THE DAMAGE CONTROL EFFECT OF PESTICIDES ON TOTAL FACTOR PRODUCTIVITY GROWTH

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Summary − This paper develops a framework for analyzing the sources of TFP changes by explicitly taking into account the damage control nature of pesticides. In the proposed framework TFP changes are decomposed into the conventional sources of growth (i.e., technical change, scale effect, and changes in technical efficiency) and the damage control effect which consists of three distinct components: the first is due to changes in the initial pest infestation, the second is a spillover effect arising from neighbors' use of preventive inputs and the third is related to abatement effectiveness. The empirical model is applied to a panel of olive-growing farms in Crete, Greece during the 1999-03 period. The empirical results indicate that the damage control effect accounted on average for 5% of the annual TFP growth and its main component was the improvements in abatement effectiveness.

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1. Introduction

The damage control nature of pesticides has not been considered in any previous study on total factor productivity (TFP). Instead pesticides have been treated as a conventional input that affects output directly while in reality their contribution is rather indirect through their ability to reduce crop damage due to pest infestation and diseases. By treating pesticides as a damage control rather than an output expanding input affects the way pesticides appear in the production function. Specifically, as a damage control input, pesticides enter into the production function indirectly through either the abatement (Lichtenberg and Zilberman) or the output damage function (Fox and Weersink). Consequently, the way of calculating pesticides' marginal product and output elasticity should be revised. In fact, the results of previous empirical studies (e.g., Lichtenberg and Zilberman; Oude Lansink and Carpentier; Oude Lansink and Silva) indicate that the marginal product of pesticides tends to be overestimated when it is modeled as a conventional rather than a damage control input.

This bias in the estimated marginal product of pesticides is going, among other things, to affect both the measurement (if output elasticities instead of cost shares are used to compute input growth) and the decomposition of TFP changes through the magnitude and the relative importance of the scale effect. However, the direction of the impact cannot be predicted with certainty: the upward bias in the estimated marginal product of pesticides results in a greater output elasticity and consequently, in an overestimation of scale elasticity compared to the case of treating pesticides as a damage control input. On the other hand, it also implies that the contribution of conventional inputs to the growth of aggregate input, defined as a weighted average over all inputs with the ratios of output to scale elasticity used as weights (Chan and Mountain), would be understated while that of pesticides would be overstateed. Thus the net effect on the growth of aggregate input is undetermined *a priori*. This in turn implies that that the impact on the scale effect, which depends on both the magnitude of the scale elasticity and the growth of aggregate input, is ambiguous.

This paper develops a framework for analyzing the sources of TFP changes by explicitly taking into account the damage control nature of pesticides. In the proposed framework, TFP changes are decomposed into the conventional sources of growth (namely, technical change, scale effect, and changes in technical efficiency), and the damage control effect which consists of three distinct components: the first is due to changes in the initial pest infestation, the second is a spillover effect arising from neighbors' use of preventive inputs, and the third is related to abatement effectiveness. To develop this decomposition framework we extend the output damage approach into two directions: *first*, we analyze the damage control nature of pesticides in the presence of technical inefficiency and *second*, we introduce a spillover variable into the abatement technology.

The rest of this paper is organized as follows: the theoretical model for analyzing the damage control effect o pesticides on TFP changes, which is the based on the output damage approach, is presented in the next section. The empirical model and the estimation procedure are discussed in section 3. The data employed and the empirical results are analyzed in section 4. Concluding remarks follow in the last section.

2. Theoretical Framework

There are two alternative approaches for incorporating pesticides as a damage control input into a production function: the abatement function (Lichtenberg and Zilberman) and the output damage function (Fox and Weersink) approach. In the former, it is assumed that the true measured impact of pesticides on the effective output is related to the purchased abatement rather than the quantity of pesticides used. As result, abatement rather than pesticides enter directly into the production function since the former is considered as an intermediate input produced by pesticides. In such a setting, the marginal productivity of pesticides reflects their ability to reduce crop damage due to pest infestation and not to increase output directly. In the abatement function approach it is assumed that the marginal productivity of pesticides is decreasing, which sometimes may be though of as a limitation. It is also assumed that the abatement function is independent of initial pest infestation. This implies that the abatement function approach is an appropriate modeling alternative when pesticides are applied in a prophylactic way according to an in-advanced planned schedule.[1] If however farmers postpone spraying until realization of pest incidence, the abatement function approach results in biased estimates of the production function parameters (Hall and Moffitt) because the error term, which necessarily includes the omitted from the abatement function initial level of pest infestation, is correlated with pesticide use.

On the other hand, in the output damage function approach, it is assumed that the effect of pesticides on the effective output is the result of a process involving two stages: (a) the effect of the damage control input on the damage agent (abatement), and (b) the effect of the remaining damage agent on the effective output. In the first stage, pest incidence depends on the untreated pest population and on the proportion of it controlled by the abatement activities. In the second stage, effective output is indirectly affected by abatement through the loss caused by the remaining damage agent incidence. By construction, the output damage function approach is more appropriate when pesticides are applied in once pest incidence is realized and in addition, for certain specifications of the damage control function, allows for increasing marginal product of pesticides. The case of increasing returns is important from a policy point of view as measures aimed to reduce pesticide use for environmental conservation by imposing a tax may have substantially different effects on the levels of different products.[2]

For the purposes of the present study that are mainly detected by the crop considered in the empirical application of the model, we employ the output damage approach as spraying for *Bactrocera oleae* (*Gmellin*), which is the main pest in olive-tree cultivation, is done once pest incidence is realized. Nevertheless, the framework for the decomposition of TFP developed below is general enough to be used, after making the necessarily adjustments, within an abatement function approach. In particular, as it would be evidence from (7), the only difference is that the component of the damage control effect which is due to changes in initial pest infestation will be absent in the case of the abatement function approach. Thus in this case the damage control effect consists of the spillover effect related to neighbors' use of pesticides and the abatement effectiveness effect.

Following Fox and Weersink, the damage caused in output by pest incidence $b \in \Re_+$ can be represented by a non-decreasing and concave function $d : \Re_+ \to \Im$, $d = g(b)$ and $\Im = [0,1]$, which measures the proportion of output loss at a given pest incidence.[3] If the damage agent is absent $(b = 0)$ then $g(\cdot) = 0$ and realized (actual) output equals effective output. If however the level of damage agent population tends to infinity $(b \to \infty)$ then $g(\cdot) \to 1$ and realized output approaches a minimum level $(y \to y^{min})$ which reflects the maximum destructive capacity of damage agents. On the other hand, pest incidence (density) depends on the initial level of pest population (b^r) and the proportion of the damage agent that is not controlled for a given level of treatment (Fox and Weersink); that is, $b = b^r(1-\phi(\cdot))$, where $\phi(\cdot)$ is the control function.

For the purposes of this paper, we enrich Fox and Weersink's specification of the control function in two ways. In particular, we assume that the proportion of the damage agent remaining after treatment depends (a) not only on the quantity of pesticides used by the individual farmer but also on the total amount of pesticides used by his neighbours and (b) on abatement effectiveness that is related to improved field coverage, higher eradication levels, etc., as suggested by Morrison-Paul.[4] Thus the control function $c : \Re_+^2 \to \wp = [0,1]$ is defined as $c = \phi(z; z^r, t)$ where $z \in \Re_+$ refers to the quantity of pesticides used by each farmer, $z^r \in \Re_+$ is the total amount of pesticides used by a farmer's neighbours and t is a time trend reflecting changes in abatement effectiveness. If $\varphi(\cdot) = 0$, pesticides have no effect on damage agent incidence and the level of damage agent affecting farm production is equal with its initial population $(b = b^r)$. If however $\varphi(\cdot) = 1$ there is a complete eradication of the damage agent and actual and effective output coincide.

The control function is non-decreasing $(\partial\phi(\cdot)/\partial z \geq 0$, $\partial\phi(\cdot)/\partial t \geq 0$ and $\partial\phi(\cdot)/\partial z^r \geq 0)$ and concave in pesticides use, abatement effectiveness and the spillover variable z^r.[5] The latter implies that there may be some synergies in the use of pesticides (e.g., positive externality). This seems quite reasonable within small geographical areas and mobile pest populations where the preventive action of every farmer accounts for the total damage caused and the aggregate intensity of the abatement effort in the area affects the individual damage control decisions. As the aggregate intensity of abatement effort increases, because more farmers involve in the use of pesticides or they use them more intensively, lesser doses are required by each farmer to achieve the same level of output damage. Consequently, for a given level of pesticide use, individual abatement does not deteriorate as neighbouring farms increase their pesticide use, and *vice versa*. In cases however that production takes place under controlled or protected conditions (*i.e.*, glasshouses), neighbors abatement effort do not affect pest incidence and hence the spillover effect is zero.

In addition, following previous studies (e.g., Chambers and Lichtenberg), we assume that conventional inputs are weakly separable from damage control inputs and thus technology may be written as:[6]

$$T \equiv \left\{ \left(\mathbf{x}, z, b^r, y \right) : y \leq f\left(\mathbf{x}; t \right) \tilde{g}\left(b^r, z; t, z^r \right) \right\} \tag{1}$$

where $\mathbf{x} \in \Re_+^k$ is a vector of conventional inputs, $y \in \Re_+$ is actual output, t captures disembodied technical change, and $\tilde{g}\left(\cdot\right) = 1 - g\left(b^r, z; t, z^r\right)$ is the percentage of maximal potential output realized in the presence of pest infestation and damage-control activities. From the aforementioned properties of $g\left(\cdot\right)$ and $c\left(\cdot\right)$, it follows that $\tilde{g}\left(\cdot\right)$ is non-decreasing in z, t and z^r and non-increasing in b^r.

On the other hand, the inequality sign in (1) implies that farms may not necessarily be technically efficient and this is the second extension we introduce to Fox and Weersink's model. In the presence of technical inefficiency the equality in (1) is restored and the production function is written as:

$$y = f\left(\mathbf{x}; t \right) \tilde{g}\left(b^r, z; t, z^r \right) TE^O\left(\mathbf{s}; t \right) \tag{2}$$

where $TE^O(\mathbf{s};t)$ is an output-oriented measure of technical inefficiency defined over the range $(0,1]$, $\mathbf{s}=(s_1,s_2,...,s_J)$ is a vector of farm-specific characteristics related to managerial and organisational ability of farmers and the general environment that production is taking place, and t is a time trend capturing autonomous changes in technical efficiency.

The optimal level of pesticides use along with that of conventional inputs is determined from the following profit maximization problem:

$$\pi(p,\mathbf{w},v)=\max_{\mathbf{x},z}\left\{py-\mathbf{w}'\mathbf{x}-vz : y=f(\mathbf{x};t)\tilde{g}\left(b^r,z;t,z^r\right)TE^O(s,t)\right\} \tag{3}$$

where $p\in\Re_+$ is the output price, $\mathbf{w}\in\Re_{++}^k$ is the vector of output expanding input prices and $v\in\Re_{++}$ is the price of pesticides. The necessary conditions require that

$$\begin{aligned} &p\frac{\partial f(\cdot)}{\partial x_k}\tilde{g}(\cdot)TE^O(\cdot)=w_k \quad \forall k \\ &pf(\cdot)\frac{\partial \tilde{g}(\cdot)}{\partial z}TE^O(\cdot)=v \end{aligned} \tag{4}$$

Using (4) it can be shown that the output elasticities of the conventional and the preventive inputs are related to cost shares as following:

$$\begin{aligned} &\varepsilon_k(x;t)=\frac{\partial \ln y}{\partial \ln x_k}=\frac{\ln f(\cdot)}{\ln x_k}=m_k E \\ &\varepsilon_z\left(b^r,z;t,z^r\right)=\frac{\partial \ln y}{\partial \ln z}=\frac{\partial \ln \tilde{g}(\cdot)}{\partial \ln z}=m_z E \end{aligned} \tag{5}$$

where m refers to factor cost shares defined as $m_k=w_kx_k/C$ and $m_z=vz/C$ with $C=\sum w_kx_k+vz$ and E is the scale elasticity defined over the conventional and the preventive inputs (namely, all inputs that are under the control of the farmer) as $E=\sum\varepsilon_k(\cdot)+\varepsilon_z(\cdot)$.

Taking logarithms of both sides of (2) and totally differentiating with respect to time results in:

$$\begin{aligned}\dot{y} &= T_t(\mathbf{x};t) + \sum_{k=1}^{K} \varepsilon_k(\mathbf{x};t)\dot{x}_k + \sum_{m=1}^{M} \frac{\partial \ln TE^O(\mathbf{s};t)}{\partial \ln s_j}\dot{s}_j + \dot{TE}^O(\mathbf{s};t) + \\ &\varepsilon_z(b^r,z;z^r,t)\dot{z} + \theta^{b^r}(b^r,z;z^r,t)\dot{b}^r + \theta^{z^r}(b^r,z;z^r,t)\dot{z}^r + \theta_t(b^r,z;z^r,t)\end{aligned} \tag{6}$$

where a dot over a variable or a function indicates its time rate of change, $T_t(\mathbf{x};t) = \partial \ln f(\cdot)/\partial t$ is the primal rate of technical change, $\theta^{b^r}(\cdot) = \partial \ln \tilde{g}(\cdot)/\partial \ln b^r = \partial \ln y/\partial \ln b^r$, $\theta^{z^r}(\cdot) = \partial \ln \tilde{g}(\cdot)/\partial \ln z^r = \partial \ln y/\partial \ln z^r$, and $\theta_t(\cdot) = \partial \ln \tilde{g}(\cdot)/\partial t = (\partial g(\cdot)/\partial b)\left[(b^r - b)/\tilde{g}\right]T_t^{\phi}(\cdot)$ with $T_t^{\phi}(\cdot) = \partial \ln \phi(\cdot)/\partial t$ being the rate of abatement effectiveness which for given technology and level of technical efficiency measures the proportional change in effective output that could have been if the quantity of preventive inputs, the initial pest incidence and the spillover variable had remained unchanged. Then, using (5) and the Divisia index of *TFP* growth defined over conventional and preventive inputs, i.e., $\dot{TFP} = \dot{y} - \sum_k m_k \dot{x}_k - m_z \dot{z}$, (6) may be written:

$$\begin{aligned}\dot{TFP} &= T_t(\mathbf{x};t) + (E-1)\left[\sum_{k=1}^{K}\left(\frac{\varepsilon_i(\mathbf{x};t)}{E}\right)\dot{x}_k + \left(\frac{\varepsilon_z(b^r,z;z^r,t)}{E}\right)\dot{z}\right] + \dot{TE}^O(\mathbf{s};t) + \\ &\sum_{j=1}^{M} \frac{\partial \ln TE^O(\mathbf{s};t)}{\partial \ln s_j}\dot{s}_j + \theta^{b^r}(b^r,z;z^r,t)\dot{b}^r + \theta^{z^r}(b^r,z;z^r,t)\dot{z}^r + \\ &\left(\frac{\partial g(b^r,z;z^r,t)}{\partial b}\right)\left(\frac{b^r - b}{\tilde{g}(b^r,z;z^r,t)}\right)T_t^{\phi}(z;z^r,t)\end{aligned} \tag{7}$$

The first four terms in the right hand side of (7) consist the traditional sources of TFP growth (*i.e.*, technical change, scale economies, technical efficiency changes). The first of then reflects the impact technical change may have on potential output. It measures the proportional change in output that could have been if either the damage agent was absent or there was complete eradication of it, given that farmers are technically efficient and input use remains unchanged. It is positive (negative) under progressive (regressive) technical change, while it vanishes when there is no technical change.

The second term in (7) refers to the scale effect. The sign and direction of this term depends on both the magnitude of the scale elasticity and the over time changes of the aggregate input, which is given by a Divisia-type aggregate of conventional and preventive inputs. The scale effect is positive (negative) under increasing (decreasing) returns to scale as long as the aggregate input use increases and *vice versa*. This term vanishes when either technology exhibits constant returns to scale with respect to both conventional and preventive inputs or the aggregate input remains unchanged over time.

The sum of the third and the forth terms in (7) is the technical efficiency changes effect that may be due to either passage of time (*e.g.*, learning-by-doing) (third term) or to changes in farm-specific characteristics affecting the managerial and organizational ability of farmers (forth term).[7] They contribute positively (negatively) to TFP growth as long as efficiency changes are associated with movements towards (away from) the production frontier. The technical efficiency change effect is zero and thus has no impact on TFP growth when technical efficiency and all farm-specific characteristics are time invariant (Karagiannis and Tzouvelekas, 2005).

The sum of the last three terms in (7), which we refer to it as the damage control effect, results from treating pesticides as a preventive rather than an output-expanding input. As it will be evidence, all three components of the damage control effect contribute to TFP changes through greater actual output rather than through input conservation reflecting the output expanding nature of damage control (abatement) activities. In addition, we should notice that the fifth term in (7), which is related to the effect of initial pest infestation to TFP growth, will be absent within an abatement function framework as in this case pest density does not depend upon initial pest population. Thus, in this case the damage control effect consists of the spillover effect related to neighbors' use of pesticides and the abatement effectiveness effect.

The first of component of the damage control effect reflects the effect of initial pest infestation (fifth term in (7)) and, given that $\theta^{b^r}\left(\cdot\right)<0$, it has a negative (positive) on TFP growth as long as initial pest incidence increases (decreases) over time, while it has no impact on TFP growth when $\dot{b}^r$. Since actual output will be lower (greater) with an increase (decrease) in the initial level of pest incidence, this is going to have a negative (positive) productivity effect when the initial level of pest incidence increases (decreases) because less actual output will be resulted from any given increase in conventional and preventive input quantities. Thus, unfavourable conditions for pest reproduction, depending on the biological cycle of the damage agent, environmental conditions, etc., may enhance TFP growth as fewer pests harm farm produce and hence less damage occurs in realized output, and *vice versa*.

The spillover effect (sixth term in (7)) is the second component of the damage control effect. In the presence of synergies in pesticide use $\left(i.e.,\ \partial\phi\left(\cdot\right)/\partial z^r \geq 0\right.$ and $\left.\theta^{z^r}\left(\cdot\right)>0\right)$, the spillover effect has a positive (negative) impact on TFP growth if the total quantity of preventive inputs used by neighbouring farms increases (decreases) over time. Since actual output will be lower (greater) with an decrease (increase) in the aggregate abatement effort of neighbouring farms, this is going to have a positive (negative) productivity effect when neighbours' abatement effort increases (decreases) as more actual output will be resulted from any given increase in conventional and preventive input quantities. The spillover effect has no impact on TFP growth if either production takes place under controlled or protected conditions (*i.e.*, glasshouses) and thus neighbours' abatement effort does not affect production $\left(i.e,\ \theta^{z^r}(\cdot)=0\right)$, or aggregate abatement effort of neighbours remains unchanged over time $\left(i.e.,\ \dot{z}^r=0\right)$.[8]

The last component of the damage control effect (seventh term in (7)) is related to the rate of abatement effectiveness. Since effective output will be greater with an improvement in abatement effectiveness, this is going to have a positive productivity effect as more effective and thus actual output will be realized from any given increase in conventional and preventive input quantities. However, the rate of abatement effectiveness does not contribute point-for-point to TFP growth but its contribution is proportional to the product of the marginal damage effect $\left(i.e.,\ \partial g(\cdot)/\partial b\right)$ and the ratio of the proportion of the damage agent that is not controlled for a given level of treatment to the proportion of actual output $\left(i.e.,\ \left(b^r-b\right)/\tilde{g}(\cdot)\right)$. Abatement effectiveness does not contribute to TFP growth if either the initial pest infestation is equal to realized pest incidence, *i.e.*, $b^r=b$, or the rate of abatement effectiveness remains unchanged, *i.e.*, $T_t^{\phi}\left(z;z^r,t\right)=0$. In the former case, the marginal effectiveness of abatement activities is zero which means that abatement has no effect on initial pest infestation. This would be the case with incorrect application or inappropriate choice of pesticides for both the farmer and his/her neighbours $\left(i.e.,\ \partial\phi(\cdot)/\partial z=0 \text{ and } \partial\phi(\cdot)/\partial z^r=0\right)$.

Last but not least it is worth mentioning that if someone is interesting in the measurement of the overall impact of pesticides on TFP growth, then the contribution of pesticides through the scale effect, *i.e.*, $\left[(E-1)\varepsilon_z(\cdot)/E\right]\dot{z}$, should be added to the damage control effect. For this reason this term is presented separately in Table 6.

3. Empirical Model

Following Fox and Weersink we assume an exponential specification for both the damage and the control functions. Then, the production frontier function in (2) may be written as:

$$y_{it} = \left\{ f\left(\mathbf{x_{it}}; t, \boldsymbol{\beta}\right)\left[1 - g\left(b_{it}; \lambda\right)\right]\right\} e^{v_{it} - u_{it}} \tag{8}$$

where subscript *i* is used to index farms, $\boldsymbol{\beta}$ and λ are parameters to be estimated, v_{it} is a symmetric and normally distributed random error representing those factors that cannot be controlled by farmers, measurement errors in the dependent variable, and omitted explanatory variables, $-u_{it} = ln\,TE_{it}^{o}$ is an one-sided error term capturing technical inefficiency and,

$$g\left(b_{it}; \lambda\right) = 1 - e^{-\lambda b_{it}} \tag{9}$$

$$b_{it} = b_{it}^{r}\left[1 - \phi\left(\mathbf{z_{it}}; z_{it}^{r}, t, \boldsymbol{\zeta}\right)\right] \tag{10}$$

$$\phi\left(z_{it}; z_{it}^{r}, t, \boldsymbol{\zeta}\right) = 1 - e^{-\zeta_p z_{it} - \zeta_s z_{it}^{r} - \zeta_t t} \tag{11}$$

where $\boldsymbol{\zeta}$ is the vector of parameters to be estimated. Substituting (9), (10) and (11) into (8) and taking logarithms we obtain:

$$ln\, y_{it} = f\left(ln\,\mathbf{x_{it}}; t, \boldsymbol{\beta}\right) - \lambda b_{it}^{r}\, e^{-\zeta_p z_{it} - \zeta_s z_{it}^{r} - \zeta_t t} + v_{it} - u_{it} \tag{12}$$

If we assume that $f(\cdot)$ is approximated by a generalized Cobb-Douglas form then (12) becomes:[9]

$$\begin{aligned} ln\, y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \, ln\, x_{kit} + \beta_T t + \frac{1}{2}\beta_{TT} t^2 + \sum_{k=1}^{K} \beta_{kT} \, ln\, x_{kit} t \\ - \lambda b_{it}^{r} e^{-\zeta_p z_{it} - \zeta_s z_{it}^{r} - \zeta_t t} + v_{it} - u_{it} \end{aligned} \tag{13}$$

The above model can be estimated using ML techniques assuming that the technical inefficiency term, u_{it}, is independently distributed according to a normal distribution with mean μ_{it} and unknown variance σ_u^2. We suppose that the pre-truncation mean to be time-varying and to depend on farm-specific characteristics as:

$$\mu_{it} = \delta_0 + \sum_{s=1}^{S} \delta_s \, ln\, s_{it} + \delta_T t + \delta_{TT} t^2 \tag{14}$$

where subscript *s* indexes farm-specific characteristics. The resulted model is non-linear and it can be estimated by extending the estimation framework suggested by Battese and Coelli.[10]

After estimation, farm-specific estimates of technical inefficiency are obtained directly from the estimated mean and variance of u_{it} as follows (Battese and Broca):

$$TE_{it}^{o} = exp\left(-\mu_{it}^{0} + 0.5\sigma_o^2\right)\left\{\frac{\Phi\left[\left(\mu_{it}^{0}/\sigma_o\right) - \sigma_o\right]}{\Phi\left(\mu_{it}^{0}/\sigma_o\right)}\right\} \tag{15}$$

where $\mu_{it}^{0} = \dfrac{\sigma_v^2 \mu_{it} - \sigma_u^2 e_{it}}{\sigma_v^2 + \sigma_u^2}$, $e_{it} = v_{it} - u_{it}$, $\sigma_o^2 = \dfrac{\sigma_u^2 \sigma_v^2}{\sigma_u^2 + \sigma_v^2}$, and $\Phi(\cdot)$ is the cumulative density function (*cdf*) of the standard normal random variable. The components of technical efficiency changes (*i.e.*, autonomous changes and changes in farm-specific characteristics) are calculated as:

$$\dot{TE}_{it}^{o} = -\xi\left(\delta_T + 2\delta_{TT} t\right) \tag{16}$$

and

$$\frac{\partial \ln TE_{it}^{o}}{\partial \ln s_{jit}} = -\xi\delta_{j} \tag{17}$$

where $\xi = 1 - \sigma_{u}^{-1}\left\{\frac{\varphi(\rho - \sigma_{u})}{\Phi(\rho - \sigma_{u})} - \frac{\varphi(\rho)}{\Phi(\rho)}\right\}$, $\rho = \mu_{it}/\sigma_{u}$ and $\varphi(\cdot)$ is the probability density functions of the standard normal variable.

On the other hand, the primal rate of technical change is measured as:

$$T = \beta_{T} + \beta_{TT}t + \sum_{k=1}^{K}\beta_{kT}\ln x_{kit} \tag{18}$$

and the scale elasticity as:

$$E = \sum_{k=1}^{K}\varepsilon_{k}^{x} + \varepsilon^{z} = \sum_{k=1}^{K}\beta_{k} + \beta_{kT}t + \zeta_{p}z_{it}\lambda b_{it}^{r}\, e^{-\zeta_{p}z_{it} - \zeta_{s}z_{it}^{r} - \zeta_{t}t} \tag{19}$$

Similarly, the spillover elasticity and the output damage elasticity of initial pest incidence are calculated as:

$$\theta^{z^{r}} = \zeta_{s}z_{it}^{r}\lambda b_{it}^{r}\, e^{-\zeta_{p}z_{it} - \zeta_{s}z_{it}^{r} - \zeta_{t}t} \tag{20}$$

and

$$\theta^{b^{r}} = -\lambda b_{it}^{r}\, e^{-\zeta_{p}z_{it} - \zeta_{s}z_{it}^{r} - \zeta_{t}t} \tag{21}$$

respectively. Finally, the rate of abatement effectiveness is measured as:

$$T_{t}^{\phi} = \zeta_{T}t\lambda b_{it}^{r}\, e^{-\zeta_{p}z_{it} - \zeta_{s}z_{it}^{r} - \zeta_{T}t} \tag{22}$$

Then the above relations are used to decompose of TFP changes using (7).

4. Data and Empirical Results

Data

The data for this study are taken from the Greek National Agricultural Research Foundation (NAgReF) and refer to 60 olive-growing farms in the island of Crete, during the period 1999-2003. The dataset contain information on production volumes and input expenses as well as pesticides application against olive-fruit fly *Bactrocera oleae* (*Gmellin*). Pest population was measured using chemical traps installed in every $500m^2$ of farm's plots. The number of flies captured in the traps was used to extrapolate the whole pest population in each plot. Farms were located in the same geographical area in the western part of the island specialized in olive-tree cultivation. In addition, the dataset contains several farm-specific information including demographic characteristics, environmental conditions and extension services provision.

One output and four inputs are considered. Output is measured as total olive-oil production measured in kgs. The inputs considered are *labour* (including family and hired workers) measured in hours, *land* measured in stremmas (one stremma equals 0.1 ha) and, *other costs*, consisting of fuel and electric power, fertilizers, storage, and irrigation water, measured in euros. The damage abatement input includes *pesticide materials* measured in litres. The pesticide spillover variable was constructed by aggregating pesticide application by each farm's neighbors. Following suggestions from the local Agricultural Experimental Stations' agronomists, we define neighboring farms as those located in the same small area with similar micro-climatic conditions that affect pest population and its biological cycle. All variables measured in money terms have been converted into 2003 constant values. Further, in order to avoid problems associated with units of measurement, all variables included in (13) were converted into indices. The basis for normalization was the farm with the smallest deviation of its output and input levels from the sample means.

In the inefficiency effect function we include the following variables which are assumed to affect efficiency differentials: farm owner's *education*, measured in years of schooling, the *family size* measured as the number of persons in the household, an *aridity index* defined as the ratio of the average annual temperature in the region over the total annual precipitation (Stallings, 1960), the *altitude* of farms' location measured in meters, and the number of *extension visits* in the farm. Summary statistics of the variables used in the empirical model are given in Table 1.

Empirical Results

The ML estimates of the generalized Cobb-Douglas stochastic production frontier are presented in Table 2. All the estimated parameters of the conventional inputs and of pesticides have the anticipated magnitude and sign and the majority of them are statistically different than zero at the 5% level of significance. As a result concavity of the production function with respect to both conventional and preventive inputs is satisfied at the point of approximation (*i.e.*, the sample means). This means that the marginal product of both conventional and damage control inputs are positive and diminishing. Thus, although our model specification allows for the presence of increasing marginal returns to pesticides, the data does not support that finding. Average values of the estimated output elasticities and marginal products are given in Table 4.

The ratio-parameter, γ, is positive and statistically significant at the 1% level of significance, indicating that the technical inefficiency is likely to have an important effect in explaining output variability among farms in the sample. According to the estimated variances, output variability is mainly due to technical inefficiency rather than statistical noise. We further examined this finding using conventional likelihood ratio test and the results are presented in Table 3.[11] *First*, the null hypothesis that $\gamma = \delta_0 = \delta_T = \delta_{TT} = 0$ is rejected at the 5% level of significance indicating that the technical inefficiency effects are in fact stochastic and present in the model.

Moreover, Schmidt and Lin's test for the skewness of the composed error term also confirms the existence of technical inefficiency.[12] *Second*, the hypotheses that there are no autonomous changes in technical inefficiency over time $\left(i.e.,\ \delta_T = \delta_{TT} = 0\right)$, or that individual characteristics do not affect technical inefficiency $\left(i.e.,\ \delta_s = 0\ \forall s\right)$ are also rejected at the 5% level of significance. This is also true when both hypotheses are examined jointly $\left(i.e.,\ \delta_s = \delta_T = \delta_{TT} = 0\ \forall s\right)$.

Mean technical efficiency is found to be 74.76% during the period 1999-03 implying that olive-oil produce could have been increased substantially if farmers' performance was improved (see Table 5). Specifically, a 25.24% increase in olive-oil production could have been achieved during this period, without altering total input use. The 50% of the farms in the sample achieved scores of technical efficiency between 70-80% and the portion of farms with technical efficiency scores below 70% consistently decreased over time. With exception of 2001, technical efficiency ratings followed an increasing pattern over time as mean efficiency scores raised from 72.46% in 1999 to 77.82% in 2003. This means technical efficiency changes have positively contributed to TFP growth.

With the exception of altitude, the farm-specific characteristics considered have had a statistically significant effect on technical efficiency. In particular, it is found that education leads to better utilisation of given inputs as it enables farmers to use technical information more efficiently. Extension services seem also to improve farmers' managerial ability to affect the efficient utilization of existing technologies by improving their know-how (Birkhaeuser, Evenson and Feder). Family size tends to result in higher efficiency due to stronger incentives by rural household members. On the other hand, adverse environmental conditions as proxied with the aridity index seem to affect negatively individual efficiency levels.

The next set of hypotheses testing concerns with returns to scale and technical change (see middle panel in Table 3). In particular, the hypothesis of constant returns to scale $\left(i.e., \sum \beta_j = 1, \sum \beta_{jT} = 0 \ \forall j, \ \zeta_P = 0\right)$ is rejected at the 5% level of significance. For the whole period under consideration returns to scale were found to be decreasing. There may be two reasons underlying this finding: either a 'safety-first' consideration for obtaining a subsistence level of family income and/or the presence of production-based subsidies may have encouraged farmers to operate at a supra-optimal scale. In any case, the scale effect is present and constitutes a source of TFP growth in this study case. On the other hand, the hypothesis of no technical change $\left(i.e., \beta_T = \beta_{TT} = \beta_{jT} = 0 \ \forall j\right)$ as well as that of Hicks-neutral technical change $\left(i.e., \beta_{jT} = 0 \ \forall j\right)$ are both rejected at the 5% significance level (see Table 3) and thus technical change has also been an important source of TFP. The average annual rate of technical change is estimated at 1.21%. Regarding technological biases, technical change is found to be labor- and other costs-saving and land-neutral as the relevant estimated parameter was found to be statistically insignificant.

The estimated parameters of the damage and control functions, reported in Table 2, have the anticipated signs and are statistically significant. Based on these, the hypothesis of zero marginal effectiveness of abatement $\left(i.e., \zeta_P = \zeta_S = \zeta_t = 0\right)$ is rejected at the 5% level of significance (see Table 3). On the other hand, both the hypotheses of a zero spillover effect and of an unchanged abatement effectiveness $\left(i.e., \zeta_S = 0 \text{ and } \zeta_t = 0\right)$ are also rejected (see Table 3). Thus pesticides had a positive contribution to damage abatement, with the impact from own use to be much greater than that of the neighboring farms (see Table 4 for the average estimated values of these impacts in elasticity form). The positive estimated parameter of the spillover variable indicates however some (even though small) synergies in pesticides use. In addition, there are evidence of improvements in abatement effectives as the relevant estimated parameter (ς_T) is found to be positive and statistically significant. All these advocate the presence of the damage control effect and its potential role in TFP changes.

The empirical results concerning the decomposition of TFP changes based on (7) are reported in Table 6. The average annual rate of TFP growth is estimated at 1.58%. The vast portion (95%) of TFP changes is attributed to the conventional sources of growth (namely, technical change, scale effect, and technical efficiency changes) and the remaining 5% to the damage control effect. Even though the damage control effect is relatively small compared to the conventional sources of growth it cannot be neglected by any means as the aforementioned hypotheses testing indicated.

Among the conventional sources of TFP growth, technical change is found to be the most important as it accounted for 76.7% of TFP growth. As it can be seen from Table 6, the neutral component of technical change is its driven force. On the other hand, the scale effect is negative due to the presence of decreasing returns to scale and increasing aggregate input. The growth of the aggregate input is mainly due to the growth of the conventional inputs as pesticides used had decreased in the period under consideration. However, neither the weight (i.e., output elasticity) nor the decrease in pesticides use was enough to outweigh the growth in conventional inputs and thus the scale effect had a negative impact on TFP growth. Technical efficiency changes were the second most important source of TFP growth after technical change and it accounted for 30.8% of TFP growth. The positive technical efficiency changes effect indicates movements toward the frontier over time. As it can been seen from Table 6, all time varying farm-specific characteristics as well as the passage of time have contributed positively to technical efficiency changes and thus to TFP growth.

Abatement effectiveness is by far the most important source of growth among the components of the damage control effect. The estimated average annual rate of abatement effectiveness of 1.48% has contributed 0.084 points of the 1.58% annual growth of TFP, which accounts for 5.3% of its annual growth rate. On the other hand, both the pest population and the spillover effect had a negative impact to TFP growth due perhaps to favorable conditions for pest reproduction and decreased pesticides application by all farmers, respectively. Even though the existence of these two components of the damage control effect cannot be challenged in statistical grounds (see Table 3), their combined impact on TFP growth is rather marginal. In particular, they accounted together for only -0.3% of annual TFP growth.

Finally, the overall contribution of pesticides to TFP growth is estimated at 5.5%. This represents the sum of the damage control effect and the proportion of the scale effect associated with pesticides use. The latter has a positive impact on TFP growth as pesticides use was declined under decreasing returns to scale. This implies that increases in the use of pesticides, even when are effective in killing pests, would not result in TFP gains if farm size is greater than that maximizing ray average productivity. In addition, the proportion of the scale effect associated with pesticides use more that offset the negative impact of the pest population and the spillover effects.

5. Concluding Remarks

This paper develops a theoretical framework for decomposing TFP growth by taking explicitly into consideration the indirect impact that pesticides have on farm output.

Recognizing the damage control nature of pesticides may correct some biases in the measurement and decomposition of TFP related to the overestimated output elasticity of pesticides when it is modelled as an output expanding input. In the proposed framework, TFP changes are decomposed into the effects of technical change, scale economies, changes in technical efficiency and the damage control effect. The latter consists of three distinct elements: that due to changes in the level of initial pest infestation, the spillover effect arising from neighbours' use of pesticides, and the effect associated with changes in abatement effectiveness.

The model is applied to a panel of olive-growing farms in Crete, Greek during the 1999-03 period. The empirical results suggest that technical change was the main source of TFP growth, following by the effect of technical efficiency changes. The damage control effect, on the other hand, accounted for a small portion (5%) of TFP growth. The small contribution of the damage control effect may be specific to the peculiarities of olive-tree cultivation and definitely does not imply that it can be neglected without making any difference. To properly decompose the sources of TFP changes we should explicitly consider the preventive nature of pesticides and thus account for the damage control effect, regardless of its magnitude in each study case.

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Table 1. Summary Statistics of the Variables.

Variable	Average	Max	Min	StDev
Output (in kgs)	18758.7	2049.7	71789	13924.5
Land (in stremmas)	8.7	1.2	66	7.5
Labour (in hours)	2867.0	437.0	12320	1912.6
Other cost (in euros)	3407.8	74.3	22249	2298.0
Pesticides (in liters)	1833.7	71.0	9604	1493.7
Spillover (in liters)	5487.0	974.0	16339	3023.3
Family Size (no of persons)	4.0	1.0	9	1.4
Altitude (in meters)	276.2	1.0	995	270.6
Aridity index	1.03	0.03	3.52	0.78
Extension Visits (no of visits)	5.8	0.0	26	5.2
Pest Population (in pests per m^2)	15.7	0.1	54.2	14.6
Education (in years)	7.1	1.0	16	3.8

Table 2. Parameter Estimates of the Generalized Cobb-Douglas Stochastic Production Frontier.

Variable	Estimate	Std Error
Production Frontier		
β_0	-0.0313	(0.0751)
β_A	0.3355	$(0.0401)^{*}$
β_L	0.3109	$(0.0408)^{*}$
β_C	0.2134	$(0.0355)^{*}$
β_T	0.2067	$(0.1032)^{**}$
β_{TT}	-0.2026	(0.1237)
β_{TA}	0.0552	(0.0673)
β_{TL}	-0.1259	$(0.0704)^{**}$
β_{TC}	-0.0799	$(0.0521)^{**}$
λ	-0.0410	$(0.0175)^{**}$
ζ_P	0.8602	$(0.2135)^{*}$
ζ_S	0.0085	$(0.0039)^{**}$
ζ_T	0.0148	$(0.0052)^{*}$
Inefficiency Effects Model		
δ_0	-0.1749	(0.7111)
δ_{FAM}	-0.5433	$(0.2447)^{**}$
δ_{ALT}	0.0027	(0.0757)
δ_{ARD}	0.7554	$(0.3482)^{**}$
δ_{EXT}	-0.5522	$(0.2368)^{**}$
δ_{EDU}	-0.3602	$(0.1362)^{*}$
δ_T	-0.2258	$(0.1087)^{*}$
δ_{TT}	0.3459	(0.2855)
γ	0.9105	$(0.0507)^{*}$
σ^2	0.6368	$(0.2366)^{*}$

where *A* stands for area, *L* for labor, *C* for other cost, *T* for time, *B* for pest population, *P* for pesticides, *S* for spillovers, *FAM* for family size, *ALT* for altitude, *ARD* for the aridity index, *EXT* for the number of extension visits and, *EDU* for farmer's education level.

$^{*\,(**)}$ indicate statistical significance at the 1 (5) per cent level.

Table 3. Model Specification Tests.

Hypothesis	LR-statistic	Critical Value (α=0.05)
Technical Efficiency:		
Technical efficiency $\left(i.e.,\ \gamma=\delta_0=\delta_T=\delta_{TT}=0\right)^1$	35.14	$\chi^2_{(4)}=8.76$
No autonomous changes in efficiency $\left(i.e.,\ \delta_T=\delta_{TT}=0\right)$	21.48	$\chi^2_{(2)}=5.99$
No-individual farm effects $\left(i.e.,\ \delta_j=0\ \forall j\right)$	28.41	$\chi^2_{(5)}=11.07$
Time invariant efficiency $\left(i.e.,\ \delta_T=\delta_{TT}=\delta_j=0\ \forall j\right)$	36.87	$\chi^2_{(7)}=14.07$
Structure of Production:		
CRTS $\left(i.e.,\ \sum_j \beta_j=1,\ \sum_j \beta_{jT}=0\ \forall j,\ \zeta_P=0\right)$	41.03	$\chi^2_{(3)}=7.82$
No technical change $\left(i.e.,\ \beta_T=\beta_{TT}=\beta_{jT}=0\ \forall j\right)$	40.23	$\chi^2_{(6)}=12.59$
Hicks-neutral technical change $\left(i.e.,\ \beta_{jT}=0\ \forall j\right)$	24.15	$\chi^2_{(4)}=9.49$
Abatement Activities:		
Zero spillover effects $\left(i.e.,\ \zeta_S=0\right)$	4.97	$\chi^2_{(1)}=3.84$
Unchanged abatement effectiveness $\left(i.e.,\ \zeta_t=0\right)$	5.02	$\chi^2_{(1)}=3.84$
Zero marginal effectiveness of abatement activities $\left(i.e.,\ \zeta_P=\zeta_S=\zeta_t=0\right)$	38.54	$\chi^2_{(3)}=7.82$

[1] In this case, the asymptotic distribution of the LR-ratio test is a mixed chi-square and the appropriate critical values are obtained from Kodde and Palm (1986).

Table 4. Output Elasticities, Returns to Scale (RTS) and Marginal Products of Conventional Inputs and Pesticides.

	1999	2000	2001	2002	2003	Mean
Output Elasticities						
Land	0.4738	0.3866	0.3355	0.2993	0.2712	0.3533
Labour	0.4492	0.3619	0.3109	0.2746	0.2465	0.3286
Other cost	0.3011	0.2458	0.2134	0.1904	0.1726	0.2247
Pesticides	0.0186	0.0115	0.0053	0.0176	0.0225	0.0151
RTS	1.2428	1.0057	0.8650	0.7819	0.7128	0.9217
Pest population	-0.0108	-0.0067	-0.0031	-0.0102	-0.0131	-0.0088
Pesticides Spillover	0.0018	0.0011	0.0005	0.0017	0.0022	0.0015
Marginal Products						
Land (euros/stremma)	135.7	104.8	65.9	94.9	55.9	91.4
Labour (euros/hour)	3.4873	3.9777	3.4174	1.5160	1.3191	2.7435
Capital (euros/euro)	2.0294	1.8410	1.3889	1.0669	1.4406	1.5534
Pesticides (euros/liter)	0.2206	0.1097	0.1654	0.2776	0.2591	0.2065

Table 5. Frequency Distribution of Technical Efficiency Ratings of Olive-Farms in Greece, 1999-03.

TE (%)	1999	2000	2001	2002	2003	1999-03
0-10	0	0	0	0	0	0
10-20	0	0	1	0	0	0
20-30	0	2	1	0	0	0
30-40	4	2	7	2	2	0
40-50	1	1	0	4	2	0
50-60	6	6	1	1	5	2
60-70	12	6	9	8	3	13
70-80	12	9	16	12	12	31
80-90	20	30	20	27	31	14
90-100	5	4	5	6	5	0
Mean	72.46	74.81	71.69	76.99	77.82	74.76
Min	30.97	22.12	17.98	34.44	33.60	53.69
Max	93.84	94.12	92.00	93.77	94.24	86.57

Table 6. Decomposition of TFP Growth of Olive Farms in Greece, 1999-03.

	(%)	
TFP Growth	1.5777	(100.0)
Technical Change:	1.2109	(76.7)
Neutral	0.9413	(59.7)
Biased	0.2696	(17.1)
Scale Effect:	-0.1988	(-12.6)
Conventional Inputs	-0.2060	(-13.1)
Pesticides	0.0072	(0.5)
Technical Efficiency Change Effect:	0.4865	(30.8)
Autonomous Changes	0.2330	(14.8)
Aridity Index	0.1308	(8.3)
Extension Services	0.1227	(7.8)
Damage-Control Effect:	0.0791	(5.0)
Abatement Effectiveness Effect	0.0839	(5.3)
Initial Infestation Effect	-0.0045	(-0.3)
Spillover Effect	-0.0003	(-0.0)

Notes: 1. values in parentheses are the corresponding percentages.

2. The time invariant farm-specific characteristics are not taken into account in the technical efficiency change effect

Endnotes

[1] Nevertheless Hennessy noticed that even in this case the omission of the initial pest population results in an identification problem as low realized farm output may be due either to a high level of initial pest density or to a low level of pesticide use.

[2] Underwood and Caputo, using a dynamic farm model found that the effects of farm programs (*i.e.*, land set aside, decoupled payments) and pesticide taxes depend crucial on the returns to scale of the output abatement function.

[3] Even with the general assumption that the marginal damage effect of damage agent is non-negative $\partial g/\partial b \geq 0$, the sign of $\partial g^2/\partial^2 b$ is underdetermined. Nevertheless, the damage function is often assumed concave.

[4] In the empirical model we have also tried the interactive specification of Saha, Shumway and Havenner but it did not work satisfactory.

[5] It is also assumed that pesticides use by farmers in the area does not induce phytotoxicity on-farm.

[6] Chambers and Lichtenberg demonstrated that separability between damage control inputs and conventional inputs implies conditional additivity of profit function. Saha, Shumway and Havenner, statistically examined the existence of separability between partitions of inputs and they found that the hypothesis of weak separability between land, machinery and miscellaneous inputs and damage control input use was maintained. They however reject that hypothesis between fertilizers and pesticides. Since our data do not provide detailed information on fertilizer applications we maintained the weak separability assumption which is common to damage control econometrics.

[7] Notice however that time invariant farm-specific characteristics have no impact on TFP growth.

[8] It is also zero in stationary pest populations.

[9] We have tried to estimate a more flexible translog production frontier but the econometric estimates provided a poor fit of the underlined production technology with the current dataset.

[10] Alternatively, as suggested by Lichtenberg and Zilberman, one can estimate the model with an iterative procedure over the values of λ described by Greene (p. 475).

[11] Generalized likelihood-ratio test statistic is computed: $\lambda = -2\left\{ln\,L\left(H_0\right) - ln\,L\left(H_1\right)\right\}$, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively

[12] The test-statistic computed as $\sqrt{b_1} = m_3 / m_2^{3/2}$ (with m_3 and m_2 being the third and second moments of the residuals and b_1 the coefficient of skewness) is 2.124, well above the corresponding critical value at the 5% level of significance (0.298).