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Eco-efficiency among dairy farmers: The importance of socio-economic characteristics and farmer attitudes

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Eco-efficiency among dairy farmers: The importance of socio-economic characteristics and farmer attitudes

Abstract The aim of this paper is to assess the eco-efficiency of dairy farms in Spain. To do so, we use data from a survey carried out in 2010 for the specific purpose of analysing the environmental performance of 50 dairy farms in the Spanish region of Asturias. The survey contains information on nutrients balances and greenhouse gas emissions which is used to calculate environmental pressure indicators. Eco-efficiency is measured using Data Envelopment Analysis (DEA). We analyse the influence of the socio-economic characteristics and farmers' attitudes in explaining these eco-efficiency scores using truncated regression and bootstrapping procedures. On average, the dairy farms are found to to be highly eco-inefficient. Among our results, farmers that are younger, that plan to continue in operation in the foreseeable future, and that have greater participation in training schemes are found to be more eco-efficient. Self-reported positive environmental habits are also reflected in actual eco-efficient performance.

1. Introduction

The environmental sustainability of agricultural activity is an issue of increasing concern to policymakers at national and international levels. At European level, Common Agricultural Policy (CAP) reforms have been giving increasing priority to the environment and future objectives point to the pursuit of economic growth in the agricultural sector while preventing environmental damage. Within the agricultural sector, dairy farming has not escaped scrutiny and the negative impacts of this activity on the environment have been well documented. In particular, land, water, air, biodiversity and the landscape can all be affected as a consequence of, among others, the generation and management of animal waste, the use of fertilizers and pesticides in the production of fodder, and the emission of greenhouse gases (CEAS, 2000; COWI, 2001; OECD, 2004). As examples, nitrate leaching and phosphorus run-off lead to eutrophication of the surface water, evaporation of ammonia and leaching to groundwater, while methane and nitrous oxide emissions from the dairy sector are significant contributors to greenhouse gas emissions (Basset-Mens et al., 2009). Concern over such effects at international level has led to policy responses such as the European Union's 1991 EU Nitrates Directive and its proposed Water Framework Directive, both of which affect the dairy sector, and the FAO has called for steps to minimize the production of environmental pollutants from dairy farming, with special emphasis on both nutrients and greenhouse gases (FAO and IDF, 2011).

The literature on assessing the environmental impacts of agricultural activities frequently invokes the concept of eco-efficiency. Eco-efficiency has been defined by the OECD as "the efficiency with which ecological resources are used to meet human needs" (OECD, 1998), and thus takes into account both the environmental and economic objectives of farms. An inefficient use of resources, particularly nutrients, can have negative effects on both the environment and the economic results of the production system (Oenema and Pietrzak, 2002). The term eco-efficiency itself was coined by the World Business Council for Sustainable Development (WBCSD) in their 1993 report (Schmidheiney, 1993) and it is based on the concept of creating more goods and services while using fewer resources, thereby generating less pollution.

While improvements in eco-efficiency do not guarantee sustainability per se insofar as higher eco-efficiency scores are compatible with (potentially unsustainable) increases in environmental pressures, Kuosmanen and Kortelainen (2005) point out that measurement of eco-efficiency is critically important for at least two reasons. Firstly, an improvement of eco-efficiency is often the most cost-effective way of reducing environmental pressures. Secondly, policies targeted at efficiency improvements are more easily implemented than policies that restrict the level of economic activity. In sectors such as dairy farming where pollution is a problem but profit margins are becoming tighter and tighter over time, it is of prime interest to policymakers to have information on the extent - if any - to which producers could reduce environmental pressures while maintaining (or improving on) their existing economic value added.

Production frontier models are a natural tool in measuring the eco-efficiency of producers,. In such models, an efficient frontier is estimated and the relative efficiency of producers is measured as the distance from this frontier (Coelli et al., 2005; Fried and Schmidt, 2008). Production frontier models have been widely used in the literature to measure environmental performance and an early survey of the literature by Tyteca (1996) discussed the usefulness of productive efficiency models in this context. Of particular relevance to the present study are what Lauwers (2009) refers to as frontier eco-efficiency (FEE) models. As these FEE models relate ecological and economic outcomes rather than the conventional inputs and outputs used in standard production efficiency models, Lauwers (2009) refers to them as the "frontier operationalisation" of the traditional eco-efficiency concept. Among studies following this approach are Callens and Tyteca (1999), Tyteca (1999), Kuosmanen and Kortelainen (2005), Kortelainen (2007) and Picazo-Tadeo et al. (2011).

The nonparametric Data Envelopment Analysis (DEA) method has been frequently used for evaluating producers performance in the presence of adverse environmental impacts (Färe et al., 1989; Ball et al., 1994). Färe et al. (1989) modify the efficiency measures proposed by Färe et al. (1985) to allow for an asymmetric treatment of desirable and undesirable outputs. Pollutants are treated as weakly (costly) disposable outputs whereas desirable outputs are strongly (freely) disposable (Färe et al., 1989). In the literature on technical and environmental performance measurement, pollutants are usually treated either as undesirable outputs (Färe et al., 1989; Ball et al., 1994; Pittman, 1983; Reinhard et al., 1999; Oude Lansink and Silva, 2003; Oude Lansink and Bezlepkin, 2003) or undesirable inputs (Tyteca, 1997), although there is no difference between the two approaches conceptually.

While eco-efficiency has been measured before using DEA in the agricultural sector (Picazo-Tadeo et al., 2011), the literature is lacking an analysis of eco efficiency in dairy farming. Furthermore, farmers' socio-economic characteristics and attitudes towards the environment have been shown to be important factors affecting the participation in agri-environmental schemes (Wynn et al., 2001; Defrancesco et al., 2008). However, the impact of farmer's attitudes on eco-efficiency has not been investigated so far.[1]

In the light of the foregoing, the objective of this paper is to measure eco-efficiency of dairy farms and to determine the impacts of farmers' socio-economic characteristics and attitudes toward the environment on their eco-efficiency.

The empirical application focuses on a sample of 50 dairy farmers from Asturias in Spain. To get improved estimates of eco-inefficiency and better inference on its determinants, we use a two-stage double bootstrap DEA procedure proposed by Simar and Wilson (2007). In the first stage of this procedure, distance functions are used to measure eco-efficiency scores, and in the second stage these scores are regressed on covariates related to attitudes towards the environment and socio-economic characteristics. Latruffe et al. (2008) applied this technique to explain technical efficiency in livestock and crop farms in the Czech Republic. The same procedure was applied by Weninger (2008) to study the technnical efficiency of a Mexican fishery and by Olson and Vu (2009) to study economic efficiency of farms in Minnesota. However, as far as we are aware, the two-stage double bootstrap DEA model has not been used previously for analysing the determinants of economic and environmental performance.

The paper proceeds as follows. In Section 2 we discuss the concept of eco-efficiency and the methodology used to estimate eco-efficiency scores and the factors determining them. Section 3 describes the data we use. The results are presented and discussed in Section 4, and Section 5 concludes.

2. Eco-efficiency: Concept and methodology used for measurement

2.1. Measuring eco-efficiency

To operationalize the concept of eco-efficiency, we follow the approach described in Kuosmanen and Kortelainen (2005) which defines eco-efficiency in the traditional way as a ratio between economic value added and environmental damage. Environmental damage, p, is measured by aggregating the K environmental pressures $(p_1, \ldots, p_K)$ which are induced by the production activity. Kuosmanen and Kortelainen (2005) use the tools of production economics and their point of departure is a pressure-generating or pollution-generating technology set $T = \{(v, p) \,\epsilon\, R^{\,(1+K)} |\; v$ can be generated by $p\}$. The technology set describes all the feasible combinations of economic value, v, and environmental damage, p.

The pressure-generating technology set and the concept of eco-efficiency are illustrated in Figure 1 below for the simple case of two environmental pressures. Production activity generates economic value added but also induces two environmental pressures, p_1 and p_2. A producer is deemed to be eco-efficient if and only if it is impossible to reduce one of the pressures without simultaneously increasing the other or decreasing economic value. The set of eco-efficient combinations is represented by the efficient frontier, T. Points below the frontier are unfeasible, while points above it are eco-inefficient. In the figure, the combination of pressures represented by A, which generates economic value added v, is clearly eco-inefficient as both environmental pressures could be reduced without reducing economic value added.

A measure of eco-inefficiency can be found by measuring the radial distance from a point A to the efficient frontier, and a farm's efficiency score is given by the ratio OE/OA which takes values less than or equal to 1, with a value of 1 implying eco-efficiency. For an inefficient combination such as A in Figure 1, $OE/OA < 1$.

[INSERT FIGURE 1 ABOUT HERE]

To empirically measure eco-inefficiency for a sample of producers, we need to aggregate individual environmental pressures into an environmental damage indicator. We follow the Data Envelopment Analysis (DEA) approach proposed by Kuosmanen and Kortelainen (2005) for aggregating environmental pressures. Eco-efficiency is defined as the ratio:

$$\frac{Economic\,value\,added}{Environmental\,pressures} = \frac{v_i}{D(p_i)} \tag{1}$$

where v_i is the Economic value added indicator of farm i and D is the function that aggregates the environmental pressures into a single environmental pressure indicator by taking a linear weighted average of the individual environmental pressures, i.e., $D(p_i) = w_1p_1 + w_2p_2 + ... + w_kp_k$ where w_k is the weight accorded to environmental pressure k.

In order to identify weights w_k, we use DEA as a nonsubjective weighting method, i.e., it determines the weights that maximize the eco-efficiency score of farm i' belonging to the sample of $i = 1, ..., N$ farms. The DEA eco-efficiency score of farm i' can be computed from the following programming problem:

$$\begin{aligned} &\underset{w_{ni}}{\text{maximize}} \quad \text{Eco} - \text{efficiency}_i = \frac{v_{i'}}{\sum_{k=1}^{K} w_{ki'}p_{ki'}} \\ &\qquad \text{subject to} \\ &\qquad \frac{v_i}{\sum_{k=1}^{K} w_{ki'}p_{ki}} \leq 1 \quad i = 1, ...N, \\ &\qquad w_{ki'} \geq 0 \quad k = 1, ...K \end{aligned} \tag{2}$$

The above formulation involves a non-linear objective function and non-linear constrains, which is computationally difficult. This problem can be linearized by taking the inverse of the eco-efficiency ratio and solving the reciprocal problem (Kuosmanen and Kortelainen, 2005; Picazo-Tadeo et al., 2011):

$$
\begin{aligned}
\underset{\theta_{i'}, z_i}{\text{minimize}} \quad & \text{Eco} - \text{efficiency}_{i'}^{-1} = \theta_{i'} \\
& \text{subject to} \\
& v_{i'} \leq \sum_{i=1}^{N} z_i v_i, \\
& \theta_{i'} p_{ki'} \geq \sum_{i=1}^{N} z_i p_{ki} \quad k = 1, ..., K, \\
& z_i \geq 0 \quad i = 1, \ldots, N
\end{aligned} \tag{3}
$$

where z_i is a set of intensity variables representing the weight of each farm i in the eco-efficient frontier.

The DEA eco-efficiency score which solves this problem for farm i, θ_i^*, can be interpreted as a distance to the eco-efficiency frontier. It indicates the maximum potential equiproportional reduction in all environmental pressures that could be achieved while maintaining the present level of economic activity. This corresponds to the ratio OE/OA for a farm operating at point A in Figure 1. Clearly, the DEA score equals one for an eco-efficient farm, in which case point A would be on the frontier, with values lower than one indicating eco-inefficiency. Obviously, the further the distance of the farm from the frontier, the lower the eco-efficiency score and the greater the scope for improvement in a farm's environmental performance.

2.2. Explaining eco-efficiency: truncated regression

A typical approach in studies computing efficiency measures using DEA is to conduct a second-stage regression analysis to relate these efficiency scores to a set of explanatory variables, with a censored Tobit regression being the method most often applied.

However, Simar and Wilson (2007) show that using a Tobit regression to perform a two-stage analysis to analyse the determinants of efficiency scores might be inappropiate because serial correlation of the first stage DEA efficiency estimates is not taken into account. Therefore, we apply the second of two truncated regression and bootstrapping procedures (Algorithm #2) proposed by Simar and Wilson (2007), which improves on inference and performs bias correction.

In order to follow the methodology described in Simar and Wilson (2007), we need a distribution with left-truncation at 1, so we transform the variable to be explained in the second stage by taking the inverse of the eco-efficiency scores estimated in the first stage according to (3).[2] The truncated regression of the eco-efficiency scores on a set of explanatory variables can be written as:

$$\Sigma_i = z_i \beta + \epsilon_i \geq 1 \tag{4}$$

where Σ_i represents (the inverse of) the efficiency scores.

Bootstrapping leads to consistent estimates of β. The following is a description of the bootstrap procedure using Algorithm #2 of Simar and Wilson (2007) which is used in this paper:

1. Use maximum likelihood to obtain estimates of β and σ_ϵ for the regression of the inverse of the eco-efficiency scores on the environmental variables using (4).
2. Loop over the following steps L times to obtain a set of bootstrap estimates for the parameters β and σ_ϵ:

$$\mathrm{B}_1 = \left\{ (\widehat{\beta}^*, \widehat{\sigma}_\epsilon^*)_b \right\}_{b=1}^{L} \tag{5}$$

(a) For each observation draw ϵ_i from the N(0,σ_ϵ) distribution with left-truncation at (1- $z_i\widehat{\beta}$).

(b) Compute for each observation $\Sigma_i^* = z_i\widehat{\beta} + \epsilon_i$

(c) Define $p_i^* = p_i$ and $v_i^* = v_i\frac{\widehat{\Sigma_i}}{\Sigma_i}$ for each observation.

(d) Compute the DEA eco-efficiency scores in (3) again by replacing v_i and p_i with v_i^* and p_i^* and take the inverse of the eco-efficiency scores.

3. Calculate for each observation the bias-corrected estimator defined as $\widehat{\widehat{\Sigma_i}} = \widehat{\Sigma_i} - \widehat{\text{BIAS}}(\widehat{\Sigma_i})$ using the original inverse of the eco-efficiency and the bootstrapped estimates obtained in Step 2.

4. Use maximum likelihood again to estimate the truncated regression, but using $\widehat{\widehat{\Sigma_i}}$ as the dependent variable. Obtain estimates of $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma_\epsilon}}$

5. Apply the following steps L times to obtain a set of bootstrap estimates:

$$\text{B}_2 = \left\{(\widehat{\beta}^*, \widehat{\sigma}_\epsilon^*)_b\right\}_{b=1}^{L} \tag{6}$$

(a) For each observation draw ϵ_i from the N(0,σ_ϵ) distribution with left-truncation at (1- $z_i\widehat{\widehat{\beta}}$).

(b) As done in Step 2.b , compute for each observation $\Sigma_i^{**} = z_i\widehat{\widehat{\beta}} + \epsilon_i$.

(c) Use maximum likelihood to estimate the truncated regression with Σ_i^{**} as dependent variable and z_i as explanatory variable. Obtain estimates of $\widehat{\widehat{\beta^*}}$ and $\widehat{\widehat{\sigma_\epsilon^*}}$

6. Finally, construct estimated confidence intervals for β and σ_ϵ by using the original estimates of $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma_\epsilon}}$ and the bootstrap values obtained in B_2.

3. Data description

The data set comes from a survey aimed at analysing the environmental performance of the dairy sector in Asturias, Spain. A questionnaire was specifically designed for the purpose of obtaining information on individual pollutants which could then be aggregated using standard conversion factors into a series of environmental pressures. Aside from pollutants, a novel aspect of the questionnaire is that it covered information on the attitudes of farmers towards aspects of environmental management and some socio-economic characteristics. The data collected correspond to the year 2010.

A total of 59 farmers responded to the questionnaire. The farms which took part in the survey all belong to one of two groups of a Dairy Cattle Management Program developed by the Board of Agriculture and Fisheries of the Principality of Asturias, Spain. These management groups are formed by a minimum of 25 dairy farms and each group is assigned a technical specialist who is responsible for collecting and processing technical and economic data from each farm and who also provide advice on how to improve the management of the farms. This information is then used to produce monthly and annual reports on the performance of the farms. We combine this economic information with the environmental data from the questionnaire to construct our dataset. Given that there were missing values for some of the variables we wished to consider, the final sample comprises 50 farms.

To calculate eco-efficiency scores, we need information on economic value added and environmental damage. Economic value added (*Econvalue*) is defined as the difference between revenues from milk production and direct costs, where revenues from milk production comprise milk sales and the value of in-farm consumption of milk. Regarding environmental damage, we use information on nutrients balances and greenhouse gas emissions. The nutrients balances, which measure the extent to which a farm is releasing nutrients into the environment, are defined as the difference between the inflows and outflows of nitrogen (*SurplusN*), phosphorus (*SurplusP*) and potassium (*SurplusK*), all measured in total kilograms. These environmental pressures are constructed using the farm gate balance approach and are calculated as the difference between the nutrient content of farm inputs (purchase of forage, concentrates, mineral fertilizers and animals, legume fixation of nitrogen in the soil and atmospheric deposition) and the nutrient content of outputs from the farm (milk sales and animal sales).

The volume of greenhouse gas emissions represents an indicator of the contribution of the farm to global warming. The dataset contains information on the emissions of carbon dioxide ($\mathrm{CO_2}$), methane ($\mathrm{CH_4}$) and nitrous oxide ($\mathrm{N_2}O$) coming both from direct and indirect emissions. As each greenhouse gas has a different global warming potential, we convert each greenhouse gas into $\mathrm{CO_2}$ equivalents to make them comparable. The variable used to denote greenhouse gas emissions is therefore measured as thousands of kilos of carbon dioxide released into the atmosphere (CO_2).

As determinants of eco-efficiency, we have information on a series of socio-economic characteristics and attitudes of farmers. The socio-economic variables we choose are: the age of the farmer (*Age*); the number of hours of specific agricultural training that the farmer carried out during the year of the sample (*Training*); and a variable capturing expected future prospects which is defined as a dummy variable taking the value 1 if the farmer considered that the farm would continue to be in operation five years later (*Prospects*). A priori, we would expect eco-efficiency to be negatively related to age (i.e., young farmers should be more eco-efficient) and positively related to specific professional training and the expectation that the farm continue.

Three attitudinal variables are constructed from information gathered on farmers' attitudes towards the management of nutrients and greenhouse gas emissions and their attitudes towards environmental regulation. On a five-point Likert scale, respondents had to state whether they strongly disagree (1), disagree (2), neither agree nor disagree (3), agree (4) or strongly agree (5), with a series of statements regarding their habits and attitudes towards aspects of environmental management. Thus, the variables $HabitsCO_2$ and *HabitsNutrients* measure farmers' attitudes towards the importance of measuring and managing greenhouse gas emissions and the nutrients balance respectively. These are constructed as dummy variables that take the value 1 if respondents stated that they agreed or strongly agreed that measurement and management of these pressures was important, and 0 otherwise. The final variable is a binary indicator measuring attitudes towards environmental regulation (*Regulation*). Here, farmers were asked whether they believed that environmental regulation was necessary. The variable is also constructed such that it takes the value 1 if respondents stated that they agreed or strongly agreed that environmental regulation should be tightened, i.e., that the farmer believes that existing regulation is insufficient, and 0 otherwise.

Some descriptive statistics of the variables used for measuring eco-efficiency and the determinants of estimated eco-efficiency are presented in Table 1.

[INSERT TABLE 1 ABOUT HERE]

4. Results

4.1. *Measuring eco-efficiency*

Some summary statistics of the eco-efficiency scores estimated using equation (3) are presented in Table 2, and a graph illustrating theindividuals scores is presented in Figure 2. These eco-efficiency scores represent the potential equi-proportional (or radial) reduction of the four environmental pressures considered while maintaining economic value added constant. The mean eco-efficiency score for the dairy farms in our sample was 0.632, implying that the dairy farmers could reduce their environmental pressures by an average of 36.8% while maintaining their economic value added. Five farms had an estimated score of 1 and were thus found to be eco-efficient, while the most eco-inefficient farm had a score of 0.232, implying that it could maintain its level of value added while reducing pressures by almost 87%.

[INSERT TABLE 2 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

Using the descriptive statistics for the environmental pressures in Table 1, the estimated eco-efficiency scores imply that the representative farm could reduce it nitrogen surplus by 0.368 x 5,966 kg = 2,194 kg, with corresponding reductions in phosphorus and potassium surpluses of 1,019 kg and 771 kg respectively. Greenhouse gas emissions, in turn, could be reduced by 157,161 kg of CO_2 equivalent.

Our results point to a high level of eco-inefficiency in Spanish dairy farms, but the fact there are no previous studies of eco-efficiency of dairy farms using the methodology we use precludes a direct comparisons of our results with existing results in the literature. However, Picazo-Tadeo et al. (2011) and Picazo-Tadeo et al. (2012) have used this methodology to assess eco-efficiency of Spanish farmers from other sectors. Picazo-Tadeo et al. (2011) estimate eco-efficiency for a sample of 171 crop farmers in the Castille-Leon region and found a potential average equi-proportional reduction of environmental pressures of 44%, whereas in a study of 55 olive farmers in southern Spain, Picazo-Tadeo et al. (2012) find that environmental pressures could be equi-proportionally reduced by 46%. For dairy farms, the closest study to ours is perhaps that of Iribarren et al. (2011), which uses data from the neighbouring Spanish region of Galicia. Using a sample of 72 dairy farms, these authors combine Life Cycle Assessment (LCA) and DEA to estimate eco-efficiency and find potential reduction of environmental pressure ranging from 23% to 31%.

4.2. Explaining eco-efficiency

The estimated coefficients and confidence intervals from the truncated regression are presented in Table 3.

[INSERT TABLE 3 ABOUT HERE]

The model we use performs quite well in the sense that all the explanatory variables were found to be highly statistically significant. The variables chosen therefore permit some insights into the factors influencing eco-efficient outcomes. Given that the dependent variable is defined as the inverse of the eco-efficiency scores, a positive estimated coefficient indicates greater eco-inefficiency and hence lower eco-efficiency, whereas a negative estimated coefficient indicates lower eco-inefficiency and therefore a higher level of eco-efficiency.

With this in mind, and beginning with the socio-economic variables, the positive estimated coefficient on the age variable indicates that older farmers are less eco-inefficient so that the age of the farmer has a negative impact on eco-efficiency. This result is in line with Reinhard et al. (2002) who found that younger farmers are more likely to be more knowledgeable about environmentally-friendly technological progress.

The estimated coefficient for the variable capturing the future *prospects* of the farm is negative, implying that farmers that will continue their activity in the next five years are running their farms more eco-efficiently. A similar result was found by Van Passel et al. (2009) and suggests that farmers that envisage their farm continuing - either run by themselves or by their successors - operate in a relatively more sustainable way.

The agricultural training variable had a negative coefficient, indicating that the greater the number of hours of specific agricultural instruction, the higher the level of eco-efficiency. However, it should be noted that this effect was found to be relatively weak at as the coefficient has quite a small value. In a similar vein, Picazo-Tadeo et al. (2011) included training as an explanatory variable of eco-efficiency scores for crop farmers and found it had no effect. This would seem to suggest that agricultural training programs could be improved in order to become a more effective tool in the effort to reduce environmental damages.

As might be expected, self-reported positive habits regarding nutrients balance management and emissions management improve eco-efficiency. This implies that farmers' responses to questions about the importance they attribute to management and control of environmental pressures provide, as we would hope, an accurate reflection of their actual behaviour, as manifested by their higher levels of eco-efficiency. We take this as lending credibility to the responses in the survey and hence to the data used.

Finally, the positive coefficient for the variable *Regulation* indicates that farmers that more strongly favour the need for regulation are less eco-efficient. In other words, the more eco-efficient farmers see less need for regulation and see no need to make it stricter.

5. **Conclusions**

Assessments of eco-efficiency can shed light on the environmental performance of agricultural producers and provide a potentially valuable source of information for policymakers in a context where sustainability is an ever-growing concern. We have estimated eco-inefficiency scores for a sample of dairy farms in northern Spain and found that they are highly eco-inefficient. On average, these farmers could maintain their present economic value added while reducing the environmental damage associated with their productive activity measured by a series of environmental pressure indicators. We find that pressures could be reduced by over 37%.

We investigate the impact of socio-economic characteristics and farmers' attitudes towards the environment on their eco-efficiency. We find that younger farmers are more eco-efficient, as are farmers who envisage their operation continuing for at least the following five years. Participation in specific agricultural training schemes had a positive but weak effect on eco-efficiency, whereas farmers who believe environmental regulation should be strenghtened were more eco-inefficient. We also found a positive relationship between the self-reported environmental habits of farmers and their actual environmental performance as reflected in higher estimated eco-efficiency levels.

The main implication of our study is that there is substantial room for costless -in terms of economic value added - improvements in the environmental performance of dairy farmers. Better management of resources and possibly improved technical efficiency would lead to relatively large reductions in nutrients balances and greenhouse gas emissions.

Our results also imply that policymakers wishing to reduce environmental damage should encourage young farmers to become more involved in the running of dairy farms. Moreover, training schemes should be improved in order to strengthen their positive effect on environmental performance. The benefits of environmental regulation should be clearly explained and measures to reduce the cost to farmers of implementing such regulation should be explored. Finally, the responses of the farmers in our sample with regard to the importance they attribute to management and control of environmental pressures are consistent with observed eco-efficient behaviour. This implies that survey information on farmer attitudes may be a valuable source of information on actual environmental performance.

Notes

[1]Picazo-Tadeo et al. (2011),while lacking the data to do so themselves, stressed the importance of taking into account attitudinal variables in the analysis as, in their own words, “other farmer features, including psychological aspects such as environmental concerns, should be considered in the future to explain eco-efficiency”.

[2]The transformed eco-efficiency measure ranges from 1 to infinity.

References

Ball, V. E., Lovell, C. A. K., Nehring, R. F. and Somwaru, A.: 1994, Incorporating Undesirable Outputs into Models of Production, *Cahiers DÉconomie et Sociologie Rurales* **31**, 60–73.

Basset-Mens, C., Ledgard, S. and Boyes, M.: 2009, Eco-efficiency of intensification scenarios for milk production in new zealand, *Ecological Economics* **68**, 1615–1625.

Callens, I. and Tyteca, D.: 1999, Towards indicators of sustainable development for firms: A productive efficiency perspective, *Ecological Economics* **28**, 41–53.

CEAS: 2000, The environmental impact of dairy production in the EU: Practical options for the improvement of the environmental impact, *Technical report*, Report submitted to European Commission (DGXI).

Coelli, T., Prasada Rao, D., O’Donnell, C. and Battese, G.: 2005, *An Introduction to Efficiency and Productivity Analysis*, 2nd edition edn, Springer, New York.

COWI: 2001, Cleaner production assessment in dairy processing, *Technical report*, Report prepared for United Nations Environment Programme and Danish Environmental Protection Agency .

Defrancesco, E., Gatto, P., Runge, F. and Trestini, S.: 2008, Factors affecting farmers' participation in agri-environmental measures: A northern italian perspective, *Journal of Agricultural Economics* **59**, 114–131.

FAO and IDF: 2011, Guide to good dairy farming practice. animal production and health guidelines, *Technical Report 8*, Rome.

Färe, R., Grosskopf, S. and Lovell, C.: 1985, *The Measurements of Efficiency of Production*, Kluwer- Nijhoff, Boston.

Färe, R., Grosskopf, S., Lovell, C. and Pasurka, C.: 1989, Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach, *Review of Economics and Statistics* **71**, 90–98.

Fried, H., C. L. and Schmidt, S.: 2008, *The Measurement of Productive Efficiency and Productivity Growth*, Oxford University Press, Oxford.

Iribarren, D., Hospido, A., Moreira, M. and Feijoo, G.: 2011, Benchmarking environmental and operational parameters through eco-efficiency criteria for dairy farms, *Science of the Total Environment* **409**, 1786–1798.

Kortelainen, M.: 2007, Dynamic environmental performance analysis: A Malmquist index approach, *Ecological Economics* **64**, 701–715.

Kuosmanen, T. and Kortelainen, M.: 2005, Measuring eco-efficiency of production with data envelopment analysis, *Journal of Industrial Ecology* **9**(4), 59–72.

Latruffe, L., Davidova, S. and Balcombe, K.: 2008, Application of a double bootstrap to investigation of determinants of technical efficiency of farms in central europe, *Journal of Productivity Analysis* **29**(2), 183–191.

Lauwers, L.: 2009, Justifying the incorporation of the materials balance principle into frontier-based eco-efficiency models, *Ecological Economics* **68**, 1605–1614.

OECD: 1998, *Eco-Efficiency*, Organization for Economic Co-operation and Development, OECD, Paris.

OECD: 2004, Agriculture, trade and the environment: The dairy sector, *Technical report*, OECD Publishing, Paris.

Oenema, O. and Pietrzak, S.: 2002, Nutrient Management in Food Production: Achieving Agronomic and Environmental Targets, *AMBIO: A Journal of the Human Environment* **31**(2), 159–168.

Olson, K. and Vu, L.: 2009, Economic efficiency in farm households: trends, explanatory factors, and estimation methods, *Agricultural Economics* **40**(5), 587–599.

Oude Lansink, A. and Bezlepkin, I.: 2003, The Effect of Heating Technologies on CO2 and Energy Efficiency of Dutch Greenhouse firms, *Journal of Environmental Management* **68**, 73–82.

Oude Lansink, A. and Silva, E.: 2003, CO2 and Energy Efficiency of Different Heating Technologies in the Dutch Glasshouse Industry, *Environmental and Resource Economics* **24**, 395–407.

Picazo-Tadeo, A. J., Beltran-Esteve, M. and Gomez-Limon, J.: 2012, Assessing eco-efficiency with directional distance functions, *European Journal of Operational Research* **220**, 798–809.

Picazo-Tadeo, A., Reig-Martínez, E. and Gómez-Limón, J.: 2011, Assessing farming eco-efficiency: a data envelopment analysis approach, *Journal of Environmental Management* **92**(4), 1154–1164.

Pittman, R. W.: 1983, Multilateral Productivity Comparisons with Undesirable Outputs, *Economic Journal* **93**, 883–891.

Reinhard, S., Lovell, C. A. K. and Thijssen, G. J.: 2002, Analysis of environmental efficiency variation, *American Journal of Agricultural Economics* **84**(4), 1054–1065.

Reinhard, S., Lovell, C. and Thijssen, G.: 1999, Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farms, *American Journal of Agricultural Economics* **81**, 44–60.

Schmidheiney, S.: 1993, Changing course: A global business perspective on development and the environment, *Technical report*, MIT Press, Cambridge, MA.

Simar, L. and Wilson, P.: 2007, Estimation and inference in two-stage, semi-parametric models of production processes, *Journal of Econometrics* **136**, 31–64.

Tyteca, D.: 1996, On the measurement of the environmental performance of firms - a literature review and a productive efficiency perspective, *Journal of Environmental Management* **68**, 281–308.

Tyteca, D.: 1997, Linear Programming Models for the Measurement of Environmental Performance of Firms: Concepts and Empirical results, *Journal of Productivity Analysis* **8**, 183–197.

Tyteca, D.: 1999, Sustainability indicators at the firm level, *Journal of Industrial Ecology* **2**, 61–77.

Van Passel, S., Van Huylenbroeck, G., Lauwers, L. and Mathijs, E.: 2009, Sustainable value assessment of farms using frontier efficiency benchmarks, *Journal of Environmental Management* **90**, 3057–3069.

Weninger, Q.: 2008, Economic benefits of management reform in the gulf of mexico grouper fishery: A semi-parametric analysis, *Environmental and Resource Economics* **41**(4), 479–497.

Wynn, G., Crabtree, B. and Potts, J.: 2001, Modelling farmer entry into the environmentally sensitive area schemes in scotland, *Journal of Agricultural Economics*

52, 65–82.

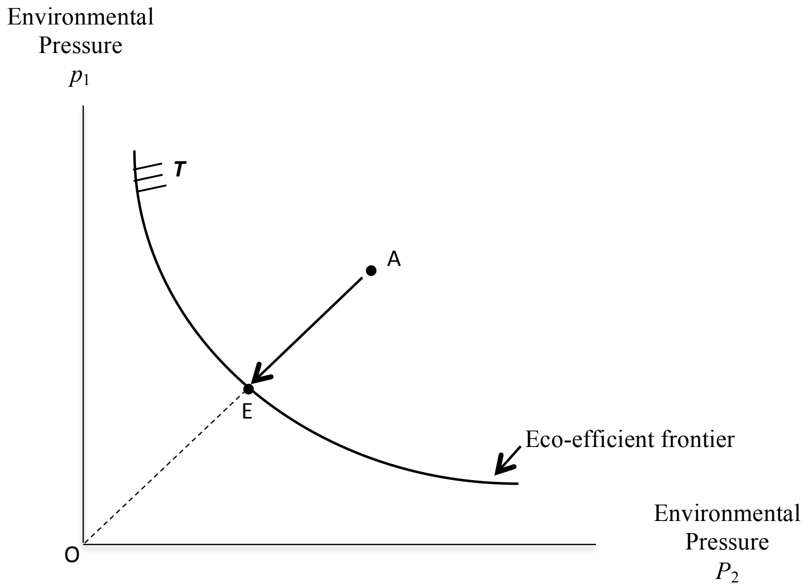

Fig. 1: Pressure-generating technology set and eco-efficient frontier

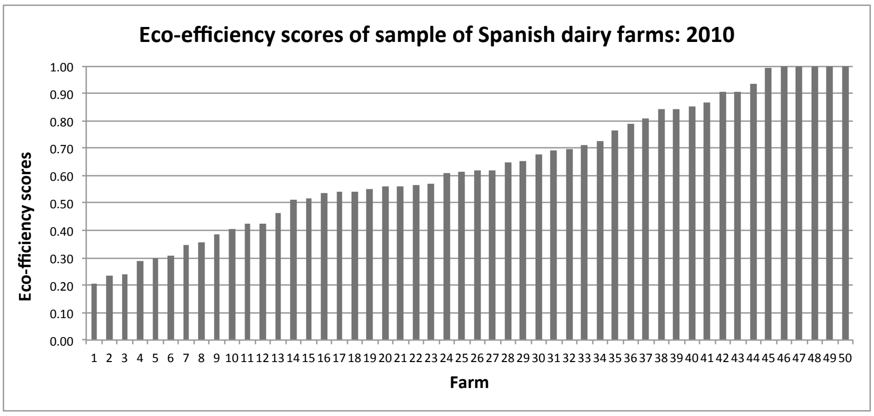

Fig. 2: Individual farm eco-efficiency scores

Table 1: Descriptive Statistics- Ecoefficiency dairy farms in Asturias

Variable	Mean	Std. Dev	Min	Max
Econvalue	77137	40423	16959	168848
Environmental Pressures				
SurplusN	5966	4705	0	16244
SurplusP	2770	2168	0	7714
SurplusK	2096	1681	0	5975
CO_2	427.3	142.0	207.2	828.6
Eco-efficiency Determinants				
HabitsCO_2	0.09	0.29	0	1
HabitsNutrients	0.77	0.43	0	1
Age	45.98	7.97	29	65
Prospects	0.98	0.14	0	1
Regulation	0.58	0.50	0	1
Training	45.14	63.10	0	400

Table 2: Descriptive statistics of computed Eco-efficiency scores

	Mean	Std. Dev	Min	1st Qt	Median	3rd Qt	Max
Radial eco-efficiency	0.6322	0.2319	0.2039	0.4772	0.6158	0.8342	1

Table 3: Truncated regression and bootstrapped confidence intervals

		(95% confidence)		(90% confidence)	
Variables	Estimated parameter	Lower bound	Upper bound	Lower bound	Upper bound
HabitsCO_2	-0.6891	-0.6897	-0.2879	-0.6606	-0.3179
HabitsNutrients	-0.2307	-0.3940	-0.1680	-0.3815	-0.1850
Age	0.0082	0.0013	0.0144	0.0025	0.0134
Prospects	-2.1438	-2.4408	-1.8411	-2.4010	-1.8781
Regulation	0.2302	0.1896	0.4041	0.2046	0.3919
Training	-0.0019	-0.0031	-0.0009	-0.0028	-0.0010
Sigma	0.1611	0.1097	0.1746	0.1147	0.1703