Could Society's Willingness to Reduce Pesticide Use be Aligned with Farmers' Economic Self-interest?

Jean-Philippe Boussemart,
Herve Leleu, and
Oluwaseun Ojo

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Could Society's willingness to reduce pesticide use be aligned with Farmers' economic self-interest?

Jean-Philippe Boussemart (LEM-IESEG School of Management and University of Lille)
jp.boussemart@ieseg.fr
Hervé Leleu (CNRS, LEM and IESEG School of Management)
h.leleu@ieseg.fr
Oluwaseun Ojo (CNRS, LEM-IESEG School of Management)
o.ojo@ieseg.fr

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Abstract

In the context of the agreement of about 50% reduction in pesticide uses according to the accords du "Grenelle de l'environnement" in France, the central part of this study involves the assessment of agricultural intensification (*AI*) and agricultural extensification (*AE*) processes in crop activities.This is done with reference to pesticide uses per ha thereby helping to proffer a solution to the lingering questions of farmers as regards the use of inputs in an intensified manner or otherwise. With respect to this, a sample of 600 farms in the Meuse department was observed over a 12-year period. The analysis was essentially to assess cost efficiency dominance between the two technologies *AE* and *AI* using non parametric cost-functions which involves different characterizations of the reference set. This therefore helps to define the relative intensive and extensive technologies in terms of pesticide uses per ha, our empirical application therefore shows that *AE* process is a better option than *AI* not only for the society but also for the producers who could significantly reduce their operating costs.

Keywords: agricultural intensification (*AI*), agricultural extensification (*AE*), pesticide reduction, environmental performance, non parametric cost-functions

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1. Introduction

Use of chemical inputs (such as pesticides) increased dramatically by farmers in developed countries from the beginning of the 1950s to the mid 1980s. This increase was due to the cost effective manner in which pesticides have enabled producers to introduce new production technologies, enhance productivity, improve product quality, and reduce the use of more expensive inputs. In that way, pesticide usage was accompanied by numerous benefits and these benefits were not confined to the users of pesticides, but reached the great majority of people across the world.

While on-farm economics have justified the extent to which pesticides have become part of agriculture in industrialized countries, there are external costs associated with their intensive use. However, negative externalities from such use which include damage to agricultural land, fisheries, fauna and flora have increased too. Thus, the main preoccupations embrace food safety, acute and chronic toxicity to humans, changing pest dominance, and environmental contamination from the disruption of natural water, air and soil functions (Brethour and Weersink, 2003). In addition, another major externality is the unintentional destruction of beneficial predators of pests thus increasing the virulence of many species of agricultural pests.

In that context, pesticides can be hazardous if not used appropriately. Hence, in order to ensure that users receive the benefits and are protected from the risks associated with its intensive use, pesticide should then be used in a reduced manner. The main advantages of pesticide use reduction include: (1) Benefits for the farmer through (a) savings in production cost, savings in energy (b) User-friendliness, improvement in time and work management, applicator safety. (2) Benefits for the environment through (a) improved biodiversity, improved water quality, wildlife protection, protection of beneficial arthropods, reduced packaging waste (b) facilitating the adoption of conservation agriculture practices, representing an opportunity for more sustainable farming methods. (3) Benefits for the consumer through improved food quality, less mycotoxin (Wood et *al.*, 2000)

The costs from the above cited externalities are large and affect long run farmers' returns (land fertility, environment and health). However, despite these high costs, farmers continue to use pesticides in increasing quantities in a process known as intensification (Wilson, 2000). This could be partly due to the incentives given by pesticide industries thereby encouraging the farmers to use pesticide in an unsustainable manner. But more fundamentally, previous studies, such as Campbell (1976) and Carlson (1977), found on average that the short run marginal returns to pesticide use were several times greater than the marginal factor costs (Carrasco-Tauber, 1990).

With such economical outcomes, the use of pesticide in an unsustainable way would not fall in line with the multiplication of initiatives for sustainable development by businesses, farmers' union and public French authorities according to the recent "Grenelle de l'environnement" agreements.

In view of this conflict of interests between individual farmers and the society, this paper attempts to know if extensification is (is not) a more economically competitive practice than intensification for crop activities in French agriculture. The reduction of pesticide use by farmers is possible based on their individual interest to do so. In this paper we try to know if there is coherence between the economic interest of the farmer in terms of cost decrease and the global benefit of the society in terms of pesticide reduction per hectare.

The question most paramount now is: *is pesticide reduction economically feasible in French's agriculture?* It is very obvious that an incorrect manner of pesticide application will definitely hold negative effects on human health and the environment. The costs from pesticide pollution are high as a result of damage done to agricultural production from the proliferation of pests and its impacts on other production processes, the environment and human health. Thus, the main objective of this research paper seeks to assess if a less pesticide use per ha is a cost competitive practice or not in crop activities by comparing non parametric cost frontiers between two technologies defined in terms of pesticide uses per ha named Agricultural Extensification (*AE)* and Agricultural Intensification (*AI).* In the context of reducing pesticide uses, *AE* and *AI* are respectively defined as technical practices with higher cost of pesticide per ha and lower cost of pesticide per ha relative to each observed farm, that is each decision making unit (DMU).

Reduction of pesticide use has been high on the political agenda in many countries and many studies by agronomists have been conducted to look into the possibilities for and consequences of a reduction in pesticide use. Most of these studies were carried out with methods that are very different from our approach. Indeed simulations or experiments on agronomical data generally assume constant returns to scale by retaining the gross margin per ha as the only economical criteria which is solely considered at the field level. As our approach is more from a managerial perspective, we choose to use economical data observed at the farm level. We analyse real and observed crop activities and we select both the best intensive and extensive practices in terms of production costs. Then we determine which of these two best practices (*AI or AE*) dominates the other on the production cost criteria without any a priori assumption about returns to scale. In that perspective, the study made use of a panel data located in a particular French department (la Meuse) which consists of 600 farms or DMUs over a 12 year period (1992-2003) producing wheat, barley and rapeseed (including rapeseed for diester).

The rest of the paper therefore unfolds as follows. Following this introduction, the next section presents the methodology to assess cost frontier comparisons between *AE* and *AI* while section 3 is devoted to empirical analysis, results and comments which identifies the variables and provides the data information used in this study. The final section (4) concludes the paper.

2. Cost efficiency assessment with the use of non parametric cost functions

Firm's performance has been estimated using a number of efficiency concepts including production and cost. Productive efficiency is derived as the distance an individual firm has from the 'optimal' or 'best practice' firm existing on the production frontier. Cost efficiency estimates how far the production cost of an individual firm differs from the production cost of a best practice firm operating under similar conditions and producing the same output. Cost efficiency is evaluated with reference to a cost function constructed from the observations of all firms considered within the sample set. The cost function which assumes the production cost of individual firm is dependent on price of inputs, the quantity or value of outputs produced, and any other additional variables accounting for the environment or particular circumstances.

This hypothesized 'best practice' firm is defined with reference to all firms retained in the sample set. Farrell (1957) originally introduced a simple method of measuring firm's specific productive efficiency that employs the actual data of the evaluated firms to generate the production frontier. Thus this method assumes that the performance of the most efficient farmers can be used to assess the benchmark. Transposing this in the cost function context, if a farm lies on the cost frontier, then it is perfectly cost-efficient but if it lies above the benchmark then it is inefficient with the ratio of the actual to potential minimal cost defining the level of cost inefficiency of the individual firm. This approach yields a relative measure as it assesses the cost efficiency of a farm relative to all other farms in the sample. Farrell argued that this is more appropriate as it compares a farm's performance with the best performance actually achieved rather than with some unattainable ideal.

Cost frontiers can be modelled, thanks to a Non Parametric Frontier Approach (NPFA) that can be evaluated with an Activity Analysis Framework (AAF) originally developed by Koopmans (1951) and Baumol (1958). AAF is a linear programming based technique for measuring relative efficiency where the presence of multiple inputs and outputs makes comparisons difficult. NPFA has both advantages and disadvantages relative to parametric frontier techniques such as the Stochastic Frontier Approach (SFA). The main advantage is that NPFA allows cost efficiency estimations without specifying any functional form between inputs and outputs. On the other hand, it is important to state that the disadvantage of the NPFA technique is that it does not allow for deviations from the efficient frontier to be a function of random error. As such, NPFA can produce results that are sensitive to outliers, model specification and data errors. As a solution to these drawbacks, an approach combining NPFA and SFA has recently been developed by Kuosmanen and Kortelainen (2010). Their framework which is known as Stochastic Non smooth Envelopment of Data (StoNED) encompasses semi-parametric frontier model that mixes DEA which satisfies monoticity and concavity with the SFA homoskedastic composite error term in a two stage-method. While StoNED seems to be a very promising approach, it is up till now developed under the mono-output context. This framework should prove useful in the future since this approach would have been extended to the multi-output setting.

The basic standpoint of relative efficiency, as applied in NPFA, is to individually compare a set of DMUs. NPFA constructs the frontier and simultaneously calculates the distance to that frontier for the (inefficient) farms above the cost-frontier. The frontier is piecewise linear and is formed by tightly enveloping the data points of the observed 'best practice' activities in the observations, that is the most efficient farms in the sample in terms of cost. NPFA uses the distance to the frontier as a measure of inefficiency. The measure provides a ratio-score for each farm from 0% (best performance) to x% meaning that the evaluated DMU would reduce its cost of x% to reach the cost frontier. For a review of the NPFA techniques see Färe et *al.* (1994) or Thanasoullis et *al.* (2008).

The input damage control technology

We follow the damage control model proposed by Lichtenberg and Zilberman (1986) and by Kuosmanen and *al.* (2006) to define the production technology. In this approach, inputs are distinguished among direct inputs (land, fertilizer, seeds, etc.) and damage control inputs such as pesticides. In the Lichtenberg and Zilberman specification, the contribution of pesticides to production differs fundamentally from that of direct inputs. Pesticides do not increase output yields directly but they are used to limit potential losses caused by damaging agents such as insects, weeds or bacteria. We therefore distinguish the maximal potential outputs obtainable from direct inputs and the observed outputs taking into account potential losses which depend on the pesticide uses.

Let us consider that K DMUs are observed and we denote the associated index set by $\mathfrak{K} = \{1,\ldots,K\}$. We also assume that DMUs face a production process with M outputs, N direct inputs and one damage control input (pesticide). We define the respective index sets of outputs and direct inputs as $\mathfrak{M} = \{1,\ldots,M\}$ and $\aleph = \{1,\ldots,N\}$. We denote by $\mathrm{y} = (y_1,\ldots,y_M) \in R_+^M$ the vector of observed output quantities, $\mathrm{x}^{\mathrm{D}} = (x_1^D,\ldots,x_N^D) \in R_+^N$ the vector of direct input quantities and $x^P \in R_+$ the damage control input (pesticide). Finally $\mathrm{w}^{\mathrm{D}} = (w_1^D,\ldots,w_N^D) \in R_+^N$ and $w^P \in R_+$ are respectively direct input and pesticide prices.

Lichtenberg and Zilberman (1986) characterize the production function (in a mono output framework) as:

$$y = F\left[\mathrm{x}^{\mathrm{D}}, G(x^P)\right] \quad (1)$$

Where $G(x^P)$ stands for the damage abatement function. It is modeled as a proportion of the pest population killed by the application of pesticide. It measures pesticide effectiveness and possesses the properties of a cumulative probability distribution. A complete eradication of pest damages is associated with $G = 1$ while $G = 0$ denoting 0 elimination. They also assume that $G(x^P) \to 1$ as $x^P \to \infty$.

We keep the spirit of Lichtenberg and Zilberman (1986), thus our model is developed in a multi-output context. Therefore, we use the more general framework of production set as developed by Shephard (1953). The production possibility set (*PPS*) of all feasible input and output vectors is defined as follows:

$$PPS = \left\{(\mathbf{x}^{\mathbf{D}}, x^P, \mathbf{y}) \in \mathbb{R}_+^{N+1+M} : (\mathbf{x}^{\mathbf{D}}, x^P) \text{ can produce } \mathbf{y}\right\} \quad (2)$$

And the technology is supposed to obey the following axioms:

A1: $(\mathbf{0}, x^P, \mathbf{0}) \in PPS, (\mathbf{0}, x^P, \mathbf{y}) \in PPS \Rightarrow \mathbf{y} = 0$, that is, no free lunch;

A2: the set $A(\mathbf{x}^{\mathbf{D}}, x^P) = \left\{(\mathbf{u}, x^P, \mathbf{y}) \in PPS : \mathbf{u} \le \mathbf{x}^{\mathbf{D}}\right\}$ of dominating observations is bounded $\forall \mathbf{x}^{\mathbf{D}} \in \mathbb{R}_+^N$, that is infinite outputs cannot be obtained from a finite direct input vector;

A3: *PPS* is closed;

A4: for all $(\mathbf{x}^{\mathbf{D}}, x^P, \mathbf{y}) \in PPS$, and all $(\mathbf{u}^{\mathbf{D}}, x^P, \mathbf{v}) \in \mathbb{R}_+^{N+1+M}$, we have $(\mathbf{x}^{\mathbf{D}}, x^P, -\mathbf{y}) \le (\mathbf{u}^{\mathbf{D}}, x^P, -\mathbf{v}) \Rightarrow (\mathbf{u}^{\mathbf{D}}, x^P, \mathbf{v}) \in PPS$ (free disposability of direct inputs and outputs);

A5: *PPS* is convex.

With these axioms, *PPS* is therefore defined as:

$$PPS = \left\{(\mathbf{x}^{\mathbf{D}}, x^P, \mathbf{y}) : \sum_{k\in\mathfrak{K}} \lambda^k y_m^k \ge y_m \;\; \forall m \in \mathfrak{M}, \sum_{k\in\mathfrak{K}} \lambda^k x_n^{D,k} \le x_n^D \;\; \forall n \in \aleph, \lambda^k \ge 0 \;\; \forall k \in \mathfrak{K}, \sum_{k\in\mathfrak{K}} \lambda^k = 1\right\} \quad (3)$$

The Cost model

Thanks to these previous definitions, we are now able to define the cost frontier including the direct input and pesticide costs. Formally, the production cost is equal to $C = \mathbf{w}^{\mathbf{D}}(\mathbf{x}^{\mathbf{D}})^T + w^P x^P$ where the superscript T denotes a transposed vector. For a DMU o with a production plan $(\mathbf{x}^{\mathbf{D,o}}, x^{P,o}, \mathbf{y}^{\mathbf{D,o}})$, the minimum cost involves solving the following model:

$$\min_{\boldsymbol{\lambda},\tilde{\mathbf{x}}^{\mathbf{D}}} \tilde{C} = \sum_{n} w_n^{D,o} \tilde{x}_n^D + w^{P,o} \sum_{k \in \mathfrak{K}} \lambda^k x^{P,k}$$

$$\sum_{k \in \mathfrak{K}} \lambda^k y_m^k \geq y_m^o, \forall m \in \mathfrak{M}$$

$$\sum_{k \in \mathfrak{K}} \lambda^k x_n^{D,k} \leq \tilde{x}_n^D, \forall n \in \aleph \qquad (4)$$

$$\sum_{k \in \mathfrak{K}} \lambda^k = 1$$

$$\lambda^k \geq 0, \forall k \in \mathfrak{K}$$

The solution of this model results in minimum cost C^* for the evaluated DMU o with an observed cost C^o. Therefore its cost inefficiency is $1-(C^*/C^o)$ and reflects the potential decrease in % of C^o. For each $\lambda^k \neq 0$, DMU k forms a part of the optimal linear combination which minimizes cost of farm *o* and can be considered as a benchmark referent. The linear program is therefore solved once for each observation in order to compute its minimal cost.

Assuming identical prices, the cost function defined above can be estimated using the production cost, since the resulting optimal costs are identical[1]. This assumption implies that farmers have the same market power which is quite plausible given their similar structure and size within a homogenous geographical area. Therefore, linear program (4) could be written as:

$$\min_{\boldsymbol{\lambda},\tilde{C}} \tilde{C}$$

$$\sum_{k \in \mathfrak{K}} \lambda^k y_m^k \geq y_m^o, \forall m \in \mathfrak{M}$$

$$\sum_{k \in \mathfrak{K}} \lambda^k C^k \leq \tilde{C} \qquad (5)$$

$$\sum_{k \in \mathfrak{K}} \lambda^k = 1$$

$$\lambda^k \geq 0, \forall k \in \mathfrak{K}$$

AI versus AE technologies and cost frontiers

Furthermore, we also considered varying the types of DMUs entering into the production possibility set of the evaluated farm *o* (all DMUs or some subset of more or less intensive DMUs than DMU*o*). By denoting $AE = \text{more or equally agricultural extensive}$ and $AI = \text{more or equally agricultural intensive}$, their production possibility sets $PPS^o(AE)$ and $PPS^o(AI)$ are respectively defined by:

$$PPS^o(AE) = \left\{ (\mathbf{x}^{\mathbf{D}}, x^P, \mathbf{y}) : \sum_{k \in \mathfrak{K}^o(AE)} \lambda^k y_m^k \geq y_m, \forall m \in \mathfrak{M}, \sum_{k \in \mathfrak{K}^o(AE)} \lambda^k x_n^{D,k} \leq x_n^D, \forall n \in \aleph, \lambda^k \geq 0 \; \forall k \in \mathfrak{K}^o(AE), \sum_{k \in \mathfrak{K}^o(AE)} \lambda^k = 1 \right\} \quad 6)$$

$$PPS^o(AI) = \left\{ (\mathbf{x}^{\mathbf{D}}, x^P, \mathbf{y}) : \sum_{k \in \mathfrak{K}^o(AI)} \lambda^k y_m^k \geq y_m, \forall m \in \mathfrak{M}, \sum_{k \in \mathfrak{K}^o(AI)} \lambda^k x_n^{D,k} \leq x_n^D, \forall n \in \aleph, \lambda^k \geq 0 \; \forall k \in \mathfrak{K}^o(AI), \sum_{k \in \mathfrak{K}^o(AI)} \lambda^k = 1 \right\} (7)$$

By defining $I(k)$ and $I(o)$ as the respective degrees of intensification of DMUs *k* and *o* which are equal to their ratios of pesticides per ha:

[1] Assuming identical prices for all farmers, we can introduce the prices in LP (4) to obtain the cost categories instead of input quantities. Rearrangements of terms to obtain the production cost and further simplifications lead to the desired LP(5). A proof is available upon request.

In (6), $\mathfrak{K}^{o}(AE) = \{k \in \mathfrak{K} : I(k) \leq I(o)\}$

And in (7), $\mathfrak{K}^{o}(AI) = \{k \in \mathfrak{K} : I(k) \geq I(o)\}$

The meanings of "more or equally agricultural extensive" and "more or equally agricultural intensive" are now clear. $\mathfrak{K}^{o}(AE)$ contains observed DMUs in the data set using less pesticide per ha than the current evaluated farm *o* while $\mathfrak{K}^{o}(AI)$ contains only the observed DMUs that has an equal or higher ratio of pesticides per ha than the evaluated DMU *o*.

Given the definition of the technologies in (6) and in (7), we now estimate the two cost functions for all farms *o* using the following programs:

$$\begin{aligned} &\min_{\lambda, \tilde{C}_{AE}} \tilde{C}_{AE} \\ &\sum_{k \in \mathfrak{K}^{o}(AE)} \lambda^k y_m^k \geq y_m^o, \forall m \in \mathfrak{M} \\ &\sum_{k \in \mathfrak{K}^{o}(AE)} \lambda^k C^k \leq \tilde{C}_{AE} \\ &\sum_{k \in \mathfrak{K}^{o}(AE)} \lambda^k = 1 \\ &\lambda^k \geq 0, \forall k \in \mathfrak{K}^{o}(AE) \end{aligned} \qquad (8)$$

$$\begin{aligned} &\min_{\lambda, \tilde{C}_{AI}} \tilde{C}_{AI} \\ &\sum_{k \in \mathfrak{K}^{o}(AI)} \lambda^k y_m^k \geq y_m^o, \forall m \in \mathfrak{M} \\ &\sum_{k \in \mathfrak{K}^{o}(AI)} \lambda^k C^k \leq \tilde{C}_{AI} \\ &\sum_{k \in \mathfrak{K}^{o}(AI)} \lambda^k = 1 \\ &\lambda^k \geq 0, \forall k \in \mathfrak{K}^{o}(AI) \end{aligned} \qquad (9)$$

Comparing the two minimal costs $\tilde{C}_{AE}$ and $\tilde{C}_{AI}$ based on their respective programs (8) and (9), one can evaluate the gap between the two technologies in order to know if *AE* is a more cost-competitive practice than *AI* for the current evaluated farm o. The originality of our approach is to consider the various subsets of DMUs used in the definition of the production possibility sets as regards the evaluated producer's level of intensification. An exogenous choice of the threshold of pesticide use practices could be difficult to justify and that is why we use a relative and endogenous degree of extensification (intensification). With respect to their own degree of intensification, the evaluated DMUs are compared to more or less intensive DMUs. At this step, it is essential to highlight the fact that our model allows for inefficiencies in production (for any DMU observed cost could be higher than optimal cost of the benchmarks (*AE*) or (*AI*)). It is well known that these inefficiencies could depend on many different factors most specifically farmers' risk attitudes, climatic effects and crop rotations. However, the gap between the two technologies may not be significantly affected by any of these potential inefficiency factors since we focus on the comparison of two cost optimal benchmarks.

3. Empirical application: data, results and comments

Data for Efficiency Analysis

A total of 600 farms were observed in the Meuse department between 1992 and 2003 forming an unbalanced panel[2]. Three outputs and four inputs were used to specify the technology of the farms for a total of 7135 observations. As the previous cropping plans are not directly available, the technology opts for a multi-output cost function model in order to limit the potential effects of crop rotations on pest management. Thus, the cost minimization models allow potential substitution effects between chemical inputs and land but constrain the optimal referents to produce the same (or more) quantities of the three retained outputs (wheat, barley and rapeseed including rapeseed for diester) than the evaluated DMUs which are significantly linked to the most frequent crop rotation observed within this geographical area. The outputs are measured in quintals with the

[2] We use a database of *Centre d'Economie Rurale de La Meuse* which assists farmers to audit their account.

inputs comprising surface (land), fertilizer, seeds and pesticides. Land surface measured in hectares is the observed surface weighted by a quality index of soil.[3] All other inputs are evaluated in constant Euros.

The production cost in Euros includes variable farm costs directly linked to the physical process of crop growth such as fertilizer, chemicals and seed plus land cost for only these three outputs. The unit price of land was estimated by the hired cost that the farmer paid to the owner when the land was rented. As regards owned land, a fictitious price equal to the hired cost of his rented land was used. The yearly average land price over the sample was applied uniformly to all the observations.

We omit the quasi fixed primary inputs labour and capital for several reasons. First, these two inputs can't be split among the different output categories (crops, milk, meat, other products) in our data, they are only available at a global level. Therefore we can't include them in our crop production function without any clear and consensual allocation keys. Second, our main focus is related to potential substitution effects between land and most important inputs contributing to environmental pollution caused by growing cash crops such as pesticide or fertilizer. Although Piot-Lepetit et *al.* (1997) argue that manual and mechanical pest control can be considered as substitutes to pesticides, we follow De Koeijer et *al.*(2002) considering that they are secondary order effects. In fact mechanical weeding is a new practice and was not spread among French farmers at this period (1992-2003). Mechanical costs are also linked to output mixes and the farm size. As our cost minimization models constrain the optimal referents to produce the same quantity of each output than the evaluated DMUs, this guarantees that the two minimal costs are always evaluated for the same output quantities which are correlated to the level of capital goods and surfaces.

Third, two arguments can be mentioned for labor. There is no consensus among agronomists as to the fact that pesticide reductions incidentally increase labor quantity for crop supervision. Some low input strategies which can be characterized by a decrease in sowing density or fertilizer application rate could help to lower yield loss resulting from the absence of fungicide application. Thus, it seems that the preventive use of fungicides on high-yielding wheat crops in the intensive cropping systems of northern Europe has obscured the fact that there are other ways of controlling diseases (Loyce et *al.*, 2008). Moreover, on French arable farms, family labor is generally not used to full capacity and don't significantly affect the operating cost given the farm's cropping plan and the cultivated surface.

Finally, despite the fact that the price evolution over time is known, the sample does not contain prices at the farm level for seed, fertilizer and pesticides, but only costs per input category. If we assume that all farms face identical input unit-prices each year (most inputs are procured within the same regional markets where prices between farms differ little), we can use the two previous minimum cost models (8) and (9) in this application.

The descriptive statistics showing the different inputs and outputs of farms are presented in table 1.

Table 1: Brief descriptive statistics of the data (period 1992-2003):

	Mean	CV	ROG (%)
Barley (quintals)	1096	0.988	3.71
Wheat (quintals)	2854	0.760	1.42
Rapeseed & diester (quintals)	984	1.033	3.65
Surface (ha)	89	0.743	2.46
Cost (€)	43002	0.837	1.98
Pesticide per ha (€)	160	0.357	1.16

ROG: tendency rate of growth, CV: coefficient of Variation

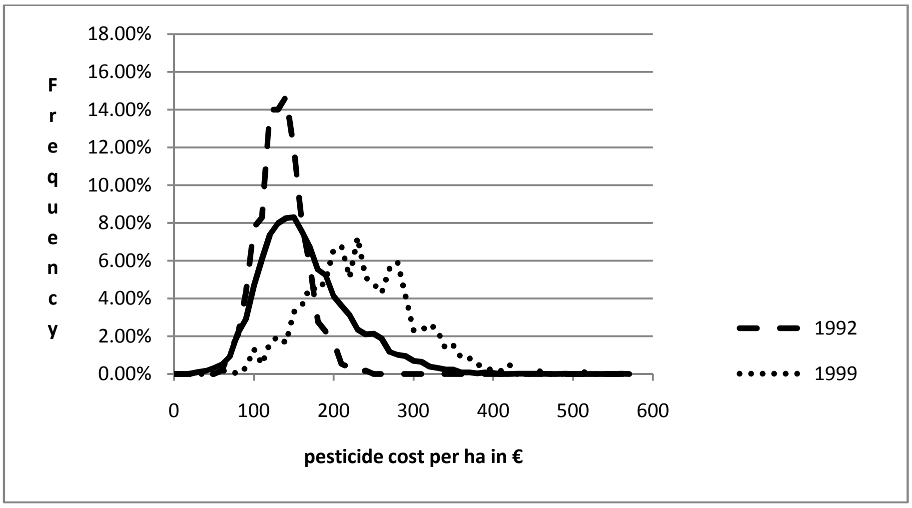
Data reveal a rather low and stable spread for the inputs (the coefficients of variation are less than one as well as the cost, surface and pesticide per ha). In addition, barley and rapeseed outputs increase faster than wheat

[3] This quality index at the micro-region level gives a measure of effective hectares of land. This index is exogenously estimated, thanks to the available soil and agronomical parameters.

production. It can be noticed that the growth rate of cost is lower than the surface hence, the ratio of cost per ha is decreasing.

From figure 1, even though the standard deviation of pesticide per ha is rather small over the whole period, one can check that the sampling distribution can vary quite significantly according to the different years of the period. This reveals some heterogeneity of pesticide uses among farmers who can individually adopt some different practices in order to respond to climatic or other random effects. In such a context, it is preferable to estimate cost function year-by-year in order to impose minimal assumptions with respect to the nature of annual technological shifts. Therefore, thanks to the panel nature of the sample, it is possible to define the previous different possibility sets (6) and (7) for each year separately from 1992 to 2003.

Figure 1: Sampling distribution of pesticide cost per ha[4]



Results and comments

Consequently the linear programming problems (8) and (9) given in the methodology section of this paper are solved for each of the observations connoting that all farms observed at year *t* are evaluated against two different annual technologies. One is composed of less extensive DMUs *(AE)* relative to the evaluated farm and the other is composed of more intensive DMUs *(AI)* also relative to the current evaluated farm. Then for each year, the two minimum costs are compared in order to select the best cost-practice for the evaluated farm. Annual cost analyses are presented in table 2.

Table 2: Observed and minimum costs between *AE* and *AI*

Year	% of cases where *AE dominates AI*	Observed Cost in €	Minimum cost in € for *AE*	Minimum cost in € for *AI*	Gap between *AI* and *AE* in %
1992	80.83	30 982	26 097	27 528	5.48
1993	72.52	26 761	21 251	23 544	10.79
1994	79.08	35 263	26 757	31 148	16.41
1995	87.58	49 683	35 161	43 903	24.86
1996	83.44	48 282	34 336	43 362	26.29
1997	86.27	47 829	36 755	42 694	16.16
1998	84.35	51 220	39 830	46 373	16.43
1999	90.30	58 321	40 584	51 627	27.21
2000	84.31	54 803	37 242	47 408	27.30
2001	66.84	39 660	33 138	33 765	1.89
2002	78.57	37 282	31 252	33 602	7.52
2003	79.03	33 148	26 793	29 510	10.14
Total	81.23	43 002	32 538	38 079	17.03

AE = Agricultural Extensification ; *AI* = Agricultural Intensification

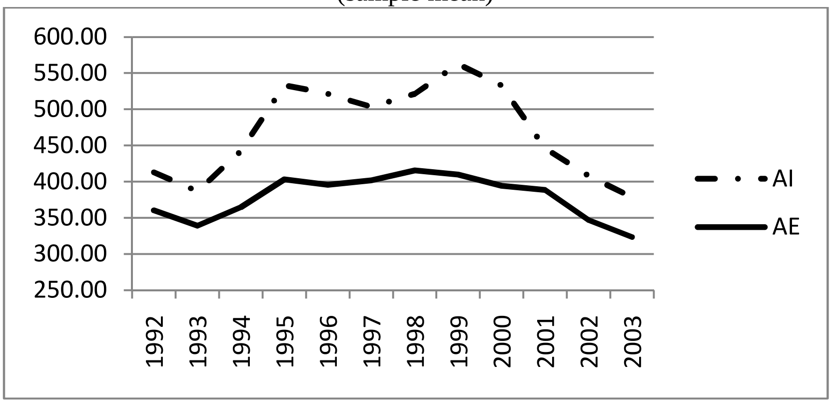
[4] Sampling distributions of pesticide cost per ha are drawn for the whole sample as well for years 1992 and 2003 which present the annual lower and higher standard deviations respectively.

Table 2 clearly shows that extensification dominates intensification in terms of cost irrespective of the annual context. Depending on the year, between 67% and 90% of farmers should operate under a more relatively extensive technology than a more intensive one (cf. column 1). The mean average of the total sample is around 81% of cost dominance in favour of the *AE* practices. The minimized costs of production under the two technologies and their gaps are shown in the last columns of table 2. Over the whole period, there is a positive gap between the two minimum costs in favour of *AE* practices which varies from 2% to 27%, the mean average of the gap is around 17%. Therefore from their actual practices, the cost reductions would be 24.3% if the farmers adopt *AE* technology against 11.5% for *AI*.

Where the results are presented in terms of cost per ha instead of global cost, the *AE* dominance is more spectacular. On average, the observed cost is 483 Euros per hectare while the costs of the *AI and AE* frontiers are respectively 478 and 382 Euros per hectare. Hence, between the two technologies, the gap is higher than 96 Euros (25%). This confirms that the cost frontier under an extensive scenario is below that of intensive scenario.

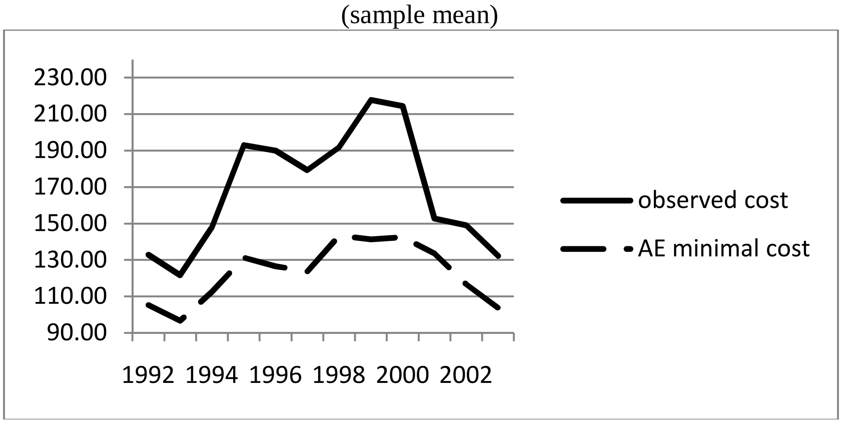
As reflected in figure 2, the technology-gap varies in terms of Euros per ha between 48 Euros (14%) and 152.6 Euros (37%) always in favour of *AE* according to the different years. Therefore, in order to improve the cost of production, it is better and very preferable to reduce the amount of pesticides use per hectare.

Figure 2: Minimal cost per ha in €
(sample mean)



Now focusing our attention on the pesticide uses per ha, it can be noted that the potential reductions of pesticide from the actual situations could reach 27% (sample mean) if the farmers adopt the best extensive practices. This is reflected by figure 3 where the gaps between the observed pesticide cost per ha and the *AE* minimal cost vary between 12% and 35% over the whole period, thus resulting to a huge pesticide saving.

Figure 3: Cost of pesticide per ha in €
(sample mean)



Of course the results gotten here depends on the sample, hence it is not easy to generalize it in conformity with all French or European's agricultures, although these results are in line with the case of Dutch sugar beet growers (De Koeijer, 2002) where a positive correlation was found between managerial and environmental efficiencies. These conclusions can also rightly be improved for future researches by taking climatic effects into account with a consideration of the fact that some micro climatic problems could exist. Crop rotations issues and the previous crops planted would also be more explicitly put into consideration.

4. Conclusion

This paper checks if the minimized cost of production which is the individual interest of the farmer is in convergence with the pesticide reduction per hectare thereby helping to know if extensification is a cost-competitive practice or not.

This was achieved by developing an activity analysis framework to assess the cost frontier comparisons between extensive and intensive technologies. It is therefore worthwhile to note that the methodological originality of this paper is the cost dominance analysis between *AI* and *AE* which is done by a definition of dynamic reference sets relative to the evaluated farm. Moreover it is important to state that the results gotten in this paper are derived from the current technology of farms which ensures its feasibility

Our results show that in 81% of cases, a more extensive technology cost dominates a more intensive one. In addition, the results clearly reveal that the interests of farmers and the policy makers could converge by achieving a win-win strategy. Indeed, the benefit for the individual producer to reduce his cost around 24% by adopting less intensive practices leads to a reduction of pesticide per ha of about 27% which is in coherence with the ecological wishes of the society. Finally, to the question “could society’s willingness to reduce pesticide use be aligned with farmers’ economic self-interest?” our answer is clearly yes in the crop activity context of Meuse department.

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