more than one cereal crop at a time, but data are collected and are available on a crop-specific basis. We invoke the input nonjointness assumption to focus exclusively on a single crop, winter wheat. This is done because different cereals have different growing seasons, and different periods of sensitivity to ozone. Wheat is among the crops known to be most sensitive to ozone, experimental evidence is available for comparison, and information exists to relatively tightly define the relevant high-risk period of ozone exposure. A multi-output representation, while more general, would have none of these features, and it would be especially hard to define the above-mentioned window.

Physical and financial information was collected from the farmer during on farm visits conducted by farm business researchers. These visits were carried out when the crops were being sown, harvested and marketed (Wilson, Hadley and Asby, 2001). Output data were recorded by the quality of grain sold, tonnes produced of each quality per farm and price obtained. The price for wheat was worked out by dividing the total wheat enterprise revenue by the quantity of wheat produced (The total wheat revenue included revenue received from the sale of straw and set-aside payment).

The amount of data collected on the inputs varied. For seed, both the quantity and the cost per tonne were recorded. Similar information was collected for fertiliser usage. One of the attractions of this dataset is that the quantity of these two variable inputs was recorded, and consequently their farm level prices can be calculated. However, as far as herbicides and labour are concerned, only expenditures were gathered on a regular basis. Hence a price index constructed by the Department of Environment, Food and Rural Affairs (DEFRA) under the 'Agriculture in the UK' data series (DEFRA, 2002) was used for herbicides. Similarly, DEFRA's national average agricultural wage rates (DEFRA, 2003) were used for labour price information. Herbicide and labour quantity estimates were derived from the expenditure data and the respective price series. Variable profits were computed as total revenue minus total variable costs for winter wheat.

Ozone data were obtained from the UK national air quality information archive (www.airquality.co.uk). In keeping with the European scientific consensus on the appropriate ozone measure applicable to vegetation effects, the measure used here is the AOT40, *i.e.*, the cumulative ozone exposure over 40 parts per billion, over a fixed growing season. The data reported by the archive were in hourly ozone concentrations, which were then converted here into AOT40 measures. The period used for AOT40 calculation is May, June and July. This choice was based on guidance from previous experimental research on ozone effects on winter wheat in England (Ollerenshaw and Lyons, 1999). Ozone data are available from 50 monitoring stations spread across the UK, although not all stations have data for all years in the analysis. The spatial locations (eastings and northings) of the monitoring stations and the ozone data were input into a GIS, along with the county-level location information on farms in the sample. Then Arcview's© 'spatial analyst' module was utilised to spatially interpolate between ozone levels from various stations so that ozone levels for each farm are defined more precisely. Information was also obtained on rainfall (over the growing season) from the monitoring stations of the Met Office, UK, and matched to farm locations. Sample means of the data appear in Table 1.

Table 1. Sample mean values of variables

Variable	Mean
Yield per ha (tonnes)	7.9
Fertiliser (kgs per ha)	767.6
Pesticide (£ per ha)	45.6
Labour (£ per ha)	39.5
Area (hectares)	106.9
Variable Profits per farm	85,025
Price of wheat (£ per t.)	123.80
Price of seed (£ per t)	242.40
Price of fertilizer (£ per t)	101.82
Price of herbicide (£ per t)	173.12
Price of labour (£ per hour)	4.82
Ozone (AOT40)	3090.1
Rain (mm)	56.3

3. Models and Methods

Estimation of both the production as well as the profit function relied on the Generalized Method of Moments (GMM) framework, using translog functional forms. The methods are described in detail below:

3.1. Production function

To retain flexibility in production function estimation, a translog production function, given by (1) is estimated:

$$LnY = LnA_0 + \sum_{k=1}^{n} A_k \ln(X_k) + \frac{1}{2}\sum_{k=1}^{n}\sum_{l=1}^{m} \boldsymbol{b}_{kl} \ln(X_k)\ln(X_l) \qquad (1)$$

Here, k and l index the input vector X, while Y is wheat output. Ozone is included as a fixed input in X.

With the panel data available to us, we use an estimation strategy based on first-differencing and using past values of inputs as instruments in a GMM procedure. This approach to estimating firm-level panel production functions has been developed in the last decade, and involves careful purging of potential endogeneity problems (see *e.g.,* Mairesse and Hall (1996); Blundell and Bond (2000); Black and Lynch (2001)). Each exogeneity assumption produces a different model, based upon the number of instrumental variables (past/present/future values of inputs) available under the specific exogeneity assumption. Using the GMM framework, nested tests can be performed on the suite of alternative models to choose a specification that is valid for the dataset. We consider 3 different models: strong exogeneity (all years inputs are valid instruments), weak exogeneity (all past and present inputs are valid instruments) and the Lag 1 model (only past values of inputs are valid instruments). Then we successively test the strong exogeneity model against weak exogeneity, and then weak exogeneity against Lag 1, using a chi-square test developed by Eichenbaum *et. al.* (1988).

We note here that our fixed effects panel model adjusts for unknown, farm-specific effects such as soil quality and technical efficiency. The GMM procedure does not impose a specific parametric distribution on errors/yields, and is also robust to heteroscedasticity and serial correlation within the sample.

The production model in (1) is log-linear. For convenience, we specify only a single input in this exposition. Thus, the panel model can be written as:

$$y_{it} = \boldsymbol{b}x_{it} + \boldsymbol{a}_i + e_{it} \qquad (2)$$

Here, y is the logarithm of output, x is the logarithm of input, i indexes farms, and t represents years. á$_i$ represents the farm-specific ‘fixed effect’ (such as farmer efficiency or soil quality) that is presumed correlated with the x_{it}.

An accepted way of removing the farm-specific effects is first-differencing.

$$y_{it} - y_{it-1} = b\,(x_{it} - x_{it-1}) + e_{it} - e_{it-1} \qquad (3)$$

Estimation of (3) by least squares will provide consistent estimates provided e_t is a pure, unanticipated shock that does not transmit to x_t and x_{t-1}. If there is cause to suspect ‘residual simultaneity’, the first-differenced equation has to be instrumented. Where values of the input variables in the dataset are the only instruments available, different years in the panel will have different numbers of instruments available to them. For example, in a six year panel such as ours, if strong exogeneity is not valid and only current and past year’s input variables can be used as instruments, then the final period (first difference between years six and five) will have more instruments available to it than the period preceding it, and so on. GMM enables such IV estimation with differing numbers of instruments available to different years.

Denoting first-differencing by Δ for notational convenience, we can write (4) as:

$$\Delta y_{it} = b\Delta x_{it} + \Delta e_{it} \qquad (4)$$

If the input from a time period s is a valid instrument for Δx_{it}, the orthogonality condition can be written as:

$$E(\Delta e_{it}\, x_{is}) = 0 \qquad (5)$$

where $\Delta e_{it} = \Delta y_{it}$ - â Δx_{it}. In practice, the number of orthogonality conditions depends upon the number of inputs x and the number of years from which the inputs can be regarded as valid instruments. As noted earlier, this implies that different years will have different numbers of instruments available. For example, under strong exogeneity, Δe_{it} is uncorrelated with inputs from all years in the sample, and we could write $E(\Delta e_{it}\, x_{is}) = 0$, s = 1...T. Under weak exogeneity, Δe_{it} is uncorrelated only with past and present values of inputs, and we write $E(\Delta e_{it}\ x_{is}) = 0$, s = 1...t. Under this setup, there are typically more instruments/moment conditons than parameters, and hence the model is overidentified. GMM minimises a weighted quadratic form in the moment conditions.

During implementation, we found the full translog model with all inputs to be plagued by multicollinearity, leading to very large standard errors. The area fixed input (wheat acres) was found to be the principal source of this problem, being highly collinear with variable inputs, particularly fertiliser and pesticide. The area variable was also seen to cause substantial collinearity between interaction terms involved in the ozone production elasticity computation (area × ozone, fertilizer × ozone, pesticide × ozone). Hence we decided to employ a Constant Returns to Scale (CRS) assumption, estimating a per-acre production function instead. We note that Wilson *et al* (2001), who perform stochastic frontier analysis on wheat farm data from Eastern England make a similar assumption to avoid collinearity problems. Their Wald test does not reject the CRS assumption. Similarly, Wilson, *et. al.* (1998) also confirm CRS for UK potato farm-level data. Information on seed input was also available, but the per-hectare seeding rate was mostly constant within farms, and was swept away by first-differencing to remove farm-specific effects.

3.2.Profit function

The translog profit function to be estimated, comprised one output (wheat) price, four input prices (seed, fertilizer, herbicide and labour) and three fixed inputs (hectares planted in wheat, ozone and rain) is given by:

$$\ln(p,k) = b_0 + \sum_{r=1}^{5} b_r \ln p_r + \sum_{r=1}^{3} a_r \ln k_r + \frac{1}{2}\sum_{r=1}^{5}\sum_{s=1}^{5} d_{rs} \ln p_r \ln p_s$$

$$+\frac{1}{2}\sum_{r=1}^{3}\sum_{u=1}^{3} e_{rs} \ln k_r \ln k_u + \frac{1}{2}\sum_{s=1}^{5}\sum_{u=1}^{3} f_{su} \ln p_s \ln k_u \qquad (6)$$

As is well known, share equations with respect to output and input prices can be derived to gain efficiency via system estimation. The i^{th} share equation is given by:

$$s_i = \frac{\partial \ln p}{\partial \ln p_i} = \frac{p_i y_i}{p} = b_i + \sum_{r=1}^{5} d_{ir} \ln p_r + \sum_{u=1}^{3} f_{iu} \ln k_u, \quad and\ i = 1,.....,5 \qquad (7)$$

Symmetry and homogeneity were imposed prior to estimation. The profit function was estimated jointly as a system along with the share equations, with the herbicide share equation dropped during estimation to avoid singularity of the covariance matrix. In parallel with the production function, the profit function was estimated on a per-hectare basis.

With a panel setup, a within transformation was employed to remove farm-specific effects by removing individual means from all variables on both sides of the equations. Subsequently, an instrumental variables framework was adopted, interpretable as a GMM estimator, which relies on orthogonality between the error term and a set of instrumental variables. The instrumental variables included all right hand side variables in the profit function and their cross-products.

4. Results

4.1 Production function

Our nested exogeneity tests revealed that the data reject the null hypothesis that the extra moment conditions implied by strong exogeneity (compared to weak exogeneity) are valid (P^2 = 67.6, 42 degrees of freedom). However, the validity of the extra moment conditions under weak exogeneity compared to the 'Lag 1 instruments' model could not be rejected (P^2 = 17.1, 12 degrees of freedom). Thus we retain the weak exogeneity model for analysis and present the estimates in Table 2.

Table 2. Translog production function parameter and elasticity estimates from weak exogeneity model

Parameter	Estimate	t-statistic
Fertiliser	-0.27	-0.30
Pesticide	3.04	5.64***
Labour	0.86	4.38***
Ozone	0.68	1.75*
Rain	-0.60	-1.77*
Fertiliser*Fertiliser	0.26	0.95
Pesticide*Pesticide	-0.30	-3.10***
Labour*Labour	0.03	3.65***
Ozone*Ozone	-0.11	-2.40**
Rain*Rain	0.10	2.03**
Fertiliser*Pesticide	-1.00	-7.96***
Fertiliser*Labour	-0.29	-5.30***
Fertiliser*Ozone	-0.22	-1.99**
Fertiliser*Rain	-0.06	-0.75
Pesticide*Labour	0.07	1.77*
Pesticide*Ozone	-0.08	-1.42
Pesticide*Rain	-0.08	-2.31**
Labour*Ozone	0.01	0.60
Labour*Rain	0.00	0.01
Ozone*Rain	0.15	4.18***
Hansen's J-stat.	81.8	
Degrees of freedom	65	
Fertilizer Elasticity	0.06	1.62*
Pesticide Elasticity	0.0017	0.08
Labour Elasticity	0.05	6.50***
Ozone Elasticity	-0.023	-2.56***

*** Significant at 1% level; ** at 5% level; * at 10% level

Parameter estimates in Table 2 suggest the chosen weak exogeneity model performs quite well. 14 out of 20 parameters are significant at least at the 10% level. Hansen's J statistic (the overidentifying restrictions test) is distributed as a chi-square variable under the null hypothesis that the overidentifying restrictions in the model (excess of moment conditions over parameters) are jointly orthogonal to the error term (Hansen, 1982; Hall, 1993). The hypothesis is interpretable as one of overall model validity, and in our case we are unable to reject the hypothesis at the 5% level. Production elasticities evaluated at sample mean values are presented at the bottom of the table. The elasticities for fertiliser, pesticide and labour are positive, but small. Given the CRS assumption, the implied elasticity for land (and seed) is 0.89. This pattern of large production elasticity for land, with much smaller elasticities for variable inputs agrees broadly with the findings of Wilson *et. al*. (2001) for wheat farms in eastern England.

Most importantly for our purposes, the estimates confirm that ambient ozone has a small, but nevertheless statistically significant negative effect on farm-level winter wheat production. At sample mean values, interpretable as an 'average' or 'representative' wheat farm in the sample, a 10% increase in ozone AOT40 would on average reduce wheat yields by only 0.23%. It would be interesting to see how our estimates tally with the experimental evidence, although it is fully recognised here that there is much difference in the data, methods, settings and philosophies of the two approaches. Führer (1994) pools data from several European as well as US open-top chamber experiments for wheat and estimates a regression based on the pooled data. Holland *et. al.* (2002) perform a similar exercise with a different set of experimental results. We extrapolate from their reported result to compute yield changes at a baseline AOT40 of 3000 ppb. h. (roughly the average for our sample). At this baseline, Führer's (1994) regression implies a yield reduction of 1.79% for a 1000 ppb. h. increase in ozone AOT40, and Holland *et. al.*'s (2002) regression implies a yield reduction of 1.18%[1]. Our own estimate using farm-level data is significantly smaller at 0.76%. This highlights the several uncertainties associated with extrapolating from experimental evidence, particularly where the data derived from open-top chamber experiments where the constant air-flow is thought to enhance ozone uptake by plants and consequently result in more adverse yield effects.

An interesting use of these estimates would be in the computation of yield losses across particular ozone scenarios. In doing this, we prefer to restrict our prediction to within-sample values rather than attempt potentially invalid out-of-sample forecasts. Ozone concentrations show considerable variation across time and space in England and Wales, sufficient to provide a notion of yield gaps between realistic elevated and low pollution scenarios. Spatially, ozone concentrations typically show an increasing gradient from the Northwest to the Southeast of the country, with concentrations peaking in the Southeastern coastal counties[2]. Temporally, in our dataset, the AOT40 levels in 'high' versus 'low' years in the same locations differed by a factor of 3 to 8 times. Although some of the spatio-temporal differences are caused by natural 'background' ozone fluctuations, emissions of precursor pollutants also have an important role to play. We computed the effects of these fluctuations on wheat yields while holding the other values fixed at sample mean values, and found that even the seemingly large variations in AOT40 levels within the sample affect yields by only 1 to 2%. For instance, during the hot summer of 1995, which saw generally elevated ozone levels, the AOT40 in Humberside was 2482, while Kent recorded 6459. However, our predictions showed that the identical 'representative' wheat farm would suffer only a 1.6% yield reduction if exposed to the elevated ozone levels observed that year at Kent in comparison to levels at Humberside.

4.2.Profit function

The results from the within-instrumental variables estimation of the profit function is presented in Table 3 below. Only 10 out of 26 parameters significant at the 5% level. The 26 parameters were estimated with 135 instruments, resulting in 109 overidentifying restrictions. We check for the validity of the overidentifying restrictions using the Hansen J-stat. Under

[1] The ozone-yield relationship for wheat used in Holland *et. al*. has been re-estimated recently using revised AOT40 measurement, for use in UNECE research. This revision indicates a stronger negative relationship between ozone and wheat yields than estimated in Holland, *et. al*. (2002), closer to the estimate of Führer (1994) (Gina Mills, personal communication, 2004).

[2] However, there is an important exception to this gradient around the Lincolnshire area, where concentrations are very low.

the null hypothesis of correct specification, the J-stat is asymptotically c^2 (109). The 5% critical value for a c^2 (109), is 126.58. Hence we do not reject the null hypothesis that the overidentifying restrictions are jointly orthogonal to the error term.

Table 3. Panel data profit function estimates

	WITHIN-IV	Std. Error
P_{wheat}	-0.018894***	0.00381
P_{seed}	0.002113***	0.00059
$P_{fertiliser}$	0.002422**	0.00103
P_{labour}	0.010919***	0.00241
Ozone	0.059885*	0.03802
Rain	-0.126295***	0.03802
P_{wheat}*P_{wheat}	-0.336148**	0.15054
P_{wheat}*P_{seed}	0.025056	0.02252
P_{wheat}*$P_{fertiliser}$	-0.010082	0.02489
P_{wheat}*P_{labour}	0.248924**	0.11814
P_{seed}*P_{seed}	0.006757	0.00689
P_{seed}*$P_{fertiliser}$	-0.008558	0.00543
P_{seed}*P_{labour}	-0.033114*	0.01917
$P_{fertiliser}$*$P_{fertiliser}$	-0.009249	0.00962
$P_{fertiliser}$*P_{labour}	0.007683	0.01868
P_{labour}*P_{labour}	-0.259287**	0.12422
Ozone*Ozone	-0.213408	0.20679
Ozone*Rain	-0.201842	0.27924
Rain*Rain	-0.012428	0.13655
P_{wheat}*Ozone	0.098302***	0.03753
P_{wheat}*Rain	-0.019322	0.02309
P_{seed}*Ozone	-0.008572	0.00589
P_{seed}*Rain	-0.00146	0.00362
$P_{fertiliser}$*Rain	0.005	0.00609
P_{labour}*Ozone	-0.076075**	0.03065
P_{labour}*Rain	0.002016	0.0152

*** Significant at 1% level; ** at 5% level; * at 10% level

Own and cross price elasticities were computed from the above estimates, and are presented in Table 4. Own price elasticities have the correct sign, apart from labour. As discussed before, farm-level labour price data were not directly available, and it is probable that the national level proxy used was less than adequate.

Table 4. Estimated price and cross price elasticities

	Wheat	Seed	Fertiliser	Herbicide	Labour
Wheat	0.03254	0.904	1.3847	-0.40676	-2.728
	(0.02012)	(0.8467)	(0.3679)	(1.3461)	(1.465)
Seed	-0.0448	-1.1692	0.01372	-0.3375	0.4704
	(0.0467)	(0.11179)	(1.3472)	(0.4321)	(0.8676)
Fertiliser	-0.1172	0.0232	-1.0248	-0.2895	-0.2355
	(0.2279)	(0.3472)	(0.5644)	(0.2077)	(0.1432))
Herbicide	-0.2649	-0.3182	-0.1609	-0.15124	15.8374
	(1.1401)	(0.8673)	(0.3177)	(0.2986)	(1.9209)
Labour	0.1306	0.4514	-0.1321	16.124	3.1269
	(0.465)	(0.8673)	(0.0932)	(2.5209)	(6.1269)

Notes: Elasticities are computed at the mean of the actual profit shares. Standard errors are in parentheses

Elasticities with respect to ozone are of prime interest to us, and these are presented below in Table 5.

Table 5. Ozone related elasticities

	Variable profits	Wheat	Seed	Fertiliser	Herbicide	Labour
Ozone	-0.9586	-0.286	-0.2293	-0.3488	0.00036	0.8667
	(1.0169)	(0.209)	(0.35105)	(0.11168)	(0.00769)	(2.7603)

At the sample mean AOT40 of 3090 ppb.h, the estimated elasticity of profits with respect to ozone is –0.9586. This suggests that a 10% increase in the ozone index above its mean value would correspond to a 9.58% decrease in variable farm profits. However, the elasticity is not estimated with precision, and is insignificantly different from zero at conventional significance levels. Thus we cannot state with confidence that ozone is found to depress wheat farm profits in the UK. Similarly, the sign of the wheat-ozone elasticity is intuitive, indicating that a 10% increase in ozone would reduce wheat supply by 2.8%. This is much higher than the production function finding from the previous section, that a 10% increase in ozone exposure results in a 0.23% reduction in wheat yields. However, while the yield elasticity was significant, the supply elasticity from the profit function is not significantly different from zero. The only input demand elasticity with respect to ozone that is significant is that of fertiliser. Here a 10% increase in ozone would result in a 2.29% decrease in the levels of fertiliser application. However, this is not in accordance with the intuition expressed by Garcia, *et. al*. (1986) that farmers would tend to apply more variable inputs to offset the deleterious effects of elevated ozone levels.

5. Conclusions

In this paper, we have investigated the farm-level effects of tropospheric ozone in the UK, using both primal and dual methods. On the basis of the evidence presented, it can be said that the production function seem to fit the data better and give statistically more plausible results. It predicts a statistically significant negative effect of ozone on wheat yields at the farm level. However, this elasticity is small, and indicates that ozone is unlikely to result in the imposition of substantial external costs. It is more informative for economists to work with profit functions since predictions about producer behaviour can be made with relatively few computations, given an estimated profit function. But the profit function implications regarding ozone are even less robust as compared to the production function. Although the estimates indicate that ozone depresses wheat farm profits and wheat supply, the elasticities are statistically insignificant, and few definite conclusions can be drawn.

Far stronger conclusions have been reached in applications involving the US and Canada. Garcia, *et. al*. (1986) concluded that a 10% increase in ozone would cause a reduction of farm profits by 4.7% in Illinois, while Young and Aidun (1993) estimated an almost 20% reduction for wheat farms in Canada. One difference between our study and these two is the ozone measure. In both North American studies, ozone exposure was expressed simply as parts per billion, while we have used the AOT40 index, *i.e*. an index based on accumulations over a threshold. Given that substantial scientific work has gone into developing this index in Europe, and that there is scientific consensus in Europe that the AOT40 is superior, we do not believe that we would get more accurate estimates by using a simple parts per billion measure instead.

One implication of these findings is that dose-response data may not translate well into farm-level outcomes. Thus it may be wise to interpret economic values based upon experimental results with some caution. Testing of farm-level outcomes of data using other European data may be a fruitful topic for further research. Ozone levels become elevated with temperature, and hence Southern Europe may be a particularly appropriate setting for such work.

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