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ORIGINAL PAPER

Modelling environmental inefficiency under a quota system

Juan Aparicio[1] · **Magdalena Kapelko**[2] · **Lidia Ortiz**[1]

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Abstract

This paper introduces the methodology necessary to evaluate inefficiency of regulated decision making units that operate under quotas through data envelopment analysis, accounting for both quotas restrictions and negative environmental externalities of production. Three technical inefficiency measures are proposed: inefficiency in the production of marketed output, environmental inefficiency, and inefficiency with quotas. It is then shown how to aggregate these measures in order to obtain indicators of overall performance. The new approach is illustrated through a numerical example that uses real data available for the European Union dairy sector. The results show that considerable differences in inefficiencies could be found when quotas restrictions are accounted for in the model than in the model without quota imposition, indicating that not accounting explicitly for quotas when measuring performance in regulated sectors may lead to a not accurate estimation of firms' technical inefficiency.

Keywords Data envelopment analysis · Environmental and technical inefficiency · Production under quotas

1 Introduction

Many types of economic sectors throughout the world are subject to intervention by government policies that control the supply side of production. One of the forms of such supply limitation consists of production quotas that impose constraints on production thereby preventing an excess being produced. Such policy is often implemented in the agriculture sector as agricultural price support programs provide

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incentives for greater production (Alvarez et al. 2006). One of the noteworthy examples of quota system is the European Union (EU) policy with respect to the limitation of milk production in the dairy sector,[1] from 1984 until its abolition in 2015. Quota restrictions were introduced through the European Common Agricultural Policy (CAP) in response to significant overproduction of milk and budgetary deficits (Naylor 1987). The quota system allowed for milk quota transfers at farm level within each country and involved the application of a levy on the overrun in the national quota.[2] In general, there were two types of quotas available: 'delivery to dairies' quota (the maximum amount of milk delivered to dairies) and 'direct sales to customers' quota (the limit for direct sales at farm level). In the part of this article devoted to provide a numerical and illustrative example, we focus our attention on the former case of quota in the dairy sector at the level of EU countries.

The impact of quotas has been analyzed from various perspectives including prices and income (e.g., De Frahan et al. 2011), herd size (e.g., Huettel and Jongeneel 2011), price and price uncertainty (e.g., Burrell 1985; Bouamra-Mechemache et al. 2008) and efficiency (e.g., Alvarez et al. 2006). Theoretical considerations on the efficiency effects of quota policy suggest the creation of economic inefficiency by this system in comparison to a free market policy (Fulginiti and Perrin 1993). However, the theory also argues that efficiency could improve and efficient producers would expand their activity at the expense of less efficient producers, especially when quotas are tradeable (Alston 1981; Colman 2000; Alvarez et al. 2006; Areal et al. 2012a), and especially when restrictions on milk quota trade are removed (Boots et al. 1997). Empirical research on the efficiency effects of a quota regime or incorporating quotas as one of the variables in efficiency measurement is rather scarce, while reported results are inconclusive (see Alvarez et al. 2006; Sauer 2010; Areal et al. 2012a, b; Steeneveld et al.; 2012; Aparicio et al. 2017a).

Additionally, the measurement of environmental efficiency of economic sectors integrating, in addition to marketed (desirable, intended or 'good') output, the negative environmental externalities into efficiency modeling (the production of so called undesirable, unintended or 'bad' outputs, such as pollution) is an increasingly important focus of recent economic research. The agriculture sector, and within it the dairy sector, are not exceptions.[3] Numerous authors have analyzed the efficiency of different agricultural sectors accounting for undesirable factors, for example, Chambers et al. (2014) study on cereals, oilseeds and protein crops, Serra et al.

[1] Despite the recent removal of the quota system from the EU dairy sector, as soon as 2016 a new policy to regulate this market with an objective similar to quotas—to reduce the quantity of milk available on the market was introduced. This policy is called 'milk production reduction scheme' (European Commission 2016).

[2] The quantities of quotas were divided among producers in each EU member country. The quota transfers and exchanges were allowed with trading rules differing across member countries leading to a large heterogeneity in the implementation of quotas between countries (Ang and Oude Lansink 2016). If the quantities of milk exceeded the quota at country level, the levy needed to be paid by the member country responsible for producing the surplus.

[3] The review of different approaches to modeling environmental efficiency in the agriculture sector is made by Oude Lansink and Wall (2014).

(2014) analysis of arable crop farms or Dakpo et al. (2017) for sheep meat farming. Regarding the environmental efficiency of dairy farming, studies include the analysis of dairy farms in Scotland by Shortall and Barnes (2013), Dutch dairy farms by Reinhard et al. (1999, 2000), Swiss dairy farms by Ferjani (2011), and dairy farms in Spain by Pérez Urdiales et al. (2016) and Orea and Wall (2017).[4]

The studies discussed here have in common the fact that the production of 'bad' outputs and quota restrictions on production when measuring inefficiency, were not considered simultaneously, which can lead to biased measures of inefficiency. This article proposes a new method to analyze inefficiency of decision making units (DMUs) accounting for both quotas and negative environmental externalities. As we will show through a numerical example, not accounting for quotas when measuring inefficiency of the system regulated by quotas could lead to substantial differences in inefficiency as compared to the situation when quotas are taken into account.

With regard to dealing with negative environmental externalities, several methodologies are available for modeling pollution-generating technologies when measuring DMUs inefficiency. In this study we build on the recent approach of by-production (Murty et al. 2012), which is based on the idea of considering two sub-technologies in parallel: one that generates good outputs and a second that generates bad outputs. Extending Murty et al. (2012), we introduce the 'by-production' output-oriented directional distance function, which allows environmental inefficiency to be measured accounting for production quotas. Our approach is operationalized using Data Envelopment Analysis (DEA). Within our approach three inefficiency measures are proposed on by-production technologies with quotas: (1) standard technical inefficiency in the production of marketed output, (2) environmental inefficiency, and (3) inefficiency with quotas. Based on these inefficiency indicators some measures of overall performance are proposed.

Our study contributes to the literature in two main ways. Firstly, we develop a novel method to measure technical inefficiency of the system in which DMUs production decisions are regulated by quotas accounting for both quotas and undesirable outputs. In particular, through the new approach we demonstrate that not accounting for quotas could lead to substantial changes in inefficiency of DMUs. Secondly, we extend the by-production model and propose the 'by-production' output-oriented directional distance function accounting for quotas to measure DMUs inefficiency.

The method developed is illustrated through a numerical example using the data on the dairy sector of 23 EU countries during 2005, 2007, 2010 and 2013. Exploring environmental inefficiency accounting for quotas could be relevant from a policy perspective as it could provide some suggestions on how the sector can improve its level of efficiency through implementing various policy measures.

The structure of the article is as follows. We start by briefly reviewing the methodologies to measure environmentally sensitive efficiency with particular attention to the by-production model. Next, we develop our model for measuring environmental inefficiency incorporating quotas, thereby extending the by-production model.

[4] The literature on modeling efficiency of dairy farms without taking into account environmental factors is more extensive including the studies by Mbaga et al. (2003), Alvarez and del Corral (2010), Emvalomatis et al. (2011) or Sauer and Latacz-Lohmann (2015).

Then, we discuss the data and the results. The final section of the article contains a summary and some conclusions.

2 The by-production approach to modeling pollution

The study of environmentally sensitive efficiency taking into account undesirable outputs has grown significantly in recent years (see, for example, Aparicio et al. 2017b). The asymmetric modeling of outputs when measuring efficiency depending on their nature, increasing those that are market oriented while reducing those that are detrimental to the environment, was initiated by Färe et al. (1986). One important question is on how to model undesirable outputs when calculating technical efficiency. Most particularly, if the axioms underlying the production technology should reflect their strong or weak disposability, and eventually, if they should be modeled as outputs or as if they were inputs. But in this latter case an infinite amount of undesirable outputs could be produced with limited inputs in the standard model, which is a controversial hypothesis. For many years there has been an ongoing debate on this issue in the framework of environmental efficiency measurement (see, on the one hand, Hailu and Veeman 2000; Färe and Grosskopf 2003; Hailu 2003; and, on the other hand, Seiford and Zhu 2002; Färe and Grosskopf 2004; Seiford and Zhu 2005). Dakpo et al. (2016) is an updated revision on how to characterize undesirable production based on alternative approaches, including: (a) the Materials Balance Principle requiring knowledge of the technical coefficients (weights) between desirable outputs, undesirable outputs and inputs, and whose most recent evolution, based on the concept of G-disposability is Hampf and Rødseth (2015); and (b) the use of two sub-technologies (by-production): one generating the desirable outputs and a second generating the undesirable outputs (Førsund 2009; Murty, et al. 2012).

Among the existing approaches for dealing with undesirable outputs and efficiency, the by-production model introduced by Murty and Russell (2002) and Murty et al. (2012) is currently considered as one of the better options (for applications in agriculture see, for example, Chambers et al. 2014; Serra et al. 2014; Dakpo et al. 2017). The by-production approach posits that complex production systems are made up of several independent processes (Frisch 1965). In this model, the technology can be separated into sets of sub-technologies; one for the production of good outputs and one for the generation of bad outputs. The 'global' technology implies interactions between several separate sub-technologies. Førsund (2018) and Murty and Russell (2018) have recently classified the by-production approach among the multi-equation modeling approaches and argued that an important advantage of this approach is that it represents pollution-generating technologies by accounting for Material Balance Principle and therefore satisfies thermodynamic laws. Additionally, as Murty et al. (2012) point out, the by-production model avoids two inconsistencies of previous approaches. In particular, there could be several technical efficiency combinations of good and bad outputs, with varying levels of bad output, that are possible holding (pollutant and non-pollutant) input quantities fixed. However, in the absence of the application of abatement activities in the firm, this type of combinations are contrary to the phenomenon of by-production, since by-production implies that at fixed levels of inputs there is only one level of pollution at the frontier of the production possibility set. Moreover, it is possible to observe a negative trade-off between the inputs associated with the pollution, like fuel, and the bad output, like CO_2, which represents a clear inconsistency (more fuel and, however, less CO_2). These are the reasons why the by-production approach is utilized in this paper for determining the efficiency of the dairy sector in EU under the generation of desirable (meat and milk) and undesirable (pollutants) outputs. In particular, we will extend this approach to the case of production taking into account milk quotas.

In order to briefly review the standard by-production approach, let us formally define $x \in R_+^n$ as a vector of inputs, $y \in R_+^m$ as a vector of good outputs, $z \in R_+^{m\prime}$ as a vector of pollutants, and let us assume that p DMUs have been observed. To work it out, Murty et al. (2012) split the input vector into two groups[5]: non-pollution causing inputs, $x_1 \in R_+^{n_1}$, and pollution-generating inputs, $x_2 \in R_+^{n_2}$, with $n_1 + n_2 = n$. The first set could comprise land and labor, while the second set could be inputs like number of cows in the production of meat and milk, and certain pollutants as by-products.

In this way, the 'global' technology, denoted by T, is the intersection of two sub-technologies, T_1 and T_2. Whereas T_1 is the standard production technology with only good outputs, T_2 represents the production of bad outputs. Both technologies are linked through the level of pollutant inputs of the evaluated DMU, for example number of cows. It is important to highlight that the recent paper by Førsund (2018) argues that non-pollution causing inputs could also be included in technology T_2 given that substitution between non-pollution causing inputs can help mitigating the pollution. Additionally, Dakpo et al. (2017) indicate that some additional constraints must be added to the by-production approach by Murty et al. (2012) in order to guarantee that the projection points for input dimensions are the same in T_1 and T_2. In our study, seeking simplicity, we extend the original model by Murty et al. (2012). Nevertheless, our model can be easily adapted to the models proposed by Dakpo et al. (2017) and Førsund (2018).

In the non-parametric framework of DEA the two sub-technologies may be expressed mathematically under Variable Returns to Scale (VRS) as[6]:

$$\begin{aligned} T_1 &= \left\{ \left(x_1, x_2, y, z\right) \geq 0 : \sum_{d=1}^{p} \lambda_d x_{1d} \leq x_1, \sum_{d=1}^{p} \lambda_d x_{2d} \leq x_2, \sum_{d=1}^{p} \lambda_d y_d \geq y, \sum_{d=1}^{p} \lambda_d = 1, \lambda_d \geq 0 \right\} \\ T_2 &= \left\{ \left(x_1, x_2, y, z\right) \geq 0 : \sum_{d=1}^{p} \mu_d x_{2d} \geq x_2, \sum_{d=1}^{p} \mu_d z_d \leq z, \sum_{d=1}^{p} \mu_d = 1, \mu_d \geq 0 \right\} \end{aligned} \tag{1}$$

5 Ayres and Kneese (1969) proposed these two same groups when introducing the materials balance to economists.

6 Bad outputs are introduced as "inputs" in sub-technology T_2, something that was criticized in the previous literature on environmental efficiency measurement, as we pointed out in this section. However, Murty and Russell (2018) have recently defended the by-production approach, indicating that there are a lower bound and an upper bound on emission generation for given amounts of emission-generating inputs. The existence of an upper and lower boundary for emissions complicates the modeling of an emission-generating technology, particularly in the study of its disposability and the implied monotonicity properties. Fortunately, as they treat emissions as undesirable by-products, efficiency requires minimization of the production of emissions, conditional on input quantities. Therefore, the attention can be restricted to the study of the properties of the lower bounds on emission generation, which is what is really estimated by the specification of T_2.

Finally, $T = T_1 \cap T_2$.

Note that the sub-technologies are defined with two different intensity variables, λ and μ. Additionally, as Murty et al. (2012) highlight, T_1 satisfies the standard free-disposability property of inputs (pollutant and non-pollutant) and the good output. On the pollution side, the bad outputs satisfy the assumption of costly disposability, which implies the possibility of observing inefficiency in the generation of pollution (see Murty 2010, for more details).

Regarding the measurement of technical efficiency, Murty et al. (2012) show that some conventional approaches, like the hyperbolic and directional distance function defined on $T = T_1 \cap T_2$, are inadequate in the context of by-production. We say 'output-oriented' in this context because these distance functions measure efficiency in both good and bad outputs at the same time. In this way, the weakness is due to the fact that the two aforementioned measures use the same coefficient (decision variable) for determining efficiency both in T_1 for the good outputs and T_2 for the bad outputs. It implies that it is possible to reach the efficiency frontier for some of the sub-technologies but we can be short in achieving the frontier of the other one. Efficiency in the by-production approach needs efficiency models that project the assessed observations onto the efficient frontier of T_1 and the efficient frontier of T_2 at the same time.

The above drawback of standard approaches motivated Murty et al. (2012) to propose a different measure for dealing with good and bad outputs under by-production. This measure is good output-specific and bad-output specific and is based on the index previously defined by Färe et al. (1985):

$$
\begin{aligned}
\min\ & \frac{1}{2}\left[\underbrace{\frac{1}{m}\sum_{j=1}^{m}\theta_j}_{\substack{\text{standard}\\ \text{efficiency}}} + \underbrace{\frac{1}{m'}\sum_{k=1}^{m'}\gamma_k}_{\substack{\text{environmental}\\ \text{efficiency}}}\right] \\
s.t.\ & \sum_{d=1}^{p}\lambda_d x_{id} \le x_{i0}, && i = 1,\dots,n \\
& \sum_{d=1}^{p}\lambda_d y_{jd} \ge y_{j0}/\theta_j, && j = 1,\dots,m \\
& \sum_{d=1}^{p}\lambda_d = 1, && \\
& \sum_{d=1}^{p}\mu_d x_{id} \ge x_{i0}, && i = n_1+1,\dots,n \\
& \sum_{d=1}^{p}\mu_d z_{kd} \le \gamma_k z_{k0}, && k = 1,\dots,m' \\
& \sum_{d=1}^{p}\mu_d = 1, && \\
& \theta_j \le 1, && j = 1,\dots,m \\
& \gamma_k \le 1, && k = 1,\dots,m' \\
& \lambda_d \ge 0,\ \mu_d \ge 0, && d = 1,\dots,p
\end{aligned}
\tag{2}
$$

The optimal value of (2) coincides with the mean of the standard good-output-oriented efficiency and the environmental bad-output-oriented efficiency. Note also that the above model is separable. In this case, this means that the optimal value can be determined as the mean of a model that minimizes $\frac{1}{m}\sum_{j=1}^{m}\theta_j$ on T_1 and a model that minimizes $\frac{1}{m'}\sum_{k=1}^{m'}\gamma_k$ on T_2:

$$
\begin{array}{llll}
\min & \frac{1}{m}\sum\limits_{j=1}^{m}\theta_j & & \\
s.t. & \sum\limits_{d=1}^{p}\lambda_d x_{id} \le x_{i0}, & i=1,\dots,n & \\
 & \sum\limits_{d=1}^{p}\lambda_d y_{jd} \ge y_{j0}\big/\theta_j, & j=1,\dots,m & \\
 & \sum\limits_{d=1}^{p}\lambda_d = 1, & & \\
 & \theta_j \le 1, & j=1,\dots,m & \\
 & \lambda_d \ge 0, & d=1,\dots,p &
\end{array}
\qquad
\begin{array}{lll}
\min & \frac{1}{m'}\sum\limits_{k=1}^{m'}\gamma_k & \\
s.t. & \sum\limits_{d=1}^{p}\mu_d x_{id} \ge x_{i0}, & i=n_1+1,\dots,n_2 \\
 & \sum\limits_{d=1}^{p}\mu_d z_{kd} \le \gamma_k z_{k0}, & k=1,\dots,m' \\
 & \sum\limits_{d=1}^{p}\mu_d = 1, & \\
 & \gamma_k \le 1, & k=1,\dots,m' \\
 & \mu_d \ge 0, & d=1,\dots,p
\end{array}
\tag{3}
$$

In the next section, we extend the by-production approach to the case of quota-constrained production for some good output, as happens in the dairy sector in the EU. To do that, we introduce the 'by-production' output-oriented[7] directional distance function, which uses a different coefficient (decision variable) for bad and good outputs. The advantage of using a directional distance function approach in contrast to the above measure is that it allows the quota to be dealt with 'naturally', i.e., we will get positive values of the inefficiency measure for firms that operate satisfying the quota and negative values for firms that violate the quota; something that is not possible in the case of resorting to model (3) and adding quotas.[8] Moreover, fixing a reference direction for the potential improvement of production of good outputs in T_1 allows the technical inefficiency of each firm to be determined and decomposed into a part due to the quota system and another due to a bias the modeler makes in case the quotas are ignored in the analysis.

[7] The reason why we select this particular orientation is twofold. First, from a methodological point of view, it seems natural to resort to the same orientation as used by Murty et al. (2012) since our approach is, in part, an extension of that model. Second, from an empirical point of view, it makes sense to investigate the direct effect of the quota on the inefficiency measure through an output-oriented framework since quota limits the output production and affects it directly.

[8] In model (3) we could substitute $\theta_j \le 1$ by θ_j free in the presence of quotas in order to avoid the possibility of infeasibilities when the assessed DMU exceeds the quota constraints. However, if we use that modified model to evaluate a unit that satisfies the quotas, then it is not possible to assure that $\theta_j \le 1$ for all j at optimum, which allows to apply the Pareto dominance notion. In this sense, the model that we propose in this paper may be seen as more natural for dealing with this type of context since we do not need to adapt it for units satisfying the quotas and for units exceeding them.

3 Environmental inefficiency measurement with quotas

Let us assume that each DMU (the dairy sector in each country) produces two outputs, milk and meat, from the consumption of several inputs, like land, labor and cows. In this case, both land and labor can be considered as non-pollution-generating inputs, while cows are related to some type of pollution like greenhouse gas emissions from manure management and enteric fermentation of cattle. Let us assume, without loss of generality, that milk represents the first output. In addition, let us suppose that the market regulator imposes DMU-specific milk quotas that must be taken into account. This is, for example, the case of the EU dairy sector which will be analyzed as an illustrative numerical example in this paper.

In this context, the (conditioned) production possibility set for DMU_0 with quota q_0 is defined as:

$$\begin{aligned} T^{q_0} &= T \cap \left\{ \left(x_1, x_2, y, z\right) \geq 0 : y_1 \leq q_0 \right\} \\ &= \left[T_1 \cap \left\{ \left(x_1, x_2, y, z\right) \geq 0 : y_1 \leq q_0 \right\} \right] \cap T_2 = T_1^q \cap T_2 \end{aligned} \tag{4}$$

Therefore, by definition, the conditioned production possibility set T^{q_0} is the original 'unbounded' technology T with a DMU-specific upper bound for the milk produced. Additionally, in our context, the quota exclusively affects T_1 since T is separable into T_1 and T_2. Note that T^{q_0} is not a standard technology under the deterministic approach since some units can exceed their corresponding quota and, therefore, they can be located outside of the set T^{q_0}.

Let us now introduce the 'by-production' output-oriented directional distance function in DEA. As we explained in the previous section, Murty et al. (2012) dismissed the conventional measures, in particular, the hyperbolic and directional distance function, because they use the same coefficient for dealing with good and bad outputs in T_1 and T_2 at the same time. Therefore, the by-production output-oriented directional distance function needs to treat good and bad outputs in a different way (see Aparicio et al. 2013, where a modified directional distance function that plays with two different 'betas' is introduced in the standard production context). The by-production output-oriented directional distance function must be calculated through the two following linear problems.

$$\begin{array}{llll|llll} \max & \beta^{T_1} & & & \max & \beta^{T_2} & & \\ s.t. & \sum_{d=1}^{p} \lambda_d x_{id} \leq x_{i0}, & & i = 1, \ldots, n & s.t. & \sum_{d=1}^{p} \mu_d x_{id} \geq x_{i0}, & & i = n_1 + 1, \ldots, n \\ & \sum_{d=1}^{p} \lambda_d y_{jd} \geq y_{j0} + \beta^{T_1} g_{j0}^{T_1}, & & j = 1, \ldots, m & & \sum_{d=1}^{p} \mu_d z_{kd} \leq z_{k0} - \beta^{T_2} g_{k0}^{T_2}, & & k = 1, \ldots, , m' \\ & \sum_{d=1}^{p} \lambda_d = 1, & & & & \sum_{d=1}^{p} \mu_d = 1, & & \\ & \beta^{T_1} \geq 0, & & & & \beta^{T_2} \geq 0, & & \\ & \lambda_d \geq 0, & & d = 1, \ldots, p & & \mu_d \geq 0, & & d = 1, \ldots, , p \end{array} \tag{5}$$

As usual, we will use actual values of the outputs of the evaluated DMU as the reference directional vectors, i.e., $(g_0^{T_1}, g_0^{T_2}) = (y_0, z_0)$. By using this reference vector, note that the optimal value β^{T_2*} is always between zero and one, with zero signaling efficiency in T_2. However, regarding the optimal value β^{T_1*}, we cannot say the same. We only know that $\beta^{T_1*} \geq 0$, with zero signaling efficiency in T_1. So, in order to define an 'overall' measure as a mix of standard and environmental inefficiency, we suggest using the aggregated measure:

$$\frac{1}{2}\left[\underbrace{\left(1-\frac{1}{1+\beta^{T_1*}}\right)}_{\substack{\text{intended inefficiency}\\ \text{without quota}}}+\underbrace{\beta^{T_2*}}_{\substack{\text{unintended}\\ \text{inefficiency}}}\right] \tag{6}$$

which is always between zero and one and a value of zero is associated with $\beta^{T_1*} = \beta^{T_2*} = 0$.

In our quota-driven context, where the first good output is upper-bounded by the regulator, the model associated with T_1 must be transformed adding a constraint associated with the quota[9],[10]:

$$\begin{aligned}
&\max\ \beta^{T_1^q} \\
&s.t.\quad \sum_{d=1}^{p} \lambda_d x_{id} \leq x_{i0}, && i = 1, \dots, n \\
&\qquad \sum_{d=1}^{p} \lambda_d y_{jd} \geq y_{j0} + \beta^{T_1^q} y_{j0}, && j = 1, \dots, m \\
&\qquad \sum_{d=1}^{p} \lambda_d = 1, \\
&\qquad y_{10} + \beta^{T_1^q} y_{10} \leq q_0, \\
&\qquad \beta^{T_1^q}\ \text{free}, \\
&\qquad \lambda_d \geq 0, && d = 1, \dots, p
\end{aligned} \tag{7}$$

[9] We assume that data observed from the DMUs, inputs and outputs, are affected by the quota restrictions because it is reasonable to think that farms have accounted for quotas in their production plans before producing. Consequently, quotas affect the input mix and thereby influence the pollutant inputs and, implicitly, the bad outputs. However, in our mathematical approach, the constraint associated with the quota appears exclusively in the model related to the standard technology (T_1) since good outputs, which are in this case the type of outputs that are regulated, are the only part of the model for measuring standard technical efficiency. Note that, in fact, following Murty et al. (2012), good outputs are not a part of the model associated with the environmental technology T_2.

[10] Brännlund et al. (1995) is related to our approach. Brännlund et al. (1995) analyzed the impact of environmental regulation in the Swedish pulp and paper industry on firms' profit. On one hand, a common feature of Brännlund et al. (1995) and our approach is the way in which regulation is introduced in the model: an upper bound for good outputs. On the other hand, there are two main differences between our model and Brännlund et al. (1995). Firstly, Brännlund et al. (1995) focused on profit inefficiency while our approach focuses on technical inefficiency. In particular, we selected the directional distance function (DDF) for measuring environmental technical inefficiency and defined a suitable DDF to work in the context of by-production (Murty et al., 2012). Secondly, Brännlund et al. (1995) introduced the bad outputs in their model as inputs in one step without distinguishing between non-pollution causing inputs and pollution-generating inputs. In our approach, which is based on the recent by-production model (Murty et al., 2012), the bad outputs are exclusively introduced in sub-technology T_2, distinguishing between the two mentioned types of inputs.

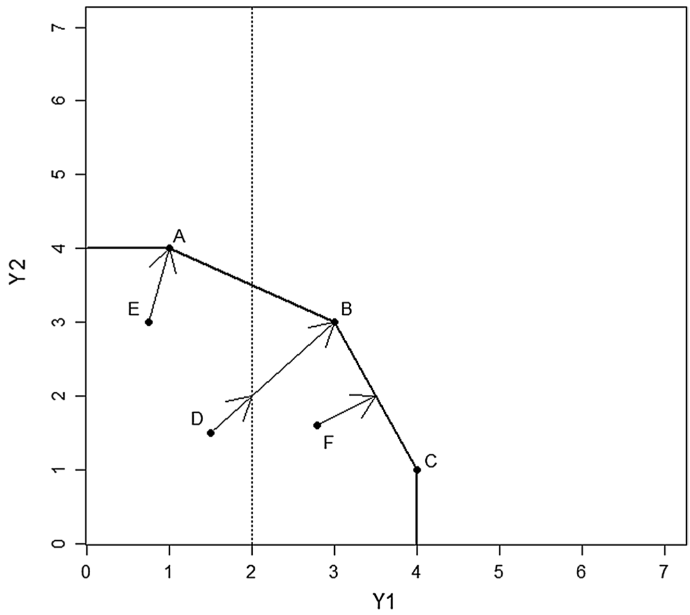

Fig. 1 Illustrative example for T_1 and T_1^q

In this case, $\beta^{T_1^q*}$ can take positive and negative values depending on whether the evaluated firm satisfies the quota or not.[11] If $\beta^{T_1^q*} \geq 0$, then its value represents the standard technical inefficiency with respect to the frontier of T_1^q, while $\beta^{T_1^q*} < 0$ is a measure of the non-fulfillment of the quota, i.e., it does not measure standard technical inefficiency. In particular, in case of being $\beta^{T_1^q*} < 0$, the bigger $\left|\beta^{T_1^q*}\right|$ is, the bigger is the non-fulfillment. For this scenario of by-production with quota, we suggest:

$$\frac{1}{2}\left[\underbrace{\left(1-\frac{1}{1+\left|\beta^{T_1^q*}\right|}\right)}_{\substack{\text{intended inefficiency with quota}\\ \text{or non - fulfillment of the quota}}}+\underbrace{\beta^{T_2*}}_{\substack{\text{unintended}\\ \text{inefficiency}}}\right] \tag{8}$$

[11] A negative value in the traditional output-oriented directional distance function reflects that the evaluated output bundle is not feasible, i.e. the inputs are not sufficient to produce the output. However, in our approach this interpretation changes and a negative value is associated with producing beyond the quota (see Fig. 1 below).

as a measure of overall performance. If $\beta^{T_1^q *} \geq 0$, then the first term in the aggregated measure is related to standard technical inefficiency, whereas if $\beta^{T_1^q *} < 0$, then its value is associated with the non-fulfillment of the quota.

An advantage of using the directional distance function in T_1 and T_1^q is that the inefficiency can be computed through the same reference direction, which implies that, for firms satisfying the quota, $\beta^{T_1 *}$ may be decomposed into $\beta^{T_1^q *}$, which is the inefficiency due to the quota, plus a bias that the modeler makes in case the quotas are ignored. We go on to show this and other scenarios through a graphical example.

In Fig. 1, the frontier of T_1 is the piece-wise linear function that envelops all the DMUs (A, B, C, D, E and F). Let us assume that the quota is fixed in $y_1 = 2$. In this way, the set T_1^q is the intersection between T_1 and the points that satisfy $y_1 \leq 2$. Consequently, the frontier of T_1^q only coincides in part with the frontier of T_1. There are several possible scenarios. DMU A represents a firm that is technically efficient for both T_1 and T_1^q and, in fact, $\beta_A^{T_1 *} = \beta_A^{T_1^q *} = 0$. DMU B represents a firm that is technically efficient in T_1, $\beta_B^{T_1 *} = 0$, but it does not satisfy the quota. So, $\beta_B^{T_1^q *} < 0$ and $\left|\beta_B^{T_1^q *}\right|$ signals how big is the non-fulfillment. Moreover, we have a DMU like D, which fulfills the quota but it is not technically efficient in T_1^q. Additionally, D can be projected onto a part of the frontier of T_1 that is not part of the frontier of T_1^q (DMU B). In this case, $\beta_D^{T_1 *} > \beta_D^{T_1^q *} > 0$. In this way, $\beta_D^{T_1 *} = \beta_D^{T_1^q *} +$ }pure (engineering) inefficiency'. DMU E represents a firm that fulfills the quota, is in the interior of T_1^q and its associated projection is part of the frontier of T_1^q (DMU A). In this case, $\beta_D^{T_1 *} = \beta_D^{T_1^q *} > 0$. Finally, DMU F represents a firm that violates the quota and is in the interior of T_1. Under this scenario, $\beta_F^{T_1 *} > 0$ and $\beta_F^{T_1^q *} < 0$.

4 Dataset and variables

This section uses data on dairy sectors in twenty-three countries from the EU for 2005, 2007, 2010 and 2013 (balanced panel).[12] The following EU countries have been excluded from the sample due to the lack of the data on quotas for some years: Poland, Slovenia, Bulgaria, Romania, and Croatia.[13] We undertake our analysis with aggregated data at the country level and not at the farm level since data on quotas is available only at the country level.[14]

[12] The data for quotas and milk production is available for the periods 2004/2005, 2006/2007, 2009/2010 and 2012/2013, which corresponds to the years 2005, 2007, 2010 and 2013, respectively, for which the rest of variables is presented.

[13] For Poland and Slovenia the period 2005/2006 was the first year of the application of the quota system, Bulgaria and Romania entered EU in 2007 and their first period of quota data was 2007/2008, while Croatia became EU member in 2013 and its first period of quota data is 2013/2014. So there is no relevant data of quotas for these countries for some of the years of the period analyzed in this paper, hence these countries were excluded from our sample.

[14] The aggregated data concerns specialist dairy farms and cattle-dairying, rearing and fattening combined farms.

In the numerical example we use the following variables: two non-pollution causing inputs, utilized agricultural area (in hectares) and total labor force (in terms of full-time labor equivalents measured in annual work units AWU);[15] one pollution-generating input, number of cows (in thousand heads of animals); two good outputs, production of cows' milk (in tons) and production of cows' meat (in thousands of tons); and two bad outputs, the greenhouse gas emissions from cattle manure management (in thousands of tons) and the greenhouse gas emissions from enteric fermentation of cattle (in thousands of tons).[16] Additionally, we consider that milk production is restricted by the quota system, hence our additional variable is quota volume (in tons).[17] To sum up, in this application, technology T_1 is composed of utilized agricultural area, total labor force, number of cows, milk production, and meat production, while technology T_2 is made by the number of cows, greenhouse gas emissions from cattle manure management, and greenhouse gas emissions from enteric fermentation of cattle. Overall, such configuration of T_1 and T_2 is consistent with the initial idea of Murty et al. (2012).[18] As was explained before, inefficiencies under technologies T_1 and T_2 are calculated by two separate DEA models (which is in line with Murty's et al. (2012) approach). Hence, we never use all input and output variables in one DEA model and both DEA models estimated comply with the 'rule of thumb' provided by Dyson et al. (2001) (that is, in order to achieve a reasonable level of discrimination in DEA one needs the number of DMUs to be at least $2\ m \times s$ where $m \times s$ is the product of the number of inputs and number of outputs).

Data on utilized agricultural area, total labor force, number of cows, meat production, greenhouse gas emissions from cattle manure management and greenhouse gas emissions from enteric fermentation of cattle was derived from Eurostat (2017). Eurostat's (2017) data comes from the Farm Structure Survey which is used to collect information on agricultural holdings in the EU member states over different geographical regions and periods. Target population of the survey is the universe of the agricultural holdings, excluding only the smallest holdings which together contribute 2 percent or less to the total utilized agricultural area and 2 percent or less to the total number of farm livestock units. Data on milk production and quotas was derived from the EU Milk Market Observatory of European Commission (2017). This observatory is prepared based on the data from surveys on dairies covering 95% of the cows' milk collected by Member States. Therefore, being the sum of data on almost all farms within each country, the data represents almost the whole dairy

[15] Full time corresponds to 1800 annual working hours.

[16] The main environmental issues of dairy sector concern water and air pollution, with the latter being mainly from manure management and enteric fermentation (OECD 2004). Due to the absence of data for water pollution of dairy sector, we restrict our analysis to bad outputs related with greenhouse gas emissions.

[17] As it was mentioned before, our analysis focuses on the delivery quotas. Hence, the variable of milk production is equivalent to quantities of milk delivered to dairies and quota is equivalent to available quota for deliveries.

[18] Usually in the literature concerning agricultural efficiency, the production technology is modeled also including general production costs or purchased feed (see for example, Emvalomatis et al. 2011). However, such data was missing in the datasets used in this study, while in other datasets such data would not be comparable to the remaining variables in our sample.

production in each country, hence it can be considered to approximate well the real production. However, because our data does not include all EU countries (due to the absence of data for some countries, as explained before), our empirical application serves mainly as an illustration and a numerical example on how the proposed method works. Finally, since only a small fraction of data is presented for every year, we are restricted to the years for which the data on all variables is available, that is 2005, 2007, 2010 and 2013.

Table 1 reports the descriptive statistics (average and standard deviation), for each input, output and quota for every country in the sample, for the data pooled for each year. This data underscores dairy sector in Malta as having the smallest values of all variables, and, by contrast, dairy sector in France and Germany exhibiting the largest values of almost all variables, on average. Table data also indicate that these two latter countries are the most polluting in terms of greenhouse gas emissions from manure management and enteric fermentation. Interesting to note from the table is that the Netherlands exceeded their quota allowance (milk production larger than quota, on average) over all years analyzed. However, as we will see later in the results obtained, other countries also exceeded their milk quota when particular years are analyzed.

5 Results

The analysis was undertaken in two steps. First, we analyzed the inefficiency results obtained for good output technology T_1 (β^{T_1*}), for bad output technology T_2 (β^{T_2*}) and for good output technology with quota T_1^q ($\beta^{T_1^q*}$), following Eqs. (5) and (7), for dairy sector in each of the analyzed countries, for each of the analyzed years and for all years together. We then computed overall performance measures given Eqs. (6) and (8) without taking into account quotas and incorporating the quota restriction, respectively, for dairy sector in each of the sample countries, for each of the sample years and for all years together. To test the differences between individual and overall performances we apply the Simar and Zelenyuk (2006) test (S–Z test). The S–Z test focuses on the comparison of the entire distributions, not on summary statistics such as the means or the medians (as it is in the case of the two-sample *t* test and the Kruskal–Wallis test, respectively). The S–Z test is based on the Li (1996) test, which measures the global distance (closeness) between two densities. The S–Z test consists of adaptation of Li (1996) test for the case of DEA efficiency scores, by accounting for the fact that efficiency distribution is bounded and that estimated rather than 'true' efficiency scores are measured by DEA. In particular, it is based on the computation and bootstrapping of the Li statistic (Li 1996) using DEA scores, where scores for efficient firms are smoothed by adding a small noise. Overall, the application of this test allows for robust statistical analysis in the context of efficiency measures estimated using DEA.[19]

[19] We apply this test using the data for all analyzed years together instead of performing it year by year to have a large enough sample size. In particular, Li (1996) shows in Monte Carlo simulations that the test performs well for moderate sample sizes. Also, Simar and Zelenyuk (2006) show through Monte Carlo simulations that the test is a reliable tool for moderate dimensions of the DEA model (as measured

We computed inefficiency results by pooling all countries together, hence we have implicitly assumed that these countries have access to similar environmental technology. This assumption is consistent with previous research on environmental efficiency (for example, Zofio and Prieto 2001; Mahlberg and Sahoo 2011; Färe et al. 2004; Vlontzos et al. 2014; Jaraitė and di Maria 2012). The assumption of technology homogeneity is reasonable when countries are advanced (Zofio and Prieto 2001). In fact, all countries in our sample are high income economies. Moreover, all countries belong to the EU and, hence, agriculture in all these countries is impacted by a variety of policies such as the European Common Agricultural Policy (CAP), regional policy, environmental policy, food safety policy, competition policy and innovation policy that render production technologies similar across these countries (European Parliament 2016).[20]

Table 2 reports the results obtained for β^{T_1*}, β^{T_2*} and $\beta^{T_1^q*}$ for the year 2005. Table 2 shows that twelve countries in the sample proved to be efficient under technology T_1, that is, they were able to produce more milk and meat using the same amount of inputs of land, labor and cows compared to remaining countries in the sample. Nevertheless, the results also show that in 2005 not all countries that were efficient under technology T_1, were also efficient under technology T_2. In particular, out of these twelve countries efficient in T_1, there were six countries that were inefficient in T_2 emitting more greenhouse gases while maintaining input of cows at its current level compared to other countries. Looking more closely at the results of β^{T_2*}, we can observe that there were ten countries that were ecologically efficient with environmental inefficiency scores equal to 0, that is, they were able to generate less pollution with the current amount of cows as compared to other countries. Table 2 seems to indicate also that for the majority of cases, the countries that were more inefficient in technology T_1 were likely to be less environmentally inefficient under T_2, and vice versa. Hence, some trade-offs existed in our sample between inefficiency in the production of good outputs and bad outputs. According to the results for $\beta^{T_1^q*}$, that is inefficiency under technology T_1^q (T_1 with quota restriction)

Footnote 19 (continued)
by the number of inputs and outputs) relative to the sample size. In particular, they concluded that the power of the test is fairly good for the DEA model of two or three inputs and one output for as many as 50 observations in each group. And, for example, for five inputs and one output for 20 observations in each group, they show that the power of the test is quite low. Given the maximum of five dimensions of the DEA model that we have (to estimate good outputs technology we have three inputs and two outputs) and 23 observations of countries in each year, the application of the test on a yearly basis would result in the low power of the test. Hence, we decide to apply the S-Z test for all years together, which results in a considerably larger sample size given the dimensions of the DEA model.

[20] We estimated frontiers separately for each year, which means that we are not able to interpret the results of inefficiency changes over time as improving or worsening with certainty. To interpret the results of inefficiency changes over time with more certainty we would need, for example, to compute inefficiency for all years together (hence, assuming that technology and frontier is not changing over time).

Table 1 Descriptive statistics of input/output data and quota in the 2005, 2007, 2010 and 2013. Average across years (standard deviations are shown in brackets)

Country	Non-pollution causing inputs		Pollution-generating input	Good outputs		Bad outputs		Quota (tons)
	Land (ha)	Labor (AWU)	Number of cows (thousand heads of animals)	Milk production (tons)	Meat production (thousand tons)	Greenhouse gases from manure (thousand tons)	Greenhouse gases from enteric fermentation (thousand tons)	
Belgium	406,425.0 (31,004.0)	12,970.0 (1644.7)	1,129,150.0 (78,428.2)	3,310,661.3 (56,568.2)	263.3 (8.4)	4335.1 (85.5)	920.8 (12.1)	3,377,875.5 (105,875.0)
Czech Republic	350,987.5 (11,379.1)	13,307.5 (1413.4)	288,395.0 (3373.8)	2,519,996.3 (108,391.5)	74.9 (6.3)	2653.6 (42.4)	1020.0 (31.7)	2,760,833.8 (98,959.2)
Denmark	511,807.5 (24,577.9)	10,470.0 (719.5)	1,112,377.5 (31,359.7)	4,614,916.0 (143,500.5)	130.6 (3.8)	3087.5 (102.6)	983.8 (14.1)	4,597,609.5 (140,892.6)
Germany	4,578,682.5 (110,139.6)	164,222.5 (11,786.5)	8,214,012.5 (116,952.6)	28,614,529.3 (790,656.9)	1161.2 (32.8)	23,422.3 (241.5)	6036.8 (243.9)	28,656,202.5 (882,318.5)
Estonia	315,320.0 (34,539.1)	10,867.5 (2653.5)	200,777.5 (10,406.0)	580,299.0 (41,313.3)	11.2 (2.8)	488.8 (21.8)	60.2 (5.9)	630,818.5 (47,256.5)
Ireland	1,038,990.0 (30,877.1)	32,300.0 (2167.5)	2,690,107.5 (106,952.3)	5,338,407.3 (215,135.6)	550.8 (22.9)	9676.5 (155.8)	1164.9 (23.6)	5,516,831.0 (137,544.6)
Greece	53,285.0 (3259.1)	7107.5 (1351.0)	245,100.0 (21,437.6)	708,754.3 (48,108.7)	56.0 (3.4)	1229.9 (17.7)	171.9 (1.2)	838,120.0 (20,665.6)
Spain	629,677.5 (55,499.7)	48,810.0 (10,476.5)	1,489,322.5 (38,854.5)	6,048,868.5 (146,422.3)	636.5 (50.6)	9836.6 (387.0)	1840.8 (106.6)	6,195,882.8 (159,594.3)
France	5,404,230.0 (329,928.9)	127,800.0 (14,091.9)	7,782,372.5 (74,119.3)	23,414,862.3 (391,464.7)	1503.8 (56.7)	30,809.3 (260.4)	4178.5 (274.3)	24,662,535.0 (746,751.2)
Italy	1,093,745.0 (87,967.1)	89,105.0 (17,587.7)	3,127,432.5 (117,964.6)	10,711,616.5 (146,866.8)	1042.9 (109.9)	11,055.4 (207.1)	2267.8 (183.9)	10,565,900.3 (317,819.8)
Cyprus	9452.5 (738.6)	682.5 (59.3)	53,077.5 (3531.0)	144,183.0 (9381.9)	4.3 (0.3)	114.7 (2.2)	18.4 (0.4)	146,566.0 (4844.1)
Latvia	401,060.0 (40,370.5)	26,735.0 (1,968.5)	244,050.0 (30,706.1)	608,107.0 (96,078.8)	19.1 (2.7)	745.2 (28.3)	106.6 (3.9)	704,986.5 (44,595.4)

Table 1 (continued)

Country	Non-pollution causing inputs		Pollution-generating input	Good outputs		Bad outputs		Quota (tons)
	Land (ha)	Labor (AWU)	Number of cows (thousand heads of animals)	Milk production (tons)	Meat production (thousand tons)	Greenhouse gases from manure (thousand tons)	Greenhouse gases from enteric fermentation (thousand tons)	
Lithuania	621,705.0 (51,797.5)	43,740.0 (8877.7)	441,115.0 (25,858.7)	1,274,259.5 (103,637.9)	47.1 (7.7)	1600.6 (59.1)	201.8 (4.5)	1,570,107.5 (175,821.0)
Luxembourg	81,427.5 (4446.5)	1715 (158.8)	140,390 (5032.9)	275,617.5 (5059.6)	9.2 (0.7)	394.6 (12)	65 (0.5)	277,166 (8471.8)
Hungary	236,027.5 (12,990.8)	14,235 (858.6)	271,995 (6194.5)	1,495,582.3 (34,618.9)	29.2 (4.6)	1429.2 (52.8)	429.2 (16.3)	1,882,233.8 (62,765.4)
Malta	482.5 (65.7)	242.5 (42.1)	15,100 (1801.2)	41,500.8 (860.3)	1.4 (0.1)	27.3 (1.8)	5.1 (0.4)	49,813.5 (1238.2)
Netherlands	855,032.5 (18,122.2)	37,102.5 (2190.4)	2,498,877.5 (90,438.9)	11,378,525.8 (314,740.2)	387.3 (6.1)	6930.4 (218.5)	1890.5 (178.3)	11,352,699 (348,406.8)
Austria	905,810 (58,995.8)	49,340 (9730.2)	1,393,277.5 (36,350.2)	2,787,796.3 (114,959.2)	217.8 (9.2)	3894.4 (23.6)	606.4 (4.6)	2,741,799.8 (95,688.1)
Portugal	170,897.5 (15,983.6)	19,420 (3509.3)	479,142.5 (11,653.1)	1,862,631.8 (36,889)	96.8 (12.8)	2783.8 (13.9)	176.2 (3.5)	1,978,632 (55,412.3)
Slovakia	336,280 (20,638.7)	13,820 (3327.1)	164,447.5 (8692.2)	880,953.5 (51,270)	18.1 (6.8)	910.2 (45.5)	103.8 (8)	1,037,402.5 (23,693.9)
Finland	595,115 (44,168.6)	25,097.5 (5023.2)	639,672.5 (37,936.3)	2,289,631.5 (57,582.3)	84.4 (3.3)	1870.4 (19.2)	407.9 (8.3)	2,478,014 (77,368.1)
Sweden	669,982.5 (68,131.3)	14,107.5 (2351.8)	819,037.5 (48,671.4)	2,986,373.5 (178,747.2)	138.4 (5.8)	2695.2 (70.5)	342.3 (5.8)	3,405,013 (103,722.5)
United Kingdom	1,831,525 (96,409.8)	45,230 (4673.6)	4,174,475 (134,815.9)	13,747,976.3 (406,380.4)	854 (59.8)	19,372.1 (447.3)	3541 (79)	14,901,591.8 (478,291.7)

in Table 2, nine countries exceeded their quota allowance, presenting the negative values of inefficiency. Out of these nine countries, Belgium, Denmark, Germany, Ireland, Spain, Italy and the Netherlands were the countries that were efficient in T_1, but they did not satisfy the quota requirement of 2005; their non-fulfillment is equal to 0.0072, 0.0004, 0.0147, 0.0084, 0.0111, 0.0383 and 0.0063, respectively. These countries present a similar behavior as DMU B in Fig. 1. On the contrary, Luxembourg and Austria, while violating the quota limit, were inefficient in T_1, presenting similar behavior as firm F on Fig. 1. Worth noting are France and Malta which are the only countries that were efficient in both T_1 and T_2, and at the same time they fulfilled the quota requirement and were efficient under the quota system. Such situation is similar to DMU A in Fig. 1. Finally, we have nine countries similar to DMU D in Fig. 1, which satisfied the quota but they were inefficient in both T_1 and T_1^q, and their $\beta^{T_1^q*}$ is lower than β^{T_1*}. Among these countries, for example, 'the bias associated with ignoring the quotas' for Estonia, that is inefficiency that is left from subtracting inefficiency in T_1^q from inefficiency in T_1, was relatively large and equal to 2.2474 (=2.3127 – 0.0653). We did not find cases of countries as DMU E in Fig. 1.

The inefficiency results for the year 2007 are provided in Table 3 and they indicate that there were twelve countries efficient under T_1, these were the same countries that were efficient in the previous period, 2005. In 2007, to the contrary to the previous period, eight countries exceeded their milk quotas, which consists of one country less than in 2005. Regarding environmental technology, there were nine countries efficient under T_2 (which is one country less than in 2005). The results of this year also suggest that in 2007 there was one country more (Ireland) that together with France and Malta were efficient in T_1, T_2 and T_1^q.

The results for the year 2010 (Table 4) highlight dairy sectors in eleven countries efficient under T_1 (which corresponds to one country less than in the previous periods, 2005 and 2007). It is worth adding that among these eleven countries only three proved to be also efficient under T_2 (Germany, France and Malta). In total, there were eight countries ecologically efficient considering the environmental technology, which consists of one country less than in 2007 and two countries less than in 2005. The results in Table 4 also indicate that during 2010 only three countries did not accomplish with their quota restriction (Denmark, Cyprus and Netherlands). Three countries, Germany, France and Malta, were efficient in all technologies T_1, T_2 and T_1^q. Finally, in this same year we encountered one country (Sweden) that presented a similar case as DMU E shown in Fig. 1, that is, it fulfilled the quota, however it was inefficient under quota and its associated projection was part of the frontier of T_1^q; as a result $\beta_D^{T_1*} = \beta_D^{T_1^q*} > 0$.

For the last analyzed year 2013, we can observe in Table 5 that in this period there were ten countries efficient under T_1 (one country less than in the previous year). Among countries efficient under the standard technology, four countries were also ecologically efficient under the environmental technology (Germany, France, Malta and Netherlands). In total, ten countries were environmentally efficient, that is, they produced less greenhouse gas emissions than other countries in the sample using the same amount of cows. The upshot of the results for the technology with quota indicates that during 2013, four countries exceeded their quota allowance (Denmark, Germany, Cyprus and Austria). France, Malta and the Netherlands were countries efficient under all scenarios, that is under T_1, T_2 and T_1^q. Finally, the results show that there were four countries (Greece, Hungary, Portugal and Sweden) that presented a similar case as DMU E shown in Fig. 1.

Table 6 summarizes the average inefficiency results for good output technology, for bad output technology and for good output technology with quota for all years together. It also presents the results of the S–Z test that allows the assessment of the statistical significance of the differences between inefficiencies.[21] To sum up, on average, the dairy sectors of the countries in the sample were more concerned about the environmental dimension of their production activities or their environmental efficiency was easier to achieve, since average environmental inefficiency was always less than in the standard production technology and these differences were statistically significant according to S–Z test. Since greenhouse gases emissions from agriculture were not regulated in the EU in the period under study, our result could imply that not regulated technology leads to lower inefficiency than technology regulated by the quota. In fact literature in general is not clear on the effects of regulations on efficiency reporting both positive and negative impacts (Alpay et al. 2002; Kapelko et al. 2015). Zhao (2017) also finds that environmental inefficiency was lower than standard inefficiency for some China's provinces.

On average, we also observed inefficiency estimates for dairy sector to be consistently higher when quota was not taken into account than when the inefficiency model considered quota restriction, and these differences proved to be statistically significant according to S–Z test as shown in Table 6. However, it should be noted that such results on the lower inefficiency when quota is included stems directly from the fact that a linear programming approach is used in estimating inefficiency, in which adding a restriction (in our case, a quota restriction) implies an increase in the minimum of the objective function. Based on this, lower values of inefficiency are not surprising. Nevertheless, such a result is important since it implies that not accounting for quotas when estimating inefficiency of DMUs being exposed to quota regulations considerably changes the DMUs efficient performance. The study by Aparicio et al. (2017a) in the context of Canadian dairy quotas also found big differences regarding efficiency when quota was accounted for in the efficiency measures. In the context of EU quotas, Areal et al. (2012a) reported positive efficiency impact of the quotas which are tradable, however this study did not compared the efficiency models with and without quotas. Similarly, Sauer (2010) provided arguments in

[21] The test (presented in Table 6 and then also in Table 8) was performed for values of inefficiencies for each DMU and not for average values of inefficiencies. The average values of inefficiencies were computed to give an additional glance on countries' performance over the entire period analyzed.

Table 2 Inefficiency values for good output technology T_1 ($\beta^{T_1}*$), for bad output technology T_2 ($\beta^{T_2}*$) and for good output technology with quota T_1^q ($\beta^{T_1^q}*$). Year 2005

Country	$\beta^{T_1}*$	$\beta^{T_2}*$	$\beta^{T_1^q}*$
Belgium	0	0.2509	−0.0072
Czech Republic	0	0.7408	0
Denmark	0	0	−0.0004
Germany	0	0	−0.0147
Estonia	2.3127	0	0.0653
Ireland	0	0	−0.0084
Greece	0	0.4660	0
Spain	0	0.5859	−0.0111
France	0	0	0
Italy	0	0.1905	−0.0383
Cyprus	0.2359	0	0.0915
Latvia	1.9799	0.3878	0.3754
Lithuania	1.7359	0.1599	0.1545
Luxembourg	0.9639	0.2099	−0.0085
Hungary	0.2581	0.5429	0.2237
Malta	0	0	0
Netherlands	0	0	−0.0063
Austria	1.3698	0	−0.0134
Portugal	0.1000	0.1022	0.0083
Slovakia	0.4805	0.6259	0.1534
Finland	0.7080	0.0254	0.0204
Sweden	0.2845	0	0.0297
United Kingdom	0	0.3351	0
Mean	0.4535	0.2010	0.0441

favor of deregulated allocation of quotas and Areal et al. (2012b) in favor of larger participation in quota market in terms of efficiency increases, without comparing the models with and without quotas. On the contrary, Alvarez et al. (2006) results cast some doubt on whether EU quotas are allocated to efficient dairy farms.

We now turn to show the results of measures of overall performance that aggregate the standard inefficiencies of good output production and inefficiencies of bad output production. Table 7 reports such results obtained for the cases of production without quota, and production taking into account quota restriction, for each of the countries and periods analyzed in this study. The first column for each year pertains to without quota inefficiency measure (6) and the second column pertains to with quota inefficiency measure (8). In addition, Table 8 reports the average values of both measures across analyzed periods together with the results of S–Z test for the assessment of the statistical significance of the differences between measures.

The results reveal that France and Malta were the only countries that sustained their efficient performance (the level of inefficiency of 0) when standard and environmental inefficiencies are aggregated both without and with consideration of the impact of quota throughout all analyzed periods. Looking in more detail into

Table 3 Inefficiency values for good output technology T_1 (β^{T_1*}), for bad output technology T_2 (β^{T_2*}) and for good output technology with quota T_1^q ($\beta^{T_1^q*}$). Year 2007

Country	β^{T_1*}	β^{T_2*}	$\beta^{T_1^q*}$
Belgium	0	0.2704	0
Czech Republic	0	0.7389	0
Denmark	0	0.0312	−0.0064
Germany	0	0	−0.0003
Estonia	2.2006	0	0.0677
Ireland	0	0	0
Greece	0	0.4862	0
Spain	0	0.5882	0
France	0	0	0
Italy	0	0.1135	−0.0570
Cyprus	0.1644	0	−0.0045
Latvia	2.1446	0.2457	0.1243
Lithuania	1.3381	0.2177	0.1719
Luxembourg	1.2672	0.1485	−0.0027
Hungary	0.2898	0.5151	0.2096
Malta	0	0	0
Netherlands	0	0	−0.0028
Austria	1.1960	0	−0.0315
Portugal	0.0748	0.0185	0.0288
Slovakia	0.6653	0.5496	0.0656
Finland	0.7226	0.0574	0.0305
Sweden	0.2377	0	0.0637
United Kingdom	0	0.2503	0
Mean	0.4479	0.1840	0.0286

particular years, Table 7 shows that the measure without quota resulted in a larger number of countries receiving an inefficiency score of 0 than does the specification with quota. The findings in Table 7 indicate that during 2005 six countries (Denmark, Germany, Ireland, France, Malta and Netherlands) were efficient according to the aggregated measure of standard and environmental efficiency without taking into account quotas; however only two of these countries (France and Malta) remained efficient when quota was considered in the measure. In 2007, five countries (Germany, Ireland, France, Malta and Netherlands) where found to be efficient as revealed by the measure that did not take into account quotas, but only two countries (Ireland and Malta) maintained their full efficiency when quota was considered in the measure. In 2010, the same three countries (Germany, France and Malta) were found to be efficient according to both measures. In 2013 Germany, France, Malta, and the Netherlands were efficient according to the measure without quotas, however Germany proved not to be efficient when quota was taken into account in computations.

As it is natural, since one technology is a subset of the other one, inefficiency in the production of good outputs (β^{T_1*}) was larger or equal to inefficiency of good

Table 4 Inefficiency values for good output technology T_1 ($\beta^{T_1 *}$), for bad output technology T_2 ($\beta^{T_2 *}$) and for good output technology with quota T_1^q ($\beta^{T_1^q *}$). Year 2010

Country	$\beta^{T_1 *}$	$\beta^{T_2 *}$	$\beta^{T_1^q *}$
Belgium	0	0.2827	0
Czech Republic	0	0.7151	0
Denmark	0	0.0341	−0.0044
Germany	0	0	0
Estonia	1.8016	0	0.1457
Ireland	0.1007	0	0.1007
Greece	0	0.5462	0
Spain	0	0.5770	0
France	0	0	0
Italy	0	0.1794	0
Cyprus	0.0164	0	−0.0030
Latvia	2.7544	0.0514	0.1783
Lithuania	1.4424	0.1376	0.3279
Luxembourg	1.1443	0.1437	0.0088
Hungary	0.3412	0.4884	0.2920
Malta	0	0	0
Netherlands	0	0.0004	−0.0041
Austria	1.1918	0	0.0153
Portugal	0.1686	0	0.0823
Slovakia	0.6646	0.4392	0.2608
Finland	0.6785	0.1122	0.1173
Sweden	0.1627	0.0531	0.1627
United Kingdom	0	0.2964	0
Mean	0.4551	0.1764	0.0731

outputs with quota consideration ($\beta^{T_1^q *}$) both for individual countries and in average terms (see Tables 2, 3, 4, 5, 6). However, the results of aggregated measures that take into account the production of bad outputs in Table 7 reveal that, in few cases, the aggregated inefficiency without quota was larger than aggregated inefficiency with quota, at the level of individual countries (for example in 2005 this was the case for Spain and Italy). Nevertheless, when considering the average values of aggregated inefficiencies across all countries, the aggregated inefficiency without quota remains larger than aggregated inefficiency with quota consideration. Table 8 further confirms that these differences observed are statistically significant as revealed by the results of S–Z test.

6 Conclusions

This paper introduces the method to evaluate inefficiency of DMUs that operate in regulated markets under production quotas accounting for negative environmental externalities. Our approach builds on Murty et al. (2012) that models the DMUs

Table 5 Inefficiency values for good output technology T_1 (β^{T_1*}), for bad output technology T_2 (β^{T_2*}) and for good output technology with quota T_1^q ($\beta^{T_1^q*}$). Year 2013

Country	β^{T_1*}	β^{T_2*}	$\beta^{T_1^q*}$
Belgium	0	0.3326	0
Czech Republic	0	0.7055	0
Denmark	0	0.0168	− 0.0038
Germany	0	0	− 0.0009
Estonia	1.6120	0	0.0700
Ireland	0.1673	0	0.0306
Greece	0.1115	0.5015	0.1115
Spain	0	0.5605	0
France	0	0	0
Italy	0	0.1714	0
Cyprus	0.0542	0	− 0.0080
Latvia	2.3282	0	0.0374
Lithuania	1.1855	0.2127	0.2662
Luxembourg	1.0466	0.0933	0.0240
Hungary	0.2404	0.5384	0.2404
Malta	0	0	0
Netherlands	0	0	0
Austria	1.0630	0	− 0.0346
Portugal	0.1051	0	0.1051
Slovakia	0.5349	0.4293	0.2477
Finland	0.6539	0.1258	0.1671
Sweden	0.2125	0.0875	0.2125
United Kingdom	0	0.3348	0
Mean	0.4050	0.1787	0.0637

Table 6 Inefficiency values for good output technology T_1 (β^{T_1*}), for bad output technology T_2 (β^{T_2*}) and for good output technology with quota T_1^q ($\beta^{T_1^q*}$), average over 2005, 2007, 2010 and 2013, and results of S–Z test

Inefficiency	Average and S–Z test
β^{T_1*}	0.4404
β^{T_2*}	0.1850
$\beta^{T_1^q*}$	0.0524
Significance	a, b, c

[a]Statistically significant differences between β^{T_1*} and β^{T_2*} at 5% level

[b]Statistically significant differences between β^{T_1*} and $\beta^{T_1^q*}$ at 1% level

[c]Statistically significant differences between β^{T_2*} and $\beta^{T_1^q*}$ at 1% level

technologies as the interaction of different subtechnologies. Extending the Murty et al. (2012) approach of by-production, in this study three inefficiency measures are proposed, namely standard technical inefficiency in the production of marketed output, environmental inefficiency, and inefficiency accounting for quotas. It is then shown how to aggregate these measures in order to obtain the overall performance indicators that represent the by-production without quota and by-production with quota.

Applying the DEA approach, we demonstrated the workability of the approach using a numerical example. In particular, we work on the dairy sector across twenty-three EU countries for the years 2005, 2007, 2010 and 2013 that until recently was regulated through the system of quotas. Our analysis suggests several conclusions. First, the potential exists for the EU dairy sector to improve its competitiveness and lower harmful environmental impact by decreasing standard and environmental inefficiencies. In particular, the results show that average inefficiency across all countries and years for standard production technology and environmental technology was approximately 0.4 and 0.2, respectively. Hence, in our numerical example, the EU dairy sector was more inefficient regarding marketed outputs of milk and meat than undesirable output of greenhouse gas emissions. Second, on average, across all sample countries and years, considerably smaller inefficiency outcomes were found under a model where quotas were taken into account than that without quota imposition. Third, France and Malta were the only countries in the sample that sustained their efficient performance across all sample years in terms of individual inefficiencies in standard technology, environmental technology and technology with quotas and in aggregated (overall performance) terms.

Our results indicate that the new approach could be utilized in future applications for deriving policy implications in more complex contexts; for example, with the aim to promote the increase of efficiency in the EU dairy sector. Integrating environmental and quota aspects into productive efficiency could provide policy makers with detailed information on sector production systems that could lead to improvement in the design of future policies. For example, policy makers could introduce environmental policy measures to encourage dairy sectors to reduce greenhouse gas emissions through incentives for acquiring new technologies that will enable these reductions.

Our result showing differences in inefficiency between the model that does not take into account quotas as compared to the model with quotas implies that not accounting for quotas, when measuring inefficiency of DMUs being impacted by this regulation, could yield a not accurate estimation of technical efficiency. Hence, we make a precautionary call to researchers to take into account quotas when measuring inefficiency of DMUs regulated by bounds in production and adopt our new model or devise one of their own.

However, further research is needed to investigate the inefficiency effects of quotas and environmental inefficiency more thoroughly. Most importantly, more recent data on the EU dairy sector already immersed in a quota-free system could allow for real conclusions regarding the comparison of efficiency of firms in the governed by quota and quota-free system. Also, the application of data at the farm level could allow for more detailed policy implications. The analysis of the transferability of the quota system in each EU country could provide more insights into understanding the differences in inefficiency found between countries. Also, the analysis of the levies applied when the countries exceeded the quota could provide some additional conclusions in the future research. The models developed in this paper could be applied in different contexts where quotas

Table 7 Measures of overall performance, for the systems without and with quotas. Years 2005, 2007, 2010 and 2013

Country	2005		2007		2010		2013	
	Without quota	With quota	Without quota	With quota	Without quota	With quota	Without quota	With quota
Belgium	0.1254	0.1290	0.1352	0.1352	0.1414	0.1414	0.1663	0.1663
Czech Republic	0.3704	0.3704	0.3695	0.3695	0.3576	0.3576	0.3527	0.3527
Denmark	0.0000	0.0002	0.0156	0.0188	0.0170	0.0192	0.0084	0.0103
Germany	0.0000	0.0072	0.0000	0.0002	0.0000	0.0000	0.0000	0.0004
Estonia	0.3491	0.0307	0.3438	0.0317	0.3215	0.0636	0.3086	0.0327
Ireland	0.0000	0.0041	0.0000	0.0000	0.0458	0.0458	0.0717	0.0149
Greece	0.2330	0.2330	0.2431	0.2431	0.2731	0.2731	0.3009	0.3009
Spain	0.2929	0.2984	0.2941	0.2941	0.2885	0.2885	0.2802	0.2802
France	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Italy	0.0952	0.1137	0.0568	0.0837	0.0897	0.0897	0.0857	0.0857
Cyprus	0.0954	0.0419	0.0706	0.0022	0.0081	0.0015	0.0257	0.0040
Latvia	0.5261	0.3304	0.4639	0.1781	0.3925	0.1014	0.3498	0.0180
Lithuania	0.3972	0.1469	0.3950	0.1822	0.3641	0.1923	0.3776	0.2115
Luxembourg	0.3504	0.1092	0.3537	0.0756	0.3387	0.0762	0.3024	0.0584
Hungary	0.3741	0.3629	0.3699	0.3442	0.3714	0.3572	0.3661	0.3661
Malta	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Netherlands	0.0000	0.0031	0.0000	0.0014	0.0002	0.0022	0.0000	0.0000
Austria	0.2890	0.0066	0.2723	0.0153	0.2719	0.0075	0.2576	0.0167
Portugal	0.0966	0.0552	0.0440	0.0233	0.0721	0.0380	0.0476	0.0476
Slovakia	0.4752	0.3795	0.4745	0.3056	0.4192	0.3230	0.3889	0.3139
Finland	0.2199	0.0227	0.2384	0.0435	0.2582	0.1086	0.2606	0.1345
Sweden	0.1107	0.0144	0.0960	0.0299	0.0965	0.0965	0.1314	0.1314
United Kingdom	0.1676	0.1676	0.1251	0.1251	0.1482	0.1482	0.1674	0.1674
Mean	0.1986	0.1229	0.1896	0.1088	0.1859	0.1188	0.1848	0.1180

and negative environmental externalities play an important role that can allow the robustness of our results to be assessed (see, for example, Cazals et al. 2002). The assessment of robustness of results will allow for formulations of more thorough policy implications. From a methodological point of view, an obvious extension would be also the development of models that measure productivity change over time. Also, an interesting future line of research is the extension towards the analysis of inefficiency in an economic sense, which could make it possible, for example, to analyze the monetary consequences of violating the quota restriction. However, such analysis would require the collection of data on market prices of inputs and outputs, which are generally not easy to obtain. In particular, getting market prices for bad outputs (separate prices for greenhouse gas emissions from cattle manure management and greenhouse gas emissions from enteric fermentation of cattle in our numerical example) can be a complicated challenge. Future research could also take into account some recent developments of the original by-production model proposed in the studies by Førsund (2018), Lozano (2015) or Dakpo et al. (2017). Also, although to test the differences in inefficiency measures we apply the test based on bootstrapping, still more robust results would be obtained by the application of bootstrap methods in the estimation of measures itself. Nevertheless, this procedure requires a previous analysis of the properties (consistency, rate of convergence, asymptotic distributions, etc.) of the estimator of the new approach. Although all these properties have been recently studied in depth in Simar et al. (2012) for the traditional directional distance function, they cannot be straightforwardly applied to our new approach as it is based on a modification of the directional distance function in the context of by-production and quotas. Hence, we leave it as an open research question to be undertaken in a future study. Finally, the proposed approach could be seen as an alternative to non-parametric efficiency models defined for dealing with exogenous variables. It would be possible to consider the fulfillment of the quota as an exogenous variable. In this case, statistical tests could be performed in order to establish the effect of the quota on technical efficiency. However, we believe that our approach presents some advantages over this last possibility. On one hand, if one does not constrain the technology regarding the feasible production of good outputs (considering the quota), then the solution of the models could determine targets above the limits set by the regulator. This is something that, a priori, should not be valid or, at least, would be problematic. In this way, the efficient point used by the model to evaluate the performance of each DMU would be not realistic. On the

Table 8 Measures of overall performance, for the systems without and with quotas, average over 2005, 2007, 2010 and 2013, and results of S–Z test

Measure	Average and S–Z test
Without quota	0.1897
With quota	0.1171
S–Z statistic	0.8415
P value	0.0090***

***Statistically significant differences at 1% level other hand, as far as we are aware, there are no models based on by-production and extended for dealing with exogenous variables. In this sense, a good avenue for further research would be to develop this new model and compare it with that introduced in this paper.

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Compliance with ethical standards

Conflict of interest The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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