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This paper redefines technical efficiency by incorporating provision of environmental goods as one of the outputs of the farm within a multi-outptut distance function framework. Permanent and rough grassland area are used as a proxy for the provision of environmental goods. The multi-output distance function approach is used to estimate technical efficiency.

A Bayesian procedure involving the use of a Gibbs sampler is used to estimate the farm specific efficiency as well as the coefficients of the distance function. In addition, a number of explanatory variables for the efficiency were introduced in the analysis and posterior distributions of those were obtained. The methodology is applied to panel data on 215 dairy farms in England and Wales from the Defra Farm Business Survey. Results show that both farm efficiency rankings and determinants of inefficiency change when provision of environmental outputs by farms is incorporated in the efficiency analysis, which may have important political implications.

Introduction

The environmental goods (e.g. habitat for insects, bird species) and bads (e.g. pollution derived from the use of fertilisers) provided by farms create positive and negative externalities respectively in that the additional benefits and costs to society derived from the farmers' actions do not result in compensation to farmers for the benefits provided nor pay to society for the harm done. The non-existence of a market for the good and/or bad provided leads to a loss of economic efficiency giving governments an argument to intervene in order to internalise the externality.

Both positive and negative externalities have characterised the Common Agricultural Policy (CAP). Thus, the CAP in the last decades was based on price support which, as well as technological progress, has favoured intensification, specialisation and concentration of production. This has led to habitat loss and a decline in biodiversity, i.e. it has produced negative externalities (Potter and Goodwin, 1998). The introduction of set-aside in 1988 aimed to reduce overproduction of crops such as cereals and oilseed rape; and to deliver environmental benefits. This measure was voluntary when it was introduced and became compulsory in 1992 with the MacSharry reform.

In recognition of the high ecological and environmental impact of intensification of agriculture, agri-environmental schemes (AES) were introduced with the MacSharry reform in 1992 and have been developed under Regulation (EEC) 2078/92, which allows MS to provide support to farmers for making environmental improvements to their land by changing farming practices (Hynes *et al.*, 2008). With the introduction of the Agenda 2000 Member States (MS) may make direct payments conditional on compliance with environmental targets (i.e. farmers are required to follow certain production practices in order to receive direct support).

Payments for environmental goods through agri-environmental schemes aim to help provide environmental outputs at the local level and effectively pay the farmers for what is considered a social benefit. This is in line with the idea of having a sustainable agricultural sector. According to this idea, the UK Government set up an independent

Policy Commission on the future of farming and food. The Commission's report provided a vision of "a sustainable, competitive and diverse farming and food sector, playing a dynamic role in the rural economy and delivering effectively and *efficiently* the environmental goals we as a society set for ourselves" (Defra, 2002). The UK Government released in 2002 its vision on sustainability of the farming and food sectors which was in harmony with the independent Policy Commission report outcomes.

It seems clear that agricultural practices (i.e. land use) have an impact on the quality and availability of natural habitats which can have an effect on wildlife and biodiversity (OECD, 1999; Mattison and Norris, 2005). For instance, many bird species depending on permanent pasture land (OECD 1999) can be affected in case this land use is changed.

Although accounting for multiple outputs has been treated to a large extent within the productivity and efficiency literature, few publications have incorporated externalities as an output of the farm (Dorfman and Koop 2005), being negative externalities such as pollutants the core of research (Färe et al. 1989; Färe, Grosskopf, and Tyteca 1996; Reinhard, Lovell, and Thijssen 1999; Färe, Grosskopf, and Pasurka 2001; Reinhard, Lovell and Thijssen 2002; Lansink and Reinhard 2004; Murty, Kumar, and Paul 2006). Yet few studies have included the provision of environmental goods (e.g. biodiversity) in production related analysis. An exception is the publication by Omer, Pascual and Russell (2007) who conducted an study in the productivity performance and biodiversity conservation in intensive agricultural systems using a stochastic production frontier approach. These authors included a biodiversity index (BI) based on measures of plant species richness to examine the relationship between the state of biodiversity and output in a specialised intensive farming system. A positive relationship between state of biodiversity and productivity was found, which suggests that implementing biodiversity conservation policies may be beneficial to productivity, rejecting the idea that environmental regulations have an adverse effect on productivity. The omission of environmental outputs provided by farms in production and efficiency analysis may lead to biased results, which if used for policy support, could mislead policy makers in their policy decisions. We take into account the environmental outputs by incorporating an indicator for environmental outputs as one of the outputs of the farms in the production function within a multi-output distance function approach.

Inferences about firm specific inefficiencies have been widely reported in the literature. It is also common to find in the literature a ranking of firms according to their mean efficiencies (Coelli and Perelman 1999; Coelli and Perelman 2000) or plots for mean, median and maximum efficiency levels (Koop 2003). We investigate the consequences in efficiency rankings when provision of environmental outputs is incorporated into efficiency analysis. Accounting for environmental outputs when measuring efficiency is in concordance with policies aiming to achieve a sustainable agriculture such as the provision of both marketable goods (e.g. cereals, milk and oilseeds) and non-marketable goods (e.g. diversity of flora and fauna and landscape views) by farms. Information about farm efficiency levels is key for policy makers to identify which farms may be in need of support (i.e. those farms that are less efficient) and implement support policies (e.g. facilitation of credit to access to new machinery, training). If the information received by policy makers about farm efficiency levels is not harmonised with policy aims, policy measures may be ineffective at supporting the right farms. In other words, using a conventional efficiency measure (i.e. by not incorporating the provision of environmental goods by farms in efficiency analysis) may lead to policy makers, whose aim is to support those farms in line with sustainable agriculture, to target the wrong farms when designing a efficiency support policy. In addition, we examine how a measure that accounts for the provision of environmental outputs may affect the results associated with explaining technical efficiency. The following sections proceed by first discussing the methodology, then the sources and construction of the data. The empirical results are then presented and discussed, and the final section concludes.

Methodology

We study milk producer farms in England and Wales. These producers have an annual milk quota and a functioning quota leasing market in which producers can lease in and/or lease out milk during the production year. Therefore we include in the analysis the annual quota Q, leasing in quota qui and leasing out quota quo by treating the total annual quota after milk quota trade $Q + qui - quo$ as a normal input.

Optimising behaviour is the assumption upon which conventional microeconomics is based. This means that producers optimise their production by not wasting resources and therefore operate near their production possibilities set. However there may be an array of motives for which not all producers are successful in optimising production. If this is the case technical efficiency is not achieved and measuring the distance between the production frontier and actual production is a crucial policy interest. From a policy and managerial perspective it is important to identify the determinants of inefficiencies and learn how inefficient producers are on average as well as individually (Färe, Grosskopf, and Lovell 1994; Farrell 1957). The departure point of any technical efficiency analysis is the definition of the production technology of a firm. This can be characterised in terms of a technology set, the output set of production technology, and the production frontier.

Distance functions are useful since they describe technology in a way that efficiency can be measured for multi-input and multi-output enterprises (Coelli et al. 2005). An output distance function describes the degree to which a firm can expand its output given its input vector. We start from a producible output set, which is the set of all outputs that can be feasibly produced using the set of all inputs. The output set for production technology is defined as

$$\begin{aligned} P\left(x, Q + qui - quo\right) &= \left\{ y \in R_{+}^{M} : x\ can\ produce\ y \right\} = \\ &= \{ y : (x, y) \in T \} \end{aligned} \tag{1}$$

where y refers to all outputs of the farm including milk and the environmental output and x refers to all inputs used in the farm including the annual allocation of quota after trade $Q + qui - quo$.

The output distance function is defined on the output set $P(x, Q + qui - quo)$ as

$$
\begin{aligned}
D_O(x, y, Q + qui - quo) &= \min \left\{ \theta : \left(\frac{y}{\theta} \right) \in P(x, Q + qui - quo) \right\} \\
& for\ all\ x \in R_+^K
\end{aligned}
\tag{2}
$$

which means that the initial allocation of quota after trade $Q + qui - quo$, is treated in the same way as conventional inputs (x) .

Assuming a translog functional form for the parametric distance function with M outputs and K inputs provides several attractive properties including flexibility, easy to derive and permit the imposition of homogeneity, which makes it the preferred in the literature (Coelli and Perelman 1999; Lovell et al. 1994; Brümmer, Glauben, and Thijssen 2002; Brümmer, Glauben, and Lu 2006).

$$
\begin{aligned}
\ln D_{Oi} &= \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K} \beta_k \ln x_{ki} + \\
& + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K} \sum_{m=1}^{M} \delta_{km} \ln x_{ki} \ln y_{mi} \\
& i = 1, ..., N
\end{aligned}
\tag{3}
$$

where i denotes the ith farm in the sample; qui and Q are included in x as inputs; and quo are part of y as an output. By using linear homogeneity of the output distance function, equation (3) can be transformed into an estimable regression model by normalising the function by one of the outputs (Brümmer, Glauben, and Lu 2006; Brümmer, Glauben, and Thijssen 2002; Coelli and Perelman 1999; Coelli and Perleman 2000; Lovell et al. 1994; Orea 2002; O'Donell and Coelli 2005). From Euler's theorem, homogeneity of degree one in output implies:

$$
\sum_{m=1}^{M} \alpha_m + \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{ni} + \sum_{m=1}^{M} \sum_{k=1}^{K} \delta_{km} \ln x_{ki} = 1 \tag{4}
$$

which will be satisfied if $\sum_{m=1}^{M}\alpha_m = 1$, $\sum_{m=1}^{M}\alpha_{mn} = 0$ for all n, and $\sum_{m=1}^{M}\delta_{km} = 0$ for all k. Substituting these constraints is equivalent to normalising by one of the outputs, which leads to the following expressions:

$$\ln D_O\left(\frac{y_i}{y_{2i}}, x\right) = \ln D_o \frac{1}{y_{2i}}\left(y_i, x_i\right) \tag{5}$$

$$\begin{aligned} -\ln \hat{y}_2 \quad = \quad & \alpha_0 + \sum_{m=1}^{M}\alpha_1 \ln\frac{y_{mi}}{y_{2i}} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln\frac{y_{mi}}{y_{2i}}\ln\frac{y_{ni}}{y_{2i}} + \\ & + \sum_{k=1}^{K}\beta_k \ln x_{ki}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{kl}\ln x_{li} + \\ & + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km}\ln x_{ki}\ln\frac{y_{mi}}{y_{2i}} + \kappa_1 t_i + \kappa_2 t_i^2 + \varepsilon_i - z_i \end{aligned} \tag{6}$$

where t and t^2 are the year and year squared, which are incorporated to account for technical change during the period studied; κ_1 and κ_2 are the parameters associated to the year and year squared variables; ε_i is a symmetric random error term that accounts for statistical noise and z_i is a non-negative random variable associated with technical inefficiency.

Monotonicity constraints involve constraints on functions of the partial derivatives of the distance function. As pointed out by O'Donnell and Coelli (2005) the elasticities of the distance function with respect to inputs and outputs are important derivatives.

$$\frac{\partial \ln D_o}{\partial \ln x_k} = \beta_k + \sum_{l=1}^{K}\beta_{kl}\ln x_{li} + \sum_{m=1}^{M}\delta_{km}\ln\frac{y_{mi}}{y_{2i}} \tag{7}$$

$$\frac{\partial \ln D_o}{\partial \ln y_m} = \alpha_m + \sum_{n=1}^{M}\alpha_{mn}\ln\frac{y_{ni}}{y_{2i}} + \sum_{k=1}^{K}\delta_{km}\ln x_{ki} \tag{8}$$

For D_o to be non-increasing in x $\frac{\partial \ln D_o}{\partial \ln x_k} \leq 0$ while for D_o to be non-decreasing in y $\frac{\partial \ln D_o}{\partial \ln y_m} \geq 0$. We did not to impose monotonicity using inequality restrictions in order to investigate the effects of including the environmental output indicator on the rest of parameters, including whether the parameter estimates were more, or less compatible with economic theory after the inclusion of the environmental output indicator.

We include in the output distance function approach the following proxy indicator for provision of environmental goods

$$EG = permanent\ grassland + rough\ grassland \tag{9}$$

where permanent pasture is the land used permanently, during 5 years or more, for herbaceous forage crops, either cultivated or growing wild (European Council 2003) and rough grassland is non-intensive grazing grassland. Permanent and rough pasture are reported to be likely to contribute to positive environmental effects. Thus, the EC Regulation 1782/2003 considers that permanent pasture has a positive environmental effect and as a consequence it is appropriate to adopt measures to encourage the maintenance of existing permanent pasture to avoid a massive conversion into arable land. Article 5 of the regulation, which establishes the principles for keeping agricultural land in a good and environmental condition, states in its second paragraph that "Member States shall ensure that land that was under permanent pasture at the date provided by the area aid... is maintained under permanent pasture". Permanent and rough grassland in agricultural systems are close to natural ecosystems. Ecological services associated with the vegetative cover of grassland are the prevention of soil erosion, renewing ground water and flooding control by enhancing infiltration and reducing water runoff (Altieri 1999). The fact that permanent grassland and rough grassland are not disturbed by tillage favours the development microorganisms in the soil which do beneficial activities decomposition of plant residues, manures and organic wastes (Altieri 1999). Gardner and Brown (1998) reviewed the publication findings on the effects of organic agriculture on micro and macro flora fauna. From this review positive impacts were found on soil organisms, invertebrates and possibly positive impacts on bird and mammal populations were associated with permanent pasture. In addition many bird species are dependent on the presence of permanent pasture land (OECD 1999).

The use of a proxy to account for provision of environmental outputs based on inputs may be seen as problematic. However, the fact that the index is based on inputs, outputs or both is largely irrelevant. The information provided by the index is crucial to account for the provision of environmental output by farms. The use of a proxy for measuring the provision of environmental outputs by farms is the best possible alternative since there is no information in the FBS that accounts for environmental goods such as ground water renewed, water infiltration, decomposition of plant residues, manures and organic matter, soil organisms, invertebrates and bird abundance. Besides, even if such information existed from other datasets (e.g. farm bird surveys) it would be difficult to associate the values with particular farms. Therefore, while the use of any proxy introduces measurement error in the variable which may lead to biased estimates, it is our best available option to account for the provision of environmental goods by the farm.

Estimation

A translog form is specified for the distance function as shown above. If we stack all variables into matrices equation we can write

$$y_i = X_i\beta + \varepsilon_i - z\iota_T \tag{10}$$

$$z \sim G\left(W\phi, \alpha\right) \tag{11}$$

Where, y_i denotes a vector of T observations on the dependent variable; X_i is $T \times m$ matrix of inputs, other outputs and interlinkages between them given a translog function; ε_i is a $T \times 1$ vector accounting for a normal error term; z is a vector $T \times 1$ that accounts for the inefficiency. It follows a gamma distribution with parameters α and farm mean efficiency; W is a $T \times r$ matrix of explanatory variables for inefficiency and ϕ is a $r \times 1$ vector of parameters associated with the explanatory variables for inefficiency.

Our choice of estimation methodology is Bayesian Markov Chain Monte Carlo (MCMC, see Koop 2003 for a detailed explanation). This method is easily implemented in the context of the frontier model employed in this paper. As with the majority of current Bayesian applications, we have limited ourselves to mainly reporting only the first two moments of the posterior distributions (the mean and standard deviation). However, the examination of the full posterior of each of the model parameters obtained using MCMC can often give the investigator further useful information. Computationally, MCMC methods do not impose any great burden, with the model being estimated in a matter of minutes. Bayesian methods are flexible, providing the optional use of prior information, and treat inequality restrictions in a way that classical estimation cannot. In this paper we have been broadly "non informative" and have chosen not imposed inequality conditions, other than those required for inefficiency to be non negative. Therefore, if classical methods (e.g. Maximum Likelihood) were employed to estimate the models within this paper they would, most likely, yield similar results to the Bayesian ones produced herein. An advantage of the MCMC approach is that the distributions of the latent variables, such as the individual firm inefficiencies, are automatically mapped as part of the estimation process, rather than having to be estimated ex-post as in the classical case.

The conditional likelihood function

The assumption about the errors defines the likelihood function. In this case a normal distribution is assumed with mean 0_T and covariance matrix $h^{-1}I_T$; X_i are fixed non stochastic variables; ε_i and ε_j are independent of one another for $i \neq j$ or in other words the errors are independent over all individuals and time periods; z_i and ε_j are independent of one another for all i and j.

$$\begin{aligned} p\left(y|\beta, h, z\right) &= \prod_{i=1}^{N} \frac{h^{\frac{T}{2}}}{\left(2\pi\right)^{\frac{T}{2}}} \left\{ \exp\left[-\frac{h}{2} \sum_{i=1}^{N} \left(y_i - X_i\beta + z_i\iota_T\right) \right] \right\} \\ &\propto h^{\frac{T}{2}} \exp\left[-\frac{h}{2} \left(y_i - X_i\beta + z_i\iota_T\right)' \left(y_i - X_i\beta + z_i\iota_T\right) \right] \end{aligned} \tag{12}$$

where $z = (z_1, \ldots, z_N)'$. Rearranging $\tilde{y}_i = [y_i + z_i\iota_T]$ the following expression is obtained

$$p\left(y|\beta,h,z\right) \propto h^{\frac{T}{2}} \exp\left[-\frac{h}{2}\left(\tilde{y}_i - X_i\beta\right)'\left(\tilde{y}_i - X_i\beta\right)\right] \tag{13}$$

The priors

The likelihood function must be complemented with a prior distribution on the parameters (β, h, z) in order to carry out Bayesian inference. A independent Normal-Gamma prior is used for the coefficients in the production frontier and the error precision (see Koop 2003 for a more detailed explanation on these priors).

The distribution of the inefficiency vector is determined by the distribution of z. The prior for z is hierarchical, as in Fernández, Koop and Steel (2000) and Koop, Osiewalski and Steel (1997) in the sense that a r-dimensional parameter vector $\phi = (\phi_1, \ldots, \phi_r)$ is added where each of the elements of the parameter vector ϕ measures the effect of the inefficiency explanatory variables w_{ij} into the inefficiency distribution. Given ϕ, z has a probability density function given by

$$p\left(z_i|\phi\right) = f_G\left(z_i|\alpha, \mu_z^{-1}\left(\phi\right)\right) = \frac{z_i^{\alpha-1}}{\mu^j\Gamma\left(\alpha\right)} \exp\left(-\mu_z^{-1}\left(\phi\right) z_i\right) \tag{14}$$

where $\Gamma\left(.\right)$ indicates the Gamma function and $f_G\left(z_i|\alpha, \mu_z^{-1}\left(\phi\right)\right)$ is the Gamma density with parameters α and $\mu_z^{-1}\left(\phi\right)$, mean $\mu_z\left(\phi\right)$, and variance $\mu_z^2\left(\phi\right)$. This prior is commonly used in the literature (van den Broeck et al. 1994; Koop, Steel, and Osiewalski 1995; and Fernández, Koop, and Steel 2000). Assuming $\alpha = 1$, the inefficiency distribution is exponential and the inefficiency prior becomes

$$p\left(z_i|\mu_z^{-1}\left(\phi\right)\right) \propto \exp\left(-\mu_z^{-1}\left(\phi\right) z_i\right) \tag{15}$$

As in Fernández, Koop and Steel (2000) we take $\mu_z^{-1}\left(\phi\right)$ to depend on ϕ in the following way

$$\mu_z^{-1}\left(\phi\right) = \prod_{j=1}^{r} \phi_j^{w_{ij}} \tag{16}$$

where w_{ij} are dummy variables and $w_{i1} = 1$. The prior for each of the elements of the vector ϕ are taken to be independent and follow a Gamma density with hyperparameters e_j and g_j which values are associated with prior information about the location of the efficiency distribution. The values for the hyperparameters are $e_1 = 1$ and $g_1 = -\ln(r^*)$ where r^* denotes the prior median of the distribution. In this case $g_1 = -\ln(0.80)$ which is consistent with the belief that under a competitive market farms must be close to the frontier (i.e. full efficiency) (van den Broeck et al. 1994). In addition this value is in concordance with results of previous empirical work by Hadley (2006) on efficiency of dairy farms in England and Wales. In the empirical analysis for $j > 1$ $e_j = g_j = 1$ which implies relatively non-informative values which centre the prior for ϕ_j over 1.

$$p(\phi) = \prod_{j=1}^{r} f_G(\phi_j | e_j, g_j) \tag{17}$$

The joint posterior

Once the likelihood and the priors are defined it is possible to obtain the joint posterior distribution, which defines the Bayesian model.

$$p(\beta, h, \mu_z, z|y) = p\left(y|\beta, h, \mu_z^{-1}, z\right) p(\beta)\, p(h)\, p\left(z|\mu_z^{-1}(\phi)\right) p(\phi) \tag{18}$$

The conditional posteriors

Under a Bayesian approach the posterior inference can be based on the conditional distributions of all the parameters given the observables (Fernández, Koop, and Steel 2000). Knowing the conditional distributions enables the simulation of the joint posterior distributions of the parameters of interest using the MCMC sampler. The conditional posterior for an informative β is a Normal distribution (Koop 2003).

$$p\left(\beta|h, \mu_z^{-1}, z, y\right) \sim N\left(\bar{\beta}, \bar{V}\right) \tag{19}$$

The conditional posterior density for h is

$$p\left(h|\beta, \mu_z^{-1}, z, y\right) \sim G\left(\bar{s}^{-2}, \bar{v}\right) \tag{20}$$

As pointed out above for the inefficiencies a hierarchical prior is used. The conditional posterior for ϕ is proportional to the product of $p\left(z|\mu_z^{-1}(\phi)\right)$ and $p(\phi)$. As pointed out by Koop, Osiewalski and Steel (1997) the fact that the w_{ij} are 0-1 dummy variables simplifies the conditional posterior for ϕ. This conditional posterior has a Gamma form

$$p\left(\phi_j|y, \beta, h, \mu_z^{-1}(\phi), z\right) = f_G\left(\phi_j|e_j + \sum_{i=1}^{N} w_{ij}, g_j + \sum_{i=1}^{N} w_{ij} z_i \prod_{s \neq j} \phi_s^{w_{is}}\right) \tag{21}$$

$$p\left(z_i|\beta, h, \mu_z^{-1}(\phi), y, \rho\right) \propto \exp\left[-\frac{hT}{2}\left[z_i - \overline{X}_i\beta + \overline{y}_i + \frac{\mu_z^{-1}(\phi)}{Th}\right]^2\right] I(z \geq 0) \tag{22}$$

where I is an indicator function which equals 1 is $z \geq 0$ and equals 0 otherwise.

Data

The analysis uses a balanced panel data from the Farm Business Survey (FBS) for the years 2000-2005. A total of 215 dairy farms in England and Wales are included in the dataset. Panel data is advantageous relative to cross-sectional data since farm specific effects can be included, unlike when cross-sectional data is only available (Kumbhakar et al. 2008).

The FBS data includes a large amount of information related to the farm enterprises. The variables we use are milk, other outputs, environmental output, utilised agricultural area (UAA), herd size, the allocation of annual quota after trade, labour, machinery and general costs and livestock costs (Table 1).

It seems reasonable to assume that the efficiency of dairy farms with similar characteristics may be related. Variables used to explain inefficiencies are shown in the Table 2. The use of dummy variables instead of continuous variables is due to the computational difficulty associated with using continuous variables under a Bayesian approach to analyse technical efficiency (Koop *et al.*, 1997). A dummy variable accounting for set-aside payment was created by dividing the total set aside payments to the farm by the total agricultural area. This effectively measures the percentage of the total agricultural area allocated to produce arable crops. By obtaining the median of this measure a dummy variable was created, which effectively differentiates between those farms that produce milk and arable crops (i.e. those above the median of the measure) and those which produce mainly milk (those below the median of the measure). Two organisational structures may be behind these type of farms: those who use part of their arable crop production to feed the animals; and, those who obtain the feedstuff from outside the farm. Environmental payments include agri-environmental payments and other environmental schemes. A dummy variable for environmental payments was created to examine the effect of such payments on farm efficiency. This was created by dividing the total environmental payments received by the farm by the total agricultural area, then giving a value of 1 for values above the median and zero for values below the median. Financial pressure has been used previously in the literature as a possible determinant of efficiency and found to be negatively significant (Hadley 2006; Paul, Johnston, and Frengley 2000; Iraizoz, Bardaji, and Rapun 2005). Hadley (2006) uses a ratio of rental equivalent (i.e. the sum of interest and rent paid, charges that must be paid when they fall due and non payment of which could result in loss of tenure or foreclosure of loans) to gross margin; Paul, Johnston and Frengley (2000) use a debt/equity ratio to account for financial pressure; and Iraizoz, Bardaji and Rapun (2005) use a ratio of paid rents and interests to gross margin. In this research a ratio between external liabilities and total assets is calculated and used to account for financial pressure. Here, financial pressure is the ratio of liabilities of the farm divided by the assets of the farm. The mean of the financial pressure ratio from the sample is 0.10 whereas the median is 0.05. A dummy variable was created allocating a value of one for those ratio values larger than 0.10.

A dummy variable was created to account for the level of participation in the milk quota market. This was obtained by adding the quota bought/sold and the quota leased in/out during the period; dividing this amount of quota traded by the initial amount of quota;

obtaining the median of this result and assigning a value of one for those farms that traded more than the median farm and assigning a value of 0 otherwise. The introduction of this dummy investigates whether farms participating in a larger scale in the quota market are different to those that participate less in terms of efficiency. This differentiation between "participants" and "non-participants" may be reflecting different types of technologies.

Farm size is considered a relevant determinant of efficiency in the literature (Hadley 2006; Iraizoz, Bardaji, and Rapun 2005). The number of cows was used to create a proxy dummy variable for farm size. This has been used in the literature by Tauer and Belbase (1987). Here a dummy variable that accounts for production intensity was also introduced. Firstly a ratio of the number of cows divided by the size of the farm was calculated. The median of the ratio was then obtained (1.07) and for values larger than the median the dummy variable takes the value 1 and 0 otherwise. A dummy accounting for farms in LFAs was included in the analysis to examine whether farms located in LFAs where less efficient that farms located in non-LFAs. Hadley (2006) found a small negative effect on efficiency of dairy farms located in LFAs. Barnes (2008) also finds similar results for dairy farms in Scotland. In addition dummy variables for GORs (Government Office Regions) in England and Wales were introduced to account for any differences in efficiency between regions. The benchmark region is West Midlands.

The unlogged data was normalised (i.e. divided by the geometric sample mean) so that each unlogged variable had a sample mean of one. This means that the monotonicity conditions in equation (6) can be expressed as $\alpha_m \geq 0$ and $\beta_k \leq 0$. However, the reported coefficients in this paper have the reverse signs due to the sign of the dependent variable being the opposite of equation (6).

Empirical results

Table 3 reports the mean coefficients of the MCMC sample observations for both models: the model that does not include the environmental output (M1); and, the model that incorporated provision of environmental outputs (M2). Initially, a total number of 150,000 iterations were generated from which every 5th iteration was retained. This makes 30,000 random draws were generated from the conditional distributions with 5,000 draws discarded and 25,000 draws retained. These 25,000 draws can be considered as a sample from the joint posterior density function of the parameters. The point estimates of the coefficients for the outputs and inputs have all the right sign except for labour and livestock costs for M2. Table 3 also shows the 90% posterior coverage regions calculated as the fifth and ninety fifth percentiles of the MCMC sample observations. By examining the estimated conditional posteriors of the output and input coefficients it can be seen that the associated coverage region for labour costs for both M1 and M2 include zero, meaning that there is a positive probability that the monotonicity is violated. This also occurs for annual allocation of quota, number of cows, machinery and general costs and livestock costs in M2. No technological effect was found in any of the models.

Technical efficiency

The technical efficiency of the sample of the dairy farms range from 0.32 to 0.98 with median 0.89 and mean 0.85 for M1 whereas technical efficiency values range from 0.01 to 0.99 with median 0.39 and mean 0.36 for M2. The two conditional posterior p.d.f. for mean efficiency across the sample of dairy farms differ between models (Figure 1) generally showing that when accounting for provision of environmental goods the efficiency levels for most of the farms in the sample is relatively low and there is room for efficiency improvement.

Table 4 shows the estimates of the parameters ϕ_j associated with the explanatory variables of efficiency. There were 76 farms receiving environmental payments in the sample. Results for M1 suggest that those farmers who receive relatively high environmental payments (i.e. they conduct complex environmental management) are less efficient than those who receive relatively small payments for managing the environment or receive no payment at all. Another interpretation of the results is that more efficient farms do not take on relatively high payments for managing the environment. However, this does not mean that when less efficient farms do take on environmental payments they do not increase efficiency. When the proxy for provision of environmental output is incorporated in the analysis, the negative effect that conducting environmental management has on efficiency under M1 disappears. This may be suggesting that there is a correlation between perceiving an environmental payment and the provision of environmental outputs.

On the contrary to what happens to environmental payments under M1, set-aside payments are negatively correlated with inefficiency. A total of 67 farms in the sample received set-aside payments during the period studied. Set-aside payments are calculated per ha of utilised agricultural area. This effectively is a measure of the percentage of arable land. Therefore, our results suggest that those milk producer farms that also specialised in arable production have lower levels of inefficiency than milk producer farms where arable production is less important. This result may indicate that linkages between arable crop production and milk production such as the use of arable crops for feeding are crucial to be more efficient. When the provision of environmental goods is incorporated in the analysis (i.e. M2) farmers who receive a relatively high set-aside payment per ha are less efficient than farmers who receive relatively less set-aside payment per ha, opposite to the result obtained using model M1 (i.e. not accounting for environmental output). The introduction of provision of environmental goods in the analysis in the way specified here means that farms where relatively more arable land is produced per ha (i.e. those receiving higher set aside payments per ha) are less efficient. The explanation for this is the following, since our measure for provision of environmental goods is based on permanent pasture and rough grassland areas, farms with large arable crop areas are likely to be *penalised*.

While the location of farms in LFAs was found unrelated to inefficiency under M1, when provision of environmental outputs is disregarded, a farm was found to be more efficient if it is located in a LFA when such provision is observed. This result highlights that it is in these areas where permanent and rough grassland (i.e. provision of environmental outputs) is likely to be concentrated. With regard to regional differences looking at the 90% posterior coverage regions only farms located in East England are less efficient than farms in West Midlands (the benchmark region) under M1. Regions do not show any difference in efficiency levels between them and the West Midlands region under M2.

Despite based on the coverage regions the rest of determinants (e.g. farmer´s age, financial pressure, intensive) of inefficiency are not relevant, there are some interesting results worth discussing. Model results show that financial pressure tends to be positively correlated with inefficiency only when environmental outputs are not taken into account. An interpretation for this may be that, when environmental outputs are not taken into consideration in the analysis, those farmers with higher financial pressure tend to be less efficient than those who are not under financial pressure because of farms finding difficulties in obtaining financial resources from banks, which prefer to loan to low risk borrowers. This would hamper indebted farmers to incorporate new technologies. This finding is in concordance with results obtained in previous studies on the influence of debt ratios on technical efficiency (Paul *et al.*, 2000, Iraizoz *et al.*, 2005, Hadley, 2006). However, this was not found under M2 which may indicate that the provision of environmental outputs by farms does not require of large financial resources, hence when such provision is incorporated into the analysis the relative relevance of financial pressure on efficiency vanishes. Results suggest that farms located in the North West also tend to be less efficient than in the West Midlands although this is not as highly supported by the coverage region as for the East England case.

Tables 5 and 6 show the 25 highest increase and drops in ranking according to their mean efficiency scores respectively once the provision of environmental outputs is incorporated to the efficiency analysis. It is clear that by introducing environmental output in the analysis (M2) the ranking changes. The largest change in ranking was found to be 196 ranking positions down by farm 118 (from position 16 to position 212) whereas the largest increase in ranking positions was found to be 187 ranking positions up by farm 139 (from position 205 to position 18). With the incorporation of environmental output 84% of the top 25 farms under the ranking using M1 are not in the top 25 under the ranking using M2, and 81% of these are not even in the top 100. Focusing in the bottom of the ranking 88% of the bottom 25 farms when using M1 are not in the bottom 25 when M2 is used to do the efficiency ranking, and 45% of these are not in the bottom 100. This result shows how crucial the efficiency measure used is for the implementation of policies aiming at improving efficiency. A policy targeting those farms with low efficiency levels using a ranking derived from a model which does not incorporate environmental outputs may be targeting the wrong farms.

In order to test whether the relative farm efficiency levels obtained in both models differ (i.e. whether rankings using M1 and M2 are different) we used Spearman's correlation which confirmed that relative farm efficiency level differ between models (p-value$>$0.05). Using the most extreme cases, farms 139 and 118, illustrate what occurs in rankings for many of the farms. As pointed out above, when the environmental output is not included in the analysis farm 118 is more likely to be more efficient than farm 139 whereas when the environmental output is included, farm 139 is more likely to be the most efficient of the two. In order to assess this, each draw corresponding to the efficiency score for farm 118 was compared with a draw corresponding to the efficiency score from farm 139. The probability that the efficiency score of farm 118 was larger than a score from farm 139 was then calculated, and the probability that farm 139 is more efficient than farm 118 with M1 is (approximately) 0% whereas this probability increases to 99.37% with M2.

Conclusions

The consideration of environmental aspects in the analysis of technical efficiency of farms enables us to create a more complete measure of efficiency, which is in line with current EU policy agenda of having a sustainable agriculture sector that delivers environmental goals as well as traditional market outputs.

The distribution of the mean and rankings of efficiencies across farms is greatly altered when the provision of environmental outputs by farms is introduced in the analysis. This finding that has policy implications. One of the pillars of EU and Defra agricultural policy is to make agriculture both economically and environmentally sustainable. Based on the results obtained, a standard view in which positive externalities are not accounted for does not provide a realistic picture of which farms are both economically and environmentally more efficient. By using a holistic approach in which environmental outputs of the farm are included, useful information can be provided to policy makers about which farms may need support in achieving both higher environmental and economic efficiency. Policy makers may be interested in identifying those farms that are less efficient in order to help them to improve. Using the traditional approach with no accountability for environmental output may well lead to targeting the wrong farms, i.e. those that are technically and environmentally efficient and overlook farms that could improve efficiency.

Farmers who received relatively high environmental payments (i.e. conducted relatively many activities regarding countryside maintenance and management) were not found to be associated with being the more or less efficient farmers, when provision of environmental goods were taken into account. On the contrary, when environmental outputs were not taken into account such environmental payments were correlated with inefficiencies. However, this difference may indicate that at least some of the activities conducted by the farmer in order to receive environmental payments are related to our environmental goods indicator.

When accounting for the provision of environmental outputs by farms our results suggest that the least efficient farms are those that have a relatively large farm area allocated to arable crop production and are located outside LFAs. Farms with relatively large arable crops areas are likely to cause negative environmental impacts to soil, water and biodiversity due to pollution derived from nutrients and pesticides use. On the other hand, an intensive dairy sector is not necessarily technically and environmentally more (or less) efficient than a non-intensive dairy sector.

Therefore, if a policy aim was to achieve higher efficiency levels for multifunctional farms, that is, farms that can provide both conventional goods such as milk, cereals and oilseeds as well as environmental goods such as providing habitats for birds, attention should be paid to all farms, and especially to those that are less efficient making sure, through incentives (e.g. environmental payments), that they conduct activities that provide environmental goods and improve their efficiency and avoid to do activities that have negative impacts to the environment (e.g. reducing arable crop production).

Fernández *et al.* (2005) pointed out that we must be cautious when using firm-specific measures to rank firms or make statements about whether a firm is more or less efficient than others. In this respect, we acknowledge that there is not a unique indicator for the provision of environmental outputs by farms that can be used in efficiency analysis and different environmental indicators may lead to different results. However, we show that the incorporation of provision of environmental goods by farms in efficiency analysis may have important consequences when supporting policy makers decisions.

Looking forward, from 2006 the FBS includes questions on environmental characteristics and activities; environmental crops and farm habitats; and countryside maintenance and management activities, which includes questions on the costs associated with conducting environmental activities. This information could be used to build an environmental output indicator of the farm which would account for more specific activities in the farm than the environmental indicator used here. Unfortunately, these questions were not introduced in the FBS during the period used in this study (2000-2005).

To conclude we would like to emphasise that more consideration should be given to including externalities, particularly positive externalities, into efficiency analysis.

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Table 1: Descriptive Statistics of the Variables Used

Variable	Min.	Max.	Mean	Std. dev.
Milk (Fisher index)	1	898	100	77
Other outputs (Fisher index)	0	678	125	94
Leasing quota out	0	15,103	208	926
Environmental output	0	0.98	0.17	0.22
Utilised Agricultural Area	16	883	118	109
Milk Quota	23,600	4,401,100	713,416	515,840
Number of cows	4	790	110	74
Leasing quota in	0	19,000	512	1,389
Machinery&General costs	4,531	195,274	40,484	30,772
Labour costs	12,009	231,573	46,101	28,835
Livestock costs (per cow)	84	1,880	511	208

Table 2: Explanatory Variables for Inefficiency

Variable	**Definition**
Set aside payment	1 if the farm above the median of the measure; 0 otherwise
Environmental payments	1 if the farm above the median of the measure ; 0 otherwise
Financial pressure	1 if financial pressure>0.10 and 0 is financial pressure<0.10
Quota market participation	1 if the farm "participates" in the quota market; 0 otherwise
Farmer's age_52	1 if the farmer's age is more than 52; 0 otherwise
Intensive	1 if the number of cows/farm size > 1.07; 0 otherwise
LFA	1 if the farm is located in a LFA; 0 otherwise
North East	1 if the farm is located in NE; 0 otherwise
Yorkshire & Humber	1 if the farm is located in Y&H; 0 otherwise
North West	1 if the farm is located in NW; 0 otherwise
East Midlands	1 if the farm is located in EM; 0 otherwise
East England	1 if the farm is located in EE; 0 otherwise
South East	1 if the farm is located in SE; 0 otherwise
South West	1 if the farm is located in SW; 0 otherwise
Wales	1 if the farm is located in WA; 0 otherwise

Table 3: Slope Parameters

		M1		M2
	Coeff.	**90% posterior**	**Coeff.**	**90% posterior**
α_0	0.037	$(0.029, 0.104)$	0.739	$(0.690, 0.771)$
Other outputs	-0.275	$(-0.316, -0.233)$	-0.021	$(-0.028, -0.013)$
Environmental output	–	–	-0.981	$(-0.992, -0.971)$
Utilised Agricultural Area	0.089	$(0.036, 0.143)$	0.944	$(0.899, 1.054)$
Milk Quota+qui-quo	0.392	$(0.292, 0.494)$	0.017	$(-0.002, 0.036)$
Number of cows	0.427	$(0.321, 0.537)$	0.011	$(-0.014, 0.037)$
Machinery&General costs	0.083	$(0.012, 0.154)$	0.012	$(-0.003, 0.026)$
Labour costs	0.005	$(-0.061, 0.071)$	-0.007	$(-0.023, 0.010)$
Livestock costs (per cow)	0.185	$(0.126, 0.246)$	-0.004	$(-0.018, 0.010)$
Year	0.013	$(-0.021, 0.048)$	0.002	$(-0.003, 0.007)$
Year sq.	-0.001	$(-0.006, 0.004)$	0.000	$(-0.001, 0.000)$

Table 4: Efficiency Without Environmental Output vs. With Environmental Output

	M1		M2	
Variable	ϕ_j	**90% posterior**	ϕ_j	**90% posterior**
Lambda	0.15	$(0.09, 0.27)$	1.25	$(0.79, 1.99)$
Environmental payment/ha	0.37	$(0.02, 0.74)$	0.11	$(-0.19, 0.42)$
Set-aside payment/ha	-0.66	$(-1.16, -0.15)$	0.49	$(0.13, 0.86)$
Financial pressure	0.22	$(-0.08, 0.52)$	0.06	$(-0.18, 0.31)$
Quota Market participation	-0.27	$(-0.55, 0.02)$	0.08	$(-0.16, 0.31)$
Age_52	-0.12	$(-0.41, 0.16)$	0.03	$(-0.20, 0.26)$
Intensive	0.34	$(-0.04, 0.74)$	-0.04	$(-0.35, 0.25)$
LFA	0.14	$(-0.21, 0.49)$	-0.38	$(-0.67, -0.08)$
North East	0.21	$(-0.82, 1.48)$	0.05	$(-0.85, 1.28)$
Yorkshire & Humber	-0.09	$(-0.84, 0.67)$	0.24	$(-0.34, 0.86)$
North West	0.49	$(-0.07, 1.06)$	0.02	$(-0.48, 0.54)$
East Midlands	-0.26	$(-0.90, 0.41)$	-0.16	$(-0.70, 0.41)$
East England	0.81	$(0.00, 1.74)$	-0.16	$(-0.70, 0.41)$
South East	0.15	$(-0.52, 0.85)$	0.09	$(-0.45, 0.68)$
South West	0.00	$(-0.53, 0.56)$	0.12	$(-0.36, 0.60)$
Wales	-0.34	$(-0.88, 0.20)$	-0.32	$(-0.79, 0.14)$

Note: Estimates based on Gibbs sample size 25,000. Numbers in parenthesis indicate 90% highest posterior density intervals

Table 5: Highest Increase in Ranking

Farm	Rank M1	Rank M2	Rank diff.
139	205	18	187
134	188	10	178
74	181	12	169
101	199	30	169
106	186	21	165
112	174	13	161
91	160	9	151
133	211	62	149
42	180	33	147
194	165	20	145
52	184	39	145
84	147	3	144
169	166	26	140
128	196	56	140
38	152	15	137
93	178	45	133
138	208	75	133
95	202	71	131
39	179	50	129
145	171	44	127
8	191	66	125
9	198	76	122
58	159	38	121
113	197	79	118
127	121	11	110

Table 6: **Highest Drop in Ranking**

Farm	Rank M1	Rank M2	Rank diff.
118	16	212	-196
117	13	206	-193
23	10	202	-192
148	18	208	-190
147	9	196	-187
195	2	180	-178
157	23	199	-176
159	29	203	-174
150	15	188	-173
15	20	192	-172
154	1	171	-170
149	45	213	-168
161	33	193	-160
176	40	200	-160
18	49	204	-155
192	51	201	-150
13	46	195	-149
29	27	175	-148
212	38	186	-148
7	66	210	-144
163	24	158	-134
182	50	182	-132
146	56	187	-131
22	7	137	-130
19	36	165	-129

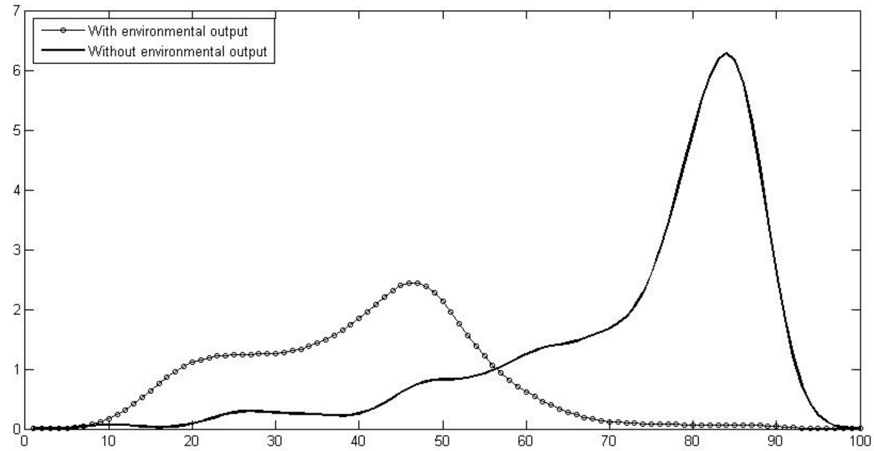

Figure 1: **Mean Efficiency Kernel Across Dairy Farms With and Without Provision of Environmental output**