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On the estimation of damage reducing functions

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Abstract

The aim of the paper is to analyze the use of pesticides in multicrops farms. To this end, we propose a framework to estimate damage reducing functions based on an extension of the Lichtenberg-Zilberman specification to a vector output. The estimation provides useful insights for farmers about the effectiveness of pesticides application among productions at farm level. Besides, from a perspective of pesticides reduction, our analysis may provide guidance for policymakers since it highlights the effective role of pesticides in production processes.

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1. Introduction

Pesticides have been a major contributor to productivity growth in agriculture over the past half-century, along with the selection of high-yielding varieties, the use of fertilizers and the development of irrigation and harvesting technologies. Given that pesticides represent a cost-efficient way to enhance productivity, and reduce the use of more expensive inputs (e.g. labor), we observe an increase in their use, from the beginning of the 1950s to the mid-1980s, regardless of the level of economic development of countries.

The publication of Rachel Carson's Silent Spring (Carson (1962)) dampened this enthusiasm towards pesticides use in agriculture. She introduced the broader public to the risks related to pesticides: negative side effects on public health and wildlife. This publication and the followings (e.g. Rudd (1964)) have raised public awareness of environmental issues and specifically the use of pesticides in agriculture and demand for regulation. Since, governments are increasingly facing the challenge of designing policies to re-orient agricultural production towards safer and sustainable practices. Debates on pesticides regulation policies lead to the functional specification of production technologies issues. Indeed, the production technology provides useful information, specifically the cost of limiting pesticide use in terms of foregone production. The appropriate pesticides modeling in agricultural process has been subject to lively debates in agricultural economics (e.g. Lichtenberg and Zilberman (1986), Carpentier and Weaver (1997)).

This analysis is a contribution to the understanding of pesticides action in agriculture. We propose an extension of the Lichtenberg-Zilberman specification to a vector output and present a framework for the estimation of damage reducing functions in the developed modeling. To our best knowledge, our analysis is the first to study pesticides management in multicrop farms, using primal production function (i.e., without the use of cost function – the dual form of production function – which requires information on the price of all inputs), while accounting for the special nature of pesticides. Indeed, analyses on this topic have been performed on mono-output farms (e.g. Oude Lansink and Carpentier (2001), Zhengfei et al. (2005), Oude Lansink and Silva (2004)). Therefore, our analysis intends to bridge this gap. Results give indication on the way pesticides are used among productions and may be useful both to farmers, and policymakers who aim at reducing the use of pesticides in agriculture. The remainder of the paper is structured as follows. Section 2 presents the model. Our estimation approach is introduced in section 3. Section 4 discusses the data and the results. Section 5 concludes.

2. The model

Lichtenberg and Zilberman (1986) were the first to discuss the special nature of pesticides and to consider it in the production technology specification, introducing the concept of damage reducing function. Indeed, starting from the observation that pesticides are not standard inputs like land and capital (from some agronomic evidences), they propose a new specification of the production technology. We begin with the presentation of their functional specification. Then we show how it could be extended to a vector output.

2.1. The Lichtenberg and Zilberman specification

In Lichtenberg and Zilberman (1986), pesticides are considered as damage reducing rather than productivity increasing inputs. The effect of pesticides on the output is indirect and results from a two-stage process: *i*) the effect of damage control inputs on the damage agent and *ii*) the effect of the remaining damage agent on the output. The Lichtenberg-Zilberman general specification is as follows:

$$y = f[\mathbf{x}, g(z,r)] \tag{1}$$

where $\mathbf{x}$ is a vector of M inputs, y the observed output and f the production function. The damage reducing function (g) depends on the level of pesticides (z) and pest pressure (r), and lies between 0 and 1. Note also that g is increasing with the level of pesticides and decreasing with the pest pressure.

As explained in Lichtenberg and Zilberman (1986) (page 264), the specification in Equation (1) may take a simple linear form:

$$y = f(\mathbf{x})g(\mathbf{z}, \mathbf{r}) \tag{2}$$

where $f(\mathbf{x})$ is the potential output. g represents the percentage of potential output obtained under pest presence, with pesticides application.

Like many studies (e.g. Zhengfei et al. (2006), page 206; Zhengfei et al. (2005), page 170, Oude Lansink and Carpentier (2001), page 13), we consider the latter specification and refer to it as the Lichtenberg-Zilberman specification. Equation (2) can be rewritten as:

$$y\eta(z,r) = y^{max} = f(\mathbf{x}) \text{ with } 1 \leq \eta(z,r) = 1/g(z,r) < \infty \tag{3}$$

where y^{max} is the potential output, i.e. the maximum output from the use of standard inputs (without pests and pesticides).

2.2. The multi-output specification

Since the Lichtenberg-Zilberman specification is a mono-output one, it fails to analyze production processes of multicrop farms. Indeed most farms produce several products in the same time period and deserve to be analyzed taking into account the specificity of pesticides. To this end, we propose a new specification that accounts for the special nature of pesticides and handles the multicrop production of farms. Let us start by the production technology:

$$q(\mathbf{y}, r, z) = f(\mathbf{x}) \tag{4}$$

$\mathbf{y}$ is the observed vector of S outputs. Recall that observed level of outputs at the farm level are obtained through the application of a certain level of pesticides z. The production technology specification can therefore be rewritten to highlight the effect of pesticides as follows for the s^{th} output:

$$y_s = y_s^{max}\delta_s(z,r) \Longleftrightarrow y_s^{max} = y_s\phi_s(z,r) \tag{5}$$

where y_s^{max} is the maximum (potential) level of output and y_s the observed one. Note that applying pesticides enables as in the Lichtenberg-Zilberman mono-output framework to protect the maximum potential output that is from the use of standard inputs. Therefore the damage reducing function δ lies between 0 and 1 and ϕ, its inverse, between 1 and infinite.

Starting from this extension of the Lichtenberg-Zilberman specification to a vector output, our objective is to estimate among productions damage reducing functions at the farm level to give insights about the effectiveness of pesticides use to both farmers and policy-makers. Note that since we opt not to constrain ϕ, choosing a functional form, we are only interested in its estimated value, which lies between 1 and infinite. Keeping this information in mind, we assume in the remainder of the analysis that ϕ can be considered as a parameter (to be estimated) which value is in the above-mentioned range.

3. The estimation

We present in this section the framework for the estimation of damage reducing functions using our extension of the Lichtenberg-Zilberman specification. The strategy followed involves the estimation of technology frontiers and associated technical efficiencies. For such estimations, two main techniques are available: Data Envelopment Analysis (DEA, see Charnes et al. (1978)) and Stochastic Frontier Analysis (SFA, see Kumbhakar and Lovell (2000)). DEA uses mathematical programming to construct a surface that envelops the observations as tightly as possible, deriving thereby a technology frontier, whereas SFA uses econometric approach that involves the use of an arbitrary functional form to approximate the unknown technology frontier. We employ in our analysis an envelopment method (DEA) rather than an econometric approach (SFA) for two main reasons. First DEA does not rely on the choice of an arbitrary functional form to estimate the production technology, though the assumption that there is no random error might be seen as a drawback.[1] Second, the DEA method unlike the SFA's, handles quite easily multi-output production technology estimation. We begin with the presentation of frontiers estimation in multi-outputs setting using DEA. Then we show how to adapt this method to estimate damage reducing functions.

3.1. The standard multi-output DEA

Let us consider a set of n farms using a common technology that transforms M inputs ($\mathbf{x}$) into S observed outputs ($\mathbf{y}$). The farms production technology is represented by the following closed, nonempty set:

$$T = \{(\mathbf{x}, \mathbf{y}) : \mathbf{x} \text{ can produce } \mathbf{y}\} \tag{6}$$

which may be fully described in terms of its sections i.e., the production possibility set:

$$P^T = \left\{\mathbf{y} \in \mathbb{R}_+^S : (\mathbf{x}, \mathbf{y}) \in T\right\} \tag{7}$$

[1] Since there as there are no measurement errors in DEA, the whole deviation from the estimated frontier of the production technology is considered as inefficiency.

If free disposability of inputs and outputs, convexity and variable returns to scale are assumed to hold, the production possibility set $P^{\hat{T}}(\mathbf{x})$ can be estimated using DEA:

$$P^{\hat{T}}(\mathbf{x}) = \left\{ \mathbf{y} : \sum_{i=1}^{n} \lambda_i \mathbf{y}_i \geq \mathbf{y}; \sum_{i=1}^{n} \lambda_i \mathbf{x}_i \leq \mathbf{x}; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i \geq 0 \right\} \tag{8}$$

where $\mathbf{y}_i$ is the observed output levels of farm i and $\mathbf{x}_i$ the vector of inputs used by farm i. λ is a $(n \times 1)$ vector of intensity variables (farm weights).

Figure 1 shows the DEA frontier of the production possibility set in the two-output case. Points a, b, c, d, e, f, g, h and u represent the various output combinations that could be produced using a given input level. Farms that lie on the frontier are technically efficient and those located in the interior of the frontier are technically inefficient (see Zhengfei and Oude Lansink (2003), pages 468-469 and Simar and Wilson (2007), page 34.).

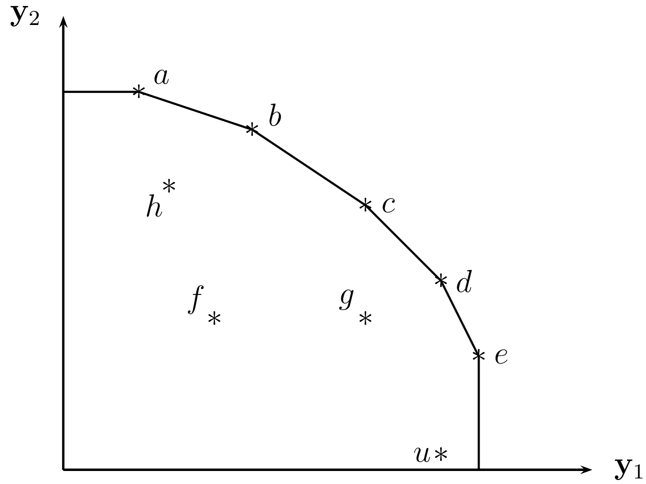

Figure 1: The DEA production possibility set

Note that technical efficiency scores resulting from the DEA estimation of the production possibility set depend on the objective of the farm under evaluation. These objectives are represented by projection direction choices. Directional distance functions (Chambers et al. (1998)) allow doing such evaluations. The general form of these distance functions, relatively to the estimated production possibility set ($P^{\hat{T}}$), is given by:

$$\overrightarrow{D}(\mathbf{x}, \mathbf{y}, g_{\mathbf{x}}, g_{\mathbf{y}}) = \sup \left\{ (\mathbf{x} - \theta g_{\mathbf{x}}, \mathbf{y} + \theta g_{\mathbf{y}}) \in P^{\hat{T}} \right\} \tag{9}$$

For example, if the evaluation is performed in the direction of y_1 ($g_{\mathbf{x}=0}$, $g_{y_1} = \theta$, $g_{\mathbf{y}_{s \neq 1}} = 0$), the technical efficiency is approximated for the farm "0", under the assumptions of free disposability of inputs, convexity and variable returns to scale, by the following linear programming:

$$\hat{\theta_T} = \arg\max_{\{\lambda,\theta\}} \Bigg\{ \theta : \sum_{i=1}^{n} \lambda_i y_{s,i} \geq y_{s,0}; \sum_{i=1}^{n} \lambda_i x_{m,i} \leq x_{m,0};$$
$$\sum_{i=1}^{n} \lambda_i y_{1,i} \geq \theta y_{1,0}; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i \geq 0; s = 2, ..., S; m = 1, ..., M \Bigg\} \quad (10)$$

Figure 2 depicts this evaluation in the two-output case. The technical efficiency of the farm h is given by the ratio oj/oh. This ratio gives an idea of the maximum feasible expansion of the output y_1 that can be produced with the input vector $\mathbf{x}$, while keeping the second output superior or equal to y_2.

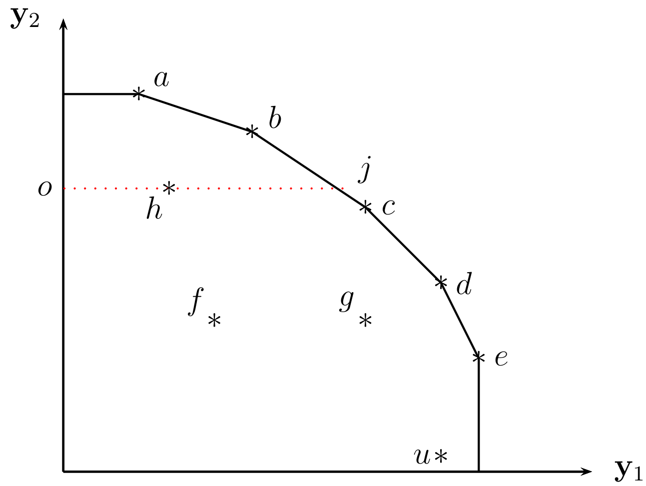

Figure 2: The technical efficiency estimation

3.2. The estimation of damage reducing functions

We set up the DEA methodology on our extension of the Lichtenberg-Zilberman specification. It leads to the following (non-observed) output possibility set:

$$P_G^{\hat{T}}(\mathbf{x}) = \left\{ \mathbf{y}^{max} : \sum_{i=1}^{n} \lambda_i \mathbf{y}_i^{max} \geq \mathbf{y}^{max}; \sum_{i=1}^{n} \lambda_i \mathbf{x}_i \leq \mathbf{x}; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i \geq 0 \right\} \quad (11)$$

Figure 3 shows the DEA frontier - dashed green line - of the production possibility set in the two-output case. The dotted red line represents the frontier of the standard production possibility set (the starting framework). The following relation exists between these two sets: $P^{\hat{T}} \subseteq P_G^{\hat{T}}$.

This example of production possibility set considers the various possible situations. Farms a, g and e have unit damage reducing functions on the two outputs considered. Farms b, c and d have small damage reducing functions on the two outputs, and farms i, f, and h have different damage reducing functions on the two outputs.

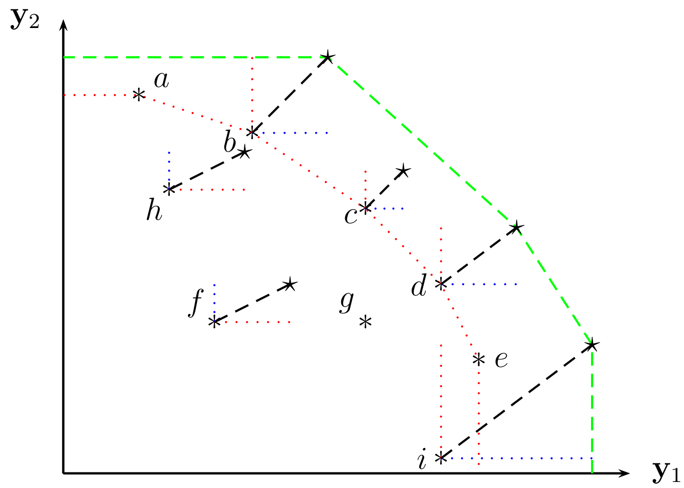

Figure 3: The DEA production possibility set (with our specification)

Farms' evaluation is performed relatively to the DEA estimation of the production possibility set $P_G^{\hat{T}}$. As seen above, applying ϕ changes the relative position of farms and the production possibility set. For instance farm b moves from its previous position to b' (Figure 4). If we still consider that the evaluation is performed in the direction of y_1^{max} ($g_{\mathbf{x}=0}$, $g_{y_1^{max}} = \theta'$, $g_{\mathbf{y}_{s\neq 1}^{max}} = 0$), the technical efficiency for the farm "0", with standard assumptions, is approximated by:

$$\hat{\theta_G} = \underset{\{\lambda,\theta'\}}{\arg\max} \left\{ \theta' : \sum_{i=1}^{n} \lambda_i y_{s,i}^{max} \geq y_{s,0}^{max}; \sum_{i=1}^{n} \lambda_i x_{m,i} \leq x_{m,0}; \right.$$
$$\left. \sum_{i=1}^{n} \lambda_i y_{1,i}^{max} \geq \theta' y_{1,0}^{max}; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i \geq 0; s = 2, ..., S; m = 1, ..., M \right\} \quad (12)$$

Let us consider now the evaluation of the farm b relatively to the estimated frontier $P_G^{\hat{T}}$, in the direction of y_1^{max}. This evaluation results from the following programming:

$$\hat{\theta}_{G-up} = \underset{\{\lambda,\theta''\}}{\arg\max} \left\{ \theta'' : \sum_{i=1}^{n} \lambda_i y_{s,i}^{max} \geq y_{s,b}; \sum_{i=1}^{n} \lambda_i x_{m,i} \leq x_{m,b}; \right.$$
$$\left. \sum_{i=1}^{n} \lambda_i y_{1,i}^{max} \geq \theta'' y_{1,b}; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i \geq 0; s = 2, ..., S; m = 1, ..., M \right\} \quad (13)$$

From this estimation, we obtain bj. This distance is the upper bound estimation of $\phi_{1,b}$ (associated to $y_{1,b}$), which exact value is the distance bv. Figure 4 illustrates this observation. The same method is applied on $y_{2,b}$ to estimate the upper bound of $\phi_{2,b}$.

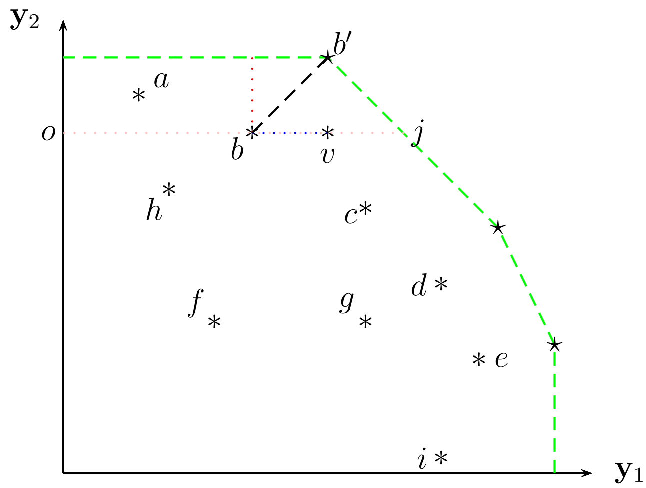

Figure 4: The upper boundary estimation

The estimation process could be refined to approach the "exact" value of ϕ. To see how, let us consider the evaluation of farms relatively to the frontier $P_{G'}^{\hat{T}}$ in dashed black (see figure 5, left graph).

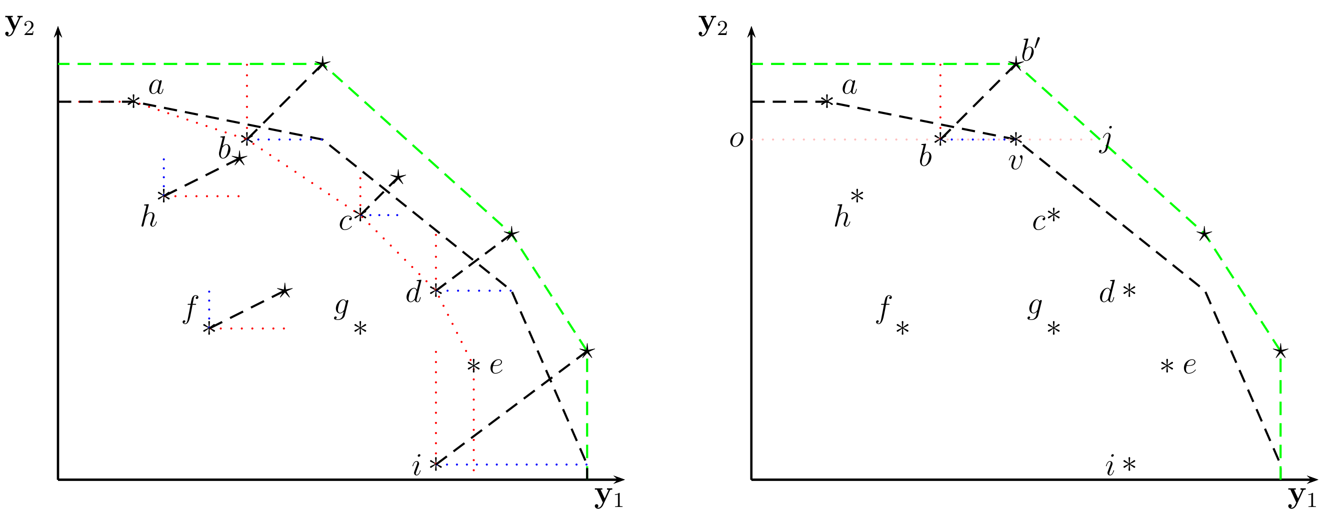

Figure 5: The upper boundary estimation, refinement

This production possibility frontier is elaborated focusing only on the output y_1 and the function ϕ_1. In other words, the frontier is constructed considering only the first output as potential output. The second is the observed one. We can note that the evaluation of the farm b relatively to the new frontier, enables us to estimate the function $\phi_{1,b}$ exactly. For some farms (see the observation c for example), we have improved their previous estimation of $\phi_{1,i}$ (but it still remains an estimation of the upper bound). At the whole, this estimation process, compared to the previous one, improves our knowledge about ϕ_1. The new estimation of ϕ_1 comes from the following programming:

$$\hat{\theta}_{G'-up} = \arg\max_{\{\lambda,\theta^*\}} \left\{ \theta^* : \sum_{i=1}^{n} \lambda_i y_{s,i} \geq y_{s,0}; \sum_{i=1}^{n} \lambda_i x_{m,i} \leq x_{m,0} \right.$$
$$\left. ; \sum_{i=1}^{n} \lambda_i y_{1,i}^{max} \geq \theta^* y_{1,0}; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i \geq 0; s = 2, ..., S; m = 1, ..., M \right\} \quad (14)$$

The problem with the programming in (14) is its nonlinearity (note that $\lambda y_1^{max} = \lambda \phi_1 y_1$). Both the damage reducing function (ϕ_1) and the intensity weights (λ) are variable. Consequently standard linear approximation models are not helpful. To perform this estimation, it has to be linearized. Following Kuosmanen (2005), we consider: $\lambda_i = \mu_i + \pi_i$, with $\mu_i = \phi_{1,i}\lambda_i$ and $\pi_i = (1 - \phi_{1,i})\lambda_i$. The upper boundary of $\phi_{1,i}$ can be retrieved using the following expression: $\phi_{1,i} = \mu_i/(\mu_i + \pi_i)$.

Using this decomposition, the nonlinear programming in (14) can be rewritten as follows:

$$\hat{\theta}_{G'-up} = \arg\max_{\{\lambda,\theta^*\}} \left\{ \theta^* : \sum_{i=1}^{n} (\mu_i + \pi_i) y_{s,i} \geq y_{s,0}; \sum_{i=1}^{n} (\pi_i + \mu_i) x_{m,i} \leq x_{m,0} \right.$$
$$\left. ; \sum_{i=1}^{n} \mu_i y_{1,i} \geq \theta^* y_{1,0}; \sum_{i=1}^{n} (\mu_i + \pi_i) = 1; \mu_i, \pi_i \geq 0; s = 2, ..., S; m = 1, ..., M \right\} \quad (15)$$

This linear programming is then used to estimate the function ϕ_1. The same process is followed for the second output, and can be generalized to S outputs.

To improve a step further the estimation results and to avoid the outliers bias, we use a sub-sampling method. To this end, for the evaluation of each farm and each direction, we randomly generate 1,000 subsets. Each of them consists of 90% of the whole sample farms drawn randomly, without replacement. Therefore, for a given farm and evaluation direction $y_{1,s}$, we get 1,000 estimations of technical efficiency (and therefore 1,000 estimations of $\phi_{1,s}$). We consider the minimum value obtained as the estimation in this direction of the function ϕ_s. This methodology enables us to converge towards the "exact" $\phi_{1,s}$.

To clearly understand how estimations are improved, let us focus on the farm c (see Figure 5) and assume that the evaluation direction is y_1. Several subsets of the starting sample (with 9 farms: from farm a to i) can be formed. Let us consider two for illustrative purpose: (a, b, d, e, g, h, i, c), (a, c, d, e, f, h, i, g). If we consider the subsample without the farm b, we could observe that the dashed "black" production frontier will pass through the point represented by its observed first output $y_{1,c}$ times ϕ_1. With this new production possibility set, we are able to estimate the function $\phi_{1,c}$ associated to c exactly. By contrast, the subsample with the farm b will produce an upper boundary estimations of $\phi_{1,c}$ (its production possibility set will remain the green one in Figure 5). Therefore, if we want the exact estimation of this damage reducing function, we should take the minimum value from subsets.

Note that in the subset generation, our method looks like standard subsampling method (see Politis et al. (1999), chapter 2). They differ in the way the final estimate is computed (average versus minimum).

4. Data and results

The data used in the present analysis come from the POPSY (Arable Crop Production, Environment and Regulation) project database. It is made up of crop farms in the Eure-et-Loir *département* in France in 2005. After cleaning for missing and inconsistent values, a sample of 188 arable farms is used. Four inputs and three outputs characterize the production technology. The variable "Land" represents the Utilized Agricultural Area of each farm, expressed in hectares. The variable "Labor" is given in Annual Work Units (aggregation of family and hired labor). The variable "Intermediate consumption" (I.C.) represents the operational costs. Finally, the variable "Depreciation" (Dep.) approximates the level of mechanization and equipment of farms. The three outputs considered are "cereal crops", "industrial crops", and "other crops" (vegetables, fruits, etc.). Descriptive statistics of these variables used to estimate the production possibility set and damage reduction functions are in Table 1.

Table 1: Descriptive statistics of DEA variables

	Labor	Land	Dep.	I.C.	Cereal	Industrial	Other
Min.	0.5000	36.63	3,144.6	16,620	19,196	5.0	40.0
Qrt.1	1.0000	100.34	20,204.8	42,854	51,097.5	19,293	5,420.3
Qrt.2	1.0000	130.99	30,682.2	63,726	69,673.5	34,166	16,267
Qrt.3	2.0000	169.37	40,670.7	84,216.3	93,974	62,577	34,922.8
Mean	1.3527	138.56	31,818.8	67,511.4	74,609.9	45,194.06	24,174.9
Max.	3.3000	328.61	72,184.7	187,501	192,840	195,852	126,993
Std	0.5438	51.89	15,556.5	29,890.2	31,098.4	35,428.58	25,506.1

Since we have three directions (three outputs), three estimations are performed for each farm to get $\phi_{1,i}$, $\phi_{2,i}$ and $\phi_{3,i}$. We implemented the linear programming in (15) and its refinement through sub-sampling. Table 2 reports the results – without and with sub-sampling – of this estimation.

Table 2: The estimation results (averages)

	ϕ_1	ϕ_2	ϕ_3
Without sub-sampling	1.2302 (0.8129)	1.9439 (0.5144)	2.2743 (0.4397)
With sub-sampling	1.1389 (0.8780)	1.5488 (0.6456)	1.9258 (0.5193)

Results from the linear programming in (15) show us that on average, estimations of ϕ_1, ϕ_2 and ϕ_3 are respectively 1.2302, 1.9439 and 2.2743. Using the sub-sampling method to refine the estimation, the average values fall to 1.1389, 1.5488 and 1.9258 respectively. From these values, we compute the damage reduction functions δ_1, δ_2 and δ_3 (recall that the damage reduction function δ_1 for instance, is the inverse of ϕ_1). Their average values, reported in Table 2 (in brackets, below the $\delta' s$), highlight that the use of pesticide enables farmers to protect the potential level of cereals by 87.80%, industrial production by 64.56% and the other productions by 51.93% on average in Eure-et-Loir.

These results point out two interesting findings. First, the values of damage reducing functions are, on average, different among outputs. More specifically, pesticides management is better in cereal crops compared to industrial and other crops in Eure-et-Loir. Our analysis may therefore be useful to farmers since it provides indications about the effectiveness of pesticides applications among productions at farm level. For instance, farmers would benefit much from improving the way pesticides are used on industrial and other crops in Eure-et-Loir. Second, since the estimation of damage reduction functions indicates that among all productions, there is a room for improvement in pesticides management at the farm level (pesticides are not protecting crops at 100% in Eure-et-Loir), policymakers may elaborate on our results to design more effective pesticides reduction policies. Indeed, they could propose to farmers pesticides reduction policies that will at least maintain their current levels of production[2]: it implies providing them tools to improve pesticides management (the use of crop varieties that are resistant to diseases, changes in tillage or planting date, assistance with skilled workers, etc.). In that way, the use of pesticides could be lowered while at least maintaining a fairly stable level of production or $\delta' s$. Note also that if the objective of policymakers is to ban the use of pesticides in agriculture, our analysis may help to see that such a policy will significantly impact more farmers specialized in cereals than others. In other words, this regulation is not crop-neutral.

5. Conclusion

This analysis is a contribution to the literature on pesticide modeling in the production process. The contribution is twofolds. First we propose an extension of the Lichtenberg-Zilberman specification to a vector output to study multicrop farms. Second we develop a framework to estimate damage reducing functions which provide an indication on the effectiveness of pesticide application among productions at farm level. Since it gives information about the role of pesticides, this estimation is useful both to farmers and policymakers who aim at reducing the agricultural use of pesticides.

[2]Farmers' most important concern about pesticides reduction policies is their cost in terms of foregone output. If they are currently protecting their productions efficiently using pesticides in addition to other farming practices, their incentive to move from this situation and get involved in a reduction program is quite low. In other words, in this context, a pesticide reduction plan is unlikely to be adopted widely.

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