Efficiency in Damage Control Inputs: A Stochastic Production Frontier Approach

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Abstract

The present paper extents the existing literature providing a theoretically consistent framework for measuring input-specific technical efficiency in damage control inputs within a stochastic production frontier model. The theoretical framework for modeling damage control agents is based on Fox and Weersink (1995) model specification that allows for increasing returns on damage control inputs. The empirical model accounts veterinary expenses as the damage control input and it is applied on a panel data set of sheep farms in Greece during the 1989-92 period. The results suggest that sheep farms in Greece are using inefficiently immunization and antibiotics in their flock as their average technical efficiency level was 72.82%. On the other hand, technical efficiency in conventional factors of production was found to be considerably higher on the average, 91.32%. Finally, our results indicate that farms that are technical efficient in the use of conventional inputs are also technical efficient in the use of damage control agents.

Key words: increasing returns, input-specific technical efficiency, damage and control function, sheep farms, Greece.

JEL classification: Q12, Q16, C23, C51

1. Introduction

Many of the innovations introduced in the farming sector over the past few decades have involved the introduction of a special class of factors of production, the damage control inputs. Profound examples of this kind of inputs in the farming sector include pesticides, weedicides, windbreaks, sprinklers for frost protection, immunization and antibiotics in feedlots etc.[1] Unlike conventional factors of production (*i.e.*, land, labor, capital) these special class of inputs do not increase farm's potential output directly.[2] Instead their distinctive feature lies in their ability to increase the share of potential output that farmers realize by reducing the negative effect of the damage agents caused either from natural or human causes. In this line, a considerable amount of empirical work has been devoted in recent years on the quantitative analysis of the distinct role of conventional and damage control inputs on farm production. The first who have dealt explicitly with the appropriate specification of damage control inputs in farm production models and the subsequent measurement of their marginal productivities were Headley (1968) and Campbell (1976). Using a simple methodological approach they concluded that pesticides have been under applied in a sense that their marginal product exceeded marginal factor cost.

However, as noted several years later by Lichtenberg and Zilberman (1986) (hereafter LZ) the marginal productivities produced by Headley (1968) and Campbell (1976) model specification, were biased as they did not account for the indirect role of damage control inputs in the production process. Unlike with Headley (1968) and Campbell (1976), LZ suggested that conventional and damage control inputs should be treated asymmetrically. They suggested that the contribution of damage control inputs to farm production may be better realized by conceiving realized output as a combination of two components: *first*, the maximum quantity of farm produce that it is attainable from any chosen conventional input combination and, *second* the losses in farm production due to the action of damaging agents that are present in the environment like insects, weeds, bacteria etc. In addressing this issue, they introduced into the traditional production function model an *output abatement* or *kill* function capturing the abatement effort by damage control agents. Subsequently, they measured marginal productivity of damage control inputs according to their ability to reduce crop damage and not to increase directly farm output. Even since, their approach has been successfully applied by several authors including Babcock, Lichtenberg and Zilberman (1992), Carasco-Tauber and Moffitt (1992), Lin *et al.*, (1993) and Chambers and Lichtenberg (1994).[3]

Besides the important contribution made by LZ in measuring damage control agent's productivity, their asymmetric functional specification has been questioned by Fox and Weersink (1995) and Carpentier and Weaver (1997) as empirical evidence provided worldwide still reported marginal products higher than marginal factor costs. Fox and Weersink (1995) (hereafter FW) pointed out that the output abatement function suggested by LZ under any arbitrary functional specification, impose *a priori* a structure on the underlying biological and physical data that ensures eventually decreasing returns for damage control inputs. Cowan and Gunby (1996) in analyzing the rate of adoption for pesticides against integrated pest management strategies at the farm level, concluded that pesticide use is subject to increasing returns mainly due to the significant R&D expenditures by chemical industries and the learning effects in their application by individual farmers. However, under increasing returns the response of damage control input use to variations in prices and thus profits is not continuous as it was initially assumed by LZ. If increasing returns are allowed, a profit-maximizing farm, at the ceiling will choose either to apply damage control inputs or not as long as it obtains higher profits. This is important from a policy point of view as a specific policy aimed to reduce pesticide use for environmental conservation by imposing a tax may have substantially different effects on the levels of use of different products. Departing slightly from the traditional LZ model and maintaining weak concavity of the output abatement function, they suggested an alternative specification of the farm production model that allows for increasing returns in damage control inputs.

On the other hand, Carpentier and Weaver (1997) addressing the same problem of the LZ model specification they relaxed the assumption of homothetic separability between conventional and damage control inputs. For doing so, they treated both kinds of inputs symmetrically introducing an input-abatement function into the farm production model. The essence behind their model hinges on the assumption that damage agents affect the marginal productivity of every conventional inputs separately at the same proportion.[4] Their model however, is highly non-linear in it's parameters making thus it's econometric estimation troublesome.[5] Although they did not do so, their model can be easily extended into FW theoretical framework allowing for increasing returns.

It is evident from the above, that the research effort during the last two decades was mainly focused on the appropriate specification of the farm production so that accurate estimates of the damage control inputs to be obtained. Although this controversory seems to have been resolved, there is still an important question that arises. The estimation of the marginal productivities for this specific class of inputs is important for several reasons like environmental degradation or health issues (*e.g.* the excess use of pesticides apart of creating severe problems in the natural environment is also harmful for both farmers and consumers). Nevertheless an equally important issue from a policy point of view, is the efficiency levels in the use of damage control inputs. If, for instance, farmers are indeed faced with increasing returns in pesticide use then imposing a tax aimed to reduce their application will certainly affect farm's total profit and therefore household income. Alternatively, if their use in farm production is not efficient, policy measures directed to improve farmers know-how may well reduce chemical use and therefore it's adverse effects on farmer's health and natural environment, increasing at the same time farm income.

Although in the efficiency literature there is plenty of empirical evidence on the measurement of technical inefficiency levels of conventional factors of production, there is only one focusing in the efficient use of damage control inputs. Oude Lansink and Silva (2004), estimated non-radial technical inefficiency measures in pesticide use for a sample of Dutch arable farms during the 1989-92 period using a DEA approach. However, besides based on non-paremetric technique which is questionable for modeling damage agents that are more vulnerable to exogenous shocks (*i.e.*, environmental conditions)[6], their index of technical efficiency does not account of the abatement effort of pesticides use.

The main objective of this paper is to provide a theoretical consistent way for modelling and econometrically estimating technical efficiency in the use of damage control agents. Based on FW theoretical foundations, a stochastic production frontier model is introduced, that accounts for the existence of technical inefficiency in the use of both conventional and damage control factors of production. Our model can be easily extended into Carpentier and Weaver (1997) input-abatement specification of the production function, requiring however additional work on the econometric estimation.[7] The empirical model is based on a Cobb-Douglas specification for the production frontier and it is applied to a panel data set of 51 sheep farms in Greece observed during the 1989-92 period. Veterinary expenses of sheep farms that include immunization and antibiotics expenses are treated as the damage control agent in the empirical analysis.

The rest of this paper is organised as follows: the theoretical model using based on FW theoretical foundations is presented in section 2. The empirical model and the estimation procedure is discussed in section 3. The data employed in the empirical model are described in section 4 and the empirical results are analysed in section 5. Concluding remarks follow in the last section.

2. Theoretical Framework

Let assume that farm *i* at year *t* is utilizes conventional inputs (*i.e.*, land, labor, capital) $x_{it} = \left(x_{i1t},\ x_{i2t},\ ...,\ x_{iJt}\right)$ to produce a single output y_{it} through a technology described by a well-behaved production function $f\left(x_{it};\beta,t\right)$, where *t* is a time index and, β is the vector of the associated parameters. Since farms may not necessarily be technical efficient $y_{it} \leq f\left(x_{it};\beta,t\right)$ or equivalently:

$$y_{it} = f\left(x_{it};\beta,t\right)e^{v_{it}-u_{it}} \qquad (1)$$

where u_{it} is an output-oriented measure of farm- and time-specific technical inefficiency and, v_{it} is a usual random noise representing those factors that cannot be controlled by farmers, measurement errors in the dependent variable, and omitted explanatory variables. Apart of conventional inputs let also assume that farms are also utilizing damage control inputs (*e.g.*, pesticides, antibiotics) $z_{it} = \left(z_{i1t},\ \mathrm{z}_{i2t},\ ...,\ \mathrm{z}_{ikt}\right)$ to prevent destruction in their potential output caused by damage agents.

According to FW model specification, the effect of these damage control inputs on farm produce consists of two-stages: the first stage includes the effect of damage control input on the damage agent density and the second involves the subsequent effect of the remaining damage agent on farm output. Under this assumption farm's *i* realized production at time *t* is obtained from:

$$\tilde{y}_{it} = \left\{f\left(x_{it};\beta,t\right)\left[1-h\left(B_{it};\lambda\right)\right]\right\}e^{v_{it}-u_{it}} \qquad (2)$$

where $h\left(\bullet\right)$ is the *output-damage function* that depends on the observed level of damage agent in farm *i* at year *t* and, λ is the associated parameter. It represents the proportion of output lost at damage agent density *B*.[8] $\tilde{y}_{it}$ is the actual level of production for a given level of damage agent *B*, the technological constraints and conventional factors use (*i.e.*, technical efficiency). Damage function is assumed to possesses the properties of a cumulative distribution function and it is concave.[9] In case that the damage agent is absent $\left(B_{it}=0\right)$ then $h\left(\bullet\right)=0$ and actual output equals with that obtained from relation (1) $\left(\tilde{y}_{it}\rightarrow y_{it}\right)$. On the other hand, when the level of damage agent population tend to infinity $\left(B_{it}\rightarrow\infty\right)$, the farm output approaches a minimum level $\left(\tilde{y}_{it}\rightarrow\tilde{y}_{it}^{min}\right)$ which, however, cannot be less than zero.

The damage agent incidence (B_{it}), depends on it's initial population and on the abatement level of damage control input use. Equivalently, the *output-damage control function* can be formalized as:

$$B_{it}=\tilde{B}_{it}\left[1-g\left(z_{it};\gamma\right)\right] \tag{3}$$

where $\tilde{B}_{it}$ is the initial damage agent incidence in farm i at year t, γ is the vector of the associated parameters and, $g\left(\bullet\right)$ is the control function which depends on the level of control inputs use z_{it}. Like the damage function, the control function it is also constrained by the $\left(0,1\right)$ interval. If $g\left(\bullet\right)=0$, the control agent has no effect on damage agent incidence and the level of damage agent affecting farm production is equal with it's initial population $\left(B_{it}=\tilde{B}_{it}\right)$. Contrary, when $g\left(\bullet\right)=1$ there is a complete eradication of the damage agent and farm production equals with that attained by relation (1). The proportion of damage agent remaining after treatment it is assumed to decrease monotonically, that is the control function is also assumed to be concave.

According to FW the curvature of the damage function relative to that of the control function is important in establishing increasing returns. Specifically they proved that increasing returns may occur whenever the following inequality holds:

$$\frac{\partial^2 g\left(\bullet\right)/\partial z_{it}^2}{\partial g\left(\bullet\right)/\partial z_{it}}\Bigg/\frac{\partial^2 h\left(\bullet\right)/\partial B_{it}^2}{\partial h\left(\bullet\right)/\partial B_{it}}<\frac{\partial g\left(\bullet\right)}{\partial z_{it}}\tilde{B}_{it} \tag{4}$$

The ratio on the left-hand side of the above relation is analogous to the Arrow-Pratt coefficient of absolute risk aversion and measures the relative degree of curvature of the control and damage functions. Thus, using their own words "the less curved the control function, relative to the damage function the more likely are increasing returns for given values associated with the marginal effectiveness of the control input and untreated damage agent density" (p.36).

So far it is assumed that damage control inputs are utilized perfectly efficiently in the production process although the opposite holds for their conventional counterpart. However, it is logical to assume that if farmers fail to utilize efficiently land or capital in their production, they will do so for any other factor of production like pesticides for instance. It is well documented in the relevant literature, that the factors determining farmer's managerial ability (e.g., level of education, hands-on experience, training) are the key determinants of their technical efficiency levels. We can reasonably assume therefore, that the same factors may well affect the way that damage control inputs are used in farm production. Hence, the abated damage agent population could less than it's maximum abated level due to improper use of damage control input. Using relation (3) we can formalize this as follows:

$$B_{it} = \tilde{B}_{it}\left[1 - g\left(\tilde{\theta}_{it} z_{it};\gamma\right)\right] \tag{5}$$

where $\tilde{\theta}_{it} z_{it}$ represents the effective amount of damage control input use in farm production, through it's impact on the abated damage agent population. The parameter $\tilde{\theta}_{it}$ is constrained by the $\left(0,1\right]$ interval. If damage control inputs are utilized efficiently in farm production then $\tilde{\theta}_{it} = 1$. Otherwise it should be $\tilde{\theta}_{it} < 1$.[10]

In order to make the above specification operational we should first assume a specific functional form for both the damage and control function. A common specification[11] used in the relevant literature is the exponential form suggested by LZ and empirically applied by Carasco-Tauber and Moffit (1992) and Oude Lansink and Carpentier (2001) among others. Specifically both functions have the following form:

$$h\left(B_{it};\lambda\right) = 1 - e^{-\lambda B_{it}} \tag{6a}$$

and

$$g\left(z_{it};\gamma\right) = 1 - e^{-\gamma\left(\tilde{\theta}_{it} z_{it}\right)} \tag{6b}$$

By plugging relation (6b) into (3) we obtain the actual damage agent incident in farm production as:

$$B_{it} = \tilde{B}_{it}\left[1 - \left(1 - e^{-\gamma\left(\tilde{\theta}_{it} z_{it}\right)}\right)\right] \Rightarrow B_{it} = \tilde{B}_{it}\, e^{-\gamma\left(\tilde{\theta}_{it} z_{it}\right)} \tag{7}$$

Substituting relation (7) into (6a) we obtain the damage control function accounting for the existence of technical inefficiency in damage control input use as:

$$h\left(B_{it};\lambda\right)=1-e^{-\lambda\tilde{B}_{it}e^{-\gamma\left(\tilde{\theta}_{it}z_{it}\right)}} \quad (8)$$

Then plugging (8) into (2) we get

$$\tilde{y}_{it}=\left\{\left[f\left(x_{it};\beta,t\right)\right]e^{-\lambda\tilde{B}_{it}e^{-\gamma\left(\tilde{\theta}_{it}z_{it}\right)}}\right\}e^{v_{it}-u_{it}} \quad (9a)$$

and by taking the natural logarithms

$$ln\,\tilde{y}_{it}=f\left(ln\,x_{it};\beta,t\right)-\alpha\,e^{-\gamma\left(\tilde{\theta}_{it}z_{it}\right)}+v_{it}-u_{it} \quad (9b)$$

where $\alpha=\lambda\tilde{B}_{it}$. If we assume that $f\left(\bullet\right)$ is approximated by the traditional Cobb-Douglas functional form under Hicks-neutral technical change, then relation (9b) becomes:

$$ln\,\tilde{y}_{it}=\beta_0+\sum_j\beta_j\,ln\,x_{jit}+\beta_T t-\alpha\,e^{-\gamma\left(\tilde{\theta}_{it}z_{it}\right)}+v_{it}-u_{it} \quad (10)$$

Relation (10) above represents an output-damage abatement production frontier that accounts for technical inefficiency in both conventional and damage control inputs. The former has an output orientation and refers to the maximum increase of farm produce given conventional input use, technological constraints and damage abatement level. The latter, has an input-orientation and it is interpreted as the maximum decrease in control input use so that the level of damage agent incidence remains constant.

3. Estimation Procedure

For the estimation of the model we need first to assume a specific distribution for the error terms appearing in (9), *i.e.*,

$$v_{it}\sim N(0,\sigma_v^2),\; u_{it}\sim N_+(0,\sigma_u^2),\; \tilde{\theta}_{it}\equiv\exp(-\xi_{it}),\; \xi_{it}\sim N_+(0,\sigma_\xi^2) \quad (11)$$

with all random variables being uncorrelated as well as independent of x_{it} and z_{it}. Let $\tau_{it} = exp\left(-u_{it}\right)$ be technical efficiency in the use of conventional inputs, and $\omega = \left[\beta', \alpha, \gamma', \sigma_v, \sigma_u, \sigma_\xi\right]$ the vector of parameters. The realized farm output $\tilde{y}_{it}$ has distribution whose density in terms of u_{it} is given by:

$$f\left(ln\,\tilde{y}_{it} \middle| ln\,x_{it}, z_{it}, \omega\right) = \left(2\pi\sigma_v^2\right)^{-1/2}\left(\tfrac{\pi}{2}\sigma_u^2\right)^{-1/2}\left(\tfrac{\pi}{2}\sigma_\xi^2\right)^{-1/2}$$
$$\int_0^1\int_0^1 exp\left[-\frac{\left\{ln\,\tilde{y}_{it} - \left(ln\,x_{it};\beta,t\right) + \alpha\,exp\left(-\gamma\tilde{\theta}_{it}z_{it}\right) + u_{it}\right\}^2}{2\sigma_v^2} - \frac{u_{it}^2}{2\sigma_u^2} - \frac{\left(ln\,\tilde{\theta}_{it}\right)^2}{2\sigma_\xi^2}\right]\theta_{it}^{-1}du_{it}d\tilde{\theta}_{it} \quad (12)$$

from which one can get:

$$f\left(ln\,\tilde{y}_{it} \middle| ln\,x_{it}, z_{it}, \omega\right) = \left(2\pi\sigma_v^2\right)^{-1/2}\left(\tfrac{\pi}{2}\sigma_u^2\right)^{-1/2}\left(\tfrac{\pi}{2}\sigma_\xi^2\right)^{-1/2}$$
$$2\left(2\pi\sigma^2\right)^{-1/2}\int_0^1 exp\left(-\frac{R_{it}^2}{2\sigma^2} - \frac{\left(ln\,\tilde{\theta}_{it}\right)^2}{2\sigma_\xi^2}\right)\Phi\left(-\frac{\eta R_{it}}{\sigma}\right)\tilde{\theta}_{it}^{-1}d\tilde{\theta}_{it} \quad (13)$$

where $\sigma^2 = \sigma_v^2 + \sigma_u^2$, $\eta = \sigma_u / \sigma_v$, $R_{it} = ln\,\tilde{y}_{it} - \left(ln\,x_{it};\beta,t\right) + \alpha\,exp\left(-\gamma\tilde{\theta}_{it}z_{it}\right)$, and Φ denotes the standard normal distribution function. Notice that R_{it} depends on $\tilde{\theta}_{it}$, and the integral above is not available in closed form. Thus, we use Gaussian quadrature to approximate the log-likelihood function. Maximum likelihood estimates can be obtained by maximizing this function using numerical techniques.[12]

To obtain estimates of farm-specific technical efficiency, we extend the classical predictor suggested by Jondrow *et al.*, (1982) using as efficiency estimates the quantities $E\left(\tau_{it} \mid ln\,\tilde{y}_{it}, ln\,x_{it}, z_{it}\right)$ and $E\left(\tilde{\theta}_{it} \mid ln\,\tilde{y}_{it}, ln\,x_{it}, z_{it}\right)$. From relation (13) it is clear that:

$$f(\tilde{\theta}_{it} \mid ln\,x_{it}, z_{it}, \omega) = exp\left(-\frac{R_{it}^2}{2\sigma^2} - \frac{\left(ln\,\tilde{\theta}_{it}\right)^2}{2\sigma_\xi^2}\right)\Phi\left(-\frac{\eta R_{it}}{\sigma}\right)\theta_{it}^{-1} \quad (14)$$

so the expected value of the distribution whose kernel density shown in (14) is given by:

$$\tilde{\theta}_{it} \equiv E\left(\tilde{\theta}_{it} \mid ln\, y_{it}, ln\, x_t, z_{it}\right) = \frac{\int_0^1 exp\left(-\frac{R_{it}^2}{2\sigma^2} - \frac{\left(ln\,\theta_{it}\right)^2}{2\sigma_\xi^2}\right)\Phi\left(-\frac{\eta R_{it}}{\sigma}\right)d\theta_{it}}{\int_0^1 exp\left(-\frac{R_{it}^2}{2\sigma^2} - \frac{\left(ln\,\theta_{it}\right)^2}{2\sigma_\xi^2}\right)\Phi\left(-\frac{\eta R_{it}}{\sigma}\right)\theta_{it}^{-1}d\theta_{it}} \qquad (15)$$

where the denominator is the normalizing constant, whereas the integrals can be numerically approximated. In fact, the integral in the denominator is available from the computation of the log-likelihood function. It can be shown easily that these integrals are expectations of $\Phi\left(-\frac{\eta R_{it}}{\sigma}\right)\tilde{\theta}_{it}^{k-1}$ for k=0,1, when $ln\,\tilde{\theta}_{it}$ follows a particular truncated normal distribution whose scale and location parameters can be found by completing the square in the term that appears inside the exponential function.[13]

The estimation of farm-specific technical inefficiency in the use of conventional inputs is based on $u_{it} = E\left(u_{it} \mid ln\, y_{it}, ln\, x_{it}, z_{it}\right)$ which can be decomposed as follows:

$$u_{it} = \int_0^1 E\left(u_{it} \mid \tilde{\theta}_{it}, ln\, y_{it}, ln\, x_{it}, z_{it}, \omega\right) \cdot f\left(\tilde{\theta}_{it} \mid ln\, y_{it}, ln\, x_{it}, z_{it}, \omega\right) d\tilde{\theta}_{it} \qquad (16)$$

In this integral, we have $E\left(u_{it} \mid \tilde{\theta}_{it}, ln\, \tilde{y}_{it}, ln\, x_{it}, z_{it}, \omega\right) = \sigma_* \left[\frac{\phi\left(R_{it}\eta/\sigma\right)}{\Phi\left(-R_{it}\eta/\sigma\right)} - \left(R_{it}\eta/\sigma\right)\right]$ where $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$, which follows from the standard Jondrow *et al.*, (1982) result (conditional on $\tilde{\theta}_{it}$). Moreover, the kernel of $f(\tilde{\theta}_{it} \mid ln\, x_{it}, z_{it}, \omega)$ is provided in (14) and thus by dividing with the appropriate normalizing constant, we obtain:

$$u_{it} = \frac{\int_0^1 \sigma_* \left[\frac{\phi\left(R_{it}\eta/\sigma\right)}{\Phi\left(-R_{it}\eta/\sigma\right)} - \left(R_{it}\eta/\sigma\right)\right] \cdot f(\tilde{\theta}_{it} \mid \ln x_{it}, z_{it}, \omega) d\tilde{\theta}_{it}}{\int_0^1 f(\tilde{\theta}_{it} \mid \ln x_{it}, z_{it}, \omega) d\tilde{\theta}_{it}} \qquad (17)$$

The integral in the denominator is available from computation of the log-likelihood function. The integral in the numerator has, again, to be approximated using numerical integration. From u_{it}, one may easily get

τ_{it}. Although not of much practical use, we may mention that Laplace's rule for integrals can be used to obtain the approximation

$$u_{it} \simeq \sigma_* \left[\frac{\phi\left(\tilde{R}_{it}\eta/\sigma\right)}{\Phi\left(-\tilde{R}_{it}\eta/\sigma\right)} - \left(\tilde{R}_{it}\eta/\sigma\right) \right] \tag{18}$$

where $\tilde{R}_{it} = ln\, \tilde{y}_{it} - \left(ln\, x_{it}; \beta, t\right) + \alpha\, exp\left(-\gamma\tilde{\theta}^*_{it} z_{it}\right)$, and $\tilde{\theta}^*_{it}$ denotes the mode of the conditional distribution of $\left(\tilde{\theta}_{it} \mid ln\, \tilde{y}_{it}, ln\, x_{it}, z_{it}\right)$. Since there is no analytical expression for the mode, we may proceed by using the mean instead.

Furthermore, we are interested in the joint distribution of τ_{it} and $\tilde{\theta}_{it}$ for a particular farm, after observing the sample. The particular farm can be one whose data is given by[14] y^*, x^*, and z^*. The required distribution has density whose kernel is given by[15]

$$f\left(\tau_{it}, \tilde{\theta}_{it} \mid ln\tilde{y}_{it}, lnx_{it}, z_{it}, ln\tilde{y}^*_{it}, lnx^*_{it}, z^*_{it}\right) =$$

$$exp\left[-\frac{\left\{ln\tilde{y}_{it} - f\left(lnx_{it}; \beta, t\right) + \alpha exp\left(-\gamma\tilde{\theta}_{it} z_{it}\right) - ln\tau_{it}\right\}^2}{2\sigma_v^2} - \frac{\left(ln\tau_{it}\right)^2}{2\sigma_u^2} - \frac{\left(ln\tilde{\theta}_{it}\right)^2}{2\sigma_\xi^2} \right] \tau_{it}^{-1}\tilde{\theta}_{it}^{-1} \tag{19}$$

The normalizing constant can be computed numerically but it is not actually needed if it is desirable to present contours or a surface plot of this bivariate kernel density. In that case, it can be normalized in a different way, for example by setting its maximum value equal to unity since this will not affect the presentation in any essential way. Here, we are interested in this joint kernel density for a "median farm" whose data are given by the median values of output, conventional factors of production and damage control input. To evaluate this kernel density, we simply compute the expression shown above over a 40x40 grid of values of τ and θ.

4. Data Description

Sheep farming is the largest livestock sector in Greece, accounting for 43 per cent of the total value of livestock output. Sheep milk and meat are also among the major agricultural commodities with a share of around 13 per cent in the total value of agricultural production. In the early 1990s (the period considered in this study), sheep milk and meat production were around 640 and 82 thousands tonnes, respectively. In that period, there were almost 130 thousand farms, with varying degrees of specialisation, most of which were located in less-favoured and mountain areas where employment opportunities outside farming were limited. The major production system was (and still is) characterised as semi-extensive (with or without transhumance) and mainly utilised dual-purpose (milk and meat) local breeds. Production is labour intensive and mainly uses family labour. Greece is the fourth largest EU producer of sheep milk and meat, accounting for 10 per cent of the total EU production.

The data for this study are taken from a questionnaire survey, conducted by the Institute of Agricultural Economics and Rural Sociology of the National Agricultural Research Foundation of Greece and financed by the Greek Ministry of Agriculture. The objective of the survey was to provide information on production costs for the major agricultural commodities during the period 1989-92. The sample of farms included in the survey constitutes a rotating panel that fulfils certain stratification criteria. In particular, the sample was stratified according to the orientation of production, geographical regions, the total number of farms in each region, and farm size in order to reflect national averages. Production orientation is determined according to the main source of revenue, using two thirds of farm revenue as a relevant benchmark figure.

Our analysis is based on a total of 51 sheep farms that received more than 95 per cent of their revenue from sheep meat, milk and wool products. The data set used is an unbalanced panel of 178 observations, which means that on average each farm is observed 3-4 times during the period 1989-92. Although a larger number of farms was classified as sheep farms, we focused on the highly specialised sheep farms (with no or very few goats) to ensure that the underlying assumption of the best practice frontier approach (*i.e.*, that the sample farms operate under a common technology) is met as fully as possible. Consequently, a number of farms combining sheep and goat production were excluded from the analysis, even though more than two thirds of their revenue came from sheep products, as it was suspected that their production technology might differ from that of highly specialised sheep or goat farms.

Summary statistics of the variables used are given in Table 1. Output is measured as total gross revenue from farm output (*i.e.*, meat, milk and wool). The inputs considered are *labour* (including family and hired workers) measured in full-time annual working days, *flock size* measured by the number of animals and, *other costs* consisting of feed expenses[16] (including grazing, and concentrates and roughage), fuel and electric power, depreciation, interest payments, veterinary expenses, fixed assets interest, taxes and other miscellaneous expenses, measured in money terms. Finally, the damage control input includes all *veterinary expenses* (immunizations and antibiotics) used by sheep farms measured also in money terms. All monetary variables have been converted first into 1990 constant drachma value and then to ECUs using the average 1990 official exchange rate between the Greek drachma and ECU.

5. Empirical Results

The maximum likelihood estimates of the stochastic production frontier in (10) are presented in Table 2. All the estimated parameters have the anticipated sign and magnitude and there are all statistical significant (except of the constant) at the 5% level of significance. The relevant parameter estimates of the damage function are also presented in Table 2. Specifically, the parameter α that accounts of the direct effect of damage agent density is negative and statistical significant at the 1% level (-0.7989), whereas the parameter capturing the effect of veterinary expenses on the damage agent is positive and also statistical significant at the 1% level (0.4194). Since the stochastic production frontier is approximated with a Cob-Douglas functional specification, these estimates coincides with the relevant output elasticities except for the case of veterinary expenses.

According to these estimates from among the conventional inputs flock size is the most important factor of production used by Greek sheep farms (0.4052) followed by labor (0.2023) and, other intermediate inputs (0.0853). For veterinary expenses the relevant point estimate is 0.1656 indicating their important contribution in reducing damage in output produced by viruses, bacteria etc. Accordingly returns to scale were found decreasing 0.8584 on the average. Finally, the coefficient of time index included in the production frontier to capture technical change was 0.0618 and statistical significant indicating the existence of technical progress for sheep farms during the 1989-92 period.

Using these estimates the marginal products were computed and presented in Table 2 next. According to these estimates an increase in the flock size by one animal will increase farm produce by 21.351 euros on the average, ranging from a low of 16.023 euros to a maximum of 28.543 euros. Similarly, an increase in labor used by one working hour will increase livestock production by 1.327 euros ranging between 0.902 and 1.823 euros, in intermediate inputs by one euro will increase production by 2.308 euros ranging between 1.634 and 3.221 euros and, in veterinary expenses by one euro will increase production by 1.508 euros ranging between 1.123 and 2.032 euros.

Technical efficiency estimates in the use of both conventional and damage control input are presented in Table 3 in the form of frequency distribution. Average point estimate over farms and time for output-oriented technical efficiency in conventional input (*i.e.*, flock size, labor, intermediate inputs) use is 84.36%. This value implies that output of sheep farms (*i.e.*, meat, milk, wool) can be increased by 15.64% without altering conventional input use, the production technology and, pest density incidence as long as farmer's know how is improved. The variation across farms is not substantial as mean efficiencies ranges from a low of 61.54% to a high of 91.32% (standard deviation was found to be only 5.91%). The majority of sheep farms in the sample (40 out of 51 farms) exhibit technical efficiency estimates in the use of their conventional inputs between 80-90%.

On the other hand, technical efficiency in the use of veterinary expenses expenses (*i.e.*, immunization and antibiotics) was found to be considerable lower, only 60.63%. This value implies that damage abatement level caused by viruses and thus output produced could be maintained by using 39.37% less of veterinary expenses given the production technology and the efficiency in the use of conventional factors of production if farmers know how is improved. The variation across farms is higher than that of output-oriented technical efficiency in conventional inputs as the corresponding standard deviation value is higher, 6.39%. Specifically, technical efficiency in veterinary expenses ranges from a low of 45.54% to a high of 72.82%. There are four (4) sheep farms in the sample for which their corresponding average technical efficiency estimates are below 50%.

Strengthening further our empirical results we have computed Spearman correlation coefficient between the two efficiency indices in order explore the potential relationship among them. The results suggest that there is a statistical significant positive correlation among the two efficiency indices, 74.75%. The result is not surprising considering that farmer's managerial ability may be reasonably assumed to affect the way that all inputs are utilized in the production process. According to the relevant literature in both developed and developing countries human capital variables are among the most important factors determining farmer's managerial ability (*e.g.*, education level, hands-on experience, extension services etc.). If farmers are not technical efficient in the use of conventional inputs this is because their respective know-how is inadequate. They make thus allocative errors in applying various inputs in sheep farming. If this is true we can expect that the same would apply for damage control inputs. So the high correlation between the two efficiency indices was expected *a priori*.

What requires further explanation, however, is the significant lower average values of technical efficiency in damage control inputs use. Recall that these include immunization and antibiotics costs against viruses affecting animal health. Given that these inputs are having a low unit cost their application depends on farmer's perceptions on animal health. It is more likely therefore for risk averse farmer's to apply this kind of inputs preventively in order to avoid losses in their flock. The same does not hold for conventional inputs like animal or physical capital which are more expensive.

6. Concluding Remarks

This paper extends the literature on damage control econometrics providing a theoretical consistent framework for the quantitative measurement of technical efficiency in both damage control and conventional factors of production. The proposed model makes use of the traditional stochastic frontier framework using the theoretical foundations suggested by Fox and Weersink (1995) that that extent the traditional model developed by Lichtenberg and Zilberman (1986) allowing for increasing returns in the use of damage control agents. The econometric estimation of the resulted model is based on maximum likelihood techniques and it can be applied to any functional specification of the production function. Finally, although our model is based on an exponential specification of both the damage and control function it can be readily extended to any other functional specification suggested in the relevant literature of damage control econometrics (*i.e.*, Pareto, logistic, Weibull, rectangular hyperbola, linear response plateau and square root response plateau).

This methodology is applied to an unbalanced panel data set of 51 sheep farms in Greece, for the period 1989-92. The empirical results suggest that sheep farmers are considerably technical inefficient in the use of both conventional and damage control inputs (*i.e.*, expenses for immunization and antibiotics). Specifically, average output-oriented technical inefficiency in conventional inputs was found to be 15.64%, whereas the corresponding value for veterinary expenses was even higher, 39.37%. Both indices of technical efficiency exhibit a strong and statistically significant correlation which was expected *a priori*. Finally, average estimates of the marginal product of veterinary expenses was found to be 1.508 euros, whereas returns to scale were strongly diminishing, 0.8584.

References

Babcock, B. (1992). The Effects of Uncertainty on Optimal Nitrogen Application, *Review of Agricultural Economics,* **14**: 271-280.

Babcock, B.A., Lichtenberg, E. and D. Zilberman (1992). Impact of Damage Control and Quality of Output: Estimating Pest Control Effectiveness, *American Journal of Agricultural Economics*, **74**: 163-174.

Blackwell, M. and A. Pagoulatos (1992). The Econometrics of Damage Control, *American Journal of Agricultural Economics*, **74**: 1040-1044.

Campbell, H.F. (1976). Estimating the Marginal Productivity of Agricultural Pesticides: The Case of Tree Fruit Farms in the Okanagan Valley, *Canadian Journal of Agricultural Economics*, **24**:23-30.

Carlson, G.A. (1970). A Decision Theoretic Approach to Crop Disease Prediction and Control, *American Journal of Agricultural Economics*, **52**: 216-222.

Carpentier, A. and R.D. Weaver (1997). Damage Control Productivity: Why Econometrics Matters, *American Journal of Agricultural Economics*, **79**: 47-61.

Carrasco-Tauber, C. and L.J. Moffitt (1992). Damage Control Econometrics: Functional Specification and Pesticides Productivity, *American Journal of Agricultural Economics*, **74**: 158-162.

Chambers, R.G. and E. Lichtenberg (1994). Simple Econometrics of Pesticide Productivity, *American Journal of Agricultural Economics*, **76**: 407-417.

Cowan, R. and P. Gunby (1996). Sprayed to Death: Path Dependence, Lock-in and Pest Control Strategies, *Economic Journal*, **106**: 521-542.

Feder, G. (1979). Pesticides, Information and Pest Management under Uncertainty, *American Journal of Agricultural Economics*, **61**: 97-103.

Fox, G. and A. Weersink (1995). Damage Control and Increasing Returns, *American Journal of Agricultural Economics*, **77**: 33-39.

Greek Ministry of Agriculture (1998). *Agricultural Statistics of Greece*. Athens, Greece: NSSG Publications.

Headley, J.C. (1968). Estimating the Productivity of Agricultural Pesticides, *American Journal of Agricultural Economics*, **50**: 13-23.

Jondrow, J., Lovell, C.A.K., Materov, I.S. and P. Schmidt (1982). On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model, *Journal of Econometrics*, **19**: 233-238.

Kopp, R.J. (1981). The Measurement of Productive Efficiency: A Reconsideration. *Quarterly Journal of Economics,* **96**: 477-503.

Lichtenberg, E. and D. Zilberman (1986). The Econometrics of Damage Control: Why Specification Matters, *American Journal of Agricultural Economics*, **68**: 261-273.

Lin, B.H., Jans, S., Ingram, K. and L. Hansen (1993). Pesticide Productivity in Pacific Northwest Potato Production. *Agricultural Resources: Inputs*, US Department of Agriculture, ERS publication No AR-29.

Norgaard, R.B. (1976). The Economics of Improving Pesticide Use, *Annual Review of Entomology*, **21**: 45-60.

Oude Lansink, A. and A. Carpentier (2001). Damage Control Productivity: An Input Damage Abatement Approach, *Journal of Agricultural Economics*, **52**: 1-12.

Oude Lansink, A. and E. Silva (2994). Non-Parametric Production Analysis of Pesticide Use in the Netherlands, *Journal of Productivity Analysis*, **21**: 49-65.

Pedigo, L.P., Hutchins, S.H. and L.G. Higley (1986). Economic Injury Levels in Theory and Practice, *Annual Review of Entomology*, **31**: 341-368.

Russell, R.R. (1985). Measures of Technical Efficiency, *Journal of Economic Theory*, **35**: 109-126.

Table 1: Summary statistics of the variables

	1989	1990	1991	1992	Average Period Values			
Variable					Mean	Min	Max	St. Deviation
Output (in €)	12,857	13,587	14,075	14,625	13,786	1,677	44,958	7,099
Labour (in days)	179	182	187	190	184	18	700	99
Flock size (number of animals)	163	171	179	186	174	21	549	92
Intermediate Inputs (in €)	6,354	6,962	7,561	8,035	7,228	257	41,895	5,669
Veterinary Expenses (in €)	88.4	95.2	93.9	97.1	93.6	21.3	156.7	60.8

Table 2: Parameter Estimates of the Cobb-Douglas Stochastic Production Frontier with Output Damage Function

Variable	Estimate	Std Error
Production Frontier		
Constant	0.1992	(0.1717)
Flock Size	0.4052	(0.0404)*
Labour	0.2023	(0.0574)*
Intermediate Inputs	0.0853	(0.0403)**
Time	0.0618	(0.0143)*
Damage Function		
α	-0.7989	(0.0559)*
γ	0.4194	(0.1551)*
σ_v	0.1572	(0.0487)*
σ_u	0.1324	(0.0523)*
σ_θ	0.7294	(0.2869)**

* (**) indicate statistical significance at the 1 (5) percent level.

Table 3: Mean Marginal Products of Conventional and Damage Control Inputs

Input	Mean	Max	Min	StDev
Flock Size[1]	21.351	28.543	16.023	5.093
Labour[2]	1.327	1.823	0.902	0.282
Intermediate Inputs[3]	2.308	3.221	1.634	0.541
Veterinary Expenses[3]	1.508	2.032	1.123	0.384

[1] in euros per animal; [2] in euros per working hour; [3] in euros per euro

Table 4: Technical Efficiency in Conventional and Damage Control Inputs Use

Efficiency (%)	TE in Conventional Inputs	TE in Veterinary Expenses
<40	0	0
40-45	0	0
45-50	0	4
50-55	0	5
55-60	0	12
60-65	1	17
65-70	1	9
70-75	2	4
75-80	4	0
80-85	13	0
85-90	27	0
90-95	3	0
95-100	0	0
R-ho	74.75*	
N	51	
Mean	84.36	60.63
Minimum	61.54	45.54
Maximum	91.32	72.82
StDeviation	5.91	6.39

* indicate statistical significance at the 1% level

Endnotes

[1] Other important examples of damage control agents outside agriculture include the use of smoke alarms and sprinklers system to prevent fire, immunization to prevent diseases in population, alarm systems to prevent crimes against property, water and air purification systems. To a certain extent even national defense can be thought as an example of damage control input.
[2] In some cases they even decrease farm production. For instance the excess use of pesticides in the early stages of plant growth or in inadequate time period may have disastrous impact on farm produce (Pedigo *et al.*, 1986).
[3] At the same time Blackwell and Pagoulatos (1992) utilized a process model of production that accounts for state variables omitted from Lichtenberg and Zilberman theoretical specification. At the same year, Babcock (1992) based on the empirical findings reported by Carlson (1970), Noorgard (1976) and Feder (1979) introduced explicitly in the model production uncertainty.
[4] Eventually, the assumption that damage control agents affects equally all conventional factors of production can be relaxed complicating, however, further the econometric estimation of the production model.
[5] Several years later, Oude Lansink and Carpentier (2001) using a flexible quadratic specification for the production function estimated via generalized maximum entropy estimator a variant of output and input abatement models.
[6] Actually the authors recognising that defficiency of their DEA model employ a sensitivity analysis to investigate the impact of outliers on the shadow price of pesticides (p.51).
[7] As noted by Carpentier and Weaver (1997, p. 51 theorem 1) their model collapses to the traditional LZ formulation either if constant returns to scale prevails or the input-abatement function is common across conventional inputs.
[8] It is assumed that damage agent only affects the quantity of output produced and not it's quality. The model can be generalized to account for quality changes (see Babcock, Lichtenberg and Zilberman, 1992).
[9] Even with the general assumption that the marginal damage effect of damage agent is non-negative $\partial h(\bullet)/\partial B_{it} \geq 0$, the sign of $\partial h^2(\bullet)/\partial B_{it}^2$ is underdetermined. Nevertheless, the damage function is often assumed concave.
[10] In the extreme case where farmers applies a wrong damage control input at an inappropriate time, $\tilde{\theta}_{it}$ could be equal to zero.
[11] Although the exponential specification has been mostly applied in damage control econometrics, several other functional specification having the properties of a cumulative distribution function have been suggested in the literature including: Pareto, logistic, Weibull, rectangular hyperbola, linear response plateau and square root response plateau. Lichtenberg and Zilberman (1986) and Fox and Weersink (1995) provide a thorough discussion on the properties and empirical implementation of these functional specifications. Our specification of technical efficiency in damage control inputs can be easily applied to any of the above functional specifications.
[12] We used ten point numerical integration rule and the BFGS optimization technique. Gauss code is available upon request.
[13] Since this does not aid the computation in a significant way, we omit the details here.
[14] This can also be a farm actually observed.
[15] The dependence of this kernel density on lny_{it}, lnx_{it}, and z_{it} comes from the fact that maximum likelihood estimates of the parameters have to be plugged in.
[16] Grazing cost is estimated using the grazing capacity standards of the grasslands in each region of the sample survey, as applied by the Greek Ministry of Agriculture (1998).