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Empirical comparison of pollution generating technologies in nonparametric modelling: The case of greenhouse gas emissions in French meat sheep farming

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Abstract

We consider different models that assess eco-efficiency with production frontier estimation when desirable outputs and undesirable outputs are considered. These models are confronted to livestock farm data (French meat sheep farms) and greenhouse gas (GHG) emissions, to discuss their suitability in eco-efficiency measurement. Our results show that under certain conditions the existing models, except for the by-production one, converge to the same results as when undesirable outputs are treated as inputs in the production frontier. The results also reveal that the by-production model augmented with dependence constraints offer some promising opportunities.

Keywords: eco-efficiency; weak G-disposability; multiple frontier technology; GHG emissions; meat sheep farming.

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EMPIRICAL COMPARISON OF POLLUTION GENERATING TECHNOLOGIES IN NONPARAMETRIC MODELLING:

THE CASE OF GREENHOUSE GAS EMISSIONS IN FRENCH MEAT SHEEP FARMING

1. Introduction

Since the pioneering work of Pittman (1983) to account for undesirable outputs (or bad outputs, or unwanted outputs, or detrimental outputs, or pollutants, or residuals) in production technology modelling, many models have been developed in this area for the case of nonparametric analysis. In general, pollutants are treated as an extra input that is added to the technology (Hailu and Veeman, 2001; Hailu, 2003; Mahlberg et al., 2011) or included as an output under the weak disposability and the null-jointness assumptions (Färe et al., 1989; Chung et al., 1997; Färe et al., 2005). These two approaches largely used for empirical applications (Zhou et al., 2008) have been criticized in the literature for their inadequacy to properly model pollution generating technologies (Coelli et al., 2007; Podinovski and Kuosmanen, 2011; Murty et al., 2012; Chen, 2014). However, in this debate some recent developments have emerged to circumvent the drawbacks associated to the previous models: first, models linked to the materials balance principles (Hampf and Rødseth, 2014), and second, models relying on the estimation of separate sub-technologies (Førsund, 2009; Murty et al., 2012; Sueyoshi and Goto, 2012; Dakpo, 2014). This latter formulation assumes that a production system cannot be represented by a single equation and uses multiple independent frontier representations[1]. Giving this abundant literature, there has been to date no empirical discussion on these models that can give more insights on their convergence or divergence.

The objective of this paper is then to carry on a systematic comparison of the aforementioned methods and discuss their suitability to real data in agriculture, with the specific case of livestock farms. The application to the livestock sector is relevant for two reasons. First, the complex interactions between agriculture and the environment can make difficult the choice of a method. Second, the last decade saw a growing attention at the international scale of the role played by livestock farming in the global greenhouse gas (GHG) emissions. Given these two issues and a projected increase in future demand of animal products, this sector is a suitable candidate to investigate the challenge of eco-efficiency computations. Besides, according to Hoang and Alauddin (2012), 'for the sake of farmers', sustainability must become an important objective since the tensions on the environment might affect the ecosystem

[1] One sub-technology is related to the production of good outputs and the other one for the generation of residuals.

which can no longer sustain the agricultural activities. In this paper, we focus on meat sheep breeding systems located in French grassland areas. Actually, the low farm profitability in this sector – due to high competition, cost increase, low public support – and the sector's key role in the viability of rural areas - through for instance the maintenance of rural landscapes – imply the double challenge of socio-economic and environmental performance. The eco-efficiency computation, based on the nonparametric Data Envelopment Analysis (DEA) methodology, aims at finding the maximal attainable ratio of a good output (here meat production) on a bad output (here an aggregation of the three main GHG emissions). Following Hampf and Rødseth (2014) we also propose a decomposition of performance into different potential sources of improvement given different assumptions on the flexibility available to producers in their decision making.

The paper is organized as follows. In **Section 2** we briefly explain the main assumptions, the basis and the significant features of each model. Within this section we also present a quick review of some applications in agriculture. **Section 3** describes the data used and the empirical results obtained. **Section 4** discusses the appropriateness of each approach to the farm data used and points out the challenges that still remain. **Section 5** concludes.

2. Pollution generating technologies modelling: theoretical basis

We begin by describing the environmental production technology which is represented by the set of good and bad outputs (y, b) that can be produced by the inputs x:

$$\Psi_{bad} = [(x, y, b)|\ x \ \in \mathbb{R}_{+}^{K}, x \geq 0, \text{can produce } y \ \in \mathbb{R}_{+}^{Q}, y \geq 0 \text{ and } b \in \mathbb{R}_{+}^{R}, b \geq 0] \quad (1)$$

We shall also assume the following classic postulates: no free lunch, non-emptiness, closeness, boundness, convexity, free (strong) disposability of inputs and good outputs[2] and variable returns to scale (VRS). One can refer to Chambers (1988) and Färe and Grosskopf (2004) for more details regarding the standard axioms of production theory. Given this framework pollution has been modelled in

[2] Good outputs are freely disposable if $y \in \Psi_{bad}(x, y, b)$ and $y' \leq y$ imply $y' \in \Psi_{bad}(x, y, b)$; inputs are freely disposable if $x \in \Psi_{bad}(x, y, b)$ and $x' \geq x$ imply $x' \in \Psi_{bad}(x, y, b)$.

different ways in the literature. For our particular case study, we consider one good output and one undesirable output[3].

2.1. Inclusion of undesirable outputs in the production technology: literature review

Considering that pollution generates social costs, and that an input orientation is straightforwardly interpreted in terms of costs savings (minimization), some authors (e.g. Dyckhoff and Allen, 2001; Prior, 2006) recommend to introduce unwanted outputs as extra inputs and to assume their free disposability. These authors argue that emissions of environmentally detrimental outputs can be viewed as the usage of the environment's capacity for their disposal. Hence, considering them as inputs is likely a good way to account for the consumption of natural resources. Under this assumption, the technology can be represented as (N being the number of Decision Making Units (DMUs)):

$$\Psi_{bad}^{inputs} = [(x,y,b) \in \mathbb{R}_{+}^{K+1+1} \big| \, y \leq \sum_{i=1}^{N} \lambda_i Y_i \, ; \, b \geq \sum_{i=1}^{N} \lambda_i B_i \, ;$$

$$x \geq \sum_{i=1}^{N} \lambda_i X_i \, ; \, \sum_{i} \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \ldots, N] \tag{2}$$

This approach has been criticized in the literature because it violates the physical laws of thermodynamics (Färe and Grosskopf, 2003).

Another modelling strategy considers residuals as extra outputs but impose the weak disposability assumption (WDA) and also the null-jointness of both types of outputs (good and bad) (Färe et al., 1989; Chung et al., 1997; Färe et al., 2007). The WDA can be summarized as follows

$$(y,b) \in \Psi_{bad} \, , 0 \leq \theta \leq 1 \implies (\theta y, \theta b) \in \Psi_{bad} \tag{3}$$

And the null-jointness property is represented by

[3] All the models presented in this paper can be easily extended to multiple good and bad outputs.

$$(y, b) \in \Psi \text{ and } b = 0 \text{ then } y = 0 \tag{4}$$

The WDA implies that it is not costless to reduce bad outputs. In fact, if one wishes to reduce undesirable outputs, good outputs must also be reduced for a given level of inputs. This implies that resources must be diverted to abatement activities in order to mitigate pollution level. Under this assumption the production technology is defined as

$$\Psi_{bad}^{weak} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} \big| \; y \leq \theta \sum_{i=1}^{N} \lambda_i Y_i \,; \; b = \theta \sum_{i=1}^{N} \lambda_i B_i \;;$$

$$x \geq \sum_{i=1}^{N} \lambda_i X_i \,; \; \sum_{i} \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N \,; 0 \leq \theta \leq 1] \tag{5}$$

As formulated in **(5)** the WDA assumes a common proportional reduction of desirable and undesirable outputs. The model thus considers that all DMUs share the same uniform abatement effort θ. Yet as pointed out by Kuosmanen (2005) and Kuosmanen and Podinovski (2009), policies should be targeted to abatement activities where the abatement costs are lowest. The authors therefore proposed an extension of the traditional WDA modelling by assuming a specific abatement effort for each producer (firm-specific abatement factor). The new technology proposed is similar to the one in problem **(5)** except that θ is replaced by θ_i. Despite the interesting feature of this model, some recent studies have cast a doubt on the relevance of the WDA. For instance Murty et al. (2012), using a transformation function to estimate the different trade-offs, showed some inconsistencies linked to this assumption. Chen (2014) also revealed some empirical drawbacks related to the WDA using an illustrative example.

Since it has been proved that the WDA does not fit with the physical laws, Hampf and Rødseth (2014) suggested to use the weak G-disposability which is based on the materials balance principles (MBP). This approach is related to the first two laws of thermodynamics[4]. Let the input set be divided into two

[4] The first law of thermodynamics gives the principle of mass conservation i.e. what goes in goes out. The second law, also known as the law of entropy, states that using polluting inputs will inevitably result in pollution.

different subsets: material inputs x^M which generate pollution and non-material inputs x^{NM} which are pollution free. The technology set can be defined as

$$\Psi_{bad}^{weak\ G} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} \big| \; y + s_y = \sum_{i=1}^{N} \lambda_i Y_i \, ; \; b - s_b = \sum_{i=1}^{N} \lambda_i B_i \; ;$$

$$x^M - s_{x^M} = \sum_{i=1}^{N} \lambda_i X_i^M \, ; \; x^{NM} - s_{x^{NM}} = \sum_{i=1}^{N} \lambda_i X_i^{NM} \; ; \tag{6}$$

$$W' s_{x^M} + H s_y - s_b = 0 \, ; \sum_i \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N \,]$$

where s_x, s_y and s_b are respectively inputs excess, good output shortfall and pollution excess that are present in the technology due to inefficiency. W is the vector of input pollution factors[5] and H represents the recuperation factor associated to the good output[6]. As pointed out in Førsund (2009) the mass conservation equation $(W' s_{x^M} + H s_y - s_b = 0)$ does not explicitly show how residuals are generated; instead the equation simply puts forward how the variables are related given the MBP. In addition, the mass balance equation introduces "some limits on derivatives in the system of equations". Besides, Hampf and Rødseth (2014) have also demonstrated that under some assumptions the weak G-disposability is equivalent to the weak disposability as proposed in Färe and Grosskopf (2012).

Recognizing the importance of the materials balance in modelling the technology that generates unwanted outputs, Førsund (2009) recommended the use of the by-production methodology proposed in Murty and Russell (2002) and generalized by Murty et al. (2012). This approach, which relies on the estimation of two separate frontiers, assumes the cost disposability of bad outputs. This assumption is based on the idea that given the level of consumption of some inputs, only a minimal level of pollution can be reached and the presence of inefficiency can lead to the generation of more quantity than this

5 For instance one liter of fuel generates around 3.24 Kg of carbon dioxide from the extraction of the raw material to its consumption.
6 The recuperation factor represents the part of the bad output that is embedded in the good output and thus prevented to be emitted. Generally the recuperation factor is set to zero.

minimal level. The global technology is viewed in the theory as the intersection of the two sub-frontiers. Empirically, Murty et al. (2012) defined this global technology as

$$\Psi_{bad}^{by} = (x^M, x^{NM}, y, b) \in \mathbb{R}_+^{K^M+K^{NM}+Q+R} | \; y \leq \sum_{i=1}^{N} \nu_i Y_i \; ;$$

$$x^M \geq \sum_{i=1}^{N} \nu_i X_i^M \; ; \; x^{NM} \geq \sum_{i=1}^{N} \nu_i X_i^{NM} \; ; x^M \leq \sum_{i=1}^{N} \xi_i X_i^M \; ; \tag{7}$$

$$b \geq \sum_{i=1}^{N} \xi_i B_i \; ; \; \sum_{i=1}^{N} \nu_i = 1; \; \sum_{i=1}^{N} \xi_i = 1; \; \nu_i, \xi_i \geq 0; i = 1, \dots, N]$$

As can be seen in **(7)**, the global technology is represented with two intensity factors, each one associated to one different sub-technology. As presented in **(7)** the by-production approach offers the advantage of separating the operational performance and the environmental performance. However, the model empirically assumes independence between the two sub-technologies. Murty et al. (2012) proposed to compute an efficiency score by adapting the Färe-Grosskopf-Lovell index (Färe et al., 1985) and thus to give a weight of 50% to each sub-efficiency score. As argued by Dakpo (2014), these weights are not data driven and the choice made by Murty et al. (2012) departs from the philosophy of DEA. Dakpo (2014) then developed an extension of the by-production model by augmenting **(7)** with some dependence constraints relative to the pollution generating inputs[7].

$$\sum_{i=1}^{N} \nu_i X_i^M = \sum_{i=1}^{N} \xi_i X_i^M \tag{8}$$

In the same line, as Murty et al. (2012), Sueyoshi et al. (2010) and Sueyoshi and Goto (2010) proposed a unification strategy that is based on the use of a single intensity factor. To this aim they separated the

[7] These dependence constraints have some interesting dual interpretations.

input slacks s_x into their positive and negative parts which are mutually exclusive $(s_x^-.s_x^+ = 0)$. The model is specified as follows:

$$\Psi_{bad}^{unified} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} \big| \, y + s_y = \sum_{i=1}^{N} \lambda_i Y_i \, ; \; b - s_b = \sum_{i=1}^{N} \lambda_i B_i \; ;$$

$$x - s_x^- + s_x^+ = \sum_{i=1}^{N} \lambda_i X_i \, ; \; \sum_i \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N; \tag{9}$$

$$s_x^-.s_x^+ = 0 \,]^{8}$$

According to the authors, the different parts associated to the inputs define the possible adaptation choice made by the firm managers. The negative part s_x^- is related to the 'natural disposability', which reflects a negative adaptation since the manager under evaluation chooses to reduce the levels of the consumption of inputs in order to decrease pollution. On the other side, the positive part s_x^+ is linked to the presence of 'managerial disposability' (positive adaptation), and in this situation some managerial efforts (adoption of new technologies, substitution of clean inputs to polluting ones...) can lead the firm to increase its consumption of inputs and simultaneously reduce the volume of pollution generated. As pointed out in Manello (2012), the non-linearity introduced in the unified framework may generate some dominated efficient DMUs and thus may create some identification problems of the efficient DMUs since the two technology sets can generate contradictory results.

2.2. Eco-efficiency assessment and decomposition

As explained in **Section 1**, we choose in this paper to consider the maximal production intensity per unit of undesirable output as the objective for each of the previous models. We retain this approach because, first, it is in line with the definition of eco-efficiency (Huppes and Ishikawa, 2005), and second, the unicity of the ratio allows the comparison and the discussion of the models presented in this paper on the same foundation. Based on these ratios an eco-efficiency score can be computed by comparing the attainable optimal ratios to the actual observed ratio. The eco-efficiency can be measured by

[8] This non-linear program can be transformed into a mixed integer program by replacing the mutually exclusive constraint $s_x^-.s_x^+ = 0$ with the new constraints: $s_x^+ \leq Mh^+$, $s_x^- \leq Mh^-$, $h^+ + h^- \leq 1$ where h^+ and h^- are binary and M is a number that needs to be defined sufficiently large to avoid corner solutions.

$$Eco_{eff} = \frac{ratio^{observed}}{ratio^{optimal}} \tag{10}$$

Based on the work of Hampf and Rødseth (2014) a decomposition of the performance score can be obtained relative to the possible choices available to the producers. These choices will be reflected by the number of decision variables in the objective function.

- The most restrictive assumption specifies that the producer cannot freely choose nor the inputs nor the good output; both variables are given and only the level of the bad output is free of choice. The interesting point relative to this assumption is that it can be used to assess the technical inefficiency in pollution generation. Let's denote by $r^*_{x,y/f}$ the optimal ratio obtained under this assumption.
- In a second less restrictive assumption both outputs are free of choice and are endogenous in the optimization programs. But the inputs are given and the producer does not have a free choice on these variables. Let's denote by $r^*_{x/f}$ the optimal ratio obtained in this case. This ratio can be helpful to evaluate the existence of allocative inefficiency in the production of good and bad outputs.
- A third more flexible possibility is to allow the free choice of the amount of inputs and both good and bad outputs. This means that all variables in the models are endogenously determined in the optimization program. Under this assumption, all DMUs converge to an optimal scale (the most productive scale size – MPSS –). Denote by $r^*_{./f}$ the optimal ratio.

Based on these possibilities and the degree of adjustment offered to the producer, we can write the following relationship between the optimal ratios:

$$r^*_{./f} \geq r^*_{x/f} \geq r^*_{x,y/f} \tag{11}$$

If the eco-efficiency score is computed as $Eco_{eff} = ratio^{observed} / r^*_{./f}$, the following decomposition can be made:

$$Eco_{eff} = \frac{ratio^{observed}}{r^*_{./f}} = \frac{ratio^{observed}}{r^*_{x,y/f}} \times \frac{r^*_{x,y/f}}{r^*_{x/f}} \times \frac{r^*_{x/f}}{r^*_{./f}} \tag{12}$$

$\frac{ratio^{observed}}{r^*_{x,y/f}}$ measures the eco-efficiency level when both inputs and good outputs are held fixed. More precisely as previously stated it evaluates the presence of technical inefficiencies in the generation of detrimental output. This measure has been coined the 'weak ratio efficiency' in Hampf and Rødseth (2014). $\frac{r^*_{x,y/f}}{r^*_{x/f}}$ refers to the possible increase in the performance score when allowing more flexibility regarding the level of good output. This second component has been termed the 'allocative ratio efficiency'. The last component $\frac{r^*_{x/f}}{r^*_{./f}}$, assesses the amount by which the ratio can be improved (relative to $r^*_{x/f}$) when the manager can freely decide the amount of inputs in addition to the amounts of both outputs. Hampf and Rødseth (2014) refer to this third component as the 'input ratio efficiency'.

It is worth mentioning that mostly the models estimated in this paper are based on fractional programming. They can be linearized by using adequate transformations and variables changes (Charnes and Cooper, 1962).

2.3. Pollution generating technologies in agriculture: a review of the literature

Numerous studies have estimated farms' efficiency in the presence of undesirable outputs. Most of this literature covers the generally known approaches of modelling pollution generating technologies. As it can be seen in the studies listed in appendix, most of the existing papers deal with nitrogen pollution arising from pig production. For instance Latruffe et al. (2013) estimated the technical efficiency of Hungarian pig producers under the production of nitrogen, a detrimental output for watershed. They assumed the strong disposability of nitrogen emissions and treated them as additional inputs. As earlier said, this approach has been vigorously attacked by Färe and Grosskopf (2003) and Färe and Grosskopf (2004) as it departs from the reality of the production process. In addition, assuming the strong disposability of bad outputs reflects situations where, with given quantities of inputs, one can produce unlimited amount of detrimental outputs, which is technically impossible. As a solution to this limit, Lansink and Reinhard (2004) developed a model that still treated bad outputs as inputs, but added the WDA of inputs which is modelled as in congestion situations (Färe and Grosskopf, 2001). On the opposite side, Yang et al. (2008), considering the presence of an abatement technology, included in their model the abated amount of bad outputs as strongly disposable outputs. However, the commonly adopted approach in modelling detrimental variables as outputs is based on the WDA. In this line, Piot-Lepetit and Le Moing (2007) considered, in pig farming systems, nitrogen surplus as outputs and assumed the WDA of these emissions. The estimation strategy is based on the directional distance function proposed by Chung et al. (1997).

By contrast to these studies, in the light of physical laws (thermodynamics), Coelli et al. (2007) applied the MBP to the case of pig-finishing farms in Belgium. Based on the mass balance equation, the authors estimated an iso-environmental cost line in a similar way as an iso-cost in a minimization scheme. They also demonstrated that under the WDA, a production system might not verify the mass conservation property which the authors assume to be inherent to all materials transformation process. Yet it seems that their approach suffers from the ambiguity in the treatment of non-material inputs (Hoang and Rao, 2010).

Recognizing the limits of some of the aforementioned methods (bad outputs treated as inputs; weak disposability), Asmild and Hougaard (2006) also proposed a 'sort of data transformation' in the case of nutrient surpluses in pig farming in Denmark. In their approach, instead of directly considering the nutrient surpluses (nitrate, potassium and phosphorous), they considered the nutrient removal by crops. Maximizing this good output (under strong disposability assumptions) indirectly reduces the nutrient surpluses. The model is set up as if the nutrient surpluses, mainly deriving from pig manure, serve as inputs to another production system (here represented by the production of crops). The authors developed in addition several two-step approaches for the estimation of technical efficiency. For instance, in a first step one can focus on the economic efficiency (traditional technical efficiency) and thus maximize the production of good outputs (gross returns) ignoring environmental variables. In a second step one can estimate the potential nutrient removal that is possible given that the farm is economically efficient. This two-step scheme gives priority to the economic efficiency, and then considers the environmental efficiency which is computed in a way that does not create any opportunity costs or increase the economic costs of the farm. This two-step approach can inversely be estimated by giving priority to environmental efficiency in the first step.

Another strand of approach can be found in Picazo-Tadeo et al. (2011), and is based on the estimation of the frontier eco-efficiency (Kuosmanen and Kortelainen, 2005). This model estimates a ratio of economic outcomes (represented by value added or profit) on environmental pressures. In a dual perspective, the model considers undesirable outputs as inputs and thus faces the same criticisms previously mentioned. A recent paper of Serra et al. (2014) explored by-production technologies modelling in the case of crop farm systems in Spain. We have not found an application in agriculture of the natural and managerial disposability concepts, nor the weak G-disposability.

Finally, few studies in the agricultural sector have focused on the emissions of GHG. We can find in Kabata (2011) an application of the WDA to the case of crop and livestock production in the United States, where bad outputs consist in methane and nitrous oxide emissions. Shortall and Barnes (2013) used a data transformation function (inverse) to account for the carbon dioxide, methane and nitrous oxide emissions in the case of Scottish dairy farms. Toma et al. (2013) used two different models, the WDA and the eco-efficiency frontier estimation. Mohammadi et al. (2014) applied the joint Life Cycle Assessment (LCA)-DEA approach to the GHG emissions in paddy rice farms in Iran.

3. Empirical application

3.1. Data description and environmental impacts' computations

The empirical application of the models described on the previous section is conducted on a sample of 1,302 farm-year observations between the period 1987 and 2013. The panel consists of 124 different farms specialized in meat sheep production and located in the centre of France in grassland areas. Several bookkeeping and production process characteristics are available in the database. Following the literature on farms' technical efficiency, we have retained four inputs, namely utilized land, farm labour, operating expenses and structural costs. Operating expenses, also called proportional costs, comprise all costs related to animal feeding, crop fertilizers, pesticides and all the other costs directly associated to the presence of livestock (veterinary costs, mortality insurance, litter straw costs, marketing costs, animal purchase…). Regarding structural costs, they are mainly made of mechanization and building costs (depreciation, maintenance costs, expenses for fuels and lubricants, related insurances) as well as overheads (electricity, water, miscellaneous insurances, financial charges, opportunity costs of capital…). Operational expenses and structural costs are both expressed in constant currency (2005 Euros) to keep relative quantity based information. Utilised land represents the total number of hectares available to the producer for the sheep farming activity. This is essentially the main fodder area associated to the sheep livestock. Labour measures the quantity of full-time workers devoted to meat sheep production. On the output side, good output is measured by the quantity of meat production expressed in kilograms of carcass, and the environmental impacts (bad output) focus on GHG. The computations of the latter are based on LCA methodology, which was used for the estimation of the three main GHG generally considered in livestock farming (carbon dioxide, methane and nitrous oxide). Since our interest is on global warming the three gases were summed up regarding their Global Warming Potential (GWP)[9] relative to carbon dioxide. The bad output is thus computed as the total GHG emissions expressed in carbon dioxide equivalent. When applying LCA we have restrained the system boundary (the perimeter of analysis) from the cradle to the farm gate. More, we adapted the GES'TIM (Gac et al., 2011) and the Dia' terre® (Ademe, 2011) tools to our sample of meat sheep farms. These tools provide us the great majority of emissions factors required for the estimation of the global warming impact. The main characteristics of the sample are summarized in **Table 1**.

On average, over the period of study, farms in our sample produced around a thousand kilograms carcass of meat on a land area of 74 hectares. The pollution intensity, which is measured as the ratio of GHG emissions on meat production, is about 38 kg of carbon dioxide equivalent per kg of carcass on average. The relative standard deviation is similar for all inputs and outputs (about 0.45), except for labour and pollution per meat kg for which it is smaller (respectively 0.35 and 0.28).

Table 1: Summary statistics of the sample (period 1987-2013)

Variables	Mean	Standard deviation	Relative deviation standard	Minimum	Maximum
Utilised land (hectares)	74.1	35.10	0.47	12.40	257.02
Labour (full-time equivalents)	1.38	0.48	0.35	0.14	3.50
Operating expenses (2005 Euros)	28, 664	13, 171	0.46	1 014	122, 730
Structural costs (2005 Euros)	22, 765	9, 728	0.43	1, 645	62, 661
Meat (kg)	9, 913	4, 614	0.47	565	33, 028
Total GHG emissions (kg CO_2-eq)	353, 141	149, 533	0.42	35, 777	1, 153, 434
Pollution intensity (kg CO_2-eq/kg meat)	38	11	0.28	19	105

Notes: CO2-eq: carbon dioxide equivalent. The relative standard deviation is computed as the ratio of the standard deviation on the mean.

3.2. Eco-efficiency comparison: empirical results

For the estimation, we consider here one single frontier which is estimated for the whole period (by pooling all observations together), that it to say we assume no technological change. In addition we

9 The GWP is warming effect relative to carbon dioxide over a period of 100-year time. It is about 25 for methane and 298 for nitrous oxide.

consider land and labour as non-material inputs that are assumed to generate no GHG emissions. By contrast, operating and structural costs are pollution generating. The average eco-efficiencies and their components calculated with all methods described in the previous section are summarized in **Table 2**. For comparison purposes, we have also estimated a classic production technology where pollution is not an issue to the producers who can freely choose both the levels of input consumption and also the level of the good output. We then evaluate the eco-efficiency for each farm given their unchanged pollution emissions. For the sake of simplicity we present the pollution intensity instead of the ratio of meat production per unit of GHG emission. As explained above, for the approaches that include pollution in the production technology, the eco-efficiency score is based on the flexible assumption of free choice of inputs, good output and bad output.

Table 2: Eco-efficiencies for different pollution-generating technologies models: sample's average over the period 1987-2013

			Three sources of inefficiency (equation 12)		
Models	Minimum pollution intensity (kg CO2-eq /kg meat)	Eco-efficiency score	Weak ratio efficiency	Allocative ratio efficiency	Input ratio efficiency
No pollution in the technology: free choice of good output and inputs	10.69	0.300	-	-	-
Pollution as input (model in **2**)	19.19	0.540	0.590	0.949	0.974
WDA with uniform abatement factor (model in **5**)	19.19	0.540	0.581	0.967	0.974
WDA with non-uniform abatement factor	19.19	0.540	0.572	0.961	0.997
Weak G-disposability (model in **6**)	19.19	0.540	0.682	0.895	0.888
By-production modelling with independent technologies (model in **7**)	1.08	0.030	0.630	0.642	0.079
By-production with an interdependence constraint across technologies	9.56	0.269	0.635	0.663	0.681
Unified model under natural and managerial disposability (model in **9**)	19.19	0.540	0.575	0.940	1.000

Notes: CO2-eq: carbon dioxide equivalent

The results in **Table 2** show that all pollution generating models except the by-production approaches, converge to the same eco-efficiency score (54% on average) and the same pollution intensity (19 kg CO2-eq/kg meat on average) as when residuals are considered as inputs. Hence these models suggest that farmers can reduce about half of their actual pollution intensity. An interesting feature of these aforementioned methodologies is that they all point out the same source of inefficiency, namely the weak inefficiency ratio. As explained earlier, this ratio accounts for the presence of technical inefficiencies in the pollution generation process since both inputs and good output are held fixed.

However, some small differences can be found for the case of the model of weak G-disposability which gives the highest score for the weak efficiency ratio. Besides, this model gives more importance to the other sources of inefficiencies. All these models also point out the quasi absence of input ratio inefficiency. For instance, for the unified model under natural and managerial disposability, the input ratio efficiency equals the unity.

The most pessimistic model is the by-production modelling under independence across the two sub-technologies. In fact this model leads to 'unrealistic' results in terms of eco-efficiency since 97% of inefficiency is found to be present in the sample. These questionable results can be explained by the fact that the model separately optimizes the operational efficiency (with the good output frontier) and the environmental efficiency (with the bad output frontier). However, when we impose an interdependence constraint, the by-production model yields more acceptable results and an average eco-efficiency score of 27%. Besides, by introducing the dependence constraints in the by-production model the three sources of inefficiency seem to play equal role in the explanation of the estimated eco-inefficiency with a contribution of about 30%.

For comparison purpose, we also show the results of the technology that completely ignores the presence of undesirable outputs. In this alternative model, we relax the assumption of fixed levels of inputs, and the producer can thus freely chose both the inputs and the good output. This new development produces an eco-efficiency score of 30%. This result is very close to the one obtained under by-production with interdependent sub-technologies. This means that under this technology farmers can reach the same eco-efficiency score as under the technology that incorporates pollution (by-production with dependence constraints) by simply eliminating all the technical inefficiencies present in meat production.

As earlier explained, under the flexible assumption that the producer can freely choose the levels of inputs, of good and of bad outputs, all the DMUs converge to the same eco-efficient farm. We can then obtain the optimal scale of operation that guarantees all farms to be eco-efficient. The results are summarized in **Table 3**.

Again, all models except the by-production[10] approach yield the same optimal size for an eco-efficient farm. In this situation, the best strategy in comparison to the sample average requires producers to

[10] We do not consider the results obtained with the by-production approach with independent technologies given the inappropriateness of the results.

reduce their consumption of inputs and still increase the levels of meat production. This reduction in input usage will also decrease the level of the GHG emissions. Based on the logic developed around the natural and managerial disposability, we can easily say here that farmers choose the negative adaptation to answer the problem of pollution reduction.

In the case of by-production modelling under dependent technologies, the consumption of the non-material input land is increased by almost 26% (in line with the observed sample average of utilised land) while the pollution generating inputs are reduced (respectively 54% and 28% for operational expenses and structural costs), in comparison to the sample's average. This leads to lower levels of GHG emissions. Actually, with this by-production approach there is a substitution between non-material inputs (here mainly agricultural land) and pollution generating ones. Under this technology farmers can still produce 20% more meat than the sample average production.

However, the highest meat production is obtained under the pollution free technology where all inputs are increased to produce more than twice amount of meat (compared to the sample average). Nevertheless, this situation creates larger levels of absolute GHG emissions (ten times more than in the by-production and five times more than the other pollution technologies). The difference between pollution free technology and by-production approach seems to be a matter of trade-off: produce more good output to compensate for the pollution emissions (pollution free technology) or pollute less by reorganizing inputs and take advantage of the possible substitution between material and non-material inputs (by-production technology), and try to produce good output as much as possible given the new inputs. This trade-off implies for the case of meat sheep producers a choice between intensification and extensification strategies.

Table 3: Optimal scale for eco-efficient DMUs

		Land (hectares)	Labour (full-time equivalents)	Operational expenses (2005 Euros)	Structural costs (2005 Euros)	Meat production (kg)	GHG emissions (kg CO_2-eq)
Sample average (actual observed levels)		74.1	1.38	28, 664	22, 608	9, 913	353, 141
			Models				
No pollution in the technology: free choice of good output and inputs		87.1	2.17	122, 730	56, 439	33, 028	1, 153, 434
Pollution as input		36.1	0.98	27, 857	18, 183	12, 123	232, 701
WDA with uniform abatement factor		36.1	0.98	27, 857	18, 183	12, 123	232, 701
WDA with non-uniform abatement factor		36.1	0.98	27, 857	18, 183	12, 123	232, 701
Weak G-disposability		36.1	0.98	27, 857	18, 183	12, 123	232, 701
By-production modelling with independent technologies	Good output technology	87.1	2.17	122, 730	56, 439	33, 028	-
	Bad output technology	-	-	1,793	1,751	-	35, 777
By-production with an interdependence constraint across technologies		93.3	1.33	13, 087	16, 339	11, 850	113, 342
Unified model under natural and managerial disposability		36.1	0.98	27, 857	18, 183	12, 123	232, 701

4. Methodologies convergence or divergence: a discussion

Although many of the presented models reach the same average optimal eco-efficiency score, they differ in their assumptions. From a theoretical perspective, models that consider pollution as input or as output under the weak disposability assumption produce arbitrary wrong trade-offs and do not capture the real nature of undesirable outputs. Murty et al. (2012) estimated these trade-offs and found a negative relation between pollution-generating inputs and the pollution level, which is definitely in opposition to the idea that these inputs are pollution generators. More, they also proved that under some conditions, for a fixed level of inputs, there exist large possibilities of good/bad output combinations that are efficient. This violates the idea behind by-production that there is only one minimal amount of undesirable outputs given the levels of inputs. Other shortcomings of the WDA have been reported by Hailu and Veeman (2001).

To overcome the drawbacks of the previous two models (namely pollution as inputs and WDA), Murty et al. (2012) developed the by-production modelling by assuming that the production process is made of different sub-technologies, and the global technology is the intersection of the good and the bad outputs sub-technologies. However, in the operationalization of the approach the authors assumed independence between both frontiers. We have seen here that under this assumption inconsistent results are generated. For this reason we rely on the new by-production modelling proposed in Dakpo (2014) by introducing some interdependence constraints which link the usage of material inputs in both sub-frontiers. Also in relation to this multiple frontier framework, Sueyoshi and Goto (2011) proposed a unification of the operational and environmental efficiency based on the use of one single intensity factor and also by allowing two possible opposite directions for the inputs. However, in light of the previous results, this interesting approach finally collapses into the model where pollution is considered as an additional input.

The model assuming the weak G-disposability and the materials balance conditions is supposed to reflect the real production process by accounting for the laws of thermodynamics. However, in terms of results, this model also converges towards the one in which GHG emissions are treated as input.

Finally, it is worth mentioning that, despite the fact that models which consider pollution under the WDA, or weak G-disposability, or unified model under natural and managerial disposability, converge to the same results in terms of eco-efficiency as the one where pollution is simply an additional input, some small differences can be found in the sources of improvements.

5. Conclusion

In performance benchmarking the impacts of environmental policies on firm's efficiency have long been investigated. For this, several models of eco-efficiency calculation have been proposed to integrate and analyze the trade-offs between 'intended outputs' and detrimental environmental outcomes. In this paper we have empirically compared eco-efficiency obtained using the main models developed in the literature, for the specific case of meat sheep farms and GHG emissions. Eco-efficiency is computed as the ratio of good output on bad output and is aimed at providing easily interpretable results. To our knowledge this is the first paper that undertakes eco-efficiency comparison in the case of livestock farming systems. Our results also prove that the commonly used models based on the WDA and some recent developments like the weak G-disposability or the unified efficiency measure under natural and managerial disposability, all converge to the same results like in the models that treat residuals as inputs. These results were obtained under the most flexible assumption which allows producers to freely choose all the variables in the technology. Given this limitation of these models, the by-production approach with the inclusion of the dependence constraints seems to provide sound results in the case of GHG emissions. In light of the obtained results, all the models come to the same conclusion of the presence of large inefficiencies in meat sheep farms. This is quite understandable since there is no effective environmental regulation to control livestock farming's GHG emissions in France. Moreover, the results also showed that there is a trade-off between intensification and extensification as response to the emissions of GHG in meat sheep production. One limitation of this study is that we did not account for carbon sequestration in soils which is a specific feature of livestock farming as a potential abatement option. This aspect could be explicitly modelled in the by-production technology.

Appendix: Undesirable outputs in agriculture: some applications

Authors	Decision Making Units	Country	Undesirable outputs	Bad outputs treated as:	Assumptions (and model) about bad outputs
Ball et al. (2001)	48 States	United States	Nitrogen and pesticide surpluses, pesticide toxicity on human health and fish	Outputs	Weak disposability (directional distance function)
Shaik and Perrin (2001)	Nebraska data from 1936 to 1997	United States	Nitrate pollution and pesticide environmenental impact	Outputs	Weak disposability (hyperbolic efficiency measure)
Shaik et al. (2002)	Nebraska data from 1936 to 1997	United States	Nitrogen pollution (surpluses)	Outputs and inputs	Two models: 1-)Weak disposability of undesirable outputs, 2-) strong disposability of undesirable outputs treated as inputs.
Lansink and Reinhard (2004)	Pig producers	The Netherlands	Phosphorus surplus and ammonia emissions	Inputs	Weakly disposable inputs (like in congestion situations)
Ball et al. (2004)	48 States	United States	Risk to human health and aquatic life of pesticide runoff and leaching	Inputs	Strong disposability
Asmild and Hougaard (2006)	Pig producers	Denmark	Nutrient removal (nitrate, potassium and phosphorus)	Outputs	Strong disposability (transformation of nutrient surpluses into nutrient removal)
Piot-Lepetit and Le Moing (2007), and Piot-Lepetit (2010)	Pig producers	France	Nitrogen surplus	Outputs	Weak disposability (directional distance function)
Coelli et al. (2007)	Pig producers	Belgium	Phosphorus emissions	Residuals	Materials balance principles
Yang et al. (2008)	Pig producers	Taiwan	Wastewater (biochemichal oxygen demand -BOD, chemichal oxygen demand -COD, suspended solid -SS)	Outputs	Assume the presence of abatement technologies and consider the abated bad outputs as strongly disposable
Hoang and Rao (2010)	29 countries	OECD countries	Balance of cumulative energy	Residuals	Materials balance principles
Picazo-Tadeo et al. (2011)	Rain-fed agricultural systems (crop producers)	Spain	Specialization (tendency towards monoculture), nitrogen and phosphorus balance, pesticide risk,	Inputs	Strong disposability (use of eco-efficiency model)

Authors	Decision Making Units	Country	Undesirable outputs	Bad outputs treated as:	Assumptions (and model) about bad outputs
			energy balance (energy ratio of inputs on outputs)		
Hoang and Coelli (2011)	30 countries	OECD countries	Nitrogen and phosphorus surpluses	Residuals	Material balance principles
Kabata (2011)	Crop/livestock production; data for States	United States	Methane and nitrous oxide gas	Outputs	Weak disposability assumption (hyperbolic efficiency measure, directional distance function)
Ramilan et al. (2011)	Virtual dairy farms	New Zealand	Nitrogen discharge	Outputs	Weak disposability assumption
Iribarren et al. (2011)	Dairy farms	Spain	methane, ammonia, nitrous oxide, wastewater,	Not incorporated in the model	LCA+DEA methodology
Arandia and Aldanondo-Ochoa (2011)	Crop farmers and vineyards	Spain	Nitrogen surplus and pesticide impacts	Outputs	Weak disposability without the equality constraints
Picazo-Tadeo et al. (2012)	Olive-growing producers	Spain	Soil erosion, pesticide risks on biodiversity, energy balance	Inputs	Strong disposability (use of eco-efficiency model)
Berre et al. (2012)	Dairy farms	Reunion Island (France)	Nitrogen surplus	Outputs	Weak disposability (directional distance function with heterogeneity in abatement factors)
Skevas et al. (2012)	Specialized arable farms	The Netherlands	Pesticide impacts on water organisms and biological controllers	Outputs and inputs	Weak disposability of undesirable inputs/outputs in a dynamic perspective (non-radial directional distance function)
Hoang and Nguyen (2013)	Rice producers	South Korea	Nitrogen and phosphorus surpluses	Residuals	Materials balance principles (mass balance equation and iso-environmental cost line)
Latruffe et al. (2013)	Pig producers	Hungary	Nitrogen produced	Inputs	Strong disposability (free)
Nin-Pratt (2013)	Livestock farms	142 countries	Nitrogen surplus	Residuals	Materials balance principles (mass balance equation and iso-environmental cost line)
Kuosmanen and Kuosmanen (2013)	Data from 1961-2009	Finland	Nitrogen and phosphorus surpluses	Residuals	Dynamic materials balance conditions
Serra et al. (2014)	Crop farms	Spain	Nitrogen and pesticide pollution, damages to human health	By-products	Cost disposability (by-production modeling)
Shortall and Barnes (2013)	Dairy farms	Scotland	Carbon dioxide, methane,	Outputs	Strong disposability (inverse data transformation

Authors	Decision Making Units	Country	Undesirable outputs	Bad outputs treated as:	Assumptions (and model) about bad outputs
			nitrous oxide		function)
Falavigna et al. (2013)	102 provinces	Italy	Nitric acid emissions	Outputs	Weak disposability (directional output distance function)
Toma et al. (2013)	Dairy farms	Scotland	GHG emissions and nitrogen surpluses	Outputs and inputs	Two models: 1-) weak disposability assumption of bad outputs, 2-) Eco-efficiency model (strong disposability)
Beltrán-Esteve et al. (2013)	Rain-fed olive farms	Spain	Pressures on environmental resources and biodiversity (soil erosion and energy used)	Inputs	Eco-efficiency model (strong disposability) adapted to the case of meta-frontier)
Mohammadi et al. (2014)	Paddy rice farmers	Iran	GHG emissions (carbon dioxide, methane, nitrous oxide, ammonia, nitrates), phosphorus emissions in water	Not incorporated in the model	LCA+DEA methodology

Note: in Toma et al. (2013) the authors refer to the first model to as the undesirable output oriented model (UO) and to the second model as the normalized undesirable output oriented model (NUO) as developed in Tyteca (1996).

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