Provision of environmental output within a multi-output distance function approach

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Abstract

This paper redefines technical efficiency by incorporating provision of environmental goods as one of the outputs of the farm within a multi-ouptut distance function framework. A ratio of permanent and rough grassland area divided by total agricultural area is used as a proxy for the provision of environmental goods. The multi-output distance function approach is used to estimate technical efficiency under a restricted supply policy.

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 farm efficiency rankings change by incorporating provision of environmental outputs in the definition of efficiency, which may have important political implications.

1 Introduction

The provision of environmental goods (e.g. habitat for insects, bird species) and bads (e.g. pollution derived from the use of fertilisers) by the farm are

positive and negative externalities respectively in the sense that they create additional benefits and costs to society derived from farmer actions, who does not receive compensation for the benefits provided nor pay for the harm done. The non-existance of a market for the good and/or bad provided leads to the market to not achieving efficiency and therefore to a market failure. This gives 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 as well as technological progress, which has favoured intesification, 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, oilseed rape, linseed, peas and beans; and to deliver environmental benefits. This measure was voluntary when it was introduced and became compulsary since 1992 with the MacSharry reform. But it was specially since the introduction of the Agenda 2000 when agricultural policies in the EU have changed from support of farm commodity prices to area based payments and payments for the supply of environmental goods, i.e. positive externalities (Cambell et al., 2007). In recognition of the high ecological and environmental impact of intensification of agriculture agri-environmental schemes (AES) have been developed under Regulation (EEC) 2078/92 which allows MS to provide support to farmers for making environmnental improvements to their land by changing farming practices (Hynes et al., 2008). These payments for environmental goods through agri-environmental schemes aim to help providing environmental outputs at local level and effectively paying the farmers for what is considered a social benefit. This is in line with the idea of having a sustainable agriculture sector. According to this idea the UK Government set up an independent Policy Commission on the future of farming and food. The Commision'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 in-

stance, many bird species are dependent on the presence of permanent pasture land (OECD, 1999) and the change of this land use may well alter the ecological system. Despite the number of publications accounting for multiple outputs in the productivity and efficiency literature is large, only some of these publications involve externalities (Dorfman and Koop, 2005) and most of them account only for negative externalities such as pollutants. Several authors have selected a multiple output framework that allow for at least one output to be undesirable (e.g. air pollutants) (Färe et al., 1989, Färe at al., 1996, Färe et al., 2001, Lansink and Reinhard., 2004, Murty et al., 2006). Yet no many studies have included the provision of environmental goods (e.g. biodiversity) in production related analysis. An exception is a recent publication by Omer et al. (2007) who conducted an study in the productivity performance and biodiversity conservation in intensive agricultural systems using a stochastic production frontier approach. They included a biodiversity index (BI) based on measures of plant species richness as to examine the relationship between the state of biodiversity and output in a specialised intensive farming system. A positive relationship was found between state of biodiversity and productivity. This result supports the implementation of biodiversity conservation policies.

As Färe et al. (2001) pointed out it has been a common practice to ignore the output (i.e., reduced emmisions) of the pollution abatement activities assuming that inputs in such activities are inproductive. This has led to conclude that environmental regulations have an adverse effect on productivity (Färe et al., 2001). In the same way it can be argued that provision of environmental outputs have been ignored, hence inputs associated with such provision of environmental goods has been ignored. This omission in the production and efficiency analysis may lead to biased results which could mislead policy makers in their policy decisions. We include an environmental output in the production function within a multi-output distance function approach in order to account for the provision of environmental goods by the farm when conducting technical efficiency analysis.

Inferences about firm specific inefficiencies has been vastly studied 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 are taken into account when measuring efficiency. Such a measure would be in concordance with policy objectives related to a sustainable

agriculture. Policy objectives regarding sustainable agriculture include keeping non-marketable benefits produced by agriculture such as diversity of flora and fauna and landscape views. If efficiency rankings change with the proposed measure for measuring efficiency there are policy and/or management implications. 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 section focuses on externalities, the difficulty associated with measuring environmental goods such as biodiversity and what this means for measuring technical efficiency and policy making. Section 2 explains the methodology used. Section 3 focuses on the data used. Results are presented in section 4 and conclusions are gathered under section 5.

2 Methodology

We study milk producer farms in England and Wales. These producers have an annual milk quota that partially binds production. This is because producers can lease in and/or lease out milk during the production year. Therefore we include in the analysis the fact that production is partially constrained by the annual quota Q, leasing in quota qui and leasing out quota quo. Not acounting for such constraints may lead to wrongly attributing the effects of such constraint to the farmer being unsuccesful in optimising production (Färe er al., 1994).

Optimising behaviour is the assumption on which conventional microeconomics is based on. 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 know the factors behind inefficiencies and how inefficient producers are on average as well as individually (Färe et al., 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 ouptuts that can be feasibly produced using the set of all inputs. The output set for production technology is defined as

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

where $\hat{y}$ refers to all ouptuts of the farm including milk, the leasing out of quota (quo) and the environmental output and $\hat{x}$ refers to all inputs used in the farm including the leasing in quota (qui) and the annual allocation of quota Q.

The output distance function is defined on the output set $P\left(\hat{x}, Q\right)$ as

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

which means that the inital allocation of quota Q, the leasing in qui and leasing out quota quo are treated in the same way as conventional inputs and outputs.

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 et al., 2002, Brümmer et al., 2006).

$$
\begin{aligned}
\ln D_{Oi} &= \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln \hat{y}_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln \hat{y}_{mi} \ln \hat{y}_{ni} + \sum_{k=1}^{K} \beta_k \ln \hat{x}_{ki} + \\
&\quad + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln \hat{x}_{ki} \ln \hat{x}_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} \ln \hat{x}_{ki} \ln \hat{y}_{mi} \\
&\quad i = 1, ..., N \qquad (3)
\end{aligned}
$$

where i denotes the ith farm in the sample. By using linear homogeneity of the output distance function in outputs equation (2) can be transformed into an estimable regression model by normalising the function by one of the outputs (Brümmer et al., 2006, Brümmer et al., 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:

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

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

$$\ln D_O \left(\frac{\hat{y}_i}{\hat{y}_{2i}}, x \right) = \ln \frac{1}{\hat{y}_{2i}} \left(\hat{y}_i, \hat{x}_i \right) \tag{5}$$

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

where 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'Donell and Coelli (2005) the elasticities of distance with respect to inputs and outputs are important derivatives.

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

$$\frac{\partial \ln D_o}{\partial \ln y_m} = \alpha_m + \sum_{m=1}^{M} \alpha \beta_{mn} \ln \frac{\hat{y}_{ni}}{\hat{y}_{2i}} + \sum_{k=1}^{K} \delta_{km} \ln \hat{x}_{ki} \tag{8}$$

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

$$EG = \frac{permanent\ grassland + rough\ grassland}{total\ agricultural\ area} \tag{9}$$

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 grassand 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).

2.1 Estimation

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

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

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

Now, y_i denotes a vector of T observations on the dependent variable. γ_i is a $T \times 1$ vector, z 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.

Bayesian econometric methods and in particular posterior simulators of Markov Chain Monte Carlo (MCMC) algorithms are being increasingly popular thanks to a large increase in computer power over the last decade. MCMC aim to simulate direct draws from a posterior distibution. Numerical Bayesian inference is performed using the Gibbs sampler, a MCMC technique (see Appendix A for a more detailed explanation).

2.1.1 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 nonstochastic 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.

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

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

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

2.1.2 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 Appendix B 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 et al. (2000) and Koop et al. (1997) in the sense that a r-dimesional 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

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

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

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

As in Fernández et al. (2000) we take $\mu_z^{-1}(\phi)$ to depend on ϕ in the following way

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

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 te frontier (i.e. full efficiency) (van den Broeck et al., 1994). In addition this value is in corcondance 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 noninformative values which centre the prior for ϕ_j over 1.

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

2.1.3 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.

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

2.1.4 The conditional posteriors

Under a Bayesian approach the posterior inference is based on the conditional distributions of the parameters given the observables (Fernández et al., 2000). Conditional distributions facilitate the obtention of the posterior distributions of the parameters of interest. Conditional distributions are obtined using MCMC sampler to generate drawings from it. The conditional posterior for an informative β is a Normal distribution (see Appendix B).

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

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 et al. (1997) the fact that the w_{ij} are 0-1 dummy variables technically simplifies obtaining the conditional posterior for ϕ. This conditional posterior has a Gamma form only with dummy variables.

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

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

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

3 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 advantegous to cross-sectional data since farm specific effects cannot be controlled for when only cross-sectional data is available (Kumbhakar et al., 2008).

The FBS data includes a large amount of information related to the farm enterprise. We use milk, leasing out quota, and environment as outputs and utilised agricultural area (UAA), milk output, herd size, leasing in quota, labour, machinery and general costs, livestock costs (Table 1).

	Variable	**Min.**	**Max.**	**Mean**	**Std. dev.**
y	Milk (Fisher index)	1	898	100	77
α_1	Cereals (Fisher index)	0	678	125	94
α_2	Leasing quota out	0	15,343	205	922
α_3	Environemental output	0	0.98	0.17	0.22
β_1	Utilised Agricultural Area	16	883	118	109
β_2	Milk Quota	23,600	4,401,100	713,416	515,840
β_3	Number of cows	4	790	110	74
β_4	Leasing quota in	0	19,000	512	1,389
β_5	Machinery&General costs	4,531	195,274	40,484	30,772
β_6	Labour costs	12,009	231,573	46,101	28,835
β_7	Livestock costs (per cow)	84	1,880	511	208

Table 1: Descriptive statistics of the variables used

It seems reasonable to assume that the efficiency of dairy farms with similar characteristics may be related. Variables used to explain inefficiencies these are shown in the Table 2. A dummy variable accounting for set-aside payment was created by dividing the total set aside payments to the farm divided by the total agricultural area. By obtaining the median of this measure a dummy variable was created. The introduction of this dummy variable effectively aims to investigate whether such payment and effectively farms that allocate a relatively large percentage of the area to produce arable crops i.e. less specialised in milk production are less efficient than more specialised milk producers. 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 divided by the total

Variabe	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
Intesive	1 if the numberof cows/farm size > 1.07; 0 otherwise
LFA	1 if the farm is located in a LFA; 0 otherwise

Table 2: Explanatory variables for inefficiency

agricultural area and 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, et al., 2000; Iraizoz et al., 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 et al. (2000) use a debt/equity ratio to account for finacial pressure; and Iraizoz et al., (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 0.09 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 farms that enter in the milk market either by leasing quota (in or out) or by buying/selling milk quota. The introduction of this dummy aims to investigate whether farms participating in the quota market are different to those that do not participate in such market in terms of efficiency. This differentiation between participants and no-particpants may be reflecting different types of technologies.

Farm size is considered a relevant determinant of efficiency in the literature (Hadley, 2006; Iraizoz et al., 2005) as well as 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 intesiveness was introduced. Firslty a ratio of number of cows divided by the size of the farm was calculated. Then the median of the ratio was obtained (1.07) and for values larger than the median the dummy variable takes value 1

and 0 otherwise. A dummy accounting for farms in a LFA was included in the analysis to examine whether farms located in LFA where less efficient that farms located in non-LFA. Hadley (2006) found a small negative effect on efficiency of dairy farms located in LFA. Barnes (2008) also finds similar results for dairy farms in Scotland.

The data was normalised so that each variable had a sample mean of one. This means that the monotonicity conditions can be expressed as $\alpha_m \geq 0$ and $\beta_k \leq 0$. It is worth noting that coefficient results have been changed the sign and therefore the expected coefficiencts should be $\alpha_m \leq 0$ and $\beta_k \geq 0$.

4 Empirical results

Table 3 reports the mean coefficients of the MCMC sample obsrvations for both models. A total number of 150,000 iterations were created from which every 5th iteration was drawed. This makes 30,000 random drawings were generated from the conditional distributions with 5,000 drawings discarded and 25,000 drawings retained. The drawings generated 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 the coefficient for leasing in quota which coefficient is insignificantly different from zero. Thus outputs coefficients are negative indicating that the distance function is non-dicreasing in outputs and non-increasing in inputs. Table 3 also shows the 90% posterior coverage regions calculated as the fifth and ninety fith percentiles of the MCMC sample observations. By examiniting the estimated conditional posteriors of the output and input coefficients it can be seen that the associated coverage region for α_1, β_4 and β_6 include zero, meaning that there is a positive probability that the monotonicity is violated. However this probability is relatively small. Full results for all coefficients are reported in Appendix C.

	M1		M2	
	Coeff.	**90% posterior**	**Coeff.**	**90% posterior**
α_0	0.072	$(0.029, 0.115)$	-0.049	$(-0.093, -0.003)$
α_1	-0.035	$(-0.097, 0.028)$	-0.071	$(-0.132, -0.009)$
α_2	-0.291	$(-0.334, -0.247)$	-0.268	$(-0.313, -0.224)$
α_3	–	–	-0.227	$(-0.257, -0.197)$
β_1	0.056	$(0.004, 0.109)$	0.054	$(-0.001, 0.110)$
β_2	0.375	$(0.271, 0.480)$	0.214	$(0.100, 0.328)$
β_3	0.456	$(0.344, 0.569)$	0.482	$(0.367, 0.599)$
β_4	-0.017	$(-0.055, 0.020)$	-0.012	$(-0.048, 0.026)$
β_5	0.080	$(0.009, 0.151)$	0.080	$(0.004, 0.015)$
β_6	0.036	$(-0.028, 0.100)$	0.037	$(-0.032, 0.105)$
β_7	0.176	$(0.112, 0.240)$	0.140	$(0.075, 0.204)$

Table 3: Slope parameters

No significant differences are found between the coefficients of both models.

4.1 Technical efficiency

Two models were estimated. One does not include the environmental output (M1) whereas the other model does (M2). For M1 the technical efficiency of the sample of the dairy farms range from 0.31 to 0.98 with median 0.88 and mean 0.83 whereas for M2 the technical efficiency values range from 0.41 to 0.98 with median 0.86 and mean 0.82. The two conditional posterior p.d.f. for inefficiency do not differ between models (Figure 1).

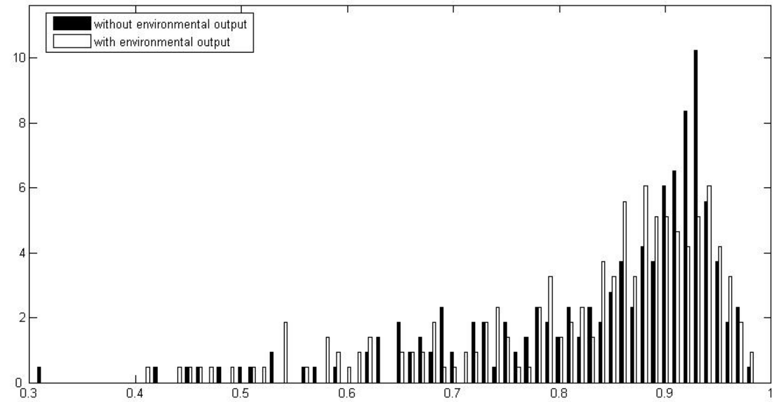

Figure 1: Efficiency distributions with and without provision of environmental goods

Table 4 shows the results for the estimates of the parameters ϕ_j associated with the explanatory variables of efficiency. There were 76 farms receiving environmental payments in the sample. Environmental payments have a positive effect on efficiency. This result suggests that more efficient farms take on environmental payments. However, this does not mean that when less efficient farms take on environmental payments they do not increase efficiency. This result is found in both models M1 and M2. On the contrary to what happens to environmental payments, set-aside payments have a negative efffect on efficiency. 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 specialise in arable production have lower levels of efficiency than milk producer farms where arable production is less important. This result is consistent in both models. Results for both models show that financial pressure has a positive impact on mean efficiency levels. With regard to the participation in the quota market by leasing in/out quota results do not show any significant impact. However, the positive sign of the coefficient suggest a small probability of a positive effect on efficiency. No impact on efficiency was found for farmer's age. Altghough higher intensive farms tend to increase efficiency under M1, when environmental output is considered this effect becomes less likely to occur. Finally, the location of

the farm on LFA is not significant for both models. However it is worth noting that the signs for both models are different. Thus, under M1 being on a LFA tends to have a negative impact on efficiency whereas under M2 the tendency of this effect is to be positive possibly due to the fact htat environmental output is included in the analysis.

	M1		**M2**	
Variable	ϕ_j	**90% posterior**	ϕ_j	**90% posterior**
Lambda	0.14	$(0.07, 0.26)$	0.15	$(0.07, 0.27)$
Environmental payment/ha	0.40	$(0.07, 0.75)$	0.31	$(0.02, 0.64)$
Set-aside payment/ha	-0.43	$(-0.83, -0.01)$	-0.38	$(-0.78, -0.02)$
Financial pressure	0.23	$(-0.04, 0.50)$	0.24	$(-0.02, 0.50)$
Quota Market participation	0.23	$(-0.43, 0.87)$	0.22	$(-0.44, 0.87)$
Age_52	-0.10	$(-0.37, 0.16)$	0.02	$(-0.24, 0.28)$
Intensive	0.23	$(-0.10, 0.56)$	0.11	$(-0.21, 0.42)$
LFA	-0.10	$(-0.39, 0.20)$	0.13	$(-0.16, 0.41)$

Table 4: Efficiency without environmental output vs. with environmental output

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

Tables 5 and 6 show the farms ranking of the 50 highest and lowest rankings according to their mean efficiency scores respectively. It is clear that by introducing environmental output in the analysis (M2) the ranking changes. The largest change in ranking was found to be 127 ranking positions up by farm 1 (from position 147 to position 20) whereas the largest fall in ranking positions was found to be 108 ranking positions down by farm 35 (from position 19 to position 127).

Farm	**Rank M1**	**Rank M2**	**Rank diff.**	**Farm**	**Rank M1**	**Rank M2**	**Rank diff.**
154	1	2	-1	61	26	58	-32
168	2	3	-1	79	27	52	-25
94	3	18	-15	19	28	64	-36
195	4	1	3	182	29	56	-27
102	5	5	0	186	30	53	-23
204	6	6	0	212	31	23	8
156	7	15	-8	108	32	74	-42
22	8	9	-1	15	33	46	-13
189	9	49	-40	59	34	93	-59
117	10	14	-4	118	35	75	-40
104	11	10	1	71	36	59	-23
23	12	13	-1	7	37	4	33
48	13	76	-63	176	38	95	-57
147	14	17	-3	150	39	61	-22
144	15	31	-16	141	40	29	11
63	16	39	-23	126	41	19	22
70	17	37	-20	16	42	45	-3
157	18	27	-9	148	43	47	-4
35	19	127	-108	87	44	100	-56
152	20	51	-31	55	45	28	17
86	21	35	-14	175	46	105	-59
50	22	32	-10	211	47	16	31
44	23	120	-97	69	48	55	-7
159	24	50	-26	24	49	68	-19
49	25	106	-81	76	50	110	-60

Table 5: Highest 50 efficiency scores

Farm	Rank M1	Rank M2	Rank diff.	Farm	Rank M1	Rank M2	Rank diff.
28	166	170	-4	52	191	205	-14
39	167	203	-36	180	192	156	36
169	168	174	-6	128	193	204	-11
115	169	91	78	166	194	147	47
188	170	73	97	8	195	192	3
213	171	136	35	129	196	138	58
90	172	191	-19	113	197	196	1
194	173	190	-17	125	198	184	14
145	174	187	-13	3	199	167	32
78	175	164	11	135	200	163	37
112	176	212	-36	95	201	200	1
134	177	173	4	197	202	210	-8
91	178	185	-7	101	203	201	2
139	179	179	0	107	204	215	-11
74	180	183	-3	105	205	202	3
9	181	1007	74	136	206	199	7
100	182	195	-13	205	207	169	38
42	183	182	1	138	208	211	-3
172	184	193	-9	133	209	180	29
178	185	181	4	174	210	206	4
199	186	143	43	153	211	213	-2
25	187	188	-1	155	212	214	-2
93	188	197	-9	167	213	208	5
193	189	144	45	196	214	207	7
106	190	209	-19	4	215	198	17

Table 6: Lowest 50 efficiency scores

Figure 2 and figure 3 show the conditional posterior distributions of efficiency for farms 1 and 35 with models M1 and M2 respectively. When the environmental output is not included in the analysis farm 35 is more likely to be more efficient than farm 1 whereas when the environmental output is included in the analysis it is farm 1 the one more likely to be the most efficient of the two. The probability that farm 1 is more efficient than farm 35 with M1 is 7.8% whereas this probability increases to 87.8% with M2.

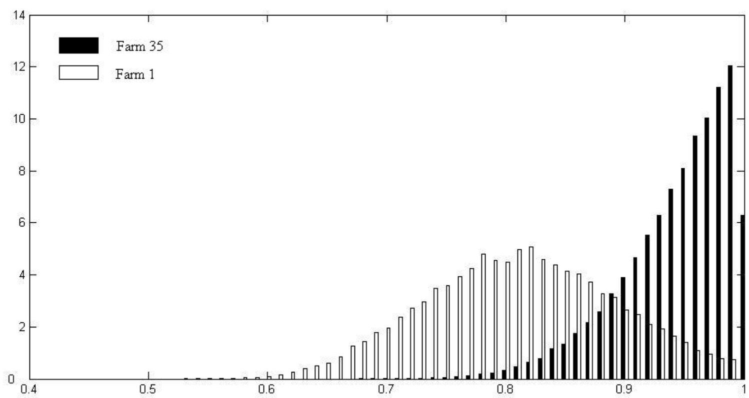

Figure 2: Efficiency distribution without environmental output (farm 1 vs farm 35)

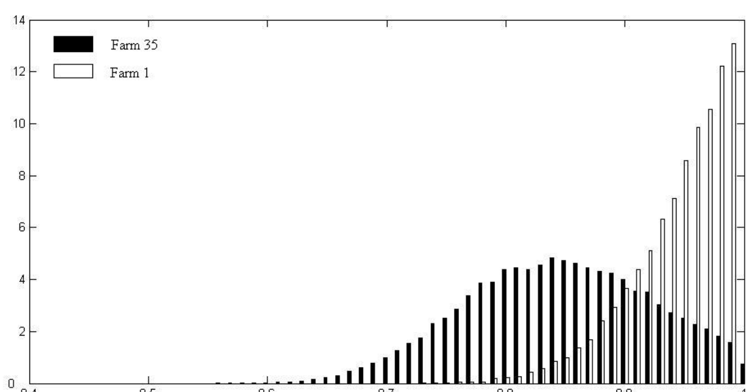

Figure 3: Efficiency distribution with environmental output (farm 1 vs farm 35)

5 Conclusions

The introduction of environmental aspects in the technical efficiency analysis provides a new perspective of the problem. By using a proxy for the provision of environmental goods enables us to create a new measure of efficiency in which positive externalities can be taken into account.

Our results show no significant differences in the production function parameters nor in the parameters associated with the explanatory variables for technical efficiency (with the exception of the farm being located in a LFA) when the environmental output is included in the analysis and when it is not. The distribution of the mean efficiency accross farms is not altered when the environmental output is introduced in the analysis. The key finding in this study is that by introducing the provision of environmental goods in the analysis of technical efficiency the ranking of farms is altered greatly when it is compared to a measure that does not include such environmental output, which has policy consequences. One of the pillars of EU and Defra agricultural policy is to make agriculture both economic and environmental 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 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 on 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 target the wrong farms, i.e. those that are technically and environmentally efficient and leave farms that could improve efficiency. 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. There is not a unique definition of efficiency and different measures may lead to different results. Results in this study show that using different measures for efficiency leads to different rankings.

Our results suggest that although efficiency is positively linked to specialisation in milk production but insignificantly related to intensive farms. This result

support the idea that a specialised and non necessarily intensive dairy sector is technically and environmentally more efficient than a dairy sector where arable crops are produced.

From 2006 the FBS includes questions on environmental characteristics and activities, environmental crops and farm habitats and countryside maintenance and management 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 and more particularly positive externalities into efficiency analysis.

6 Aknowledgements

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8 Appendix

8.1 Appendix A

Essentially, MCMC methods use previous sample values to randomly generate the next sampling value, generating a Markov Chain. The Bayesian rule states that

$$p\left(\theta|y\right)=\frac{p\left(y|\theta\right)p\left(\theta\right)}{p\left(y\right)} \tag{23}$$

where $p\left(\theta|y\right)$ is known as the posterior density distribution, which captures all the information about the unknown parameters; $p\left(y|\theta\right)$ is the likelihood function of the data given the parameters of the model; $p\left(\theta\right)$ is the prior density which reflects what the researcher knows about θ before seeing the data, it does not depend on the data; $p\left(y\right)$ is the marginal distribution of the data (Koop, 2003). The term $p\left(y\right)$ does not involve θ, therefore it can be ignored and the Bayes rule can be written as

$$p\left(\theta|y\right)\propto p\left(y|\theta\right)p\left(\theta\right) \tag{24}$$

8.2 Appendix B

The independent Normal-Gamma prior for β and h is

$$\beta\sim N\left(\underline{\beta},\underline{V}\right) \tag{25}$$

$$h\sim G\left(\underline{s}^{-2},\underline{v}\right) \tag{26}$$

Informative priors are selected for β and h. These represent the prior information about these parameters of the model. Thus, it is assumed that β and h are normally distributed and gamma distributed respectively.

$$p(\beta) = \frac{1}{(2\pi)^{\frac{k}{2}}} |\underline{V}|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}\left(\beta - \underline{\beta}\right)' \underline{V}^{-1}\left(\beta - \underline{\beta}\right)\right] \tag{27}$$

$$p(\beta) \propto \exp\left[-\frac{1}{2}\left(\beta - \underline{\beta}\right)' \underline{V}^{-1}\left(\beta - \underline{\beta}\right)\right] \tag{28}$$

$$\begin{aligned} p(h) &= \frac{2}{\Gamma(\underline{v}/2)} \left(\frac{\underline{vs}^2}{2}\right)^{\frac{\bar{v}}{2}} h^{\frac{(\underline{v}-2)}{2}} \exp\left(-h\frac{\underline{vs}^2}{2}\right) \\ &\propto h^{\frac{(\underline{v}-2)}{2}} \exp\left(-h\frac{\underline{vs}^2}{2}\right) \end{aligned} \tag{29}$$

where $\underline{V}$ is the prior covariance matrix of β; $\underline{\beta}$ is the prior mean for β; $\underline{s}^2$ and $\underline{v}$ are the prior mean and degrees of freedom of h.

The joint posterior distribution is given by

$$p(\beta, h, \mu_z, z|y) = p\left(y|\beta, h, \mu_z^{-1}, z\right) p(\beta) p(h) p\left(z|\mu_z^{-1}(\phi)\right) p(\phi) \tag{30}$$

$$\begin{aligned} p\left(\beta, h, \mu_z^{-1}, z|y\right) = \; & h^{\frac{TN}{2}+\frac{(\underline{v}-2)}{2}} \exp\Bigg(-\frac{h}{2}\left(\tilde{y}_i - X_i\beta\right)'\left(\tilde{y}_i - X_i\beta\right) \\ & -\frac{1}{2}\left(\beta - \underline{\beta}\right)' \underline{V}^{-1}\left(\beta - \underline{\beta}\right) - h\frac{\underline{vs}^2}{2} \\ & -\mu_z^{-1}(\phi) z_i\Bigg) \end{aligned} \tag{31}$$

The conditional posterior for an informative β is

$$p\left(\beta|h, \mu_z^{-1}, z, y\right) \propto \exp\left[\frac{1}{2}\left[s + \left(\beta - \bar{\beta}\right)\left(\underline{V}^{-1} + hX'X\right)\left(\beta - \bar{\beta}\right)\right]\right] \tag{32}$$

where $s = h\tilde{y}'\tilde{y} - \bar{\beta}'\left(\underline{V}^{-1} + hX'X\right)\bar{\beta} + \underline{\beta}'\underline{V}^{-1}\underline{\beta}$ and $\bar{\beta} = \left(\underline{V}^{-1} + hX'X\right)^{-1}\left(\underline{V}^{-1}\underline{\beta} + hX'\tilde{y}\right)$.

The conditional posterior for h is

$$p\left(h|\beta, \mu_z^{-1}, z, y\right) \propto h^{\frac{TN}{2}+\frac{(\underline{v}-2)}{2}} \exp\left[-h\left(\frac{\left(\tilde{y} - X\beta\right)'\left(\tilde{y} - X\beta\right) + \underline{vs}^2}{2}\right)\right] \tag{33}$$

Since $G\left(\theta|s^{-2}, v\right) = \frac{1}{\Gamma\left(\frac{v}{2}\right)}\left(\frac{vs^2}{2}\right)^{\frac{v}{2}} h^{\frac{v-2}{2}} \exp\left(-h\frac{vs^2}{2}\right)$ and using $\frac{TN+\underline{v}-2}{2} =$

$\frac{v-2}{2}$ and $\frac{(\tilde{y}-X\beta)'(\tilde{y}-X\beta)+\underline{vs}^2}{2} = \frac{vs^2}{2}$ it is obtained

$$v = TN + \underline{v} \tag{34}$$

$$s^{-2} = \frac{\underline{v}}{(\tilde{y} - X\beta)' (\tilde{y} - X\beta) + \underline{vs}^2} \tag{35}$$

8.3 Appendix C

Slope parameters and 90% posterior regions for model M1.

	Coeff.	**90% posterior**		**Coeff.**	**90% posterior**
α_0	0.072	$(0.029, 0.115)$	β_{16}	-0.066	$(-0.187, 0.050)$
α_1	-0.035	$(-0.097, 0.028)$	β_{17}	0.136	$(0.014, 0.258)$
α_2	-0.291	$(-0.334, -0.247)$	β_{22}	0.148	$(0.084, 0.213)$
β_1	0.056	$(0.004, 0.109)$	β_{23}	-0.053	$(-0.264, 0.156)$
β_2	0.375	$(0.271, 0.480)$	β_{24}	-0.010	$(-0.133, 0.114)$
β_3	0.456	$(0.344, 0.569)$	β_{25}	0.018	$(-0.171, 0.208)$
β_4	-0.017	$(-0.055, 0.020)$	β_{26}	0.092	$(-0.093, 0.275)$
β_5	0.080	$(0.009, 0.151)$	β_{27}	-0.202	$(-0.106, 0.002)$
β_6	0.036	$(-0.028, 0.100)$	β_{33}	-0.003	$(-0.199, 0.195)$
β_7	0.176	$(0.112, 0.240)$	β_{34}	0.072	$(-0.068, 0.211)$
α_{11}	-0.025	$(-0.057, 0.007)$	β_{35}	0.126	$(-0.106, 0.359)$
α_{12}	0.119	$(0.040, 0.199)$	β_{36}	-0.081	$(-0.290, 0.127)$
δ_{11}	-0.097	$(-0.193, -0.003)$	β_{37}	0.052	$(-0.188, 0.291)$
δ_{12}	0.018	$(-0.133, 0.168)$	β_{44}	-0.004	$(-0.027, 0.018)$
δ_{13}	0.098	$(-0.051, 0.246)$	β_{45}	-0.149	$(-0.234, -0.065)$
δ_{14}	-0.004	$(-0.059, 0.051)$	β_{46}	0.061	$(-0.014, 0.136)$
δ_{15}	-0.054	$(-0.201, 0.094)$	β_{47}	0.020	$(-0.048, 0.090)$
δ_{16}	0.021	$(-0.076, 0.117)$	β_{55}	-0.074	$(-0.206, 0.059)$
δ_{17}	0.041	$(-0.050, 0.133)$	β_{56}	0.036	$(-0.135, 0.208)$
α_{22}	-0.077	$(-0.091, -0.063)$	β_{57}	0.037	$(-0.123, 0.195)$
δ_{21}	-0.007	$(-0.077, 0.064)$	β_{66}	0.014	$(-0.080, 0.108)$
δ_{22}	0.171	$(0.055, 0.285)$	β_{67}	-0.115	$(-0.258, 0.028)$
δ_{23}	-0.100	$(-0.197, -0.005)$	β_{77}	0.015	$(-0.066, 0.097)$
δ_{24}	-0.023	$(-0.073, 0.027)$	D_{qui}	-0.008	$(-0.042, 0.256)$
δ_{25}	0.144	$(0.043, 0.245)$			
δ_{26}	0.034	$(-0.063, 0.132)$			
δ_{27}	-0.101	$(-0.189, -0.013)$			
β_{11}	0.023	$(-0.030, 0.078)$			
β_{12}	-0.024	$(-0.184, 0.135)$			
β_{13}	0.096	$(-0.101, 0.295)$			
β_{14}	0.006	$(-0.048, 0.060)$			
β_{15}	-0.063	$(-0.199, 0.070)$			

Table 7: Slope parameters for M1

Slope parameters and 90% posterior regions for M2.

	Coeff.	**90% posterior**		**Coeff.**	**90% posterior**
α_0	-0.049	$(-0.093, -0.003)$	δ_{34}	0.008	$(-0.010, 0.026)$
α_1	-0.071	$(-0.132, -0.009)$	δ_{35}	-0.056	$(-0.108, -0.004)$
α_2	-0.268	$(-0.313, -0.224)$	δ_{36}	0.045	$(0.005, 0.086)$
α_3	-0.227	$(-0.257, -0.197)$	δ_{37}	-0.034	$(0.077, 0.008)$
β_1	0.054	$(-0.001, 0.110)$	β_{11}	0.029	$(-0.020, 0.079)$
β_2	0.214	$(0.100, 0.328)$	β_{12}	-0.080	$(-0.230, 0.070)$
β_3	0.482	$(0.367, 0.599)$	β_{13}	0.137	$(-0.050, 0.324)$
β_4	-0.012	$(-0.048, 0.026)$	β_{14}	0.001	$(-0.049, 0.050)$
β_5	0.080	$(0.004, 0.015)$	β_{15}	-0.159	$(-0.287, -0.032)$
β_6	0.037	$(-0.032, 0.105)$	β_{16}	0.006	$(-0.106, 0.117)$
β_7	0.140	$(0.075, 0.204)$	β_{17}	0.267	$(0.145, 0.388)$
α_{11}	-0.028	$(-0.058, 0.003)$	β_{22}	0.080	$(0.017, 0.142)$
α_{12}	0.042	$(-0.032, 0.118)$	β_{23}	0.051	$(-0.142, 0.246)$
α_{13}	-0.011	$(-0.037, 0.014)$	β_{24}	0.019	$(-0.096, 0.133)$
δ_{11}	-0.035	$(-0.125, 0.053)$	β_{25}	0.091	$(-0.087, 0.269)$
δ_{12}	0.024	$(-0.118, 0.165)$	β_{26}	0.049	$(-0.124, 0.220)$
δ_{13}	0.003	$(-0.134, 0.140)$	β_{27}	-0.119	$(-0.314, 0.074)$
δ_{14}	0.010	$(-0.041, 0.062)$	β_{33}	-0.069	$(-0.258, 0.120)$
δ_{15}	-0.001	$(-0.138, 0.137)$	β_{34}	0.047	$(-0.083, 0.175)$
δ_{16}	-0.015	$(-0.104, 0.074)$	β_{35}	0.090	$(-0.130, 0.310)$
δ_{17}	0.028	$(-0.069, 0.126)$	β_{36}	-0.048	$(-0.244, 0.147)$
α_{22}	-0.048	$(-0.061, -0.034)$	β_{37}	-0.073	$(-0.305, 0.165)$
α_{23}	-0.029	$(-0.054, -0.004)$	β_{44}	-0.009	$(-0.030, 0.013)$
δ_{21}	-0.026	$(-0.092, 0.040)$	β_{45}	-0.097	$(-0.174, -0.020)$
δ_{22}	0.097	$(-0.010, 0.203)$	β_{46}	0.012	$(-0.057, 0.081)$
δ_{23}	-0.126	$(-0.221, -0.029)$	β_{47}	0.020	$(-0.045, 0.084)$
δ_{24}	-0.014	$(-0.060, 0.032)$	β_{55}	-0.037	$(-0.157, 0.085)$
δ_{25}	0.249	$(0.153, 0.344)$	β_{56}	0.009	$(-0.151, 0.170)$
δ_{26}	-0.068	$(-0.160, 0.023)$	β_{57}	-0.051	$(-0.201, 0.099)$
δ_{27}	-0.158	$(-0.244, -0.073)$	β_{66}	0.012	$(-0.079, 0.103)$
α_{33}	-0.043	$(-0.052, -0.034)$	β_{67}	-0.029	$(-0.169, 0.112)$
δ_{31}	0.035	$(-0.005, 0.074)$	β_{77}	0.021	$(-0.056, 0.099)$
δ_{32}	-0.052	$(-0.112, 0.007)$	D_{env}	0.159	$(0.118, 0.200)$
δ_{33}	0.026	$(-0.038, 0.089)$	D_{qui}	-0.027	$(-0.058, 0.004)$

Table 8: Slope parameters for M2