Agri-environmental subsidies and French suckler cow farms' technical efficiency accounting for GHGs

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Abstract

In this article we assess the impact of agri-environmental subsidies on farms' technical efficiency, when the latter is measured with and without accounting for greenhouse gases (GHGs). The application is to a sample of beef cattle farms located in grassland areas in France during the period 1993-2013. In a first stage we calculate robust technical efficiency accounting for both good output (meat) and bad output (GHGs). In a second stage we regress the different technical efficiency scores on a set of explanatory variables including agri-environmental subsidies as an amount received by the farmer related per livestock unit. The results indicate that these subsidies had a positive impact on farms' technical efficiency among the farmers that have adopted agri-environmental measures. This is the first work on the effect of subsidies on technical efficiency including environmental outputs, and it does not confirm the negative effect generally found in existing studies based on classic technical efficiency.

Keywords: by-production, GHG emissions, agri-environmental subsidies, livestock

JEL CODES: D24, O47, Q10, Q50

1. Introduction

Till the late eighties agriculture in developed countries was characterised mainly by productivity increase and farming intensification without little mention to environmental management or outputs (either positive or negative). In the early nineties the emergence of multifunctionality and sustainability concepts have given rise to new strands of thought emphasising environmental concerns (landscape, biodiversity, water pollution, pesticides use, atmospheric pollution, erosion…) in policy design (Bohman et al., 1999). In the European Union (EU) farmers are subsidised by the Common Agricultural Policy (CAP), whose objective has gradually shifted from supporting farmer's income and modernising the sector, to enhancing farms' competitiveness and promoting a sustainable use of resources (Cooper et al., 2009 p85). Among the different CAP policy instruments that embed the challenges of environmental protection, agri-environmental and cross compliance measures are the main ones. Other instruments have a more indirect impact on environmental output provision, such as farm modernisation support, training and advice measures, and payments for location in disadvantaged regions, the so-called Less Favoured Areas (LFA) subsidies. (See Cooper et al., 2009 pp86-88 for more details).

Agri-environmental measures (AEMs) are the most direct measures for which the 'provision of public goods is the primary rationale' (Cooper et al., 2009 p86). They are also the 'most significant both in terms of its spatial coverage and the financial resources allocated to it' (Cooper et al., 2009 p89). AEMs are examples of payments for environmental services (PES), a generic instrument used to pay farmers for mitigating (respectively increasing) the production of negative (respectively positive) externalities from agricultural activities (Baylis et al., 2008). The effectiveness of AEMs has been debated in the literature regarding the variability (and contrastability) in terms of impact results (Kleijn and Sutherland, 2003, Oréade-Brèche, 2005, Kleijn et al., 2006, Scheper et al., 2013). We contribute here to studies on the impact of these measures on farm performance, and focus more precisely on greenhouse gases (GHGs) and farm technical efficiency. Although AEMs are not explicitly designed for GHGs mitigation, some specific measures can directly affect the level of atmospheric pollution. For instance actions towards the reduction of nitrous oxide and inputs' usage (e.g. fertilisers), and towards the preservation of water quality can affect the levels of GHGs releases (Oréade-Brèche, 2005). Land management initiatives can also increase the potential of carbon storage in soils. However, there is a quasi-inexistence of ex-post scientific studies that assess the potential relation between AEMs and GHG emissions. This may be explained by limits on data availability, and by the only recent growing interest on GHG emissions in the agricultural sector. Our paper contributes to this gap by providing an analysis of the impact of AEMs on farms' technical efficiency in a French case study, when technical efficiency is measured with and without accounting for atmospheric pollution, and more precisely GHGs and carbon sequestration in grasslands. This can provide insights for the low carbon and resource efficient economy objective of the EU (EEA, 2010).

Numerous researches have been conducted on the impact of subsidies on farms' technical efficiency (see Minviel and Latruffe (2014)'s meta-analysis). The most frequent finding is a negative impact, suggesting that farms that receive more subsidies are less technically efficient. This is explained by the possibility that farmers reduce their managerial effort (based on Martin and Page (1983)'s suggestion for firms) or change their risk attitudes (suggested for the agricultural sector by Serra et al. (2008)) when they receive these additional certain payments. The case of the impact of subsidies from AEMs, that is to say agri-environmental subsidies, on farms' technical efficiency has been less studied than other types of subsidies. The particularity of agri-environmental subsidies is that they are provided to farmers who voluntary enrol in AEMs aimed at promoting environmental-friendly practices. Hence, when contracting such schemes, farmers may modify their practices and increase their input use in order to comply with the scheme requirements, e.g. labour increase in order to plant hedges or land increase in order to become more extensive. However, this input increase may not be accompanied by an increase in the output, implying that one would conclude to a negative impact of agri-environmental subsidies on technical efficiency. But the conclusion may change if environmental non-marketed goods are included in the computation of technical efficiency. If AEMs effectively lead to an increase in the environmental good (or a decrease in the environmental bad) produced by the farms, then farms implementing environmental-friendly practices (and receiving the subsidies) may have a better environmentally-adjusted-technical efficiency than other farms. Our paper is the first one to assess the effect of subsidies on such pollution-adjusted efficiency, the literature having so far been restricted to the classic technical efficiency that do not account for environmental goods.

In the past few years the literature has integrated environmental bads in the computation of technical efficiency, with an improvement of the available methods along the years (see the review by Dakpo et al. (2016)). In this paper we use the most recent approach suggested by Dakpo (2015), the 'extended by-production' approach, to incorporate GHGs in the calculation of pollution-adjusted technical efficiency for a sample of beef cattle farms located in grassland areas in central France. Carbon sequestration in grasslands is also accounted for. The period studied is 1993 to 2013, which encompasses the very first period of AEMs' implementation in France (the effective implementation started in 1995) as well as the following two rural development programming (RDP) periods (2001-2006 and 2007-2013) in which AEMs are included.

At the crossroads of many international debates (as for instance the COP21 held in Paris, 2015), it is widely admitted that anthropogenic GHG releases in the atmosphere are responsible for the acceleration of the global warming phenomena. In light of the expected consequences, mitigation actions need to be implemented in all sectors of human activities. Livestock farming is no exception to this, since, according to several FAO reports, this sector is responsible for 13 to 18% of the total GHG emissions, mainly through methane emissions but also carbon dioxide and nitrous oxide (Steinfeld et al., 2006, Gerber et al., 2013). This confirms the relevance of including GHG emissions as bad outputs in an assessment of pollution-adjusted technical efficiency for livestock farming.

In summary, the contributions of our paper are twofold. Methodologically, we extend the by-production model in an innovative way by using an order-m approach for robustness purposes (Cazals et al., 2002, Daraio and Simar, 2007a). Empirically, we provide a first understanding of the impact of AEMs on farmers' technical efficiency when one considers atmospheric pollution in the shape of GHG emissions.

The rest of the paper is structured as follows. Section 2 is an overview of the implementation of the AEMs in France. Section 3 presents the methodology and Section 4 describes the data. Section 5 explains the results and Section 6 concludes.

2. Overview of AEMs in France

France adopted of the EU regulation 797/1985 in 1991 making this country one of the latest applicants of article 19 of this regulation (Desjeux et al., 2007). As put forward in Buller et al. (2000 p9) 'France appeared to regard agri-environmental debate as an almost quaint, essentially British, obsession with wildlife that had little in common with the reality of French farming culture and with French rural environmental concerns'. This apparent reluctance may be explained by the fact that for many agricultural organisations, AEMs are impediments to the traditional productivism concept, due to extensification and land set-aside measures. From another perspective, the existence of extensive systems (pastures, mountain farming) with high environmental value have strengthened the perception that agriculture is already a producer of environmental outputs without the need to resort to AEMs to encourage the maintenance of this activity in such areas (Buller et al., 2000).

Regulation 2078/93[1] has taken three forms in France: first, support for extensive rearing activities, with the creation of the grassland premium ('prime à l'herbe'); second, design of various local agri-environmental programs ('programmes agri-environnementaux' – PAE); and third, implementation of sustainable development plans ('plans de développement durable' – PDD). Grassland premiums are aimed at encouraging de-intensification and restraining the reduction of (permanent) grasslands areas.[2] Regarding local agri-environmental programs, they are more localised (regions, sub-regions or smaller areas) and include for example measures for water protection (through inputs' reduction, reconversion of croplands to grasslands, long term – 20 years – leys, protection of threatened local breeds, farmers' training programmes), support to conversion into organic farming, incentives for extensive suckler/sheep farming. As for sustainable development plans (which appeared around 1996), they relate to the three sustainability pillars, namely economic, environmental and social aspects. They are based on the production system itself (i.e. the farm), by integrating economic and environmental data. In summary regulation 2078/93 set two objectives in France: the reduction of agriculture's polluting impact, and the maintenance of natural spaces.

In 2000 (with EU regulation 1257/99) a new scheme including contracts based on regional farming practices ('contrat territorial d'exploitation' - CTE) was enforced under the RDP 2000-2006 (Baschet, 2005). These contracts aimed at encouraging the adoption of environmental-friendly cropping and rearing practices. Similarly to any AEM, their subsidy amount is based on the estimation of the farmer's foregone income and includes also an

[1] Regulation 2078/93 has extended the EU co-funding to a minimum of 50%. It also implies that AEMs are not only aimed at fragile natural zones.

[2] A farmer must commit to keep at least 75% of the farm's total agricultural area in grasslands, and to maintain the stocking rate (number of livestock unit per hectare) lower than 1.4. The farmer must also comply with the maintenance of grasslands' hedgerows.

incentive (up to 20% as much as the previous generation payments). With these contracts, farmers are committed for a period of five years (more details on the difference between these contracts and previous instruments are discussed in Desjeux et al. (2007 pp32-33)). However, these contracts were suspended in August 2002 after the change of the parliamentary majority, and were removed in October 2003. The same year they were replaced by another instrument coined 'contrat d'agriculture durable' (CAD), which was more devoted to agri-environmental matters than previous contracts.

During the CAP Health Check and discussions on the RDP for years 2007-2013 (EU regulation 1698/2005), the existing AEMs were revised and reinforced to strengthen their environmental impact. The main change is the creation of territorialised AEMs, that are more specific and targeted towards pre-identified territories. In France AEMs represent 30% of the CAP RDP expenses, i.e. 5% of total CAP budget in 2011, which makes them still marginal. In 2009 only 12% of the French utilised agricultural area were under AEMs (compared to 91% in Finland).[3] The 2014-2020 CAP reform has reinforced the focus on territorialised AEMs with climatic and agri-environmental measures, which stress more on the whole farm system commitments rather than plots' specific environmental stakes.

3. Methodology

Let's define by $(x, y, b, z) \in \mathbb{R}^{P+Q+R+S}$ the vectors of respectively the farm's inputs, good outputs, bad outputs and environmental factors; the latter are exogenous variables that play a role on technical efficiency. N is the total number of decision making units (DMUs) on the sample and t represents each period of time.

3.1. Non-parametric robust efficiency measures

Classically, the production technology (free of bad outputs) can be defined as:

$$\Psi = \{(x, y) \in \mathbb{R}^{P+Q} \mid x \text{ can produce } y\} \tag{1}$$

[3] http://ec.europa.eu/eurostat/statistics-explained/index.php/Agri-environmental_indicator_-_commitments.

In the non-parametric DEA framework, a (good) output efficiency score for DMU_a assuming variable returns to scale (VRS) (Banker et al., 1984) can be computed as follows:

$$
\begin{aligned}
& D_{Oa}(x,y) = \max_{\phi,\mu} \phi_a \\
& s.t \quad \sum_{n=1}^{N} \mu_n x_{np} \leq x_{ap} \quad p = 1,\dots,P \\
& \sum_{n=1}^{N} \mu_n y_{nq} \geq \phi_a y_{aq} \qquad q = 1,\dots,Q \\
& \sum_{n=1}^{N} \mu_n = 1 \quad ; \quad \mu_n \geq 0
\end{aligned}
\tag{2}
$$

where D_{Oa} is the efficiency score of DMU_a, and μ and ϕ are scalars.

Due to its non-parametric nature, DEA can be very sensitive to outliers and extreme observations especially when data are plagued by measurement errors. In this non-parametric framework robust versions have been proposed: order-m and order-α quantile frontiers (Cazals et al., 2002, Aragon et al., 2005). These partial or robust frontiers not only overcome the drawback associated to extreme points, but also offer the advantage of limiting the curse of dimensionality inherent to the non-parametric approaches, given that they have the same rate of convergence as parametric estimators. Operationally, these partial frontiers allow a percentage of the cloud of observations to lie above the frontiers. In this paper we use the order-m robust frontier. The partial frontiers have mostly been discussed in relation to the free convex hull technology, or free disposal hull (FDH), where the convexity assumption is not maintained (Deprins et al., 1984)). Yet, as underlined in Daraio and Simar (2007b p13), 'convexity has always been assumed in mainstream production theory and general equilibrium. In addition, in many empirical applications, the convexity assumption can be reasonable and sometimes natural'. Following this, all the developments carried out in this paper are related to convex technologies.

In the case of the partial version of convex technologies, the robust equivalent of the output efficiency score in equation **(2)** can be obtained by using Monte-Carlo simulation, as follows:

[1] Given an input level x_a, draw with replacement m observations among $\{x_n\}_{n=1,\dots,N}$ such that $x_n \leq x_a$. The obtained sample can be denoted as $(x_{1,c}, x_{2,c}, \dots, x_{m,c})$;

[2] Solve the following linear program:

$$\widehat{D}_{Oa}^{m,c}(x,y) = \max_{\phi,\mu} \phi_a^{m,c}$$

$$s.t \quad \sum_{i=1}^{m} \mu_i y_{iq} \geq \phi_a^{m,c} y_{aq} \qquad q = 1, \dots, Q \tag{3}$$

$$\sum_{i=1}^{m} \mu_i = 1 \quad ; \quad \mu_i \geq 0$$

[3] Do again steps [1] to [2] for $c = 1, \dots, C$ where C is a large number;

[4] Compute the robust efficiency score as $D_{Oa}^{m}(x,y) = \frac{1}{C}\sum_{c=1}^{C} \widehat{D}_{Oa}^{m,c}(x,y)$.

The quality of the estimation can be improved by increasing C. In this paper we chose a very large $(C = 2000)$.[4] Regarding the choice of m, this can be guided by the elbow property which states in this case to retain the value of m for which the proportion of observations above the frontier is stable (Simar, 2003). In this case one can argue that the obtained attainable set is a 'full' frontier robust to the presence of outliers.

Regarding the inclusion of undesirable outputs b in the production technology, we rely on the model proposed by Dakpo (2015). This approach enables representing adequately a multi-ware technology when outputs may not all be substitutable and may not all be produced by the same inputs. More precisely, it models two types of sub-technologies, one for the good output and one for the bad outputs, and links both sub-technologies. This linkage is an extension of the classic by-production model proposed by Murty et al. (2012). It allows for interconnectedness between the different production processes present in a DMU, while in Murty et al. (2012) independence is maintained. To define the technology, inputs are split into two categories: non-polluting inputs $(x_1 \in \mathbb{R}^{P_1})$ and pollution-generating inputs $(x_2 \in \mathbb{R}^{P_2})$. The by-production technology can be represented as follows:

$$\Psi^{by} = \Psi_1 \cap \Psi_2$$

where

$$\Psi_1 = \{(x_1, x_2, y, b) \in \mathbb{R}^{P_1+P_2+Q+R} \mid f(x_1, x_2, y) \leq 0\} \tag{4}$$

and

$$\Psi_2 = \{(x_1, x_2, y, b) \in \mathbb{R}^{P_1+P_2+Q+R} \mid g(x_2, b) \geq 0\}$$

[4] As noticed in Daraio and Simar (2007b), the model in **(3)** assumes local convexity, and a global convex technology can be estimated. However, in our paper we only consider local convexity (global convexity can be easily estimated).

where f is the good output production function and g is the bad output production function.

Murty et al. (2012) proposed the following DEA representation:

$$\Psi^{by} = \left\{ (x_1, x_2, y, b) \in \mathbb{R}^{P_1+P_2+Q+R} \mid x_1 \geq \sum_{n=1}^{N} \nu_n x_{1n}\, ; x_2 \geq \sum_{n=1}^{N} \nu_n x_{2n}\, ; y \leq \sum_{n=1}^{N} \nu_n y_n\, ; \sum_{n=1}^{N} \nu_n = 1;\ x_2 \leq \sum_{n=1}^{N} \lambda_n x_{2n}\, ; b \geq \sum_{n=1}^{N} \lambda_n b_n\, ; \sum_{n=1}^{N} \lambda_n = 1; \nu, \lambda \geq 0 \right\} \tag{5}$$

where ν and λ are the intensity variables given weights to each observation in the reference set.

In model **(5)** the two sub-technologies are represented by two distinct intensity variables (ν, λ) which represent the weights given to each DMU in the benchmark of an evaluated observation. In model **(5)** independence between the sub-technologies is maintained, and Dakpo (2015) added the following dependence constraints to overcome this:

$$\sum_{n=1}^{N} \nu_n x_{2n} = \sum_{n=1}^{N} \lambda_n x_{2n} \tag{6}$$

As underlined in Coelli et al. (2007) physical processes are ruled by materials balance principles, i.e. the amount of pollution generated is proportional to the levels of polluting inputs consumed. Under this circumstance one can consider constant returns to scale (CRS) for the bad output sub-technology (by removing the convexity constraint $\sum_{i=1}^{N} \lambda_n = 1$). In terms of efficiency evaluation there are two situations possible: first, good output efficiency is estimated under the fixed levels of inputs and bad outputs; second, a pollution-adjusted technical efficiency can be measured where good and bad outputs are respectively maximised and minimised. Here we consider this latter situation. However, given the materials balance laws, bad outputs cannot be minimised by holding the levels of polluting inputs fixed. One strategy is to minimise those inputs along with the bad outputs. Here, in order to capture allocation inefficiency, we propose to measure the efficiency under the free choice of polluting inputs. The efficiency program therefore assumes endogenous levels of polluting inputs, as expressed in **(7)**:

$$
\begin{aligned}
& D_{OUa}(x,y,b) = \max_{\phi,\nu,\lambda,x_2} \frac{\phi_a}{\theta_a} \\
& x_{1a} \geq \textstyle\sum_{i=1}^{N} \nu_n x_{1n} \\
& x_{2a} \geq \textstyle\sum_{i=1}^{N} \nu_n x_{2n} \\
& \phi_a y_a \leq \textstyle\sum_{i=1}^{N} \nu_n y_n \\
& \textstyle\sum_{i=1}^{N} \nu_n = 1 \\
& x_{2a} \leq \textstyle\sum_{i=1}^{N} \lambda_n x_{2n} \\
& \theta_a b_a \geq \textstyle\sum_{i=1}^{N} \lambda_n b_n \\
& \textstyle\sum_{i=1}^{N} \nu_n x_{2n} = \sum_{i=1}^{N} \lambda_n x_{2n}\ ;\ \nu,\lambda \geq 0\ ;\ (x_1,x_2,y,b) \in \mathbb{R}^{P_1+P_2+Q+R} \\
& \theta_a \leq 1\ ; \phi_a \geq 1
\end{aligned}
\tag{7}
$$

where ϕ, θ, ν and λ are scalars.

In model **(7)** the inclusion of bad outputs in the objective function implies endogeneising the levels of polluting inputs. The program that we propose in **(7)** is a fractional program which can be easily linearised using Charnes and Cooper (1962)'s transformation. To our knowledge, robust frontiers are designed for single system technologies. However, our by-production model here is made of two unified sub-technologies. Hence, we propose an extension of the order-m to assess efficiency in **(7)**. The robust version needs to account for the endogenous levels of polluting inputs. We therefore propose the following algorithm:

[1] Given that polluting inputs imply two distinct orientations under good and bad outputs sub-technologies, it may seem intuitive to consider the draw of two samples.[5] However, for consistency, since in our model in **(7)** polluting inputs are endogeneised, the draw of a sample may neglect these polluting inputs. Hence, for a given level of non-polluting input x_{1a}, we draw a sample of size m with replacement among $\{x_{1n}\}_{n=1,\dots,N}$ such that $x_{1n} \leq x_{1a}$. Let's denote the sample by $(x_{11,c}\,, x_{12,c}\,, \dots, x_{1m,c})$;

[2] Solve the following fractional program:

$$
\begin{aligned}
& \widehat{D}_{OUa}^{m,c}(x,y,b) = \max_{\phi,\nu,\lambda,x_2} \frac{\phi_a^{m,c}}{\theta_a^{m,c}} \qquad (8) \\
& x_{2a} \geq \textstyle\sum_{i=1}^{m} \nu_i x_{2i}
\end{aligned}
$$

[5] One can refer to conditional free and cost disposability discussed in Murty (2015) for a discussion on these two orientations.

$$\phi_a^{m,c} y_a \leq \sum_{i=1}^{m} \nu_i y_i$$
$$\sum_{i=1}^{m} \nu_i = 1$$
$$\theta_a^{m,c} b_a \geq \sum_{i=1}^{m} \lambda_i b_i$$
$$x_{2a} \leq \sum_{i=1}^{N} \lambda_i x_{2i}$$
$$\sum_{i=1}^{m} \nu_i x_{2i} = \sum_{i=1}^{m} \lambda_i x_{2i} \; ; \; \nu, \lambda \geq 0 \; ; \; (x_1, x_2, y, b) \in \mathbb{R}^{P_1+P_2+Q+R}$$

In **(8)** the two sub-technologies are considered independently but the dependence constraints link them. $\phi_a^{m,c}$ and $\theta_a^{m,c}$ can be greater or less than one:

[3] Do again steps [1] to [2] for $c = 1, \ldots, C$ where C is a large number;

[4] Compute the robust efficiency score as $D_{OUa}^{m}(x, y, b) = \frac{1}{C} \sum_{c=1}^{C} \widehat{D}_{OUa}^{m,c}(x, y, b)$. As explained previously, the choice of m here also follows the elbow property (proportion of DMUs for which $D_{OUa}^{m}(x, y, b) < 1$).

The models above show two types of efficiency scores: the classic one obtained in model **(2)** and the pollution-adjusted one obtained in model **(7)**.

3.2. Role of AEMs on technical efficiency

We investigate the role of AEMs on farms' technical efficiency in a second stage using econometric procedures. This is investigated according to two questions:

(1) Does the adoption of AEMs raise farms' efficiency?

(2) Does the level of subsidies received when contracting AEMs, affect farms' efficiency?

To shed light on the first question, we assess the effect of adoption of AEMs on farm technical efficiency using a binary variable for AEMs and considering the whole sample; this is our econometric Model A. To answer the second question, we investigate whether there is a subsidy effect on farm technical efficiency among those farmers who adopted AEMs, namely whether the level of AEM subsidies (as a continuous variable) plays a role on the efficiency of those farmers who have contracted AEMs; this is our econometric Model B.

Model A is equivalent to the estimation of equation **(9)**:

$$D = h(Z, A) + \epsilon \tag{9}$$

where D is the farm efficiency score, A is a dichotomous variable which equals 1 if the farmer has adopted AEMs and 0 otherwise, Z is a vector that includes the other variables explaining efficiency (the environmental factors mentioned above), h is a specific function, and ϵ is an error term.

Equation **(9)** can be estimated using a simple ordinary least squares (OLS) since D is the robust version of the efficiency score and therefore is not bounded by one. However, though for EU Member States it is compulsory to design a policy programme for AEMs, the latter are voluntary-based for farmers. In impact evaluation this creates a typical problem known as self-selection, where the decision of farmers to adopt AEMs is not randomly distributed but is rather associated to a number of observable and unobservable features (Clougherty et al., 2015). Self-selection is a problem of omitted variables which can potentially affect both the level of efficiency D and the AEM adoption variable A, this latter variable being deemed endogenous in equation **(9)**. To correct for this endogeneity we estimate in a first step the latent variable A^* associated to A using a probit regression:

$$A = \Theta(Z, W, Z * W, Z^2, W^2) + \mu \tag{10}$$

where W can be viewed here as instrumental variables which are correlated to A but do not explain D; Θ is a specific function and μ is an error term. **(10)** can be viewed as the selection equation. The deterministic part of **(10)** is then used as a prediction for A^* which can be considered as an estimated instrument for the endogenous variable A. Using this instrument in a classic two-stage least squares enables correcting for the endogeneity problem associated to variable A. Since here we use an estimated instrument, we also include cross terms and squared variables in the selection equation in **(10)**. This strategy for estimating an instrument to correct for the endogeneity problem is particularly useful when the endogenous variable is dichotomous as in **(9)**. In the case of a continuous endogenous variable as in Model B below, this is not necessary.

Model B is equivalent to the estimation of equation **(11)**:

$$D_{A=1} = k(Z, S) + \kappa \tag{11}$$

where where $D_{A=1}$ is the farm technical efficiency score for farms having contracted AEMs; S is the amount of subsidies received by the farms through AEMs (agri-environmental subsidies); k is a specific function and κ is an error term. Here also there is an endogeneity issue associated to the variable S, since farmers may decide simultaneously on the level of S and the level of inputs and outputs. The use of instrumental variables allows correct for this. The instrumentation equation that is estimated using a classic instrumental variable approach (two-stage least squares) is as follows:

$$S = \pi(Z, W) + u \tag{12}$$

where π is a specific function and u is an error term.

4. Data description

The application is to a sample of beef cattle farms located in central France in the Massif Central region, an area with grasslands. The sample is unbalanced: around 78 farms are included in the sample each year, making a total number of 1,651 farm-year observations over the 21 year period (1993-2013). The good output considered in the DEA model is the meat production in tons of live weight. The four inputs used are the fodder area (in hectares) for beef cattle production, labour (in full-time equivalent working units) devoted to beef production, herd size (in livestock units) and beef production-related costs (in 2005 Euros). These production costs include operational and structural costs, and more precisely on and off farm feed costs; veterinary and rearing expenses; costs related to fertilisers, seeds, fuel, electricity, water, equipment and buildings (depreciation and maintenance); and all other expenses associated to the production activity.

As for the bad output, is includes GHGs released into the atmosphere. Three gases are generated in livestock farming: carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O). We quantified these GHGs using Life Cycle Analysis (LCA). This methodology helps evaluating the environmental impacts associated to products during their whole life cycle (Finnveden et al., 2009). Here the product considered is meat production in livestock farms and the boundary is from cradle to the farm gate.[6] The LCA methodology has been adapted to the particular case of French suckler cows using the French tools GES'TIM (Gac et al., 2011) and Dia' terre® (ADEME, 2011) which are grounded on Tier 1 and Tier 2 methodologies of IPCC. Methane is mainly related to enteric fermentation and a small share of it arises from manure stocking and spreading. Nitrous oxide is associated to nitrogen fertilisers and animal excreta. Carbon dioxide comes from fossil fuels' burning, and from manufacturing and transportation of animal feeds, fertilisers, seeds, pesticides, machineries, buildings, veterinary products and other farm inputs. The total GHGs emissions are computed by summing the three gases using their global warming potential (GWP) related to carbon dioxide.[7] The total GHG emissions are expressed in carbon dioxide equivalent.

To account for carbon sequestration in grassland areas, we adapted the tools developed in the national expertise conducted for the French Institute for Agricultural Research (INRA) by Arrouays et al. (2002). In this study the authors report equations to estimate the quantities for carbon sequestration by taking into account rotation between cash crops and grasslands. Carbon sequestration is also expressed in carbon dioxide equivalent.

Descriptive statistics of inputs and outputs for our sample are provided in **Table 1**. Over the whole period 1993-2013 farms in the sample operated on average 149.9 hectares of total agricultural area, among which 118.3 hectares of fodder area, and the stocking rate was 1.27 livestock unit per hectare of fodder area. More than three quarter of the observations (78%) display a stocking rate below 1.4, a threshold which characterises more extensive farms. The average quantity of GHGs emitted was 14.5 kg of carbon dioxide equivalent per kg of live meat. This result falls within the large range of emissions intensity found in the literature (de Vries and de Boer, 2010, Desjardins et al., 2012, de Vries et al., 2015). When accounting for carbon sequestration in soils, the pollution intensity is decreased on average by a little more than 12%.

[6] Several studies have used LCA to assess the environmental impacts of meat production in livestock systems and in particular GHG emissions (Wiedemann et al., 2015, Cardoso et al., 2016).

[7] The GWP equals 25 for methane and 298 for nitrous oxide (Forster et al., 2007).

Table 1: Descriptive statistics of inputs and outputs used for the whole period (1993-2013)

	Mean	Minimum	Maximum	Standard deviation	Relative standard deviation
Fodder area (hectares)	118.3	32.3	442.2	51.9	0.44
Labour (working units)	1.7	0.5	4.6	0.6	0.36
Herd size (livestock units)	149.8	42.6	465.0	70.9	0.47
Production-related costs (thousands 2005 Euros)	73.2	8.4	329.3	39.4	0.54
Meat production (tons of live weight)	46.9	7.4	173.9	24.4	0.52
GHG emissions (tons)	669.1	158.9	2,589.4	344.2	0.51
Pollution intensity (kg CO_2-eq/kg of live meat)	14.5	9.6	28.0	2.0	0.14
Net GHG emissions (tons)	591.8	126.4	2,356.4	316.4	0.53
Net pollution intensity (kg CO_2-eq/kg of live meat)	12.7	7.8	24.3	1.8	0.14

Notes: Sample size: 1,651 farm-year observations. The livestock unit is a reference unit used for the aggregation of different types of animals on the basis of their nutritional or feed requirement; one livestock unit corresponds to one dairy cow which produces about 3,000 litres of milk per year. Net GHG emissions implies that carbon sequestration is accounted for. CO_2-eq: carbon dioxide equivalent.

The exogenous variables (environmental factors) used in the regression analysis are presented in **Table 2**. The agri-environmental subsidies considered here are mainly grassland premiums, and also include extensification and other related subsidies. The subsidies were provided to farmers who committed to keep a large share of permanent grasslands on their farm and long temporary leys (five years). They aim at limiting the stocking rate (i.e. the number of livestock units per hectare of fodder area) on farms, improving nitrogen management, reducing the quantity of fertiliser spread on land, and increasing carbon sequestration in land. In other words, these subsidies create incentives towards extensive farming and a more efficient input consumption. They can thus directly or indirectly affect the levels of GHGs.

Over the whole period 64% of the farm-year observations of the sample received agri-environmental subsidies. The subsidy variables are incorporated in the regression as a ratio of the amount in Euros per livestock unit, in order to control for size effects. On average farms that have adopted AEMs received 44.9 Euros of agri-environmental subsidies per livestock unit. All farms in our sample are conventional farms (no organic farms). Several explanatory variables are included in the regressions of technical efficiency scores, based on the literature review: farm total land area (in hectares); capital to labour ratio, as the value of assets (in Euros) related to the number of working units; share of hired labour in total labour; debt to asset ratio; stocking rate as the number of livestock units per hectare of fodder area; share of permanent grassland in farm total area; numerical productivity as the number of live-weaned calves born per cow multiplied by 100; quantity of concentrates per cow (in kg); feed autonomy in percentage, which represents the share of animal feed that is produced on farm; the proportion of land that is rented in; subsidies received when the farm is located in LFA; other subsidies, that is to say excluding agri-environmental subsidies and LFA subsidies; the quantity of nitrogen spread per hectare of fodder area.

Table 2: Descriptive statistics of the exogenous variables used for the whole period (1993-2013)

	Mean	Minimum	Maximum	Standard deviation	Relative standard deviation
Proportion of farm-year observations that received agri-environmental subsidies	64%	-	-	-	-
Amount of agri-environmental subsidies per livestock unit among farmers who received those subsidies (2005 Euros)	44.9	0.5	260.3	21.8	0.49
Total farm land area (hectares)	149.9	38.6	442.2	66.3	0.44
Capital to labour ratio (thousands 2005 Euros)	220.6	66.0	1,207.5	133.8	0.61
Share of hired labour in total labour (%)	11.7	0.0	69.4	16.5	1.40
Debt to asset ratio	27.9	0.0	529.2	24.2	0.87
Stocking rate (livestock units per hectare of fodder area)	1.3	0.7	2.0	0.2	0.16
Share of permanent grassland in farm total area (%)	63.0	2.4	100.0	27.2	0.43
Numerical productivity	87.1	0.0	111.4	7.9	0.09
Quantity of concentrates per cow (kg)	1,130.6	0.5	4,387.1	558.8	0.49
Feed autonomy (%)	92.3	51.3	100.0	5.5	0.06
Proportion of land rented in (%)	64.2	0.0	100.0	31.1	0.49
LFA subsidies per livestock unit (2005 Euros)	39.1	0.0	192.8	32.2	0.82
Other subsidies per livestock unit (2005 Euros)	211.9	38.4	467.8	87.6	0.41
Nitrogen quantity per hectare of fodder area (Kg)	29.3	0.0	172.8	25.8	0.88

Notes: Sample size: 1,651 farm-year observations.

5. Empirical results

5.1. Technical efficiency

In a first stage we compute technical efficiency of farms (including or excluding GHGs), and in a second-stage we investigate with econometric models (Models A and B) the impact of AEMs (adoption and subsidies) on this technical efficiency. For the first stage, we considered four different DEA models, thereby four different robust efficiency scores, depending on whether GHGs are included or excluded and depending on the assumptions regarding inputs. The first DEA model, Model (i), is related to the case where we do not consider GHG emissions (as in **(3)**). The second DEA model, Model (ii), is the one where gross GHG emissions are considered, and herd size and production-related costs are endogenous in the optimisation program (as in **(8)**). In the third DEA model, Model (iii), net GHG emissions are considered, i.e. carbon sequestration in soil is accounted for. Herd size and production-related costs are endogenous in the optimisation program as in Model (ii). The fourth DEA model, Model (iv), is the same as Model (iii), except that in addition to herd size and production-related costs, fodder area is also treated as endogenous in the maximisation program. Fodder area is linked to the level of carbon sequestration in grasslands. This endogenous variable is also present in the technology that generates net GHG emissions (i.e. the dependence constraints account for three variables: herd, other production-related costs and land). We considered a pooled frontier for the estimation of the efficiency scores, that is to say one single frontier is estimated for the whole period. We retained this strategy in order to increase the number of observations under analysis and limit the curse of dimensionality inherent to non-parametric estimation. In addition, due to the unbalance nature of the data, this approach makes the different years more comparable. Descriptive statistics of the four robust technical efficiency scores are shown in **Table 3**.

Table 3: Descriptive statistics of the robust efficiency scores given different DEA models for the whole period (1993-2013)

DEA models	Mean	Minimum	Maximum	Standard deviation	Proportion of super-efficient observations (%)
Model (i): No GHG emissions in the model	0.943	0.050	1.250	0.107	37.8
Model (ii): gross GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	0.815	0.406	1.192	0.099	2.4
Model (iii): net GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	0.786	0.395	1.229	0.101	1.5
Model (iv): net GHG emissions are considered and herd size, production-related costs and fodder area are endogenous in the maximisation	0.798	0.409	1.230	0.103	1.6

Table 3 shows that Model (i) displays the highest good output efficiency score average, of 94.3%. Such high score compared to the three models incorporating GHGs, suggests that inefficiency in these three models is mainly due to bad output inefficiency. This is confirmed by decomposing, for the three models incorporating GHGs, the global pollution-adjusted efficiency into good and bad outputs efficiency components. The figures, presented in **Table 4**, show that most farms are super-efficient in terms of good output production (efficiency scores greater than one). The average robust good output efficiency score is greater than 1.20 for all three models. By contrast, the potential inefficiency ranges from 25% to 34% in the case of the bad output.

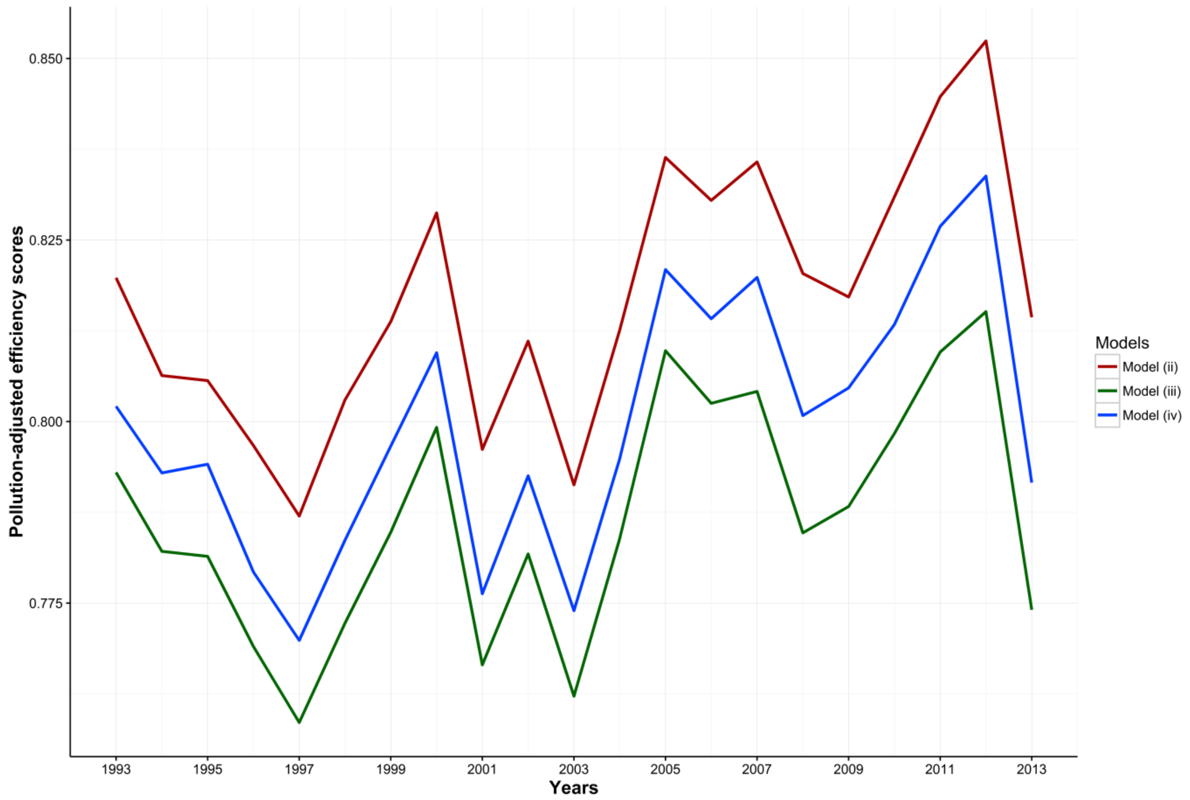
Table 4: Robust pollution-adjusted efficiency scores' components (good and bad outputs) given different DEA models for the whole period

Models	Efficiency components	Mean	Minimum	Maximum	Standard deviation	Proportion of super-efficient observations (%)
Model (ii): gross GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	Good output efficiency	1.234	0.524	2.860	0.344	79.0
	Bad output efficiency	0.697	0.264	1.289	0.165	3.8
Model (iii): net GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	Good output efficiency	1.266	0.531	2.943	0.353	81.6
	Bad output efficiency	0.663	0.240	1.529	0.176	3.6
Model (iv): net GHG emissions are considered and herd size, production-related costs and fodder area are endogenous in the maximisation	Good output efficiency	1.206	0.299	3.454	0.469	65.1
	Bad output efficiency	0.750	0.213	2.297	0.266	15.0

The distribution of the robust efficiency scores compared to the non-robust version (see Tables A.1 and A.2 in Appendix) confirms the presence of potential outliers and the necessity to compute robust efficiency scores. Results in **Table 3** also show that pollution-adjusted efficiency is lower when considering carbon sequestration (i.e. net GHG emissions) than not (i.e. gross GHG emissions). This may reveal heterogeneous practices of farmers in terms of carbon sequestration in soils. Model (iii) in **Table 3** yields the lowest average pollution-adjusted efficiency score, namely 78.6%. Though Models (ii), (iii) and (iv) exhibit similar descriptive statistics of efficiency in **Table 3**, the non-parametric Kolmogorov, Smirnov and Wilcoxon rank sum tests are significant at less than 5%, indicating that the farms are not ranked similarly in the three models. The same is true for the good and bad output efficiency scores whose descriptive statistics are shown in **Table 4**.

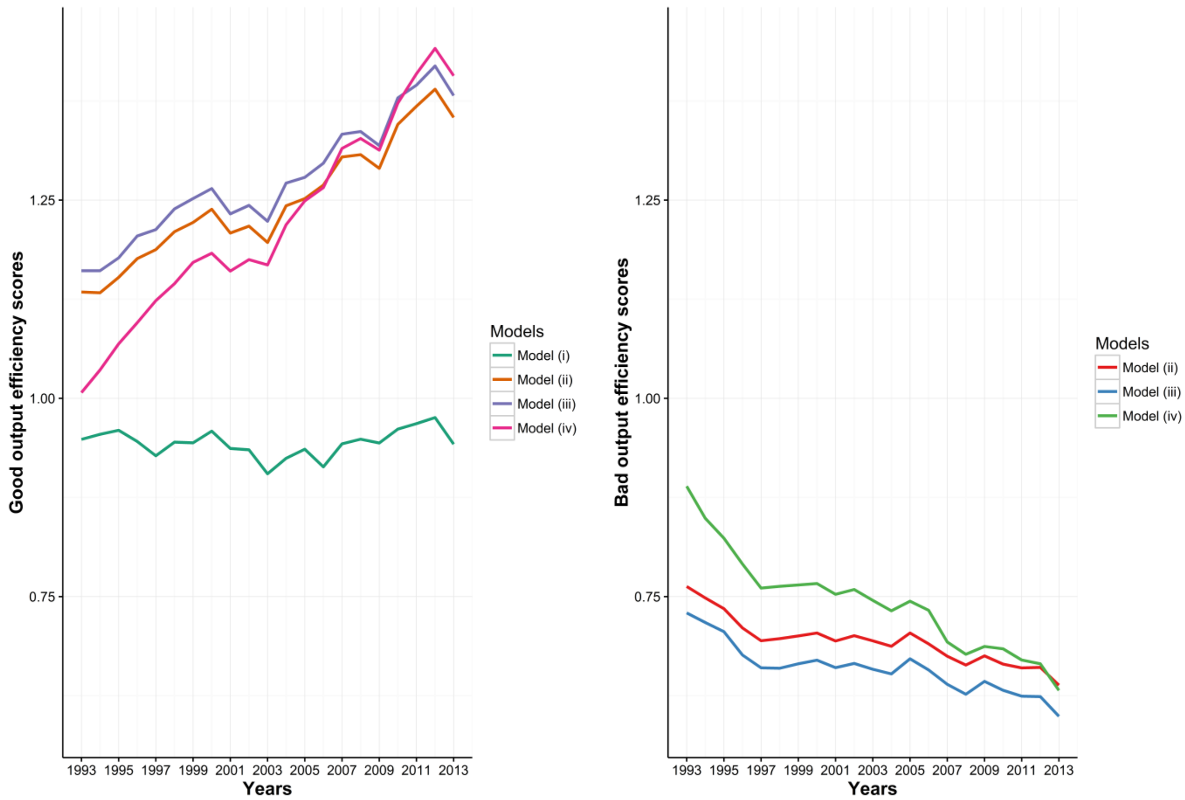
In terms of time evolution, the annual averages of the pollution-adjusted efficiency scores are displayed on **Figure 1**. There is a slight increasing trend, though from year to year there is large variability. This may reveal the sensitivity of this livestock sector to environmental conditions. For instance the drop in 2003 may be due to the drought that has occurred in the region at that time and that has affected farmers differently.

Figure 1: Evolution of annual averages of pollution-adjusted efficiency scores over the whole period (1993-2013)



A closer look at the time evolution of the components of pollution-adjusted efficiency reveals an opposite direction for good and bad output efficiency scores' evolution, as shown on **Figure 2**: good output efficiency tends to improve while bad output efficiency exhibits a decreasing trend. The decreasing trend of bad output efficiency may be compensated by the increase in good output efficiency, as when pollution is not considered (Model (i)), output efficiency stagnates.

Figure 2: Evolution of annual averages of good and bad outputs efficiency scores over the whole period (1993-2013)



5.2. Econometric results

Table 5 presents the regression results from the second stage of Model A, namely equation **(9)**, where the dependent variables are in turn the four efficiency scores (Models (i) to (iv)) and where the main exogenous variable of interest is a dummy variable that captures whether or not the farmer has adopted AEMs. The other exogenous variables are those presented in **Table 2**, as well as year and regional dummies (23 years and 5 regions in total). Given the (unbalanced) panel structure of the data, we included individual (farm) effects, fixed or random depending on the Hausman test results. To correct for the endogeneity associated to the AEM adoption variable, we used two instruments (*W* in equation **(10)**): beef price and farm revenue per labour unit, both in constant Euros. These two instruments, as well as their cross terms and their squared values, are firstly used in a selection equation (equation **(10)**) in order to construct a latent variable which is used as an estimated instrument in a classic two-stage least squares (equation **(9)**). Descriptive statistics of the instruments are shown in **Table 6**. In our case of two-stage least squares for panel data (with farm fixed or random effects), we used the Balestra-Varadharajan-Krishnakumar's transformation.

Figures in **Table 5** indicate a significant negative effect of the binary variable representing the adoption of AEMs on technical efficiency in the case where GHGs are not considered only, that is to say when (good) technical efficiency is calculated with Model (i). Still in the case of Model (i), total agricultural area, stocking rate, numerical productivity, quantity of concentrates per livestock unit and other subsidies have a significant positive impact on (good) efficiency, while capital to labour ratio, the debt to asset ratio and the nitrogen quantity per hectare of fodder area have a negative impact. When pollution is included in the analysis, in all Models ((ii), (iii), (iv)) capital to labour ratio, share of hired labour and nitrogen quantity per hectare of fodder area have a significant negative influence on pollution-adjusted technical efficiency, whereas numerical productivity, feed autonomy and other subsidies have a significant positive impact.

Table 5: Regression results of the effect of adoption of AEMs on farms' technical efficiency (Model A) for the whole period (1993-2013)

Variables	**Efficiency calculated with Model (i)**	**Efficiency calculated with Model (ii)**	**Efficiency calculated with Model (iii)**	**Efficiency calculated with Model (iv)**
Dummy variable which captures whether or not farmers received agri-environmental subsidies	-0.03891^{*}	0.00436	0.00033	0.00929
Total farm land area (hectares)	0.00046^{***}	0.00001	-0.00003	0.00008
Capital to labour ratio (thousands 2005 Euros)	-0.00010^{*}	-0.00010^{***}	-0.00010^{**}	-0.00011^{**}
Share of hired labour in total labour (%)	-0.00033	-0.00069^{***}	-0.00071^{***}	-0.00063^{***}
Debt to asset ratio	-0.00065^{***}	0.00018^{*}	0.00022^{*}	0.00009
Stocking rate (livestock units per hectare of fodder area)	0.12987^{***}	0.07352^{***}	-0.02394	-0.06253^{***}
Share of permanent grassland in farm total area (%)	-0.00005	0.00018	0.00011	0.00016
Numerical productivity	0.00211^{***}	0.00224^{***}	0.00201^{***}	0.00200^{***}
Quantity of concentrates per cow (kg)	0.00002^{*}	0.00001^{*}	0.00002^{*}	0.00001
Feed autonomy (%)	0.00063	0.00190^{**}	0.00194^{***}	0.00158^{*}
Proportion of land rented in (%)	-0.00023	0.00010	0.00015	0.00010
LFA subsidies per livestock unit (2005 Euros)	-0.00009	0.00024^{*}	0.00015	0.00015
Other subsidies per livestock unit (2005 Euros)	0.00020^{**}	0.00024^{***}	0.00023^{***}	0.00016^{**}
Nitrogen quantity per hectare of fodder area (kg)	-0.00062^{***}	-0.00180^{***}	-0.00178^{***}	-0.00194^{***}
R^2	0.168	0.244	0.470	0.258
Number of observations	1,651	1,651	1,651	1,651

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Results for year and regional dummies are not shown.

Table 6: Descriptive statistics of instrumental variables for the whole period (1993-2013)

	Mean	Minimum	Maximum	Standard deviation	Relative standard deviation
Beef price (2005 Euros per kilogram)	1.95	1.34	2.93	0.22	0.11
Revenue per labour (2005 Euros)	4,449	-11,940	24,200	2,728	0.61

For robustness check we replicated the analysis with a balanced panel. More precisely, we balanced the panel over the whole period 1993-2013 (with a total of 52 farms per year) and computed the robust efficiency scores on this new sample. In terms of evolution and averages of efficiency scores, the results are very similar to the unbalanced panel case described in the previous section. However, as shown in **Table 7**, the results of the econometric analyses are different. Compared to the unbalanced panel case (that was shown in **Table 5**), in the balanced panel case (**Table 7**) the adoption of AEMs has no effect on the distribution of farms' technical efficiency except when efficiency is obtained from Model (iv), that is to say where GHGs are incorporated and where the three variable inputs (herd size, production-related costs, fodder area) are endogenously considered. In this model the adoption of AEMs has a significant positive effect on technical efficiency. As regard the other subsidies (excluding agri-environmental subsidies and LFA subsidies), they also clearly exhibit a positive significant impact.

Table 7: Regression results of the effect of adoption of AEMs on farms' technical efficiency (Model A) for the whole period (1993-2013) with balanced panel data

Variables	**Efficiency calculated with Model (i)**	**Efficiency calculated with Model (ii)**	**Efficiency calculated with Model (iii)**	**Efficiency calculated with Model (iv)**
Dummy variable which captures whether or not farmers received agri-environmental subsidies	-0.03081	0.03299	0.02529	0.05074**
Total farm land area (hectares)	0.00005	-0.00004	-0.00009	0.00009
Capital to labour ratio (thousands 2005 Euros)	0.00005	-0.00001	-0.00002	-0.00001
Share of hired labour in total labour (%)	0.00035	-0.00047*	-0.00042	-0.00036
Debt to asset ratio	-0.00080***	-0.00045*	-0.00047*	-0.00045*
Stocking rate (livestock units per hectare of fodder area)	0.15789***	0.14766***	0.06079*	0.13311***
Share of permanent grassland in farm total area (%)	0.00016	0.00038*	0.00050**	0.00036*
Numerical productivity	0.00183***	0.00288***	0.00283***	0.00295***
Quantity of concentrates per cow (kg)	0.00002*	0.00002**	0.00002	0.00003**
Feed autonomy (%)	-0.00002	0.00168*	0.00137	0.00147*
Proportion of land rented in (%)	-0.00014	0.00006	0.00006	0.00007
LFA subsidies per livestock unit (2005 Euros)	-0.00009	0.00003	0.00005	-0.00007
Other subsidies per livestock unit (2005 Euros)	0.00022**	0.00018**	0.00016*	0.00019**
Nitrogen quantity per hectare of fodder area (kg)	-0.00039*	-0.00159***	-0.00179***	-0.00151***
R^2	0.155	0.222	0.237	0.194
Number of observations	1,092	1,092	1,092	1,092

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Results for year and regional dummies are not shown.

When we consider only those farmers who have adopted AEMs (Model B), the regression results of the effect of agri-environmental subsidies (equation **(11)**) are presented in **Table 8** (for the unbalanced case). Here we also treated the potential endogeneity associated to agri-environmental subsidies (equation **(12)**) using a panel two-stage least squares estimation with the instruments of **Table 6** introduced as such (no cross terms nor square terms). Results show a significant positive impact of agri-environmental subsidies for those farms that have adopted AEMs on technical efficiency obtained from all Models (i), (ii), (iii), (iv), that is to say whatever the type of technical efficiency (including or excluding GHGs). Results also show a significant positive impact of stocking rate and numerical productivity, and a significant negative impact of LFA subsidies on all four types of technical efficiency.

Table 8: Regression results of the effect of agri-environmental subsidies on farms' technical efficiency (Model B) for the whole period (1993-2013)

Variables	**Efficiency calculated with Model (i)**	**Efficiency calculated with Model (ii)**	**Efficiency calculated with Model (iii)**	**Efficiency calculated with Model (iv)**
Amount of agri-environmental subsidies per livestock unit (2005 Euros)	0.00656***	0.00394***	0.00415***	0.00427***
Total farm land area (hectares)	0.00060***	0.00005	0.00005	0.00022*
Capital to labour ratio (thousands 2005 Euros)	-0.00016	-0.00015*	-0.00016*	-0.00017*
Share of hired labour in total labour (%)	-0.00028	-0.00055*	-0.00038	-0.00047
Debt to asset ratio	0.00008	0.00002	-0.00004	-0.00003
Stocking rate (livestock units per hectare of fodder area)	0.38153***	0.22147***	0.12707*	0.12503*
Share of permanent grassland in farm total area (%)	-0.00023	-0.00030	-0.00012	-0.00008
Numerical productivity	0.00240***	0.00315***	0.00299***	0.00320***
Quantity of concentrates per cow (kg)	0.00002	0.00005***	0.00003**	0.00003**
Feed autonomy (%)	-0.00187	0.00145	0.00039	0.00038
Proportion of land rented in (%)	0.00007	0.00019	0.00015	0.00016
LFA subsidies per livestock unit (2005 Euros)	-0.00128***	-0.00091***	-0.00089***	-0.00092***
Other subsidies per livestock unit (2005 Euros)	-0.00006	0.00016	0.00012	0.00009
Nitrogen quantity per hectare of fodder area (kg)	0.00030	-0.00125***	-0.00143***	-0.00140***
R2	0.146	0.258	0.182	0.159
Number of observations	1,049	1,049	1,049	1,049

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Results for year and sub-region dummies are not shown.

Again, for robustness check we conducted the same estimations using a balanced panel sample extracted from our data (with a total of 52 farms per year). Results, shown in **Table 9**, confirm the significant positive impact of AEMs subsidies on farm technical efficiency, except for the case when technical efficiency is calculated with Model (iii) where this impact is insignificant.

Table 9: Regression results of the effect of agri-environmental subsidies on farms' technical efficiency (Model B) for the whole period (1993-2013) with the balanced panel data

Variables	**Efficiency calculated with Model (i)**	**Efficiency calculated with Model (ii)**	**Efficiency calculated with Model (iii)**	**Efficiency calculated with Model (iv)**
Amount of agri-environmental subsidies per livestock unit (2005 Euros)	0.00813**	0.00444*	0.00364	0.00418*
Total farm land area (hectares)	0.00092*	0.00001	-0.00015	0.00018
Capital to labour ratio (thousands 2005 Euros)	-0.00050*	-0.00035*	-0.00031*	-0.00034**
Share of hired labour in total labour (%)	-0.00069	-0.00065	-0.00041	-0.00063
Debt to asset ratio	-0.00045	-0.00066	-0.00089*	-0.00069
Stocking rate (livestock units per hectare of fodder area)	0.34014**	0.20621**	0.07206	0.20011**
Share of permanent grassland in farm total area (%)	-0.00035	-0.00021	-0.00013	-0.00017
Numerical productivity	0.00211*	0.00253***	0.00249***	0.00272***
Quantity of concentrates per cow (kg)	0.00006*	0.00005**	0.00004*	0.00005**
Feed autonomy (%)	0.00194	0.00261	0.00191	0.00281*
Proportion of land rented in (%)	0.00013	-0.00009	-0.00006	-0.00006
LFA subsidies per livestock unit (2005 Euros)	-0.00019	-0.00031	-0.00035	-0.00035
Other subsidies per livestock unit (2005 Euros)	0.00012	0.00021	0.00019	0.00020
Nitrogen quantity per hectare of fodder area (Kg)	-0.00081	-0.00202***	-0.00221***	-0.00197***
R2	0.09675	0.38353	0.42352	0.39366
Number of observations	692	692	692	692

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Results for year and sub-region dummies are not shown.

6. Conclusion

We investigated in this paper the impact of the adoption of AEMs and the impact of subsidies received in this frame, on farms' technical efficiency when the latter includes or excludes GHGs emissions as a bad output, and considers carbon sequestration or not. The application was for the specific case of beef cattle farming in French grassland areas during 1993-2013.

Our results do not confirm the general finding of the literature, namely a negative effect of public subsidies on farms' technical efficiency. On the contrary, we found here that among farmers who had adopted AEMs, agri-environmental subsidies received had a positive impact on farms' technical efficiency either with or without the inclusion of GHGs. However, the adoption of AEMs itself does not lead to a significant increase in technical efficiency.

From a policy point of view, this indicates that what matters for technical efficiency is the level of subsidies received by farmers when contracting AEMs. It also suggests that the AEMs designed during the period considered here were adequate to enhance farms' technical efficiency, whether it is the classic technical efficiency or the efficiency adjusted for GHG pollution.

The approach undertaken in this paper assumes that the exogenous variables do not influence the level of the technology attainable by inefficient farms. This strong assumption of separability between exogenous variables and the technology could be relaxed using conditional frontier estimation, which can also allow assess the effect of these exogenous conditions on technical efficiency distribution. Another avenue for future research is to investigate the impact of AEM adoption and subsidies on the components of pollution-adjusted efficiency scores (namely good output efficiency and bad output efficiency), which can provide further insights on the effect on AEMs on farms' technical efficiency.

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Appendix

Table A.1: Non-robust efficiency scores given different DEA models for the whole period (1993-2013)

	Mean	Minimum	Maximum	Standard deviation
Model (i): No GHG emissions in the model	0.798	0.456	1.000	0.166
Model (ii): gross GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	0.658	0.325	0.997	0.084
Model (iii): net GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	0.524	0.259	0.887	0.071
Model (iv): net GHG emissions are considered and herd size, production-related costs and fodder area are endogenous in the maximisation	0.542	0.269	0.919	0.078

Table A.2: Non-robust pollution-adjusted efficiency scores' components (good and bad outputs efficiency) given different DEA models for the whole period (1993-2013)

Models	Efficiency components	Mean	Minimum	Maximum	Standard deviation
Model (ii): gross GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	Good output efficiency	0.927	0.448	1.000	0.110
	Bad output efficiency	0.717	0.472	1.000	0.111
Model (iii): net GHG emissions are considered and herd size and production-related costs are endogenous in the maximisation	Good output efficiency	0.962	0.453	1.000	0.081
	Bad output efficiency	0.548	0.296	1.000	0.082
Model (iv): net GHG emissions are considered and herd size, production-related costs and fodder area are endogenous in the maximisation	Good output efficiency	0.888	0.321	1.000	0.154
	Bad output efficiency	0.630	0.325	1.000	0.142