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► **To cite this version:**

K Hervé Dakpo, Alfons Oude Lansink. Dynamic pollution-adjusted inefficiency under the by-production of bad outputs. *European Journal of Operational Research*, 2019, 276 (1), pp.202-211. 10.1016/j.ejor.2018.12.040 . hal-02163756

**HAL Id: hal-02163756**

**<https://hal.science/hal-02163756>**

Submitted on 22 Oct 2021

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## Dynamic pollution-adjusted inefficiency under the by-production of bad outputs

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### Acknowledgements

The authors are grateful to the Auvergne Regional Board (Conseil Régional d’Auvergne) for funding this research. They also thank the INRA Egeé team of UMRH, Clermont-Ferrand, France, for their support. The authors acknowledge financial support from the FP7 EU project ‘FLINT’ (‘Farm level indicators for new topics in policy evaluation’, grant number 613800).

## **Dynamic pollution-adjusted inefficiency under the by-production of bad outputs**

### **Abstract**

This article extends the by-production model to the dynamic context of adjustment costs associated with investment. The empirical application focuses on panel data of French suckler cow farms over the period 1978–2014, considering emissions of greenhouse gases as bad output. The paper estimates input and output-specific technical inefficiency scores in the dynamic context and compares them with efficiency measures from the conventional static context. Our results reveal significant differences between inefficiency scores derived from the static and the dynamic frameworks. For all variables except meat production (the good output), the inefficiency score is lower in the dynamic context than in the static context.

**Key words:** data envelopment analysis; by-production; adjustment costs; dynamic inefficiency; French suckler cows

## 1-Introduction

Productive entities operate in competitive markets and the production decisions they make today will inevitably affect future outcomes. Productive entities are continuously confronted with changes in policies, new prices and new technologies. All this requires Decision Making Units (DMUs) which are able to adjust to changes in their environment (Gardebroek, 2004). An important feature of these adjustments is materialized through investment strategies aiming at firms' structural change. Previous literature pointed out that adjustment costs associated with investments in quasi-fixed inputs, i.e. inputs that can be stored or accumulated like capital, prevent firms from making instantaneous adjustments (Cooper and Haltiwanger, 2006; Eisner et al., 1963; Gould, 1968; Lucas, 1967). Silva and Stefanou (2003) refer to this situation as the presence of "sluggish" adjustments in some production factors within a productive entity. The presence of quasi-fixed inputs causes production decisions to be linked intertemporally. The foundation of dynamic economic analysis is then grounded on this distinction between variable and quasi-fixed inputs which also implies a separation between short- and long-run decisions (Caputo, 2005; Stefanou, 2009).

The literature on efficiency and productivity analysis has predominantly evolved around the static context, which assumes that producers instantaneously adjust their inputs and outputs (as opposed to gradually) (Nemoto and Goto, 2003), or has compared static technologies over time (Färe and Grosskopf, 1997)<sup>1</sup>. Both approaches ignore intertemporal linkages between production decisions. In the neoclassic theory, the adjustment cost model is a well-known approach to cope with intertemporally linked decision in the presence of quasi-fixed inputs. The logic behind this idea is that investments in capital inputs generate some adjustment costs. These costs can be internal (learning effects or retraining, reorganization of production processes, installation costs, administrative costs, search costs) or external (incomplete markets)<sup>2</sup>, and are assumed to increase with the level of investment. The presence of 'costs of adjustment can explain why firms tend to

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<sup>1</sup> As presented by these authors the time comparison of static technologies can be based on the estimation of the Malmquist productivity index.

<sup>2</sup> In this work, we assume that adjustment costs are internal to the production system. However, the developments in this article can be easily extended to the presence of external adjustment costs.

conduct investments in smaller proportions, spread over time, rather than to adjust to new conditions instantaneously' (Oude Lansink et al., 2001 p359). Generally these costs are incorporated in the producer objective function (as an intertemporal value function: cost minimization, revenue and profit maximization) through (unobserved) adjustment costs (Kapelko et al., 2014). In the presence of adjustment costs in quasi-fixed factors of production, static efficiency measures do not correctly assess the firm's performance (Nick and Wetzel, 2016). In the same vein, according to Nemoto and Goto (1999) and in the presence of quasi-fixed inputs, a static measure of efficiency will lead to biased estimations where allocative efficiency is overestimated.<sup>3</sup>

Sustainable production behavior is crucial to overcome environmental challenges in a situation of competition for scarce resources. Efforts must be undertaken by firms to internalize the production of environmentally detrimental outputs which can no longer be ignored by managers. In the same line, the International Resource Panel has recommended a two-way strategy based on the concept of decoupling: first 'using less resources per unit of economic output' and second 'reducing the environmental impact of any resources that are used...' (Fischer-Kowalski and Swilling, 2011 p xiii). The double objective of economic and environmental efficiency associated with this new challenge has then led to the proposition of eco-efficiency or pollution-adjusted efficiency tools for DMU benchmarking. In the nonparametric framework of Data Envelopment Analysis (DEA), many approaches have been proposed to assess the technical and environmental efficiency of production units (Färe et al., 2005; Hailu and Veeman, 2001; Sahoo et al., 2011). However, as underlined and discussed in Dakpo et al. (2016), most developments have not properly modelled the inclusion of undesirable outputs in the production technology. Only more recently, Murty et al. (2012) introduced the concept of the by-production model and showed that this approach offers more flexibility in representing the production of undesirable outputs. In the DEA framework, Dakpo (2015) has extended the by-production approach of Murty et al. (2012) to overcome the independence assumption maintained by the former in their formulations. To the best of the authors' knowledge, no efforts have been made to date to model pollution-adjusted efficiency in the dynamic context. A better understanding of the role of undesirable outputs in the

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<sup>3</sup> For more details on the literature on adjustment costs models, one can also refer to Abel et al. (1995); Epstein (1981); Gardebreek and Oude Lansink (2004); Luh and Stefanou (1993); Luh and Stefanou (1996); Oude Lansink and Stefanou (1997); Treadway (1969, 1970).

dynamic production technology could provide more insights into the mechanisms behind pollution-adjusted efficiency to policy makers and other stakeholders.

In light of the foregoing, the aim of this article is to propose a dynamic pollution-adjusted efficiency measure which extends the approach of Murty et al. (2012) and Dakpo (2015) to the dynamic context. For comparison purposes, dynamic technical pollution-adjusted efficiency is computed and analyzed along with a conventional static technical pollution-adjusted efficiency measure. The by-production model (Dakpo, 2015; Førsund, 2009; Murty et al., 2012) is based on the idea that a pollution-generating technology cannot be represented by a single reduced form and thus requires the use of different sub-technologies, i.e. one for the production of good outputs and another for the generation of bad outputs. The benefit of this approach over other existing models (such as the ones that treat pollution as input or output under the weak disposability assumption) is the explicit representation of the different processes involved in a production system. Moreover, the by-production approach provides the right trade-offs between the different variables involved. The empirical application focuses on panel data of French suckler cow farms over the period 1978–2014. The bad output considered is the total greenhouse gas emission associated with livestock breeding expressed in carbon dioxide equivalents ( $CO_2 - eq$ ).

## **2-Dynamic aspects in pollution-generating technologies**

Let  $v(t)$  represent a vector of variable inputs ( $v \in \mathbb{R}_+^J$ ),  $k(t)$  a vector of quasi-fixed inputs ( $k \in \mathbb{R}_+^L$ ),  $i(t)$  a vector of gross investments ( $i \in \mathbb{R}_+^L$ )<sup>4</sup>,  $f(t)$  a vector of fixed inputs ( $f \in \mathbb{R}_+^S$ ),  $y(t)$  a vector of intended outputs ( $y \in \mathbb{R}_+^Q$ ),  $b(t)$  the vector of unintended outputs ( $b \in \mathbb{R}_+^R$ ),  $N$  the number of DMUs, and  $t$  the time variable. The representation of pollution-generating technology here is based on the by-production model (Dakpo, 2015; Førsund, 2009; Murty et al., 2012). The approach adopted in this article is the by-production approach extended with some dependence constraints developed in Dakpo (2015). Following Murty et al. (2012), inputs must be separated into material inputs which generate pollution and non-materials inputs which do not.

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<sup>4</sup> Investment can be zero for some of the quasi-fixed inputs.

In this work, fixed inputs ( $f \in \mathbb{R}_+^S$ ) are assumed to be immaterial i.e. they do not generate pollution. The dynamic production technology  $\Psi(t)$  can be represented by the intersection of two dynamic sub-technologies, one for good outputs and the second for bad outputs:

$$\Psi(t) = \Psi_g(t) \cap \Psi_b(t) \quad (1)$$

where

$$\Psi_g(t) = \{ (v(t), i(t), y(t)): (v(t), i(t)) \text{ can produce } y(t) \text{ given } k(t) \text{ and } f(t) \} \quad (2)$$

and

$$\Psi_b(t) = \{ (v(t), i(t), b(t)): (v(t), i(t)) \text{ can generate } b(t) \text{ given } k(t) \text{ and } f(t) \} \quad (3)$$

Properties of  $\Psi_g(t)$  (Silva et al., 2015; Silva and Oude Lansink, 2013; Silva and Stefanou, 2003)

- G1** No free lunch and inactivity
- G2** Input essentiality and attainability
- G3** Non-emptiness and closeness
- G4** Boundedness
- G5** Positive monotonicity in  $v(t)$ : if  $v(t) \in \Psi_g(t)$  and  $v'(t) \geq v(t)$  then  $v'(t) \in \Psi_g(t)$
- G6** Negative monotonicity in  $i(t)$ : if  $i(t) \in \Psi_g(t)$  and  $i'(t) \leq i(t)$  then  $i'(t) \in \Psi_g(t)$ <sup>5</sup>
- G7** Free disposability of good outputs: if  $y(t) \in \Psi_g(t)$  and  $y'(t) \leq y(t)$  then  $y'(t) \in \Psi_g(t)$

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<sup>5</sup> Property **G6** along with the convexity in **G9** implies the presence of adjustment costs.

**G8** Reverse nestedness in  $k(t)$  and  $f(t)$ : if  $k(t) \in \Psi_g(t)$  and  $k'(t) \geq k(t)$  then  $k'(t) \in \Psi_g(t)$ . Similarly, if  $f(t) \in \Psi_g(t)$  and  $f'(t) \geq f(t)$  then  $f'(t) \in \Psi_g(t)$

**G9** Convexity in  $(v(t), i(t), f(t), y(t))$

Given these different properties and assuming variable returns to scale (VRS),<sup>6</sup> the good output sub-technology is defined under DEA as:

$$\Psi_g(t) = \{(v(t), i(t), k(t), f(t), y(t), b(t)) : y_o(t) \leq \sum_{n=1}^N \mu_n^g y_n(t),$$

$$v_o(t) \geq \sum_{n=1}^N \mu_n^g v_n(t), \quad f_o(t) \geq \sum_{n=1}^N \mu_n^g f_n(t) \quad (4)$$

$$i_o(t) - \delta k_o(t) \leq \sum_{n=1}^N \mu_n^g (i_n(t) - \delta k_n(t)), \quad \sum_{n=1}^N \mu_n^g = 1, \forall n,$$

$$(v(t), i(t), k(t), f(t), y(t), b(t)) \in \mathbb{R}_+^{J+L+L+S+Q+R}\}$$

where  $\delta$  is the depreciation rate vector associated with quasi-fixed input  $k$ , therefore  $i_o(t) - \delta k_o(t)$  represents the net investments.

### Properties of $\Psi_b(t)$

The main property of pollution-generating technologies is the costly disposability of pollution as expressed in Murty et al. (2012). This property expresses the fact that given a fixed level of polluting inputs, there is a minimal amount of pollution that is jointly produced by the technology. Poor management can create inefficiency in the production that could yield an even higher level of undesirable outputs. An economic intuition behind this costly disposability property can be given if one considers a cost production function where a minimum level of cost

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<sup>6</sup> In this article we present and discuss the models under VRS. However, it can be easily extended to other returns-to-scale assumptions (e.g. constant returns to scale).



can be reached if price and allocative inefficiency are eliminated. In the case of a bad output technology, the prices in a cost frontier can be associated with the abatement coefficient (more intuition can be found in Coelli et al. (2007) with the estimation of iso-environmental lines). The main postulates, which are polar opposite to the ones associated with the good output sub-technology  $\Psi_g(t)$  are then expressed as:

**B1** Negative monotonicity in  $v(t)$ : if  $v(t) \in \Psi_b(t)$  and  $v'(t) \leq v(t)$  then  $v'(t) \in \Psi_b(t)$

**B2** Positive monotonicity in  $i(t)$ : if  $i(t) \in \Psi_b(t)$  and  $i'(t) \geq i(t)$  then  $i'(t) \in \Psi_b(t)$

**B3** Negative monotonicity in  $k(t)$ : if  $k(t) \in \Psi_b(t)$  and  $k'(t) \leq k(t)$  then  $k'(t) \in \Psi_b(t)$

**B4** Positive monotonicity in  $b(t)$ : if  $b(t) \in \Psi_b(t)$  and  $b'(t) \geq b(t)$  then  $b'(t) \in \Psi_b(t)$

**B5** Convexity in  $(v(t), i(t), k(t), b(t))$

**B6** Polluting inputs essentiality  $[v(t), k(t)]$

**B7** Boundedness

B1–B7 impose the costly disposability assumption:  $(v(t), i(t), k(t), f(t), y(t), b(t)) \in \Psi_b(t)$  then

$$\begin{aligned} b'(t) \geq b(t) \wedge v'(t) \leq v(t) \wedge i'(t) \geq i(t) \wedge k'(t) \leq k(t) \\ \Rightarrow (v'(t), i'(t), k'(t), f(t), y(t), b'(t)) \in \Psi_b(t) \end{aligned}$$

Positive monotonicity in investments (property **B2**) has a very important implication since it means that investments in quasi-fixed inputs can help to mitigate pollution. This assumption is understandable if one considers that new investments embed new technologies which are cleaner than old ones. From another perspective, given that investments generate good outputs in addition to losses through adjustment costs, *ceteris paribus* and with the positive correlation between good and bad outputs, it can be argued that adjustment costs indirectly create pollution mitigation. The **B6** property implies that it is not possible to generate pollution without using any material inputs, while property **B7** reflects the fact that for each level of material inputs there is a minimum amount of unwanted outputs that is generated.

The bad output sub-technology can be represented under VRS by:

$$\begin{aligned}
\Psi_b(t) &= \{(v(t), i(t), k(t), f(t), y(t), b(t)) : b_o(t) \geq \sum_{n=1}^N \mu_n^b b_n(t), \\
v_o(t) &\leq \sum_{n=1}^N \mu_n^b v_n(t), \\
i_o(t) - \delta k_o(t) &\geq \sum_{n=1}^N \mu_n^b (i_n(t) - \delta k_n(t)), \sum_{n=1}^N \mu_n^b = 1, \forall n, \\
(v(t), i(t), k(t), f(t), y(t), b(t)) &\in \mathbb{R}_+^{J+L+L+S+Q+R}\}
\end{aligned} \tag{5}$$

To properly represent the by-production model, two different intensity variables associated with each sub-technology  $(\mu_n^g, \mu_n^b)$  have to be considered. Following Murty et al. (2012), the overall technology  $\Psi(t)$  is represented by:

$$\begin{aligned}
\Psi(t) &= \{(v(t), i(t), k(t), f(t), y(t), b(t)) : y_o(t) \leq \sum_{n=1}^N \mu_n^g y_n(t), v_o(t) \\
&\geq \sum_{n=1}^N \mu_n^g v_n(t), \\
f_o(t) &\geq \sum_{n=1}^N \mu_n^g f_n(t), i_o(t) - \delta k_o(t) \leq \sum_{n=1}^N \mu_n^g (i_n(t) - \delta k_n(t)), \sum_{n=1}^N \mu_n^g = 1 \\
b_o(t) &\geq \sum_{n=1}^N \mu_n^b b_n(t), \quad v_o(t) \leq \sum_{n=1}^N \mu_n^b v_n(t), \\
i_o(t) - \delta k_o(t) &\geq \sum_{n=1}^N \mu_n^b (i_n(t) - \delta k_n(t)), \sum_{n=1}^N \mu_n^b = 1, \forall n, \\
(v(t), i(t), k(t), f(t), y(t), b(t)) &\in \mathbb{R}_+^{J+L+L+S+Q+R}\}
\end{aligned} \tag{6}$$

However, as argued in Dakpo (2015), the model as displayed in (6) assumes the independence of the two sub-technologies  $\Psi_g(t), \Psi_b(t)$ . Dakpo (2015) recommended introducing an interdependence constraint to link the different sub-technologies. An adaptation to the presence of adjustment costs due to investment in quasi-fixed inputs is proposed here through the following additional constraints:

$$\begin{aligned} \sum_{n=1}^N \mu_n^g v_n(t) &= \sum_{n=1}^N \mu_n^b v_n(t) \\ \sum_{n=1}^N \mu_n^g (i_n(t) - \delta k_n(t)) &= \sum_{n=1}^N \mu_n^b (i_n(t) - \delta k_n(t)) \end{aligned} \quad (7)$$

The idea behind the interdependence constraints expressed in (7) is that in order to link the different sub-processes of a production system one has to equalize the optimal values of the common variables involved in the different sub-systems. Dakpo (2015) refers to these constraints as the factor band concepts, which involve a relation between input variables independently of the levels of either the good or the bad outputs (Førsund, 2009; Frisch, 1965). The dependence constraints in (7) ensure that any projection towards the different frontiers reaches consistent benchmarks between the different sub-technologies involved (Dakpo, 2015). Without these constraints, it is for instance possible that the benchmark for an inefficient observation might use fewer inputs under the good output sub-technology than the optimal consumption found under the bad output sub-technology, which is not logical. Moreover, these constraints are simply the fulfillment of the materials balance principle which must be verified at any point of the production technology.<sup>7</sup>

In all the previous developments, the role played by immaterial inputs (or service inputs) has only been limited to the good output sub-technology as in some applications of the by-production approach (Dakpo et al., 2017; Levkoff, 2013). Yet recently, Førsund (2017) has stressed the fact that ‘a service input improves the utilization of the given raw materials through better process control, fewer rejects, and increased internal recycling of waste materials’. Therefore, immaterial

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<sup>7</sup> By analogy, the materials balance principle can be associated to the mass/energy conservation equation of the first law of thermodynamics.

(service) inputs can have a direct impact on pollution generation through substitution possibilities with pollution generating inputs. Earlier attempts in accounting for these latter possibilities can be found in Chambers et al. (2014) and Serra et al. (2014). A more theoretical underpinning has been provided by Førsund (2017). We propose an extension of the bad output sub-technology with a **eighth** postulate:

**B8** Positive monotonicity in  $f(t)$ : if  $f(t) \in \Psi_b(t)$  and  $f'(t) \geq f(t)$  then  $f'(t) \in \Psi_b(t)$

This property states that immaterial inputs (here fixed inputs) can have a direct impact in mitigating pollution. The bad output production sub-technology in (5) is extended with constraints on fixed inputs, as  $f_o(t) \geq \sum_{n=1}^N \mu_n^b f_n(t)$ . Similarly, the overall technology in (6) is extended by the same constraints. To keep in line with the interdependence between technologies of Dakpo (2015), additional constraints on the equality of optimal inputs need to be considered  $\sum_{n=1}^N \mu_n^g f_n(t) = \sum_{n=1}^N \mu_n^b f_n(t)$ .

### 3-Dynamic vs. static pollution-adjusted efficiency estimation

The dynamic pollution-adjusted efficiency approach in this article uses the Directional Distance Function (DDF) as proposed by Chambers et al. (1998). DDF has been largely used to measure pollution-adjusted inefficiency (Berre et al., 2013; Chung et al., 1997; Hampf and Krüger, 2015; Njuki and Bravo-Ureta, 2015). It is a generalization of Farrell's or Shephard's proportional approach, but with more flexibility (i.e. several direction possibilities). However, the results are sensitive to the choice of the directional vector (Vardanyan and Noh, 2006). Here we use a general representation of the non-radial form of DDF (Zhang and Choi, 2014) which is summarized in (8) for its dynamic version:

$$\begin{aligned} \vec{D}_t^{dyn}(v(t), i(t), k(t), f(t), y(t), b(t); \vec{g}_y, \vec{g}_b, \vec{g}_v, \vec{g}_i) \\ = \max_{\beta, \mu^g, \mu^b} \frac{1}{N_{\vec{g}}} [\beta_y + \beta_b + \beta_v + \beta_i] \\ \text{s. t. } y_o(t) + \beta_y \vec{g}_y \leq \sum_{n=1}^N \mu_n^g y_n(t) \end{aligned} \quad (8)$$

$$v_o(t) - \beta_v \vec{g}_v \geq \sum_{n=1}^N \mu_n^g v_n(t)$$

$$f_o(t) \geq \sum_{n=1}^N \mu_n^g f_n(t)$$

$$i_o(t) - \delta k_o(t) + \beta_i \vec{g}_i \leq \sum_{n=1}^N \mu_n^g (i_n(t) - \delta k_n(t))$$

$$b_o(t) - \beta_b \vec{g}_b \geq \sum_{n=1}^N \mu_n^b b_n(t)$$

$$v_o(t) - \beta_v \vec{g}_v \leq \sum_{n=1}^N \mu_n^b v_n(t)$$

$$f_o(t) \geq \sum_{n=1}^N \mu_n^b f_n(t)$$

$$i_o(t) - \delta k_o(t) + \beta_i \vec{g}_i \geq \sum_{n=1}^N \mu_n^b (i_n(t) - \delta k_n(t))$$

$$\sum_{n=1}^N \mu_n^g v_n(t) = \sum_{n=1}^N \mu_n^b v_n(t)$$

$$\sum_{n=1}^N \mu_n^g f_n(t) = \sum_{n=1}^N \mu_n^b f_n(t)$$

$$\sum_{n=1}^N \mu_n^g (i_n(t) - \delta k_n(t)) = \sum_{n=1}^N \mu_n^b (i_n(t) - \delta k_n(t))$$

$$\sum_{n=1}^N \mu_n^g = 1$$

$$\sum_{n=1}^N \mu_n^b = 1$$

where  $N_{\vec{g}}$  represents the number of decision variables in the objective function. This means that we give the same weight to each inefficiency score. For the generalization of the non-radial approach, each of the  $\beta$  inefficiencies can be individualized with the different corresponding variables  $(\beta_{yq}, \beta_{br}, \beta_{jv}, \beta_{il})$ .

The results of the dynamic pollution-adjusted efficiency model are compared with a static pollution-adjusted efficiency model. Under the static technology, the quasi-fixed inputs are assumed to adjust instantaneously, so the objective function of the DDF also includes  $\beta_k$ , the inefficiency associated with the quasi-fixed inputs  $k$ . Furthermore, the static DDF has no constraints on investments. A general formulation of the static DDF can be found in (9):

$$\begin{aligned}
\vec{D}_t^{static}(v(t), f(t), y(t), b(t); \vec{g}_y, \vec{g}_b, \vec{g}_v, \vec{g}_k) \\
&= \max_{\beta, \mu^g, \mu^b} \frac{1}{N_{\vec{g}}} [\beta_y + \beta_b + \beta_v + \beta_k] \\
\text{s. t. } y_o(t) + \beta_y \vec{g}_y &\leq \sum_{n=1}^N \mu_n^g y_n(t) \\
v_o(t) - \beta_v \vec{g}_v &\geq \sum_{n=1}^N \mu_n^g v_n(t) \\
f_o(t) &\geq \sum_{n=1}^N \mu_n^g f_n(t) \\
k_o(t) - \beta_k \vec{g}_k &\geq \sum_{n=1}^N \mu_n^g k_n(t) \\
b_o(t) - \beta_b \vec{g}_b &\geq \sum_{n=1}^N \mu_n^b b_n(t) \\
v_o(t) - \beta_v \vec{g}_v &\leq \sum_{n=1}^N \mu_n^b v_n(t)
\end{aligned} \tag{9}$$

$$\begin{aligned}
f_o(t) &\geq \sum_{n=1}^N \mu_n^b f_n(t) \\
k_o(t) - \beta_k \vec{g}_k &\leq \sum_{n=1}^N \mu_n^b k_n(t) \\
\sum_{n=1}^N \mu_n^g v_n(t) &= \sum_{n=1}^N \mu_n^b v_n(t) \\
\sum_{n=1}^N \mu_n^g f_n(t) &= \sum_{n=1}^N \mu_n^b f_n(t) \\
\sum_{n=1}^N \mu_n^g k_n(t) &= \sum_{n=1}^N \mu_n^b k_n(t) \\
\sum_{n=1}^N \mu_n^g &= 1 \\
\sum_{n=1}^N \mu_n^b &= 1
\end{aligned}$$

Another important difference between the static evaluation and the dynamic one is that in model (9), the quasi-fixed inputs are treated in the same way as variable inputs to materialize the instantaneous adjustments.

Following Chung et al. (1997), the directional vectors are set as the observed values corresponding to the DMU under evaluation for all variables except investments i.e.  $\vec{g}_y = y_o$ ,  $\vec{g}_b = b_o$ ,  $\vec{g}_v = v_o$ ,  $\vec{g}_k = k_o$ .<sup>8</sup> For these variables, the DDF provides an inefficiency score that can be conveniently interpreted as a percentage of inefficiency.

Our analysis has been carried out for a sample with 3,148 observations. Given the high heterogeneity in the investment variable, the directional vector was set to 20% of the capital stock i.e.  $\vec{g}_i = 0.2 \times k_o$ . The inefficiency score obtained should be interpreted relative to this particular

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<sup>8</sup> As previously mentioned, several other directional vectors are possible.

vector. Another advantage of this vector is to also allow zero values to be accounted for in the estimation.

#### 4-Distribution comparison

Practically, to compare for instance the results between the static and the dynamic models, we have used the density equality test of Li (1996) extended to DEA and Farrell output efficiency by Simar and Zelenyuk (2006). This extension accounts for two particular features of the nonparametric DEA: i) the bounded support of the efficiency scores with a concentration of observations near the boundary; and ii) the use of estimated efficiency scores (rather than the true efficiency) (Simar and Zelenyuk, 2006). If  $u_s$  and  $u_d$  are two vectors of random variables in a population, the Li (1996)'s test evaluates:

$$H0 : f_{s(u_s)} = f_{d(u_d)} \quad (10)$$

$$HA : f_{s(u_s)} \neq f_{d(u_d)} \text{ for a set of positive measures}$$

where  $f_l$  denotes the density distribution function of the random variable  $u_l$ . This paper uses an algorithm developed by Simar and Zelenyuk (2006) that is robust to the dimensionality problem. Since this paper estimates inefficiency scores with a lower bound at zero (rather than efficiency scores bounded at 1), the smoothing procedure is:

$$\hat{\beta}_n^{l*} = \begin{cases} \hat{\beta}_n^l + \epsilon_n^l & , \text{if } \hat{\beta}_n^l = 0 \\ \hat{\beta}_n^l & \text{otherwise} \end{cases} \quad (11)$$

$\epsilon_n^l = Uniform(0, \min\{N_l^{-2/D}, a\})$  where  $a$  is the  $\alpha$  – quantile (e.g. 5%) of the empirical distribution of  $\hat{\beta}_n^l > 0$ ,  $l$  represents each distribution  $l \in \{s, d\}$ , and  $D$  is the dimension associated with the convergence rate of the DEA model at hand. Classically,  $D = \text{card}(\text{inputs}) + \text{card}(\text{outputs (good)}) + 1$ . However, since this paper deals with a multi-technology approach, the global convergence rate of the by-production is defined as the smallest convergence rate among each independent sub-technology.

#### 5-Empirical application



The empirical application uses panel data of specialized suckler cow farms in France (Massif Central and its northern periphery). The farm data are provided by the survey team within the livestock economic unit of the French National Institute of Agricultural Research (INRA) located in Clermont-Ferrand-Theix. The sample contains 3,206 farm-year observations covering the period 1978–2014, with an average of 86 farms per year. A total of 170 different farms have been surveyed over the period of study, so the panel is unbalanced (due to farms rotating in and out of the sample). Over the 37-year period of analysis, farms stay on average a little more than 25 years in the sample. To better capture the dynamics, one frontier should be estimated per year, i.e. 37 different temporal frontiers. However, the non-parametric DEA approach is well-known for its sensitivity to the curse of dimensionality which produces many efficient DMUs when the number of variables is large (Cooper et al., 2007). The curse of dimensionality suppresses the discriminatory power of the DEA which has a very slow convergence rate (Daraio and Simar, 2007). To overcome this situation, the sample was split into three periods: 1978–1992, 1993–2005 and 2006–2014. These periods were chosen in order to account for the important shifts (reforms) in the common agricultural policy (CAP) in France. Another benefit of time pooling is to provide smooth efficiency scores exempt from high inter-annual variability. The major problem of this grouping strategy is that within each period, technological change is assumed to be absent, i.e. all changes in technology within a sub-period are attributed to modifications in technical inefficiency. It is worth noting here that the dynamic aspect of inefficiency is captured here through the adjustment costs associated to investments and has little if nothing to do with year-to-year based comparison of production frontiers through productivity indices (Malmquist-Luenberger for example).<sup>9</sup>

The empirical model distinguishes two variable inputs, one quasi-fixed input, one good output and three undesirable outputs. Fixed inputs are land which was measured in hectares and labor which was measured in annual working units. Labor was assumed fixed because most of the farm workers are family members. The quasi-fixed input is associated with the capital stock of machinery and equipment, buildings and land improvements, all measured in 2005 constant prices. The two variable inputs are intermediate consumption and livestock units (herd size).

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<sup>9</sup> Examples of this latter approach can be found in Aparicio et al. (2017); Arabi et al. (2017); Bampatsou and Halkos (2018); Tamini et al. (2012).

Intermediate consumption, also measured in constant prices of 2005, is the aggregation of different operational expenses and structural costs (feed costs, veterinary, miscellaneous supplies, other breeding costs, seeds, fertilizers, pesticides, fuels and lubricants, maintenance costs and overheads). Livestock was assumed to be a variable input as farmers can easily buy and sell suckler cows. The herd size is expressed in livestock units which represents a reference unit used for the aggregation of different types of animals on the basis of their nutritional or feed requirements. One livestock unit is equivalent to one dairy cow. The good output is the total weight of live meat produced on the farm, in kilograms, net from animal purchase. It is the only good output considered given that all other variables are related to this production. The bad output variable is the estimated greenhouse gas (GHG) emissions associated with the suckler cows' activity, and were measured using life cycle assessment (LCA) (Guinée et al., 2002). For some inputs, the GHG emissions encompass all the associated flows from the cradle to the farm gate boundary. Three GHGs are considered: methane (CH<sub>4</sub>), nitrous oxide (N<sub>2</sub>O) and carbon dioxide (CO<sub>2</sub>), and these three gases are aggregated using their global warming potential (GWP) in comparison to the basis of carbon dioxide. The GWP for methane and nitrous oxide are respectively 25 and 298. Thereby, the total GHG emission can be computed and expressed in carbon dioxide equivalents. The descriptive statistics of the sample used for our analysis are displayed in Table 1.

**Table 1: Summary Statistics of the Pooled Sample (Average over the Period 1978–2014)**

Variables	Mean ( $\bar{x}$ )	Standard deviation ( $Sd$ )	Relative standard deviation ( $Sd/\bar{x}$ )	Minimum	Maximum
Utilized land (hectares)	105.1	49.1	0.5	24.3	442.3
Labor (full-time equivalent)	1.7	0.6	0.3	0.3	4.6
Intermediate consumption (1000 Euro)	46.4	30.0	0.6	4.7	263.8

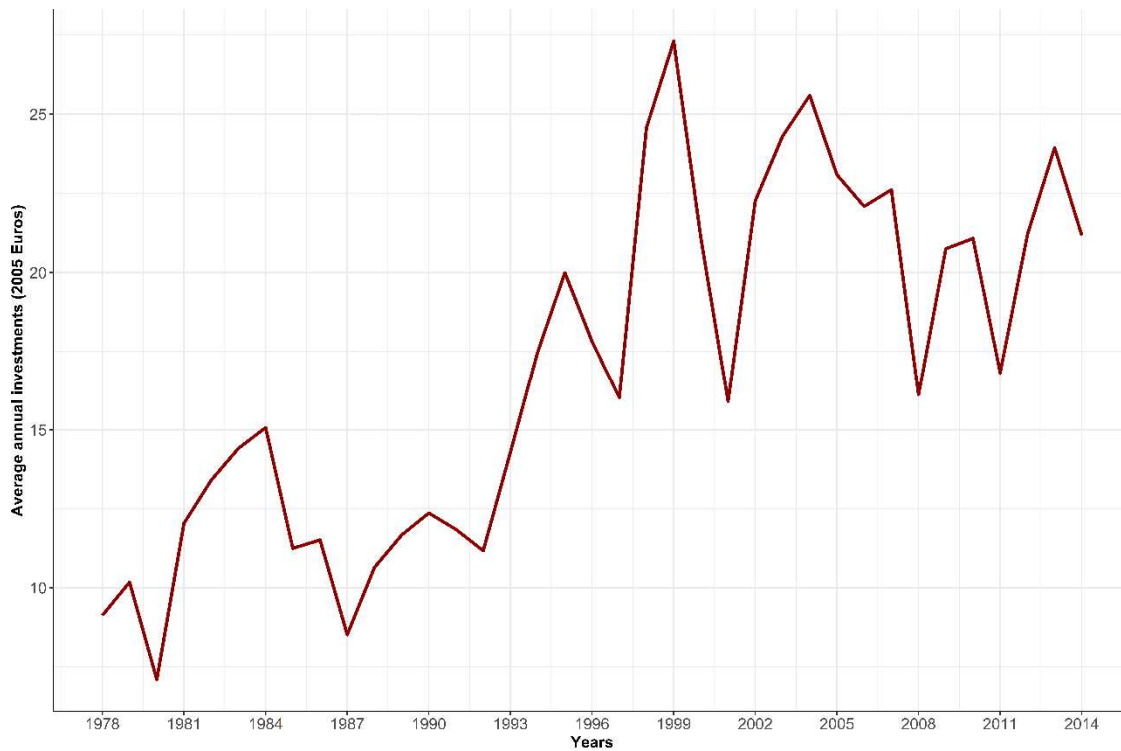
in 2005)					
Herd size (livestock units)	129.6	64.9	0.5	14.4	465.0
Capital (1000 Euro in 2005)	92.6	57.6	0.6	4.0	443.4
<b>Investments (1000 Euro in 2005)</b>	<b>16.3</b>	<b>20.8</b>	<b>1.3</b>	<b>-24.9</b>	<b>230.7</b>
Meat (tons of live weight)	38.8	22.2	0.6	5.0	173.9
Total GHG emissions (tons of CO <sub>2</sub> -eq)	564.9	309.1	0.5	58.1	2,580.4
Number of farms	3,206	-	-	-	-

The investment variable, which is also expressed in Euro constant for 2005, is characterized by a large variation (i.e. a coefficient of variation greater than one) which might simply reflect the heterogeneity in investment behavior among farmers. For example, many farms prefer to lease farm machinery (contracting services) from machinery cooperatives instead of buying their own equipment. Thus, a farmer can borrow specific equipment (e.g. tractors) from a cooperative, but in return the farmer is charged with a price depending on the job that has been done (e.g. harvesting, mowing). Therefore, many farmers with this opportunity choose to invest very little in quasi-fixed inputs, a strategy which can partly explain the high heterogeneity for this variable. Moreover, 1.8% of the sample exhibits disinvestments and 9.1% zero investments.<sup>10</sup> Figure 1 reveals an increasing tendency in investments over the whole period (1978–2014) even if this growth rate seems to slow down from 1999 onwards. From this year, the average investment levels stabilize which may imply that farmers have reached their optimal size. Investments in machinery and equipment represent the biggest part of the total investments with at approx.

<sup>10</sup> The negative and zeros values present in the sample for the investments variable raise some issues associated to the DEA approach that has been discussed in the literature. Indeed, DEA requires all variables to be positive. To be consistent with this property, we have deleted all observations with negative investments. As mentioned, they only represent 1.8% of the total sample.

81.3%, followed by investments in buildings which represent about 13.4%, and land improvements which constitute around 5.3%.

**Figure 1: Average Annual Evolution of Investments over the Period 1978–2014**



In terms of GHG emissions, the average sample pollution intensity decreases by 14.9 Kg of CO<sub>2</sub> equivalent per Kg of live meat. Methane is by far the most important GHG with a share of 68%. It is followed by nitrous oxide which represents 18% and carbon dioxide 14% of total GHG emissions. Methane is mainly generated by enteric fermentation, which is associated with the biological processes of animals. A small share of methane is also associated with manure management. Nitrous oxide derives from the use of mineral fertilizers and also manure spreading. Carbon dioxide is produced from the consumption of fossil combustibles but also from the manufacture of inputs such as feed and fertilizers (Beauchemin et al., 2010; Chobtang et al., 2016; Dick et al., 2015).

## 6-Results

Tables 2 and 3 present the results for the dynamic and static approaches, respectively. The inefficiency scores are displayed for each period and also for the whole sample. Tables 2 and 3 also display the inefficiency associated with each input and output, except for land and labor as they were assumed to be fixed inputs.<sup>11</sup>

**Table 2: Dynamic Pollution-adjusted Inefficiency Scores: Averages over Different Periods (1978–1989, 1990–2001 and 2002–2013) with Service Inputs Included in the Good and the Bad Output Sub-technology**

<b>Inefficiencies per period and variable</b>	<b>1978–1992</b>	<b>1993–2005</b>	<b>2006–2014</b>	<b>Whole period</b>
<b>Intermediate consumption</b>	0.071	0.049	0.104	0.044
<b>Herd size</b>	0.059	0.042	0.034	0.049
<b>Investments</b>	6.223	4.836	4.019	6.783
<b>Meat</b>	0.010	0.025	0.015	0.021
<b>GHG emissions</b>	0.080	0.056	0.067	0.071
<b>Number of observations</b>	1,365	1,127	656	3,148

**Table 3: Static Pollution-adjusted Inefficiency Scores: Averages over Different Periods (1978–1992, 1993–2005 and 2006–2014) with Service Inputs Included in the Good and the Bad Output Sub-technology**

<b>Inefficiencies per period and variable</b>	<b>1978–1992</b>	<b>1993–2005</b>	<b>2006–2014</b>	<b>Whole period</b>
<b>Intermediate consumption</b>	0.259	0.200	0.149	0.237
<b>Herd size</b>	0.170	0.161	0.219	0.207
<b>Opening capital</b>	0.470	0.536	0.478	0.586
<b>Meat</b>	0.002	0.000	0.002	0.002
<b>GHG emissions</b>	0.249	0.227	0.265	0.284

<sup>11</sup> All computations were made using R software (R Core Team, 2017).

<b>Number of observations</b>	1,365	1,127	656	3,148
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Comparison of the results in Tables 2 and 3 provides some interesting observations. The inefficiency associated with the variable inputs, namely intermediate consumption and herd size, are higher in the static context than in the dynamic context. Actually, under the static context, the inefficiency associated with these variable inputs is at least 50% larger than the dynamic pollution-adjusted inefficiency. In the dynamic context, intermediate consumption and herd size can be decreased, by 4.4% and 4.9%, respectively, while they can be reduced by 23.7% and 20.7%, respectively, in the static context. The same outcome was found by Silva et al. (2015) and Nick and Wetzel (2016), comparing static and dynamic input technical efficiency. Next, Simar and Zelenyuk (2006)'s algorithm with 2000 bootstrap iterations was applied to test the difference between the inefficiencies in the dynamic and the static context. Since the comparison of each pair of tables implies 20 different tests, the algorithm was only run for the last column of each table which considers the whole sample. The p-values corresponding to intermediate consumption, herd size, meat and GHG emissions are all equal to  $2.22 e - 16$ , implying there is a statistically significant difference between static and dynamic inefficiency scores. This result shows that the inefficiency is significantly different when accounting for adjustment costs (via investments) in pollution-generating technologies.

For meat production, the situation is different. The results show that the potential for increased meat production is slightly larger in the dynamic context than in the static context. In the static context, the farmers are actually almost fully efficient. More explicitly, under the dynamic technology the meat production can be increased by almost 2.1%, while under the static technology the potential for increasing output is only 0.2%. When accounting for the changes in quasi-fixed inputs, producers can produce more meat by fully taking advantage of the investment potential in comparison to the static case.

For GHG emissions, the results go in the opposite direction, i.e. the dynamic inefficiency levels are much lower than their static counterparts. When considering dynamic measures, the levels of GHG can be reduced by 7.1% and this reduction potential increases to 28.4% in the static context. This result suggests that adjustment costs associated with gross investments are attributed to inefficiency in the static context.

The heterogeneity in the investment variable is clear from the high associated inefficiency scores in the performance evaluation (average scores between 4 and 7 over the different periods). The presence of farms that invest very small amounts (or do not invest at all) and some which invest large amounts can explain some of the high inefficiency levels associated with investments. However, this inefficiency can be tampered by splitting the sample based on the ratio of investment per capital stock. Using quartile distribution, the sample was split into four groups depending on the investment share (% of investment in the opening capital). The results (see Tables 4 and 5<sup>12</sup>) show that the investment inefficiency levels reduce substantially. For example, the inefficiency score falls to almost 0.273 for farmers who invest between 4 and 11% in proportion to their capital stock. Although the inefficiency scores are still high (especially for farmers who invest more than 26%), by accounting for the different strategies of farmers in terms of investments, the heterogeneity is partly captured. Nevertheless, this situation might point out serious issues associated to investments in agriculture in general and to the case of suckler cow farms in France. The large room of potential improvement in investment management requires a deeper analysis of the determinants of farmer decisions in terms of investments. In both the static and dynamic cases, the highest inefficiencies are associated with the quasi-fixed inputs or investments in those inputs. Furthermore, given the level of investment, it appears that there is no obvious difference between the static and the dynamic approach when investment levels are lower than 11%. From 11% of investment or more, there are large differences in the inefficiency levels obtained under both approaches. This suggests that a dynamic approach is particularly meaningful in the case of significant levels of investment.

**Table 4: Dynamic Pollution-adjusted Inefficiency Scores under Different Ratio of Investment to Capital: Averages over the Period 1978–2014 (with Service Inputs Included in the Good and the Bad Output Sub-technology)**

Inefficiencies per ratio of investment to	< 4%	4–11%	11–26%	> 26%
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<sup>12</sup> We have also run the Li test to compare the static and dynamic inefficiency distributions under the different levels of investments. The results reveal that except for the when the investment share is lower than 4% (where herd size, intermediate consumption and GHG emissions are not significantly different), all the variables are (significantly) different between the static and the dynamic framework.

<b>capital and variable</b>				
<b>Intermediate consumption</b>	0.266	0.250	0.186	0.042
<b>Herd size</b>	0.216	0.126	0.072	0.044
<b>Investments</b>	0.292	0.273	1.064	6.126
<b>Meat</b>	0.004	0.001	0.024	0.018
<b>GHG emissions</b>	0.280	0.202	0.124	0.061
<b>Number of observations</b>	818	736	795	799

**Table 5: Static Pollution-adjusted Inefficiency Scores under Different Ratio of Investment to Capital: Averages over the Period 1978–2014 (with Service Inputs Included in the Good and the Bad Output Sub-technology)**

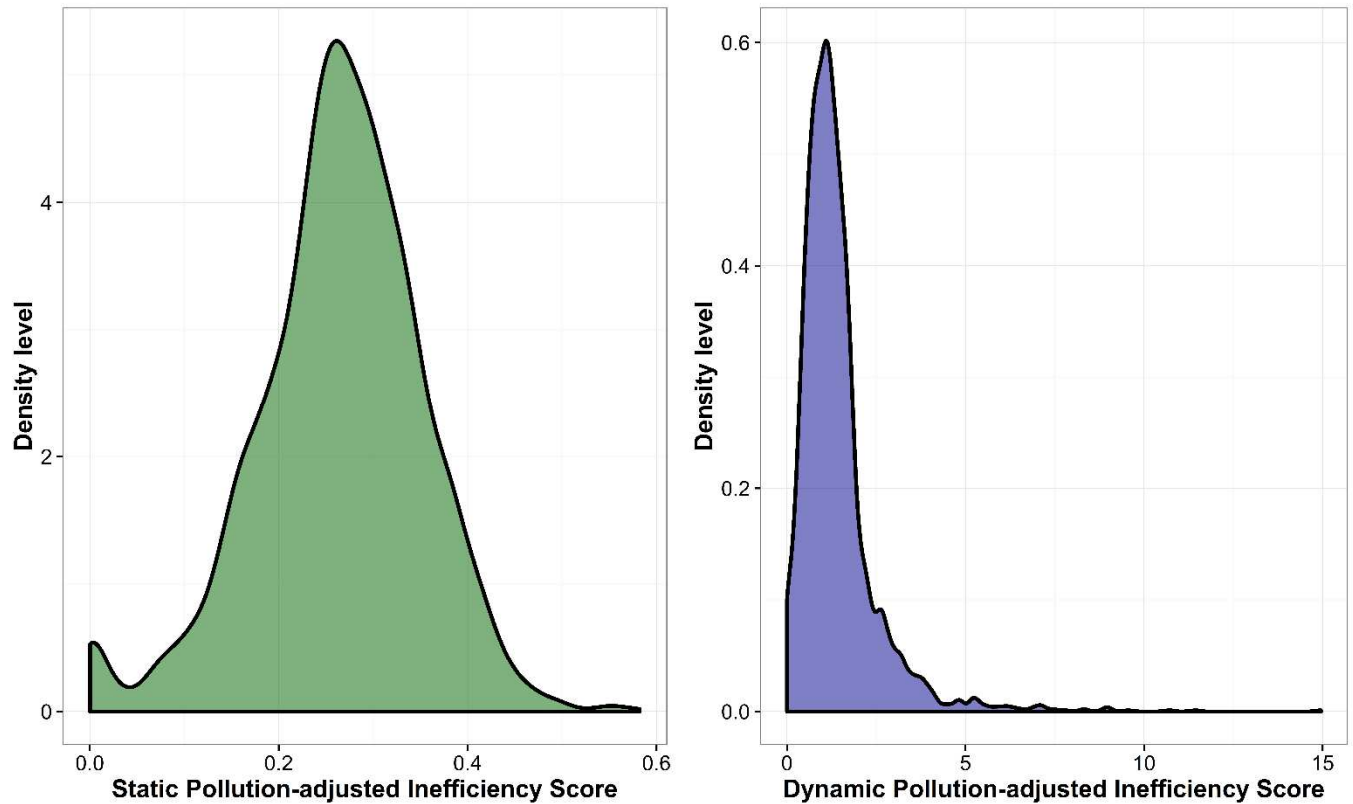
<b>Inefficiencies per ratio of investment to capital and variable</b>	<b>&lt; 4%</b>	<b>4–11%</b>	<b>11–26%</b>	<b>&gt;26%</b>
<b>Intermediate consumption</b>	0.253	0.199	0.195	0.150
<b>Herd size</b>	0.212	0.165	0.150	0.159
<b>Opening capital</b>	0.539	0.415	0.464	0.499
<b>Meat</b>	0.005	0.000	0.000	0.000
<b>GHG emissions</b>	0.275	0.220	0.222	0.222
<b>Number of observations</b>	818	736	795	799



When evaluating the changes in inefficiency across periods, the reader should note that the inefficiency was measured for each input and output relative to period-specific frontiers. Hence, they provide information about the extent to which the productive potential of each input and output is utilized in each period. The evolution of static and dynamic inefficiency values shows some differences. For example, in the dynamic model, the inefficiency in herd size management decreases, while in the static case a major increase in the inefficiency is observed in the last period (2006–2014). In terms of intermediate consumption, the static technology shows an inefficiency decrease, whereas in the dynamic case, the inefficiency is lowest in the period 1993–2005 and increases in the last period (2006–2014). In the static case, the efficiency related to meat production peaks in the period 1993–2005 before it drops in the last period. In the dynamic case, it is the inefficiency that reaches a peak in the second period. In both cases (dynamic and static), the inefficiency of GHG emissions decreases up until the second period (1993–2005) before it increases in the last time period. Overall, the average pollution-adjusted inefficiency decreases in the dynamic and static context, but this decrease is more distinct in the dynamic context (see also appendix 1 for yearly evolution). The inefficiency of investment decreases over the whole period of study with the main improvements realized during the last period (2006–2014). Under the static technology, the inefficiency associated with the capital stock peaks in the second period before dropping in the last one.

The comparison of the density plots (Figure 2) of the dynamic and static pollution-adjusted-inefficiency also reveals large differences between these two scores for the sample of suckler cow farms. It appears that under the static technology, the distribution of the inefficiency score is highly concentrated displaying a leptokurtic distribution, while the distribution of the inefficiency under the dynamic framework is wider and exhibits a platykurtic distribution. This last result is again a reflection of the high heterogeneity in investments.

**Figure 2: Dynamic and static Pollution-adjusted inefficiency score density plots comparison**



## 7-Conclusion

This article proposes an adaptation of the by-production model (Dakpo, 2015; Murty et al., 2012) to account for adjustment costs in the presence of undesirable outputs. The paper measured and discussed dynamic pollution-adjusted inefficiency and compared it with a model that does not account for the presence of adjustment costs (i.e. static technology).

Applying the model on a sample of suckler cow farms in France underscored the importance of accounting for the presence of adjustment costs when estimating technical inefficiency. The analysis also revealed very high inefficiency in investments for the farms under analysis. However, these high levels can be explained by the large heterogeneity in investment levels among the farms. The results also show that the investment inefficiency levels decrease substantially when splitting the sample in groups based on investment intensity, and that the

differences between the static and dynamic inefficiency levels are much smaller for farms that have low investments. In terms of policy implications, the Common Agricultural Policy (CAP) has been providing farmers with financial incentives through second pillar investments and modernization subsidies. The high inefficiency associated with investments suggest that these subsidies are partly lost to poor investment choices and partly also through adjustment costs associated with investments.

The results also demonstrate that the inefficiency of the intermediate consumption, herd size and GHG emissions are lower under the dynamic framework, i.e. farms are actually performing better compared to a static situation where adjustments costs are not accounted for. In addition, for meat production, the improvement potential is higher under the dynamic technology and therefore underestimated under the static technology. All these observations imply that it is important to account for the presence of adjustment costs in the estimation of pollution-adjusted inefficiency. Hence, future research in modelling pollution-generating technologies should account for the quasi-fixed nature of some inputs.

Finally, this work can be extended to productivity analysis and to the estimation of dynamic shadow prices of pollutants (see e.g. Chambers et al. (2014) for estimation in the static by-production context). In addition, farmers that rely on machinery cooperatives will have lower investment levels than farmers that purchase machinery. Hence, future research could investigate the benefits to farmers participating in machinery cooperatives in terms of their avoided adjustment costs.

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## Appendix

### Appendix 1: Overall Inefficiency Evolution under the Static and Dynamic Approach over the Period 1978–2014 for the whole Sample

