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Pollution-adjusted productivity change in French suckler cow farms:

The use of a generalized multiplicatively complete Färe-Primont index

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Abstract

The generalized multiplicatively complete Färe-Primont index is used here to assess pollution-adjusted total factor productivity (TFP) change and its components in French suckler cow farms. The results reveal that, when pollution (from greenhouse gases) is not considered in the model, productivity has stagnated over the whole period studied (1990 to 2013). Although some technological progress is recorded, it is totally offset by technical efficiency decrease. By contrast, there is a decrease in pollution-adjusted TFP, due to technological regress for more than one third, and to technical efficiency decrease for almost two third. This suggests that farmers did not have the right incentives to implement actions that would reduce such emissions during the period studied. An investigation of the characteristics of farms that have experienced an increase or stagnation of TFP vs. those that have recorded a decrease, indicates that rooms for improvement mainly relate to changing the feed system of the farms.

Keywords: Generalized-Färe-Primont index, total factor productivity, pollution, greenhouse gases, suckler cow farms, France

JEL CODES: D24, O47, Q10, Q50

1. Introduction

In the economic literature productivity gains are known as main sources of revenue improvement (Fulginiti and Perrin, 1997). In the agricultural sector, many research papers have conducted productivity evaluation, based on various methodologies (Darku et al., 2013). The methodologies can be split in three categories: index numbers, parametric estimation (econometric approaches), and non-parametric estimation (like data envelopment analysis). The assumptions inherent to each approach are different from one model to another. As recently argued by O'Donnell (2008), O'Donnell (2011), most of the existing approaches do not satisfy all the required axioms and tests a productivity index should verify.

Our objectives in this paper are, first, to measure the productivity of French suckler cow farms during 1990-2013 by using an improved approach based on the Färe-Primont index (O'Donnell, 2011). Second, given the particularity of livestock systems regarding their contribution to greenhouse gas emissions, we develop a generalized Färe-Primont index which accounts for undesirable outputs. Third, we characterize the farms that have recorded some (pollution-adjusted) productivity gains in comparison to farms that have experienced (pollution-adjusted) productivity losses.

The paper is organised as follows. Section 2 presents the methodological background and the approach used for the (pollution-adjusted) productivity computation. Section 3 describes the database and Section 4 discusses the results. Section 5 concludes.

2. Methodology

2.1. Background on productivity change and decomposition

Let's first formalize the production technology and present usual measures of productivity change. We start by letting N denote the number of decision making units (DMUs) observed over T periods of time. Each DMU_n uses $x_{nk}^t = (x_{n1}^t, \dots, x_{nK}^t)'$ vector of inputs (with $x \in \mathbb{R}_+^{\mathrm{K}}$) and $y_{nq}^t = (y_{n1}^t, \dots, y_{nQ}^t)'$ vector of outputs (with $y \in \mathbb{R}_+^{\mathrm{Q}}$) in a specific period t, with $t = 1, \dots, T$. The production technology in period t can be defined as:

$$\Psi_t = \left[(x^t, y^t) \in \mathbb{R}_+^{\mathrm{K+Q}} \mid x^t \text{ can produce } y^t\right] \tag{1}$$

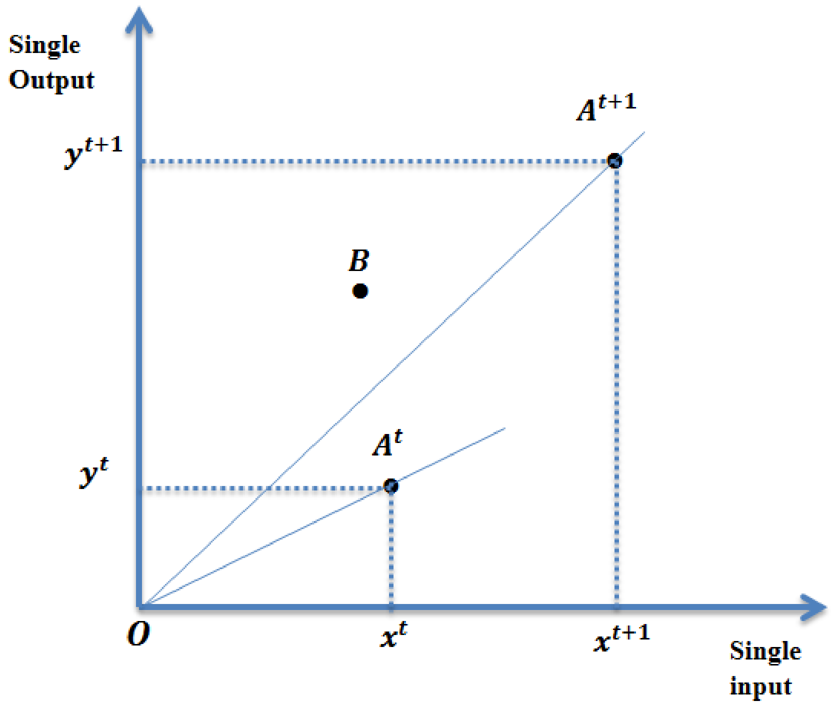
Ψ_t verifies the regularity conditions which are the standard axioms of the production theory available in Färe and Primont (1995), Färe and Grosskopf (2004).

Traditionally, in the case of one input x^t and one output y^t, total factor productivity (TFP) in period t, TFP_t, is measured as the ratio of output per unit of input (y^t/x^t) (Cooper et al., 2007). TFP change between two periods t and $t+1$ can then be estimated by $\frac{y^{t+1}/x^{t+1}}{y^t/x^t}$.[1] As such defined, TFP change is only based on the observed quantities of the different variables, independently from the structure of the production technology or the market behaviour. Graphically, in **Figure 1**, the TFP change of DMU_A equals the ratio of the slopes of the rays from the origin and passing through the different points A_t and A_{t+1}:

$$TFP_{t,t+1}^{A} = \frac{\text{Slope } OA_{t+1}}{\text{Slope } OA_t} \tag{2}$$

[1] This is also equivalent to the ratio of output change on input change: $\frac{y_{t+1}/y_t}{x_{t+1}/x_t}$.

Figure 1: TFP change in the case of a single output and a single input



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When dealing with multiple inputs/outputs, some weights are required to build an aggregate input and output index. As discussed in O'Donnell (2008), the choice of an aggregator function must lie on the satisfaction of a number of axioms and tests any productivity index should verify (the axioms being monotonicity, linear homogeneity, homogeneity of degree 0, identity, proportionality, commensurability[2]; and the tests being circularity or transitivity, time reversal…).[3] If $X^t \equiv X(x^t)$ and $Y^t \equiv Y(y^t)$ denote the scalars of the aggregated input and output, then:

[2] This axiom is also equivalent to independence of units of measurement or dimensionality.

[3] More on these axioms and tests can be found in Eichhorn (1976).

$$TFP_{t,t+1} = \frac{Y^{t+1}/X^{t+1}}{Y^t/X^t}{}^{4} \quad (3)$$

O'Donnell (2008) uses the term of '*multiplicatively complete*' to characterize productivity measures that are in line with the ratio of an output quantity change index on an input quantity change index as shown in **(3)** (Jorgenson and Griliches, 1967).[5] Index numbers like the Laspeyres, Paasche, Fisher, or Törnqvist indexes,[6] use prices for the aggregation of several inputs or outputs and the computation of quantity indexes (Färe et al., 2008). As mentioned in O'Donnell (2008), O'Donnell (2010), these indexes verify the multiplicatively completeness property. However, they do not verify the circularity test,[7] thereby they can only be used for binary comparisons (O'Donnell, 2011). Other price-based indexes like the Lowe productivity measure (O'Donnell, 2012) and the Geometric Young index (IMF, 2004 p10) can be used instead and they satisfy the circularity property.

In the performance benchmarking literature and particularly in the non-parametric framework (in which one can find the Data Envelopment Analysis – DEA – approach (Charnes et al., 1978)), the Malmquist productivity index introduced by Caves et al. (1982), Caves et al. (1982) has been proposed to handle the case of multi input/output technology (Färe et al., 1994, Färe and Grosskopf, 1996) without resorting to price information. This measure uses the distance function to evaluate the efficiency of a DMU relative to a benchmark that defines the production frontier

[4] When dealing with multiple inputs/outputs the term multi-factor productivity (MFP) is better than total factor productivity (TFP) (O'Donnell, 2011). In this paper we use TFP or MFP interchangeably to refer to multi-factor productivity.

[5] The input and output aggregator functions $X^t, Y^t, X^{t+1}, Y^{t+1}$ are non-negative, non-decreasing and linearly homogenous (homogeneity of degree 1). These properties are particularly important for the construction of meaningful TFP indexes.

[6] These indexes can be used to evaluate productivity change.

[7] The circularity test states the following: if there are three consecutive periods of time t_1, t_2, t_3 and an index I, the circularity test is satisfied if $I(t_1, t_3) = I(t_1, t_2) \times I(t_2, t_3)$ (Fried et al., 2008).

(Shephard, 1953).[8] Although many applications have computed the oriented Malmquist productivity change[9] in the literature using agricultural data (Fulginiti and Perrin, 1997, Färe et al., 1998 pp162-164, Coelli and Rao, 2005, Latruffe et al., 2008), this widespread measure does not verify the completeness property and it cannot always be interpreted as a measure of productivity change (O'Donnell, 2012). Besides, Grifell-Tatjé and Lovell (1995) argued that the Malmquist index ignores changes in the scale of operations. Later, O'Donnell (2011) also demonstrated that the Malmquist fails to account for changes in the input/output mix (such changes may lead to economies of scope). Nevertheless, O'Donnell (2008) showed that the Moorsteen-Bjurek[10] productivity index, which is a ratio of a Malmquist output productivity index on an Malmquist input productivity index, verifies the completeness property. However, this index fails the transitivity test and thus is not suitable for multi-lateral and multi-temporal comparisons (O'Donnell, 2011). As argued by O'Donnell (2011), the Färe-Primont index[11], further discussed in O'Donnell (2012), is multiplicatively complete and also passes the transitivity test. In this paper we extend this Färe-Primont index for our pollution-adjusted productivity change appraisal. Only a few applications of this index to the agricultural sector can be found in the literature (Rahman and Salim, 2013, Baležentis, 2015). These applications solely focus on the good outputs side, neglecting incidental outputs, by-products of agricultural activities.

As explained by O'Donnell (2012 p255) all the 'multiplicatively complete TFP indexes can be exhaustively decomposed into measures of technical change and efficiency change'. Besides, the efficiency change can be further decomposed into technical, mix and scale efficiency change

[8] The distance function is a way of aggregating several inputs and outputs by implicitly estimating levels of shadow prices for each variable.

[9] The Malmquist is said to be oriented because it is either input or output oriented (Lovell, 2003).

[10] We can also refer to this index as the Hicks-Moorsteen index suggested in Diewert (1992) who attributes this productivity measure to Hicks (1961) and Moorsteen (1961). This index has been reformulated and discussed in Bjurek (1996), Färe and Grosskopf (1996), Briec and Kerstens (2011). A further interest of this index is that it overcomes the infeasibility problem generally encountered in the Malmquist productivity index when computing cross periods efficiency (under variable returns to scale).

[11] This index has been initially proposed in Färe and Primont (1995 pp36-38) as a quantity index.

components. The operationalization of this decomposition requires some assumptions about the production technology. Actually several types of decompositions are possible given the completeness property. For instance in **Figure 1**, a complete TFP change index for DMU_A can be decomposed by using a third reference point B (the transitivity test must be verified) or several other points. For instance the formula in **(2)** can be equivalently decomposed into:

$$TFP_{t,t+1}^{A} = \frac{\text{Slope } OA_{t+1}}{\text{Slope } OA_t} = \frac{\text{Slope } OA_{t+1}}{\text{Slope } OB} \times \frac{\text{Slope } OB}{\text{Slope } OA_t} \tag{4}$$

For the next developments, point B has been chosen to match with the concept of input/output efficiency measure (O'Donnell, 2010). Given the monotonicity and the linear homogeneity of the distance functions (Farrell, 1957, Shephard, 1970), they can be easily used as input/output aggregators. As underlined in O'Donnell (2008) the TFP decomposition in the literature has been conducted either in a top-down approach where for instance a Malmquist index is computed and then decomposed into generic factors – see Färe et al. (1994), or in a bottom-up procedure where the different independent components of TFP are first computed and later combined into a productivity index (Balk, 2001). The decompositions in this paper take advantage of both approaches.

2.2. The Färe-Primont productivity (FPP) index: computation and decomposition

The Färe-Primont productivity (FPP) index for DMU_n from t to $t+1$ can be written as:

$$FPP_n^{t,t+1} = TFP_n^{t,t+1} = \frac{D_O(x_0, y_n^{t+1}, t_0)}{D_O(x_0, y_n^{t}, t_0)} \times \frac{D_I(x_n^{t}, y_0, t_0)}{D_I(x_n^{t+1}, y_0, t_0)} \tag{5}$$

where $D_O(-)$ and $D_I(-)$ are respectively the Shephard output and input distance functions and t_0 defines the observations that serve as benchmark to draw the representative frontier.

$$D_I(x^t, y^t, t) = \max_{\theta}\left[\theta^t > 0 \mid \frac{x^t}{\theta^t} \text{ can produce } y^t\right] \tag{6}$$

$$D_O(x^t, y^t, t) = \min_{\phi}\left[\phi^t > 0 \mid \frac{y^t}{\phi^t} \text{ can be produced by } x^t\right]^{12}$$

(x_0, y_0, t_0) is the vector of input/output quantities and time period respectively of an arbitrary observation which is chosen to be representative of the observations. O'Donnell (2011) used by default the sample mean of all the observations in all the periods.

Using **(5)**, the output aggregator is equal to $Y(y) = D_O(x_0, y, t_0)$ and the input aggregator corresponds to $X(x) = D_I(x, y_0, t_0)$.

For the decomposition of TFP, as earlier said we need to make some assumptions about the production technology. Based on these assumptions the efficiency component of TFP (TFPE) can be defined as:

$$TFPE_t = \frac{TFP_t}{TFP_t^*} \leq 1 \tag{7}$$

where TFP_t is the observed productivity and TFP_t^* is the maximum possible TFP $[TFP_t^* = \max_n TFP_{nt}]$ in period t.[13]

From **(7)** we can deduce that TFP change equals to:

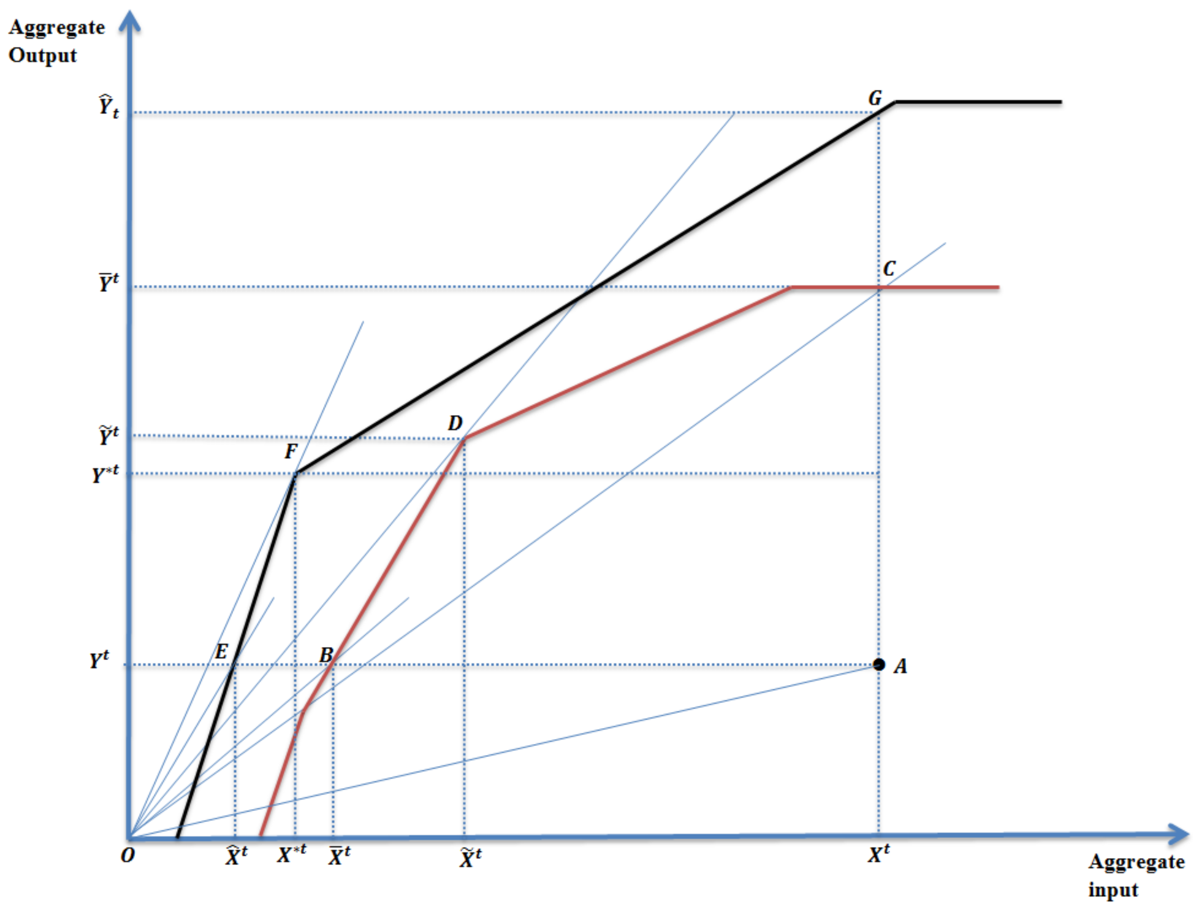
$$TFP_{t,t+1} = \frac{TFP_{t+1}}{TFP_t} = \frac{TFP_{t+1}^*}{TFP_t^*} \times \frac{TFPE_{t+1}}{TFPE_t} \tag{8}$$

[12] The output distance function is homogenous of degree -1 in x (non-increasing) and linearly homogenous in y.

[13] The maximum TFP may not exist in the case of technologies that exhibit increasing returns to scale everywhere. Under this circumstance other decompositions are available (see O'Donnell (2010 p538) for other possible decompositions).

From **(7)** it makes sense to denote $\frac{TFP_{t+1}^{*}}{TFP_{t}^{*}}$ as the technical change (TC) component and $\frac{TFPE_{t+1}}{TFPE_{t}}$ as the efficiency change (EC) component. The latter can be further decomposed into technical efficiency change (TEC), scale efficiency change (SCE) and mix efficiency change (MEC).

Figure 2: Input and output technical, scale and mix inefficiencies for aggregate input/output



Source: the authors

To make the decomposition more intuitive, let's define the following efficiency scores (O'Donnell, 2012):

- The output technical efficiency score (OTE)

$$OTE_t = D_O(x^t, y^t, t) = \frac{Y^t}{\bar{Y}^t} \leq 1 \tag{9}$$

where $\bar{Y}^t$ is the maximum technically attainable aggregate levels of output. Graphically on **Figure 2**, the OTE score is equivalent to $E_t = \frac{slope\ OA}{slope\ OC}$ [14].

- The output scale efficiency score (OSE)

The OSE relates to the optimal size of the operations in relation to points that are technically efficient regarding the previous definitions.

$$OSE_t = \frac{\bar{Y}^t / X^t}{\tilde{Y}^t / \tilde{X}^t} \leq 1 \tag{10}$$

where $\tilde{Y}^t$, $\tilde{X}^t$ are respectively the aggregate outputs and inputs at a point that is optimal in terms of scale. Scale efficiency has been largely discussed in Balk (2001). More simply, this efficiency score can be obtained by estimating the output distance function under constant returns to scale (CRS): $OSE_t = \frac{D_O(x^t, y^t, t)^{CRS}}{D_O(x^t, y^t, t)^{VRS}}$. Graphically on **Figure 2**, $OSE_t = \frac{slope\ OC}{slope\ OD}$.

- The output mix efficiency (OME)

The computation of the mix inefficiency is not as straightforward as OTE and OSE. Till now all the efficiency scores have been evaluated under a mix-restricted production technology. Therefore mix inefficiency can be evaluated by relaxing this constraint, which results in an expansion of the input-output combinations available to DMUs (O'Donnell, 2012).[15] The mix inefficiency is related to the combination of the different inputs and outputs without considering

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[14] Considering the nature of the inputs (variable or fixed), a decomposition of the output efficiency OTE is possible into output technical efficiency at full capacity and capacity utilization (see De Borger and Kerstens (2000), Färe et al. (2000)).

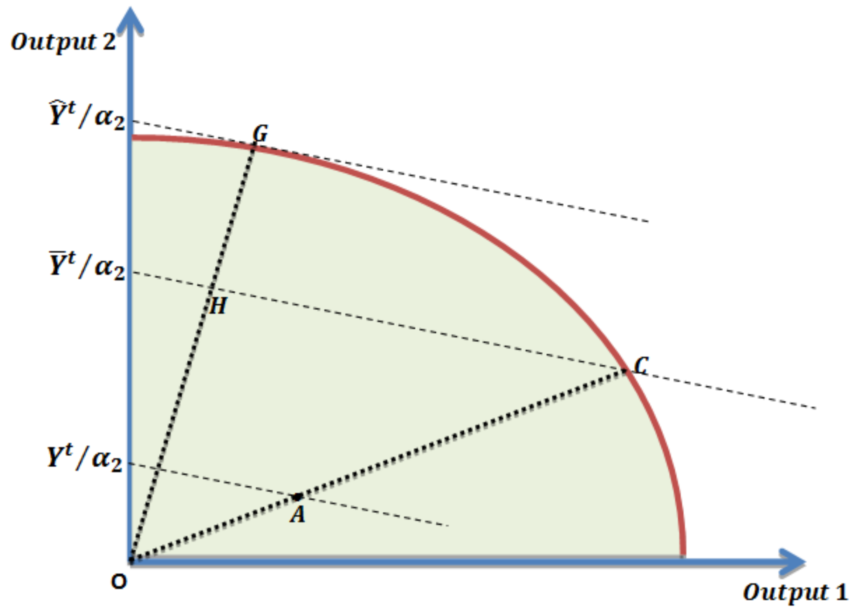
[15] The mix-inefficiency here is different from the allocative inefficiency that is value-related.

their aggregate levels. In other words, the output mix inefficiency is related to iso-aggregate-output lines in the same way iso-revenue lines operate. For instance, $(y^t) = \alpha_1 y_1^t + \alpha_2 y_2^t$ $(\alpha_1, \alpha_2 \geq 0)$. Graphically, the mix unrestricted technology is defined by the points E, F, G on **Figure 2**. On this graph, the restricted production possibilities set is bounded by the curve passing through points B, D, C. The OME index is then defined as:

$$OME_t = \frac{\bar{Y}^t / X^t}{\hat{Y}^t / X^t} = \frac{\bar{Y}^t}{\hat{Y}^t} \leq 1 \qquad (11)$$

where $\hat{Y}^t$ is aggregation of $\hat{y}^t$ such that $\hat{y}^t = \arg\max_{y>0}[Y(y)|\,(x^t, y) \in \Psi_t]$. The output mix efficiency is defined graphically as $OME_t = \frac{slope\ OC}{slope\ OG}$ on **Figure 2**. For another illustration see **Figure 3** where the iso-output line is tangent to the output isoquant on point G. On Figure 3, the output mix efficiency equals to $OME_t = \frac{OH}{OG}$. As underlined in O'Donnell (2010) mix inefficiencies are related to economies of scope while scale inefficiencies are directly linked to economies of scale.

Figure 3: Output oriented mix inefficiency



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- The residual output scale component (ROSE)

On **Figure 2**, starting from the mix-efficient point G we can see that it is still possible to improve productivity by moving towards point F, the point of maximum productivity. The ROSE index can be defined as:

$$ROSE_t = \frac{\hat{Y}^t/X^t}{Y^{*t}/X^{*t}} \leq 1 \tag{12}$$

where (Y^{*t}, X^{*t}) are aggregates of $(y^{*t}, x^{*t}) = \arg\max_{x>0,y>0}[Y/X \mid (x, y) \in \Psi_t]$.[16]

Graphically on **Figure 2**, $ROSE_t = \frac{slope\ OG}{slope\ OF}$.

[16] Y^{*t}/X^{*t} is simply the maximal productivity recorded in period t for all the DMUs.

- Residual mix efficiency (RME)

Starting from a scale efficient point under a mix-restricted technology, we can compute the residual mix efficiency (RME) scores as follows:

$$RME_t = \frac{\tilde{Y}^t/\tilde{X}^t}{Y^{*t}/X^{*t}} \leq 1^{17} \tag{13}$$

Graphically on **Figure 2**, this is equivalent to $RME_t = \frac{slope\ OD}{slope\ OF}$. Point D is denoted as the mix-invariant optimal scale (MIOS) from an inefficient firm operating at point A.

- TFP decompositions

Among the infinite possibilities of decomposition of a TFP measure, the efficiency components defined above help to illustrate two of them:

$$\begin{gathered} TFP_t = TFP_t^* \times TFPE_t \\ TFP_t = TFP_t^* \times OTE_t \times OME_t \times ROSE_t \\ TFP_t = TFP_t^* \times OTE_t \times OSE_t \times RME_t \end{gathered} \tag{14}$$

Using aggregate quantities, the following decomposition is also equivalent

$$\begin{gathered} TFP_t = \frac{Y^t}{X^t} = \frac{Y^{t^*}}{X^{t^*}} \times \frac{Y^t}{\bar{Y}^t} \times \frac{\bar{Y}^t}{\hat{Y}^t} \times \frac{\hat{Y}^t/X^t}{Y^{*t}/X^{*t}} \\ TFP_t = \frac{Y^t}{X^t} = \frac{Y^{t^*}}{X^{t^*}} \times \frac{Y^t}{\bar{Y}^t} \times \frac{\bar{Y}^t/X^t}{\tilde{Y}^t/\tilde{X}^t} \times \frac{\tilde{Y}^t/\tilde{X}^t}{Y^{*t}/X^{*t}} \end{gathered} \tag{15}$$

All the decompositions in **(14)** and **(15)** can also be extended to the input orientation i.e. the input equivalence of $OTE, OSE, OME, ROSE$ can be similarly derived (which would be denoted respectively $ITE, ISE, IME, RISE$).

[17] $\tilde{Y}^t = \frac{Y^t}{OTE_t \times OSE_t}$ and $\tilde{X}^t = X^t \times ITE_t \times ISE_t$

- TFP change components

After having defined the previous efficiency scores for periods t and $t+1$, the TFP change between t and $t+1$ can then be computed and decomposed as follows:

$$TFP_{t,t+1} = \frac{TFP_{t+1}^*}{TFP_t^*} \times \frac{OTE_{t+1}}{OTE_t} \times \frac{OME_{t+1}}{OME_t} \times \frac{ROSE_{t+1}}{ROSE_t}$$

$$TFP_{t,t+1} = \frac{TFP_{t+1}^*}{TFP_t^*} \times \frac{OTE_{t+1}}{OTE_t} \times \frac{OSE_{t+1}}{OSE_t} \times \frac{RME_{t+1}}{RME_t} \qquad (16)$$

As earlier mentioned the ratio $\frac{TFP_{t+1}^*}{TFP_t^*}$ is a 'natural' measure of technical change which expresses progress when it is greater than one and regress when it is lower than one. The other ratios are measures of technical efficiency change, (residual) scale efficiency change, (residual) mix efficiency change. The same decomposition is also valid for the input side:

$$TFP_{t,t+1} = \frac{TFP_{t+1}^*}{TFP_t^*} \times \frac{ITE_{t+1}}{ITE_t} \times \frac{IME_{t+1}}{IME_t} \times \frac{RISE_{t+1}}{RISE_t}$$

$$TFP_{t,t+1} = \frac{TFP_{t+1}^*}{TFP_t^*} \times \frac{ITE_{t+1}}{ITE_t} \times \frac{ISE_{t+1}}{ISE_t} \times \frac{RME_{t+1}}{RME_t} \qquad (17)$$ [18]

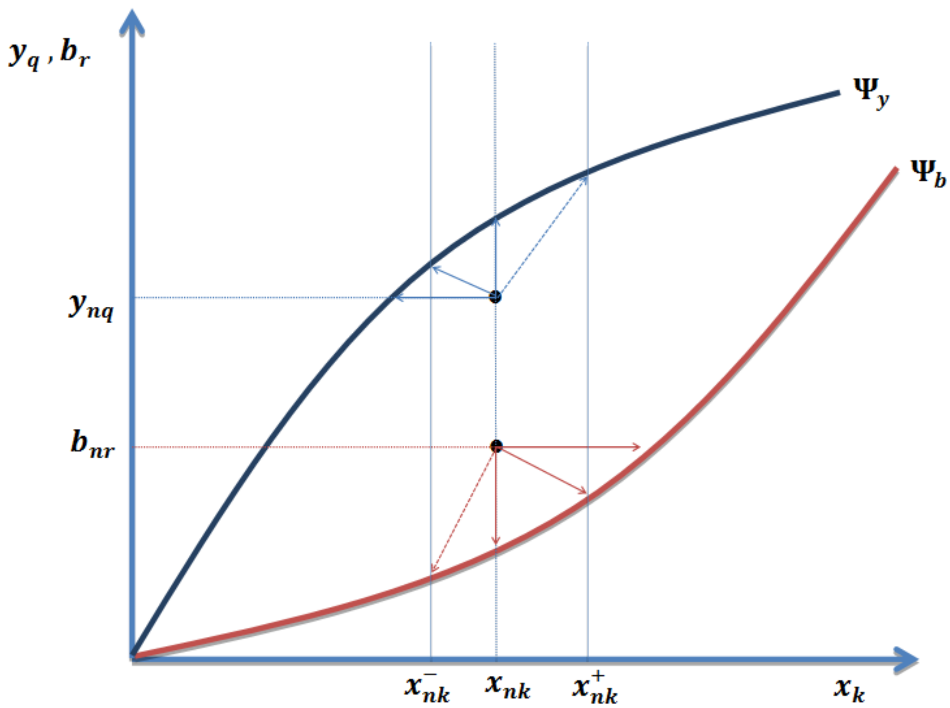
2.3. Inclusion of undesirable outputs: pollution-adjusted productivity measure

Modelling pollution generating technologies has received an important attention in the literature with the development of several approaches (Dakpo et al., 2015). In this paper we develop our measures based on the recent extension of the by-production approach discussed in Dakpo (2015), which is an extension of the original by-production model introduced by Murty et al.

[18] $ITE_t = D_I(x,y,t)^{-1} = \frac{\bar{X}^t}{X^t} \leq 1$, $ISE_t = \frac{Y^t/\bar{X}^t}{\tilde{Y}^t/\tilde{X}^t} \leq 1$, $IME_t = \frac{Y^t/\bar{X}^t}{Y^t/\hat{X}_t} = \frac{\hat{X}_t}{\bar{X}^t} \leq 1$, and $RISE_t = \frac{Y^t/\hat{X}^t}{Y^{*t}/X^{*t}} \leq 1$.

(2012). The idea of the by-production approach lies mainly in the representation of two independent production processes: one associated to the production of good (intended) outputs and the other one to the generation of bad (unintended) outputs (**Figure 4**).

Figure 4: The by-production representation with two sub-technologies



Source: the authors

Formally, let's expand the production technology in **(1)** with the generation of undesirable outputs $b \in \mathbb{R}_+^{\mathrm{R}}$, and split the input set into two categories: non-emission-causing inputs $x_1 \in \mathbb{R}_+^{\mathrm{K}_1}$ and emission-causing inputs $x_2 \in \mathbb{R}_+^{\mathrm{K}_2}$. The new production technology can be presented as follows

$$\Psi^t = \Psi_y^t \cap \Psi_b^t$$

$$\Psi_y^t = \left[(x_1^t, x_2^t, y^t, b^t) \in \mathbb{R}_+^{\mathrm{K+Q+R}} \mid x^t \text{ can produce } y^t\right] \tag{18}$$

$$\Psi_b^t = \left[(x_1^t, x_2^t, y^t, b^t) \in \mathbb{R}_+^{\mathrm{K+Q+R}} \mid b^t \text{ can be generated by } x_2^t\right]$$

The global technology Ψ_t lies at the intersection of two independent sub-technologies. The by-production assumes cost disposability for undesirable outputs and conditional free/cost disposability assumptions for polluting inputs. Good and non-polluting inputs satisfy the free disposability property. More on the axiomatization of the by-production can be found in Murty (2015). The following sets can be defined:

$$\mathcal{Y}(x_1^t, x_2^t, b^t) = [y^t \mid (x_1^t, x_2^t, y^t, b^t) \in \Psi^t]$$

$$\mathfrak{B}(x_1^t, x_2^t, y^t) = [b^t \mid (x_1^t, x_2^t, y^t, b^t) \in \Psi^t] \tag{19}$$

$$\mathcal{W}(y^t) = [(x_1^t, x_2^t, b^t) \mid (x_1^t, x_2^t, y^t, b^t) \in \Psi^t]$$

The first set is the space of all intended outputs, given a fixed vector of inputs and bad outputs. The second set represents the projections into the space of unintended outputs, while the third set is the projections into the space of (all) inputs and emissions. In the DEA framework, Murty et al. (2012) proposed the following program assuming variable returns to scale (VRS):

$$\Psi^t = \left[(x_1^t, x_2^t, y^t, b^t) \in \mathbb{R}_+^{\mathrm{K+Q+R}} \mid y^t \leq Y^t \nu^t \,; x_1^t \geq X_1^t \nu^t \,;\, x_2^t \geq X_2^t \nu^t \,;\; b^t \geq B^t \xi^t \,;\, x_2^t \leq X_2^t \xi^t \,;\, {\nu'}^t \mathbb{1} = 1 \;;\; {\xi'}^t \mathbb{1} = 1 \;;\; \nu, \xi \geq 0\right] \tag{20}$$

The two sub-technologies are represented using two distinct intensity variables (ν, ξ). (X, Y, B) denote the matrix of inputs, good outputs, and undesirable outputs of the N DMUs which serve as benchmark. In the efficiency assessment, for consistency Dakpo (2015) introduced in his extension some dependence constraints to bind the two sub-technologies. These constraints can be written as

$$X_2 \nu = X_2 \xi \tag{21}$$

Considering that materials balance principles rules the generation of pollution in agriculture, the assumption of CRS is maintained under the bad output sub-technology i.e. we have removed the constraints $\xi'^{t}\mathbb{1} = 1$ from the DEA technology in **(20)**.[19]

Following some literature on environmental index computation (Färe et al., 2004, Zaim, 2004), a pollution-adjusted productivity ($PTFP$) measure can be computed as follows:

$$PTFP^t = \frac{Y(y^t)}{B(b^t)} = \frac{Y^t}{B^t} \tag{22}$$

where $B(b^t)$ or B^t is the aggregated undesirable outputs. However, to keep in line with the traditional definition of a productivity indicator (as ratio of aggregated output on aggregated input), Abad (2015) introduced a generalized Hicks-Moorsteen index which is a ratio of an environmental good output index on an environmental input index. The particular feature of this generalized form lies in the definition of the environmental input index based on a distance function in $\mathcal{W}(y^t)$ space. Formally the productivity measure expressed in **(22)** is equivalent to

$$PTFP^t = \frac{Y^t}{\mathcal{A}(X^t, B^t)} \tag{23}$$

In the case $B^t = 0$ the formula in **(23)** is equivalent to the traditional productivity measure, and when $X^t = 0$ it is equivalent to formula **(22)**. The relation in **(23)** makes perfect sense given that if we assume that production is a physical process governed by materials balance principles, a reduction in polluting inputs should be systematically followed by a decrease in bad outputs (see Ayres and Kneese (1969) and Lauwers (2009) for details on materials balance principles). In this paper we thereby propose a generalized Färe-Primont index in light of the work of Abad (2015).

- A generalized Färe-Primont index

[19] The CRS assumption here implies that with no polluting inputs there will be no pollution at all.

As previously, for the generalized version of the Färe-Primont pollution-adjusted productivity (GFPP) for a DMU_n from t to $t+1$ we propose to use the following formulation

$$GFPP_n^{t,t+1} = \frac{D_O^E(x_0, y_n^{t+1}, b_0, t_0)}{D_O^E(x_0, y_n^t, b_0, t_0)} \times \frac{D_I^E(x_n^t, y_0, b_n^t, t_0)}{D_I^E(x_n^{t+1}, y_0, b_n^{t+1}, t_0)} \tag{24}$$

where $D_O^E(-)$ and $D_I^E(-)$ are respectively the environmental Shephard output and input distance functions, and $(x_0^{t_0}, y_0^{t_0}, b_0^{t_0})$ is a represented DMU properly chosen.

$$\begin{aligned} D_I^E(x, y, b, t) &= \max_{\theta}\left[\theta^t > 0 \mid \left(\frac{x^t}{\theta^t}, \frac{b^t}{\theta^t}\right) \in \mathcal{W}(y^t)\right] \\ D_O^E(x, y, b, t) &= \min_{\phi}\left[\phi^t > 0 \mid \frac{y^t}{\phi^t} \in \mathcal{Y}(x_1^t, x_2^t, b^t)\right] \end{aligned} \tag{25}$$

Like in the case without undesirable outputs, the different components of the pollution-adjusted TFP can be derived in the same way as developed in **section 2.2**. As pointed out in O'Donnell (2012 p263) 'there are at least as many ways to decompose TFP efficiency as there are points in the production possibilities set.' In this paper we focus on the output decompositions because of 'the substantial lag between purchasing inputs and selling outputs' as underlined by Blancard et al. (2006 p351).

- Environmental output technical efficiency score (EOTE)

This efficiency score is computed as the OTE, except that here the technology is based on the use of the by-production. In terms of DEA formulation, $EOTE_t$ can be estimated using the envelopment approach in **(26)**.

$$\begin{aligned} & D_O^E(x_n^t, y_n^t, b_n^t, t)^{-1} = EOTE_{n,t}^{-1} = \max_{\phi,\nu,\xi} \phi_n^t \\ & s.t \quad \sum_{i=1}^N \nu_i^t y_{iq}^t \geq \phi_n^t y_{nq} \quad q = 1, \dots, Q \\ & \sum_{i=1}^N \nu_i^t x_{ik_1}^t \leq x_{nk_1}^t \quad k_1 = 1, \dots, K_1 \\ & \sum_{i=1}^N \nu_i^t x_{ik_2}^t \leq x_{nk_2}^t \quad k_2 = 1, \dots, K_2 \end{aligned} \tag{26}$$

$$\sum_{i=1}^{N} \xi_i^t b_{ir}^t \leq b_{nr}^t \quad r = 1, \dots, R$$
$$\sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \geq x_{nk_2}^t \quad k_2 = 1, \dots, K_2$$
$$\sum_{i=1}^{N} \nu_i^t x_{ik_2}^t = \sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \quad k_2 = 1, \dots, K_2$$
$$\sum_{i=1}^{N} \nu_i^t = 1 \ ; \ \nu_i^t, \xi_i^t \geq 0; i = 1, \dots, N$$

- Environmental output scale scale efficiency score (EOSE)

This efficiency score is computed the same way as the OSE. Practically it is equivalent $EOSE_t = D_O^E(x^t, y^t, b^t, t)^{CRS} / D_O^E(x^t, y^t, b^t, t)^{VRS}$ where $D_O^E(x^t, y^t, b^t, t)^{CRS}$ can be estimated by removing the convexity constraint from **(26)** ($\sum_{i=1}^{N} \nu_i^t = 1$).

- Environmental output mix efficiency (EOME)

The ideas around the mix inefficiencies have been discussed previously in the case of the good outputs only OME. Here we only focus on practical computations in the DEA framework. Basically, to compute the mix inefficiency we need to estimate the shadow prices associated to inputs and outputs in order to derive the slope of iso-aggregate-output line. It is at this stage that we can take advantage of the Färe-Primont output aggregator using the arbitrary representative observation. Recalling that DEA provides a piecewise linear representation of the technology (i.e. segments that are interconnected), we need to determine the feature of the iso-aggregate-output line by estimating $D_O^E(x_0, y_0, b_0, t_0)$ using the dual of the model in **(26)**.

$$D_O^E(x_0, y_0, b_0, t_0)^{-1} = \min_{V,Z,U,W,D,\delta} \sum_{k_1=1}^{K_1} V_{k_1} x_{0k_1}^{t_0} + \sum_{k_2=1}^{K_2} \left(V_{k_2} - Z_{k_2}\right) x_{0k_2}^{t_0} + \sum_{r=1}^{R} W_r b_{0r} + \delta$$

$$s.t - \sum_{q=1}^{Q} U_q y_{iq}^t + \sum_{k_1}^{K_1} V_{k_1} x_{ik_1}^t + \sum_{k_2=1}^{K_2} \left(V_{k_2} + D_{k_2}\right) x_{ik_2}^t + \delta \geq 0 \quad i = 1, \dots, N; \ t = 1, \dots, T \qquad (27)$$

$$\sum_{r=1}^{R} W_r b_{ir}^t - \sum_{k_2=1}^{K_2} \left(Z_{k_2} + D_{k_2}\right) x_{ik_2}^t \geq 0 \quad i = 1, \dots, N; \ t = 1, \dots, T$$

$$\sum_{q=1}^{Q} U_q \, y_{0q}^{t_0} = 1$$

$V, Z, U, W \geq 0$; D, δ unrestricted [20]

Since (x_0, y_0, b_0) is a representative observation (based on central tendency) for the whole sample, the multipliers (V, Z, U, W, D) are estimated using the whole sample $(N \times T)$. Actually, the program **(27)** is the linearization of a fractional program where:

$$D_O^E(x_0, y_0, b_0, t_0) = Y(y_0) = \frac{\sum_{q=1}^{Q} U_q y_{0q}}{\sum_{k_1=1}^{K_1} V_{k_1} x_{0k_1}^{t_0} + \sum_{k_2=1}^{K_2} (V_{k_2} - Z_{k_2}) x_{0k_2}^{t_0} + \sum_{r=1}^{R} W_r b_{0r} + \delta} \tag{28}$$

From **(28)** we can then derive the revenue deflated shadow price associated to each output as:

$$\frac{\partial D_O^E(x_0, y_0, b_0, t_0)}{\partial y_q} = P_{0q} = \frac{U_q}{\sum_{k_1=1}^{K_1} V_{k_1} x_{0k_1}^{t_0} + \sum_{k_2=1}^{K_2} (V_{k_2} - Z_{k_2}) x_{0k_2}^{t_0} + \sum_{r=1}^{R} W_r b_{0r} + \delta} \tag{29}$$

The aggregated good output of each DMU_n can be determined as:

$$Y(y_n) = \sum_{q=1}^{Q} P_{0q}^* y_{nq} \tag{30}$$

Using these prices, the EOME index can be evaluated as:

$$\begin{aligned}
& EOME_{n,t}^{-1} = \max_{y,\nu,\xi} \frac{Y(y_n^t)}{\bar{Y}(y_n^t)}{}^{21} \\
& s.t. \ \sum_{i=1}^{N} \nu_i^t y_{iq}^t \geq y_{nq} \quad q = 1, \dots, Q \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_1}^t \leq x_{nk_1}^t \quad k_1 = 1, \dots, K_1 \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_2}^t \leq x_{nk_2}^t \quad k_2 = 1, \dots, K_2
\end{aligned} \tag{31}$$

---

[20] Regarding the inequalities in **(27)**, it should be noted that polluting inputs x_2 can be weighted positively or negatively given their weights under each sub-technology. This situation may sometimes generate some residual (scale or mix) efficiency scores greater than one.

[21] $\bar{Y}(y_n^t) = \frac{Y(y_n^t)}{EOTE_{nt}}$.

$$\sum_{i=1}^{N} \xi_i^t b_{ir}^t \leq b_{nr}^t \quad r = 1, \dots, R$$
$$\sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \geq x_{nk_2}^t \quad k_2 = 1, \dots, K_2$$
$$\sum_{i=1}^{N} \nu_i^t x_{ik_2}^t = \sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \quad k_2 = 1, \dots, K_2$$
$$\sum_{i=1}^{N} \nu_i^t = 1 \; ; \; y, \nu_i^t, \xi_i^t \geq 0; i = 1, \dots, N$$

When using DEA it is not rare to obtain zero shadow prices for some variables. In this case O'Donnell (2011) recommended, when relying on the Färe-Primont index, to use sample average solutions of U_q instead. By contrast, in this paper we follow a different strategy. We rely on the estimation of full dimensional efficient facets (FDEFs) on which the representative DMU can be projected, and for which all prices are well defined (more discussion on the FDEFs can be found in Olesen and Petersen (2003), Portela and Thanassoulis (2006), Zhu (2015 pp145-190)). The idea is to estimate all the hyperplanes associated to FDEF. In this paper we use the Qhull algorithm for generation of all FDEFs for all the sub-technologies (independently). Then for each face we compute the efficiency score and retain the appropriate hyperplane. To obtain the shadow prices as in **(29)**, the coefficients of the hyperplane need to be normalized and deflated. This way of overcoming zero shadow prices is more robust than the sample average proposed in O'Donnell (2011).

- Environmental residual output scale component (EROSE)

The assessment of this component requires estimating the maximum possible pollution-adjusted TFP $\left(PTFP^{*t} = \frac{Y^{*t}}{\mathcal{A}(X^{*t}, B^{*t})}\right)$ similarly as in formula **(12)**. For this reason we need to define the input aggregator and therefore use the input equivalence of models **(26)** to **(30)**. These models can be seen in **Annex 2**. The maximum PTFP can then be estimated as:

$$PTFP^{*t} = \arg \max_{x>0, y>0, b>0} [Y/\mathcal{A}(X, B) \mid (x, y, b) \in \Psi_t] \tag{32}$$

More explicitly, this maximum can be estimated as follows using DEA

$$
\begin{aligned}
& PTFP^{*t} = \max_{y,x,b,\nu,\xi} \sum_{q=1}^{Q} P_{0q}^{*} y_{nq} \\
& s.t. \ \sum_{i=1}^{N} \nu_i^t y_{iq}^t \geq y_{nq} \quad q = 1, \dots, Q \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_1}^t \leq x_{nk_1}^t \quad k_1 = 1, \dots, K_1 \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_2}^t \leq x_{nk_2}^t \quad k_2 = 1, \dots, K_2 \\
& \sum_{i=1}^{N} \xi_i^t b_{ir}^t \leq b_{nr}^t \quad r = 1, \dots, R \\
& \sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \geq x_{nk_2}^t \quad k_2 = 1, \dots, K_2 \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_2}^t = \sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \quad k_2 = 1, \dots, K_2 \\
& \sum_{k_1=1}^{K_1} w_{0k_1}^{*} x_{nk_1} + \sum_{k_2=1}^{K_2} w_{0k_2}^{*} x_{nk_1} + \sum_{r=1}^{R} \Re_{0r}^{*} b_r = 1 \\
& y, x, b, \nu_i^t, \xi_i^t \geq 0; i = 1, \dots, N
\end{aligned}
\tag{33}
$$

Using **(33)**, EROSE can be easily estimated. In addition, the environmental residual mix efficiency (ERME) can also be derived.

TFP decompositions and TFP change components can be assessed as in formulas **(14)** and **(16)**.

3. Database and by-production technology specification

We use data from a network of French suckler cow farms located in the grassland areas of the centre of France (north Massif Central: Allier, Creuse, Nièvre, Puy de Dôme, Saône et Loire). These farms are specialized in beef production using the 'Charolaise' breed. All the data used in this paper relate to the beef production activity only. In the case several activities are present on the farm, for instance crops and other animal rearing, only inputs allocated to beef production are used (Charroin and Ferrand, 2010)). The data is a balanced panel of 49 farms surveyed over the period 1990 to 2013 (1,176 observations in total).

We use the four following inputs: land (fodder area in hectares devoted to suckler cows production); labour devoted to beef production (in working units); herd size (in livestock units);

and beef production related costs (operational and structural costs[22] in 2005 Euros). The single good output used here is the meat production estimated in tons of live weight. The pollution-adjusted productivity is adjusted for greenhouse gases (GHGs). The three GHGs, namely carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), emitted by livestock farming are considered as bad outputs.

For generalization of the by-production, we estimate a factorially determined production system where each output is described by its own technology (Frisch, 1965, Førsund, 2009). The global technology that is estimated is then the intersection of several sub-technologies as presented in **(34)**.

$$\Psi = \Psi^{Meat} \cap \Psi^{CO_2} \cap \Psi^{CH_4} \cap \Psi^{N_2O} \tag{34}$$

Prior to this paper, the different GHGs were assessed using the life cycle assessment (LCA) tool which evaluates at different stages of the production the corresponding environmental impacts (Guinée et al., 2002). In this case of suckler cow farms, emission factors for over three hundreds variables provided by GES'TIM (Gac et al., 2011) and Dia' terre® (ADEME, 2011) and further adapted to our sample, were used to estimate the different GHGs levels. The boundary associated to the LCA incorporates all processes from the cradle to the farm gate. Given then the knowledge on the process of the generation of each GHG, inputs separation can be easily operated: carbon dioxide is generated by the production related costs variable; methane emissions are associated to the herd size; nitrous oxide is linked to the two polluting inputs, namely production related costs and herd size.

Table 1 displays descriptive statistics of the data used. Over the period (1990-2013) the 49 farms considered operated on average 123 hectares of land for the beef production activity, with an annual growth of this input of 2%. A similar annual growth trend is observed for the herd size, production costs, and meat output. By contrast, labour use has been reduced by 0.12% per year,

[22] Operational costs also include the value of the cereals produced on the farm and purchased. To be consistent with an analysis based on quantities, some costs like loan interests, insurances, marketing costs and management costs were removed from the total production related costs.

with an average value over the period of 1.82 working unit. This suggests that labour efficiency has increased over the period. More details on the sample and on the previous variables can be found in Veysset et al. (2015). As regard bad outputs, the increase in farm size and polluting inputs consumption is also reflected in the increasing trend of GHGs over the period of study. The total GHG emissions are computed here by converting methane and nitrous oxide emissions into carbon dioxide equivalent using their global warming potential (for methane it is 25 and for nitrous oxide it is 298). Given this conversion, the pollution intensity (on average 14.4 kg of CO_2 equivalent per kg of live meat) has recorded a very small decrease over the whole period (cumulative decrease of 2% between 1990 and 2013).

Table 1: Descriptive statistics of the 49 farms over the period 1990-2013

	Minimum	Maximum	Mean (μ)	Standard deviation (σ)	Coefficient of variation (σ/μ)	Average annual growth (%)	Cumulative growth (%)
Land (hectares)	40.6	442.2	**122.8**	55.3	0.45	**2.08**	*60.54*
Labour (working units)	0.49	4.55	**1.82**	0.64	0.35	**-0.12**	*-2.64*
Herd size (livestock units)	41.7	457.0	**155.8**	71.2	0.46	**1.83**	*51.71*
Production related costs (thousands 2005 Euros)	13.7	329.3	**76.3**	40.7	0.53	**2.34**	*70.12*
Meat production (tons of live weight)	12.1	173.9	**48.7**	24.7	0.51	**2.01**	*58.16*
Carbon dioxide emissions (tons)	13.4	787.0	**106.1**	75.3	0.71	**2.60**	80.53
Methane emissions (tons)	4.9	53.2	**18.1**	8.3	0.46	**1.83**	51.71
Nitrous oxide emissions (tons)	0.1	1.7	**0.5**	0.2	0.54	**1.72**	48.16
Total GHG emissions (tons of CO_2-eq)	160.7	2589.4	**696.1**	348.0	0.50	**1.92**	54.89
Pollution intensity (kg CO_2-eq/kg of live meat)	10.8	26.0	**14.4**	2.0	0.14	**-0.09**	-2.07

Notes: 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. CO_2-eq: carbon dioxide equivalent.

Source: the authors

4. Results

4.1. Partial productivity indexes

The partial productivity of a specific production factor is computed as the ratio of an output (quantity of meat production or GHGs) to this specific factor. **Table 2** shows that land productivity has slightly decreased over the period 1990-2013 (the cumulative decrease rate is about 1.5% over the 23 years). In the same time, herd size productivity has increased by 4% mainly thanks to genetic improvements as well as to an accrued recourse to veterinary products (veterinary expenses have increased in volume[23] by more than 37% from 1990 to 2013[24]). Labour productivity has spectacularly increased by more than 62% over the whole period (2%/year), a very high figure compared to the other factors. Increase in structural fixed costs[25] (mechanization, buildings, overheads…) and the simplification of agricultural practices with the systematic purchase of concentrated (concentrates feed per cow have fluctuated from 927 kg in 1990 to 1,172 kg in 2013) can explain this increase in labour productivity. Nevertheless, an immediate consequence of the increase in feed and structural costs is the deterioration of the productivity of the associated production costs, namely by 7%.

Regarding the bad outputs, the increase in production related costs directly implies an increase in carbon dioxide partial productivity index (CO_2/production related costs). However, the nitrous oxide partial productivity index with respect to production related costs has substantially decreased over the whole period, by almost 13%. The main factor associated to nitrous oxide emission is the use of nitrogen fertilizer, which in this case has strongly decreased from the nineties. Nitrogen fertilizer in kg per hectare of fodder area has decreased from 39 in 1997 to 21 in 2013, that is to say a decrease of 46%. This induced a high decrease in nitrous oxide emissions, which also explains the negative tendency of the partial productivity index with regard to herd size (but at a smaller rate). Finally, the figures show that the major component of methane emissions is linked to the animal physiology and mainly enteric fermentation. This explains the zero change in the partial productivity of methane emissions relative to herd size.

[23] The volume of veterinary expenses is approximated by using constant currency (2005 Euros).

[24] In 1990 the veterinary expenses represented 5,901 Euros while in 2013 they were about 8,131 Euros (in constant prices).

[25] In volume (2005 Euros) these costs have increased on average from 24,020 in 1990 to 43,535 in 2013, that is to say an increase of more than 80%.

Table 2: Partial productivities' changes over the period 1990-2013: averages for the 49 farms

	Average annual growth (%)	Cumulative growth (%)
Land productivity index	-0.07	-1.48
Labour productivity index	2.13	62.44
Herd size productivity index	0.18	4.25
Production related costs productivity index	-0.32	-7.02
CO_2 per production related costs index	0.26	6.12
CH_4 per herd size index	0	0
N_2O per herd size index	-0.10	-2.34
N_2O per production related costs index	-0.60	-12.91

Source: the authors

4.2. Productivity change, pollution-adjusted productivity changes and their components

Table 3 presents the results in terms of Total Factor Productivity change (dTFP) and its efficiency change components, while the results for the pollution-adjusted TFP change (dETFP) are presented in **Table 4**. **Figure 5** represents the evolution of dTFP and two of its components (dTC: technical change; and dEC: efficiency change) over the period of analysis, while **Figure 6** shows the same but when pollution is accounted for. For simplicity and comparison purpose we have retained year 1990 as reference base, i.e. all the variations are compared with respect to this specific year.

The change in TFP varies across years but with no clear temporal trend. However, a closer look to **Figure 5** indicates that between 1990 and 2003, TFP has recorded a decreasing trend while between 2003 and 2013 the tendency is increasing (comparatively to year 1990). Overall, the last row in **Table 3**, which corresponds to the cumulative productivity change, indicates a very small negative change between 1990 and 2013 (the index for dTFP is 0.991, indicating a 0.9% decrease) (see last row in **Table 3**). When we consider pollution in the model, the decrease in the productivity index is stronger, by 8.4% (see last row in **Table 4**). Besides, on **Figure 6** the decreasing trend of pollution-adjusted productivity is more obvious.

A closer look at the components of total productivity reveals a technical progress (dTC) of 3.6%, but this progress is offset by a decrease in technical efficiency (dEC) of 4.3%, resulting in unchanged TFP. In the case of pollution-adjusted productivity index, the major source of TFP decrease is technical efficiency deterioration (dEEC) (-5.4%), followed by technological regress

(- 3.1%). **Figures 5** and **6** clearly show the systematic opposite patterns between technical change and efficiency change. In the previous section we gave evidence of a substantial change in partial factor productivity, indicating significant changes in farmers' practices. As explained by Latruffe et al. (2012), technical change and technical efficiency change often develop oppositely, since it takes time for farms to adapt to a new technology and use it efficiently. An interesting pattern in **Figure 6** is that efficiency change index mainly remains above one during the period, while technical change index remains below one.

The deterioration in technical efficiency when not accounting for pollution, is imputable first to a decreasing efficiency of output production (Output Technical Efficiency – OTE – decreases by 3%), and to a lower extent to sub-optimal operation scale (Residual Output Scale Efficiency – ROSE – decreases by 1.3%). When GHG pollution is included in the model these two efficiency components seem to play equal role (respectively decreases by 2.6% and 3%).

Table 3: Productivity and efficiency changes over the period 1990-2013: averages for the 49 farms

Period of time	dTFP	dTC	dEC	dOTE	dROSE	dOSE	dRME
1990	**1.000**	1.000	1.000	1.000	1.000	1.000	1.000
1991	**1.004**	1.019	0.985	0.992	0.993	1.003	0.990
1992	**1.027**	1.008	1.019	0.998	1.021	1.013	1.008
1993	**1.054**	1.057	0.998	0.997	1.001	1.029	0.972
1994	**1.035**	1.041	0.994	0.996	0.998	1.026	0.973
1995	**1.043**	1.044	0.999	1.002	0.997	1.042	0.956
1996	**1.026**	1.046	0.981	1.002	0.978	1.007	0.972
1997	**1.029**	1.027	1.002	1.004	0.998	1.017	0.981
1998	**1.030**	1.032	0.998	0.985	1.014	1.020	0.994
1999	**1.037**	1.091	0.951	0.997	0.953	0.981	0.972
2000	**1.050**	0.990	1.060	1.020	1.040	1.034	1.006
2001	**1.017**	1.036	0.982	0.985	0.996	1.000	0.996
2002	**1.020**	1.012	1.007	0.949	1.062	1.032	1.029
2003	**0.962**	1.057	0.911	0.968	0.941	1.014	0.928
2004	**0.990**	0.960	1.031	1.000	1.031	1.014	1.017
2005	**1.007**	1.077	0.935	0.991	0.943	0.973	0.970
2006	**0.993**	0.987	1.007	1.016	0.991	0.997	0.993
2007	**1.009**	0.963	1.048	1.029	1.018	1.020	0.999
2008	**1.012**	1.074	0.942	0.998	0.944	0.987	0.957
2009	**1.012**	1.069	0.947	0.988	0.958	0.980	0.978
2010	**1.032**	1.075	0.960	0.994	0.966	0.989	0.976
2011	**1.017**	1.005	1.012	1.005	1.007	1.008	0.999
2012	**1.037**	1.047	0.991	0.979	1.012	1.018	0.995
2013	**0.991**	1.036	0.957	0.970	0.987	1.003	0.984

Notes: We use the prefix 'd' to underline that the table shows changes in the indices between two years where 1990 is the based year. dTC is a measure of technical change and dEC stands for the change in TFPE and is related to efficiency change. dOME equals one because there is only one output, and thus no mix inefficiencies can be found. The averages are computed using geometric means. Figures greater than one indicate a growth in the index considered (productivity or its components), while figures less than one indicate deterioration. Figures equal to one indicate no change. All computations were carried out using the R software.

Source: the authors

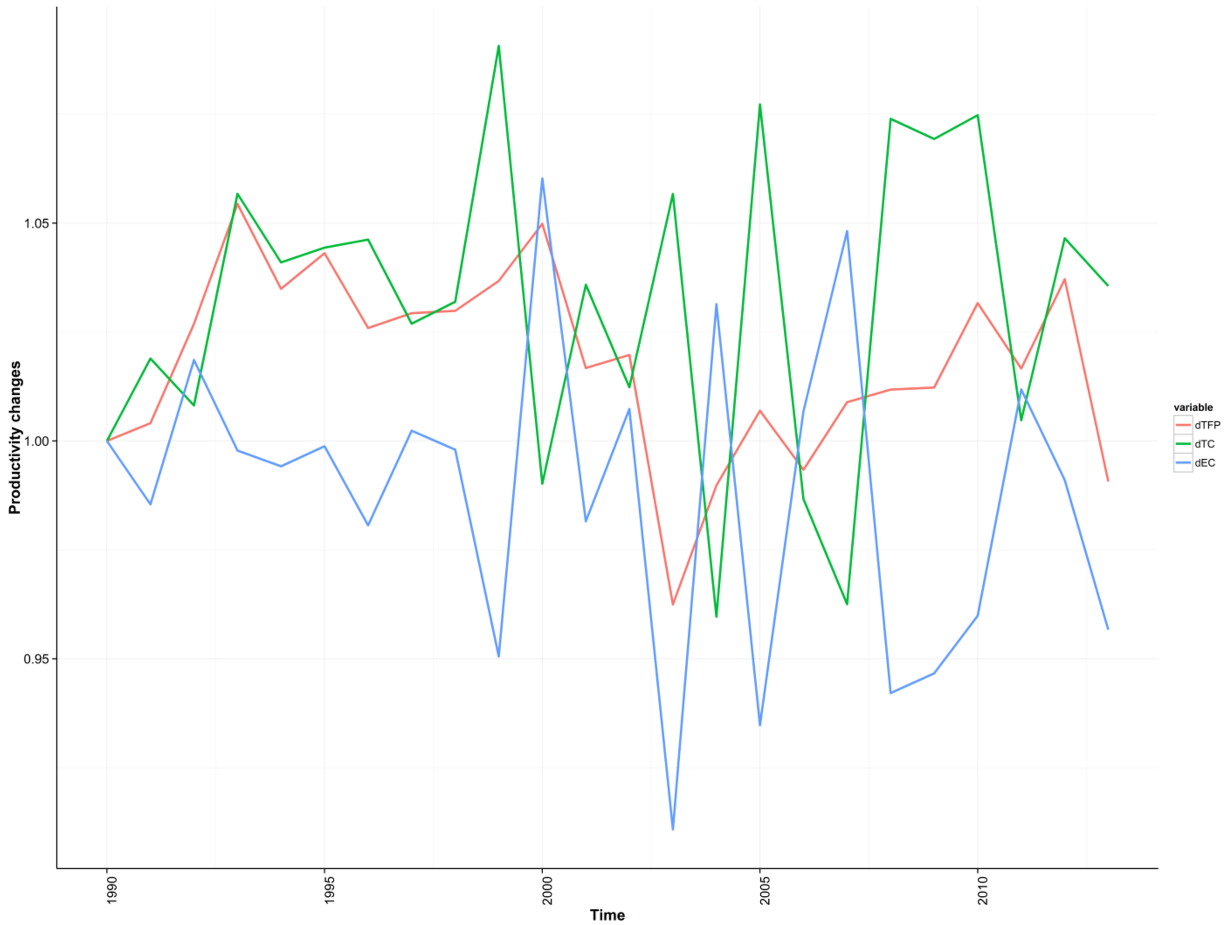
Table 4: Pollution-adjusted productivity and efficiency changes over the period 1990-2013: averages for the 49 farms

Period of time	dETFP	dETC	dEEC	dEOTE	dEROSE	dEOSE	dERME
1990	**1.000**	1.000	1.000	1.000	1.000	1.000	1.000
1991	**0.984**	1.057	0.930	0.995	0.935	0.996	0.938
1992	**1.005**	0.974	1.032	0.997	1.034	1.020	1.014
1993	**1.056**	0.967	1.093	0.993	1.100	1.035	1.063
1994	**1.040**	0.959	1.084	1.013	1.070	1.019	1.051
1995	**1.038**	1.030	1.008	0.986	1.023	1.035	0.988
1996	**1.020**	0.975	1.046	1.009	1.036	1.003	1.034
1997	**0.955**	0.869	1.100	1.016	1.082	0.997	1.085
1998	**0.944**	0.907	1.041	0.999	1.042	1.016	1.026
1999	**0.977**	0.920	1.063	1.021	1.041	0.993	1.048
2000	**0.988**	0.972	1.016	1.008	1.008	1.026	0.983
2001	**0.958**	0.833	1.150	0.993	1.158	0.999	1.159
2002	**0.974**	0.979	0.994	0.958	1.038	1.006	1.032
2003	**0.886**	0.856	1.035	0.973	1.064	0.996	1.068
2004	**0.912**	0.832	1.097	0.997	1.100	1.000	1.100
2005	**0.991**	0.926	1.070	1.000	1.071	0.992	1.079
2006	**0.973**	1.007	0.966	1.019	0.948	0.980	0.967
2007	**0.982**	0.913	1.076	1.015	1.060	1.017	1.042
2008	**0.947**	0.825	1.148	0.992	1.157	0.990	1.169
2009	**0.983**	0.950	1.035	0.984	1.052	0.969	1.085
2010	**0.990**	1.046	0.947	0.987	0.959	1.004	0.955
2011	**0.992**	1.001	0.991	0.994	0.997	0.999	0.998
2012	**0.963**	0.937	1.027	0.978	1.050	1.016	1.034
2013	**0.916**	0.969	0.944	0.974	0.970	0.999	0.971

Notes: We have added the prefix ‘dE’ to denote that environmental changes are accounted for in the index. As previously, dEOME equals one because of the presence of only one good output.

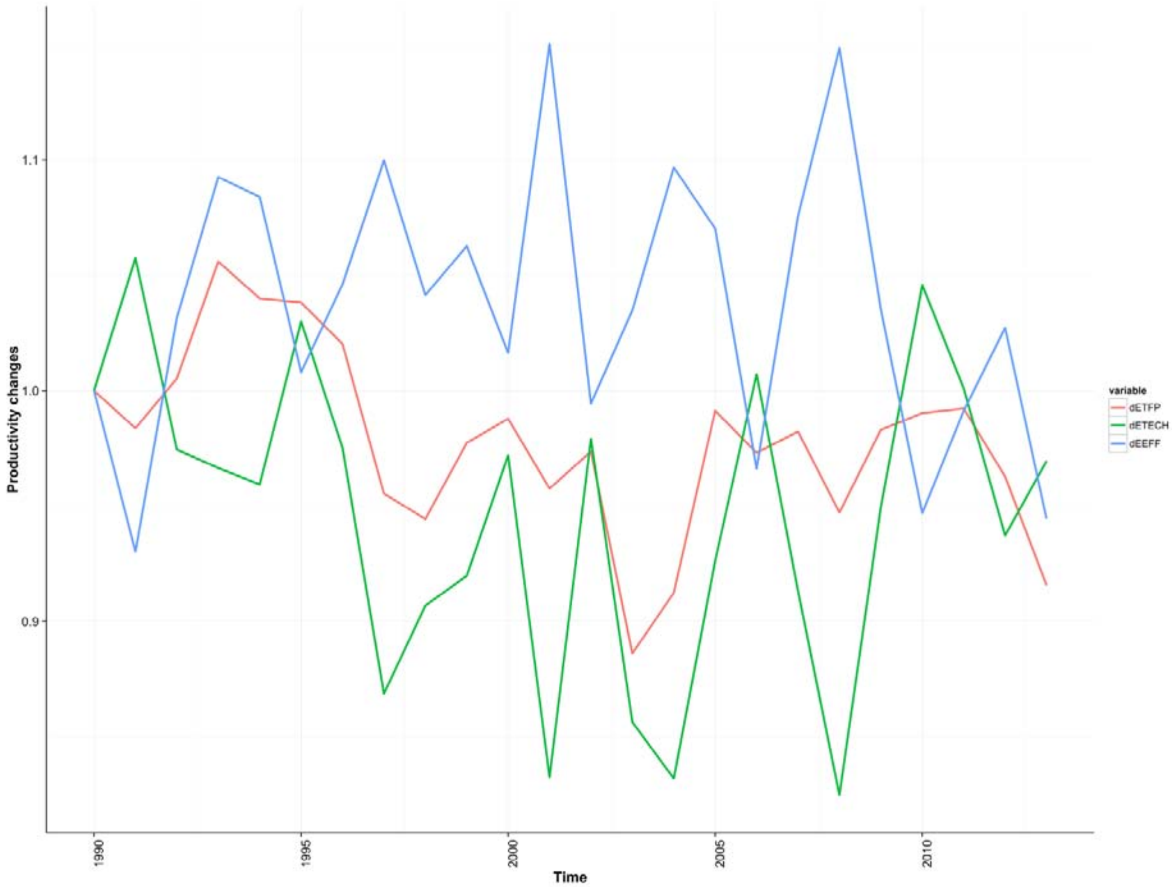
Source: the authors

Figure 5: Evolution of the 49 farms' average annual productivity change (dTFP in red) and its components (technical change, dTC, in green and efficiency change, dEC, in blue) over the period 1990-2013



Source: the authors

Figure 6: Evolution of the 49 farms' average annual pollution-adjusted productivity change (dETFP in red) and its components (technical change, dETECH in green and efficiency change, dEEFF in blue) over the period 1990-2013



Source: the authors

4.3. Characteristics of farms with high (pollution-adjusted or not) TFP growth

For each farm we compute the cumulative (pollution-adjusted or not) productivity growth from 1990 to 2013 (see Annex 2). Based on this, we split the observations in two groups: the first group includes farms that have recorded no decrease in cumulative (pollution-adjusted or not) productivity change (i.e. they have experienced an increase or no change in (pollution-adjusted or not) productivity over the whole period; these are the higher performers), and the second group includes the farms for which a decrease in their cumulative (pollution-adjusted or not) productivity change is observed (this, the lower performers). We then compare the characteristics of both groups using some parametric and non-parametric tests. The results for non-pollution adjusted TFP are presented in **Table 4**, which clearly shows (top row) that the total productivity change is significatively different between the two groups we have built. The results for pollution-adjusted TFP are in **Table 5**.

Surprisingly the partial productivities of the factors are not significatively different between the two groups. This confirms that partial productivities cannot always be good indicators of the performance of firms. The limits of partial productivities also coined ‘key performance indicators’ have been largely discussed in (Bogetoft, 2013).

Both groups of farms differ significantly in terms of several characteristics. First, numerical productivity, defined by the number of live-weaned calves born per cow serviced multiplied by 100 (Veysset et al., 2014), is the most significant characteristic that distinguishes between both groups of farms: farms which have experienced an increase in TFP (namely TFP greater or equal to one) have on average a larger numerical productivity than farms which have experienced a decrease in TFP (namely TFP less than one). Second, the share of permanent grassland in fodder area is lower for farms that recorded TFP improvement than for farms that recorded TFP deterioration. This indicates that extensive livestock farming is not favourable to productivity progress. Third, farms with TFP increase were less indebted than farms experiencing TFP decrease, suggesting that farmers relied more on internal resources or subsidies than on debts for technological improvements.

Finally, a few other characteristics distinguish between the two groups of farms, although the difference is not strongly significant. Farms with positive TFP change or no change used more concentrates per livestock unit than farms with negative TFP change, a finding in line with the above finding regarding the share of permanent pasture. Nitrogen released per hectare of fodder area weakly distinguishes both groups of farms in one of the three tests: this pollution quantity is higher on average for farms with increased TFP than for farms with reduced TFP. This suggests that economic productivity may not be favourable to the environment. Total subsidies received per livestock unit also distinguish weakly both groups in one of the three tests: farms which performed best (TFP greater or equal to one) received on average less subsidies than farms which performed poorly. However, this finding needs to be toned down due to potentially endogeneity: during the period studied, farms located in disadvantage areas received lump sum subsidies in the frame of the Common Agricultural Policy (CAP), and those farms may be the lowest performers due to the difficult environmental conditions in which they operate.

When accounting for pollution in TFP (**Table 5**), results indicate that one main characteristics distinguishes between both types of farms. The higher performers (TFP greater or equal to one) are characterized by a lower resort to concentrates per livestock units than low performers (TFP less than one). This finding is accentuated by the other characteristic that significantly distinguishes, although weakly, between both groups: the feed autonomy is slightly higher for better performing farms than for poorly performing farms.

Table 4: Characteristics of farms categorised according to their cumulative productivity change: means and tests of equality of means

	dTFP<1 (22 farms)	dTFP>=1 (27 farms)	Kolmogorov Smirnov test	Wilcoxon rank test	t-test
Variables	***Mean***		***P-value***		
dTFP	**0.87**	**1.11**	**<5%**	**<5%**	**<5%**
Labour (working units)	1.83	1.82	>15%	>15%	>15%
Land (hectares)	128.95	117.87	>15%	>15%	>15%
Herd (livestock units)	157.89	154.09	>15%	>15%	>15%
Production related costs (thousand 2005 Euros)	74.11	78.04	>15%	>15%	>15%
Meat production (tons of live weight)	47.38	49.85	>15%	>15%	>15%
Labour productivity	87.00	86.69	>15%	>15%	>15%
Land productivity	*0.38*	*0.42*	*>15%*	*<10%*	*<5%*
Herd productivity	*0.30*	*0.32*	*>15%*	*<10%*	*<5%*
Production related costs productivity	0.66	0.65	>15%	>15%	>15%
Farms characteristics					
Numerical productivity (%)	**84.92**	**89.00**	**<5%**	**<5%**	**<5%**
Feed autonomy (%)	*92.94*	*92.46*	*<15%*	*>15%*	*>15%*
Grazing autonomy (%)	80.05	78.00	>15%	>15%	>15%
Share of permanent grassland in fodder area (%)	**69.72**	**56.90**	**<15%**	**<10%**	**<10%**
Total subsidies per livestock unit (2005 Euros)	*255.53*	*240.59*	*>15%*	*<15%*	*>15%*
Stocking rate (livestock units per hectare)	1.25	1.30	>15%	>15%	>15%
Share of hired labour in total labour (%)	10.72	11.90	>15%	>15%	>15%
Average debt to asset ratio (%)	**34.30**	**26.26**	**<15%**	**<5%**	**<5%**
Share of maize silage in fodder area (%)	3.85	3.86	>15%	>15%	>15%
Nitrogen per hectare of fodder area (kilogram)	*28.44*	*33.22*	*<15%*	*>15%*	*>15%*
Concentrates per livestock unit (kilogram)	*568.60*	*656.93*	*<10%*	*>15%*	*<15%*
Gross margin per livestock unit (2005 Euros)	542.81	543.44	>15%	>15%	>15%
Revenue per labour unit (2005 Euros)	4121	4348	>15%	>15%	>15%
Share of lean animals sold in the total number of animals sold (%)	0.75	0.74	>15%	>15%	>15%

Notes: Feed autonomy represents the share of the herd's energy needs that are covered by own resources (produced on the farm), while grazing autonomy stands for the feed energy requirements that are covered by the own grassland areas. The stocking rate represents the number of livestock unit per unit of fodder area.

Source: the authors

Table 5: Characteristics of farms categorised according to their cumulative pollution-adjusted productivity change: means and tests of equality of means

	dETFP<1 (33 farms)	**dETFP>=1 (16 farms)**	**Kolmogorov Smirnov test**	**Wilcoxon rank test**	**t-test**
Variables	***Mean***		***P-value***		
dETFP	**0.82**	**1.20**	**<5%**	**<5%**	**<5%**
Labour (working units)	1.86	1.75	>15%	>15%	>15%
Land (hectares)	125.62	117.13	>15%	>15%	>15%
Herd (livestock units)	162.10	142.79	>15%	>15%	>15%
Production related costs (thousand 2005 Euros)	*80.72*	*67.12*	*>15%*	*>15%*	*<15%*
Meat production (tons of live weight)	50.81	44.48	>15%	>15%	>15%
Carbon dioxide emissions (tons)	*115.10*	*87.67*	*>15%*	*>15%*	*<10%*
Methane emissions (tons)	18.86	16.62	>15%	>15%	>15%
Nitrous oxide emissions (tons)	*0.49*	*0.40*	*>15%*	*>15%*	*<15%*
Total GHG emissions (tons of CO_2-eq)	732.40	621.32	>15%	>15%	>15%
Pollution intensity (kg CO_2-eq/kg of live meat)	14..56	14.20	>15%	>15%	>15%
CO_2 per production related costs index	1.35	1.28	>15%	>15%	>15%
CH_4 per herd size index	0.12	0.12	>15%	>15%	>15%
N_2O per herd size index	0.003	0.003	>15%	>15%	>15%
N_2O per production related costs index	0.006	0.006	>15%	>15%	>15%
Farms characteristics					
Numerical productivity (%)	86.88	87.74	>15%	>15%	>15%
Feed autonomy (%)	**92.15**	**93.76**	**<10%**	**<15%**	**<15%**
Grazing autonomy (%)	*77.47*	*81.87*	*>15%*	*<10%*	*<10%*
Share of permanent grassland in fodder area (%)	61.26	65.54	>15%	>15%	>15%
Total subsidies per livestock unit (2005 Euros)	*242.93*	*256.30*	*>15%*	>15%	>15%
Stocking rate	1.29	1.25	>15%	>15%	>15%
Share of hired labour in total labour (%)	12.16	9.73	>15%	>15%	>15%
Average debt to asset ratio (%)	30.29	29.00	>15%	>15%	>15%
Share of maize silage in fodder area (%)	*4.23*	*3.07*	*>15%*	*<15%*	*>15%*
Nitrogen per hectare of fodder area (kilogram)	32.55	28.04	>15%	>15%	>15%
Concentrates per livestock unit (kilogram)	**651.67**	**546.31**	**<10%**	**<5%**	**<10%**
Gross margin per livestock unit (2005 Euros)	535.20	559.58	>15%	>15%	>15%
Revenue per labour unit (2005 Euros)	4385.40	3958.61	>15%	>15%	>15%
Share of lean animal sold in the total number of animals sold (%)	0.72	0.80	>15%	>15%	>15%

Source: the authors

5. Conclusion

The multiplicatively complete Färe-Primont index has been used here to assess productivity changes and its components in French suckler cows. The results reveal the absence of productivity gains over the whole period of observation (1990 to 2013). Although some technical progress has been recorded over the period, it has been offset by technical efficiency decrease.

The first finding arises from the calculation of TFP changes and decompositions, both without accounting for GHG emissions and when accounting for them. The figures revealed a more gloomy picture when GHGs are taken into account than when they are not: there is a decrease of pollution-adjusted TFP, while when GHGs are not integrated there is a stagnation of TFP. The decrease of pollution-adjusted TFP is due to both technological regress and efficiency deterioration. Thus, while when GHGs are not considered technological progress has offset efficiency deterioration, this is not the case when GHGs are fully included in the farm technology. This indicates that technological regress is mainly due to the increase of GHG emissions during the period. It suggests that farmers did not have the right incentives to implement actions that would reduce such emissions.

The second main finding regards the comparison of highly and low performers, both without accounting for GHG emissions and when accounting for them. When GHG emissions are not accounting for, farms that recorded an increase in TFP during the period studied are characterized by a higher numerical animal productivity, a lower indebtedness ratio and a lower reliance to grass compared to maize. By contrast, when GHGs are integrated in the computation, farms that recorded an increase in TFP are those that relied less on external feed such as concentrates. This suggests that rooms for improvement mainly relate to changing the feed system of the farm, which is something that may be more easily implemented than changes in other pollution-emitting materials or reduction of enteric fermentation.

We finish with some methodological discussions. First, as regard to the computation of the Färe-Primont index itself. As largely explained in the methodology section, this index requires the definition of an arbitrary reference point. For our case study we have retained a representative DMU which is simply the average of the pooled sample. Fortunately our results are robust to the choice of reference point which is simply a mean to the goal of productivity assessment. Second, we have compared the features of the farms that have recorded productivity gains to farms that have faced some productivity losses. Parametric and non-parametric tests were conducted. These analysis are bivariate and do not account for possible interactions among the different variables. A multivariate analysis could certainly provide more insightful results. Third, one limit of the empirical analysis relates to the labour input which is measured in full time equivalent workers. This measure is an estimation but the number of working hours would be more precise; unfortunately is not available in our database. Besides, the very high partial productivity of this factor may suggest an analysis without considering this input to check for the robustness of the findings. Fourth, in our estimation we have allowed for technological regress which for the specific case of livestock farming captures some environmental impacts. An interesting extension could be an analysis which precludes for regression in the technology. A sequential Färe-Primont index can be considered for this new decomposition.

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Annex 1:

Environmental input aggregator

- Environmental input technical efficiency score (EITE)

$$
\begin{aligned}
& D_I^E(x_n^t, y_n^t, b_n^t, t)^{-1} = EITE_{n,t}^{-1} = \min_{\theta,\nu,\xi} \theta_n^t \\
& s.t \quad \sum_{i=1}^{N} \nu_i^t y_{iq}^t \geq y_{nq} \quad q = 1, \dots, Q \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_1}^t \leq \theta_n^t x_{nk_1}^t \quad k_1 = 1, \dots, K_1 \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_2}^t \leq \theta_n^t x_{nk_2}^t \quad k_2 = 1, \dots, K_2 \\
& \sum_{i=1}^{N} \xi_i^t b_{ir}^t \leq \theta_n^t b_{nr}^t \quad r = 1, \dots, R \\
& \sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \geq \theta_n^t x_{nk_2}^t \quad k_2 = 1, \dots, K_2 \\
& \sum_{i=1}^{N} \nu_i^t x_{ik_2}^t = \sum_{i=1}^{N} \xi_i^t x_{ik_2}^t \quad k_2 = 1, \dots, K_2 \\
& \sum_{i=1}^{N} \nu_i^t = 1 \ ; \ \nu_i^t, \xi_i^t \geq 0; i = 1, \dots, N
\end{aligned}
\tag{35}
$$

The dual of this model at the representative point (x_0, y_0, b_0) can be written as follows

$$
\begin{aligned}
& D_I^E(x_n^t, y_n^t, b_n^t, t)^{-1} = \max_{V,Z,U,W,D,\delta,\sigma} \sum_{q=1}^{Q} U_q\, y_{0q}^{t_0} + \delta \\
& s.t \ \sum_{q=1}^{Q} U_q y_{iq}^t - \sum_{k_1}^{K_1} V_{k_1} x_{ik_1}^t - \sum_{k_2=1}^{K_2} (V_{k_2} - D_{k_2}) x_{ik_2}^t + \delta \leq 0 \quad i = 1, \dots, N\ ; \ t = 1, \dots, T \\
& -\sum_{r=1}^{R} W_r b_{ir}^t + \sum_{k_2=1}^{K_2} (Z_{k_2} - D_{k_2}) x_{ik_2}^t \leq 0 \quad i = 1, \dots, N\ ; \ t = 1, \dots, T \\
& \sum_{k_1=1}^{K_1} V_{k_1} x_{0k_1}^{t_0} + \sum_{k_2=1}^{K_2} (V_{k_2} - Z_{k_2}) x_{0k_2}^{t_0} + \sum_{r=1}^{R} W_r b_{0r} = 1 \\
& V, Z, U, W \geq 0 \ ; \quad D, \delta \text{ unrestricted}
\end{aligned}
\tag{36}
$$

Like previously, the program in **(35)** is the linearization of the fractional program in **(36)**.

$$
D_I^E(x_0, y_0, b_0, t_0) = \mathcal{A}(X_0\,, Y_0) = \frac{\sum_{k_1=1}^{K_1} V_{k_1} x_{0k_1}^{t_0} + \sum_{k_2=1}^{K_2} (V_{k_2} - Z_{k_2}) x_{0k_2}^{t_0} + \sum_{r=1}^{R} W_r b_{0r}}{\sum_{q=1}^{Q} U_q y_{0q}^{t_0} + \delta} \tag{37}
$$

From **(36)** we can then derive the cost deflated shadow price associated to each input and bad output as:

$$\frac{\partial D_I^E\left(x_0, y_0, b_0, t_0\right)}{\partial x_{k_1}} = \mathcal{w}_{0k_1} = \frac{V_{k_1}}{\sum_{q=1}^{Q} U_q\, y_{0q}^{t_0} + \delta} \tag{38}$$

$$\frac{\partial D_I^E\left(x_0, y_0, b_0, t_0\right)}{\partial x_{k_2}} = \mathcal{w}_{0k_2} = \frac{V_{k_2} - Z_{k_2}}{\sum_{q=1}^{Q} U_q\, y_{0q}^{t_0} + \delta} \tag{39}$$

$$\frac{\partial D_I^E\left(x_0, y_0, b_0, t_0\right)}{\partial b_r} = \Re_{0r} = \frac{W_r}{\sum_{q=1}^{Q} U_q\, y_{0q}^{t_0} + \delta} \tag{40}$$

The aggregated environmental input of each DMU_n can be determined as:

$$\mathcal{A}(X_n, B_n) = \sum_{k_1=1}^{K_1} \mathcal{w}_{0k_1}^{*} x_{nk_1} + \sum_{k_2=1}^{K_2} \mathcal{w}_{0k_2}^{*} x_{nk_1} + \sum_{r=1}^{R} \Re_{0r}^{*} b_r \tag{41}$$

Annex 2

Cumulative productivity change and its components' changes between 1990 and 2013 for each of the 49 farms

Farm #	dTFP	dTC	dEC	dETFP	dETC	dEEC
1	0.912	1.036	0.880	1.002	0.969	1.033
2	1.239	1.036	1.196	1.098	0.969	1.133
3	0.873	1.036	0.843	1.080	0.969	1.114
4	0.839	1.036	0.810	0.704	0.969	0.727
5	0.725	1.036	0.700	0.946	0.969	0.975
6	0.991	1.036	0.957	0.873	0.969	0.900
7	0.780	1.036	0.753	0.721	0.969	0.744
8	1.083	1.036	1.045	0.787	0.969	0.812
9	1.016	1.036	0.981	1.341	0.969	1.383
10	0.742	1.036	0.716	0.489	0.969	0.504
11	1.015	1.036	0.980	0.697	0.969	0.719
12	1.020	1.036	0.985	0.758	0.969	0.781
13	0.956	1.036	0.923	1.514	0.969	1.561
14	1.139	1.036	1.100	1.351	0.969	1.393
15	0.747	1.036	0.722	0.986	0.969	1.017
16	1.477	1.036	1.426	1.554	0.969	1.603
17	0.990	1.036	0.956	0.916	0.969	0.945
18	1.342	1.036	1.296	1.067	0.969	1.101
19	1.036	1.036	1.000	0.946	0.969	0.976
20	1.227	1.036	1.185	1.111	0.969	1.146
21	1.007	1.036	0.973	0.978	0.969	1.008
22	1.029	1.036	0.993	0.841	0.969	0.868
23	0.945	1.036	0.912	0.848	0.969	0.875
24	1.089	1.036	1.052	1.045	0.969	1.078
25	0.847	1.036	0.818	0.608	0.969	0.627
26	0.872	1.036	0.842	0.863	0.969	0.890
27	0.972	1.036	0.939	0.746	0.969	0.769
28	0.933	1.036	0.901	0.806	0.969	0.832
29	1.127	1.036	1.088	0.988	0.969	1.019
30	1.081	1.036	1.044	0.855	0.969	0.882
31	1.099	1.036	1.061	1.167	0.969	1.204
32	1.112	1.036	1.074	0.812	0.969	0.838
33	1.170	1.036	1.130	0.882	0.969	0.910
34	0.534	1.036	0.516	0.510	0.969	0.526
35	1.051	1.036	1.015	0.866	0.969	0.893

Farm #	dTFP	dTC	dEC	dETFP	dETC	dEEC
36	1.171	1.036	1.131	1.124	0.969	1.159
37	1.120	1.036	1.081	0.998	0.969	1.029
38	1.070	1.036	1.033	0.744	0.969	0.767
39	1.045	1.036	1.009	1.087	0.969	1.121
40	1.018	1.036	0.983	0.792	0.969	0.817
41	1.067	1.036	1.030	1.248	0.969	1.287
42	0.813	1.036	0.785	0.962	0.969	0.993
43	0.986	1.036	0.952	1.342	0.969	1.384
44	0.965	1.036	0.932	0.846	0.969	0.872
45	0.926	1.036	0.895	1.023	0.969	1.055
46	0.863	1.036	0.833	0.878	0.969	0.906
47	1.071	1.036	1.034	0.844	0.969	0.871
48	1.085	1.036	1.048	0.789	0.969	0.814
49	0.996	1.036	0.962	0.727	0.969	0.749

Source: the authors

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