The impact of environmental legislation on technical and environmental efficiency of arable farms in France and Germany : a comparison of parametric and non-parametric approaches

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The Impact of Environmental Legislation on the Technical and Environmental Efficiency of Arable Farms in France and Germany:

A Comparison of Parametric and Non-parametric Approaches

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1. Introduction

The loss of environmental quality and of rural landscapes is one of the major contemporary challenges for developed countries. Growing demands for environmental quality forces policy-makers to take care of the environmental impacts of their political choices more frequently. In the European Union (EU), the agricultural and environmental situation has been strongly influenced by the Common Agricultural Policy (CAP). Although it is difficult to assess the precise influence of CAP on environment and countryside, there is no doubt that CAP has had a serious impact on the development and intensification of the agrarian sector. As agriculture is the main land user, the CAP has also had major impacts on the European countryside. However, this impact has recently been recognized at European level and common policies have been developed emphasizing countryside management (VAN HUYLENBROECK et al., 1999).

The 1992 EU agricultural policy reform introduced, for the first time, policy measures which address environmental issues with the so-called 'accompanying measures'. These instruments are aimed at convincing farmers and landowners to implement certain measures in exchange for various advantages. Compensation for higher costs or lower revenues, due to maintenance of certain land uses and related to the production of positive externalities or the prevention of negative externalities, is the most common tool. The concession of payments is taken as conditional on the adoption of environmental friendly techniques, the so-called 'eco-conditionality'.

Originally these policies started with Regulation 797/85, Article 19 permitting member states to pay farmers in environmental sensitive areas in return for their adherence to traditional practices. Regulation 1760/87 provided some opportunities of co-financing for actions aiming at stimulating positive contributions of the agricultural sector to the conservation of the environment. They have become more important under Regulation 2078/92, one of the so-called accompanying measures of the 1992 CAP reform. Under Agenda 2000 these policies are continued and reinforced through the structural policies. At the end of 1999 member states have made proposals for the new generation of agri-environmental measures.

Each member state is responsible for the implementation of these measures. Thus, agri-environmental measures are very heterogeneous in their design and reflect differences in attitude and resource availability. However, they usually involve voluntary agreements and

provide payments for maintaining or introducing extensive farming practices and related environmental amenities.

As the agricultural policy objectives have evolved from one concentrating on increasing agricultural productivity into one enhancing the sustainable development of a competitive agriculture, farms have to choose production plans which are the most friendly towards environment but still competitive. That is, among many output and pollution emission combinations, they favour the production plan that maximizes the desirable outputs while simultaneously minimizing the polluting residues. This encourages the transformation of the production process from one with freely disposable outputs (desirable or undesirable), and no cost to the producer, to one with limited disposability of detrimental outputs, by making their disposal costly.

The purpose of this paper is twofold. Firstly, it develops technical and environmental efficiency indexes that allow the evaluation of both, production improvement and pollution reduction for French and German arable farms. These measurements are obtained by using two different approaches. The first one is radial and uses a directional output distance function, while the second one is non-radial and provides an hyperbolic output efficiency measurement. Secondly, it provides a measurement of these efficiencies by using both parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis (DEA) in order to evaluate the impact of agricultural and environmental policy changes in France and Germany on the technical and environmental efficiencies of arable farms.

The paper is organized as follows. Section 2 provides a brief overview of the literature on productive efficiency measurement and its extension to environmental efficiency. The theoretical framework is provided by section 3 which is devoted to the definition of the two different measurements used in this paper: the directional output distance function and the hyperbolic output efficiency measurement. Section 4 describes parametric and non-parametric models. Section 5 provides the empirical application on a sample of French and German arable farms in 1998 drawn from the Farm Accountancy Data Network (FADN). Results obtained by using both parametric and non-parametric techniques are compared. The last section formulates final conclusions.

2. Overview of the Literature on Productive Efficiency Measurements

FARRELL'S (1957) seminal article has led to the development of several techniques for the measurement of production efficiency. These techniques can be broadly categorized into two

approaches: parametric and non-parametric. The parametric stochastic frontier approach (AIGNER et al., 1977; MEEUSEN and VAN DEN BROECK, 1977) and the non-parametric mathematical programming approach, commonly referred to as Data Envelopment Analysis (CHARNES et al., 1978) are the two most popular techniques used in efficiency measurements.

Among many authors, COELLI (1995) presents a relatively recent review of various techniques used in efficiency measurement, including their limitations, strengths and applications in agricultural production. The main strengths of Stochastic Frontier Approach (SFA) are that it deals with stochastic noise and permits statistical tests of hypotheses pertaining to the production structure and to the degree of inefficiency. The need to impose an explicit parametric form for the underlying technology and an explicit distributional assumption for the inefficiency term are the main weaknesses of the parametric approach. The main advantages of the DEA approach are that it avoids parametric specification of technology as well as the distributional assumption for the inefficiency term. However, since DEA is deterministic and attributes all the deviations from the frontier to inefficiencies, the estimated production frontier is likely to be sensitive to measurement errors or other noises in the data. Given the different strengths and weaknesses of the parametric and non-parametric approaches, it is of interest to compare the empirical performance of the two approaches. In literature, few studies compare these two approaches (for example, FERRIER and LOVELL, 1990; HJALMARSSON et al., 1996; SHARMA et al., 1999).

All this literature refers to production frontiers (SHEPHARD, 1970; FÄRE et al., 1985, 1994). It has been further extended and modified to measure the environmental performance in addition to the capture of technical efficiency at a micro-economic level. Among the empirical applications, REINHARD et al. (1996) used SFA to construct environmental efficiency indices at farm level while BALL et al. (1994) and TYTECA (1997) adopted DEA to measure the environmental performance. Moreover, various measures of environmental performance can be proposed depending on how undesirable output reductions are sought. For example, among studies which use DEA to measure the environmental performance, FÄRE et al. (1996) rely on the comparison of two input oriented technical efficiency measurements. The first one accounts for the production of environmentally detrimental goods while the second one ignores the by-production of wastes with desirable outputs. In another study, FÄRE et al. (1989) suggested hyperbolic measurement of technical efficiency which allows for simultaneous equiproportionate reduction in the undesirable outputs with an expansion in the desirable outputs while CHUNG (1996) introduces a directional distance function in measuring

a firm's performance. It is a radial measure which allows for both expansion of desirable and contraction of undesirable outputs

The environmental efficiency indices used in this study, rely on comparing the production process under alternative assumptions on the disposability of pollutants. In the theory of production, it is assumed that outputs are strongly disposable which implies that the disposal of any output can be achieved without any cost in terms of decrease in the production of other outputs. However, when some outputs are pollutants, this assumption cannot be maintained. In regulated environments, farms are forced to reduce their levels of pollution, and thus, detrimental and desirable outputs cannot be treated symmetrically in terms of disposability. In the absence of strong regulations, increased environmental consciousness in society also requires this asymmetrical treatment of pollutants as weakly disposable. Their disposal is achieved by a proportional reduction in the level of desirable goods.

At present, the 'accompanying measures' of the CAP involve voluntary agreements. Thus, producers can be more or less concerned with the environmental impacts of their activities without being compelled to adopt environmental friendly practices. However, the EU willingness to undertake cross compliance or 'eco-conditionality' under Agenda 2000 would provide more incentives for arable producers to take into account the social cost of their production activities. The output sacrifice due to this transformation determines the environmental efficiency of farms. In this study, environmental efficiency indices are constructed by comparing production processes under alternative assumptions of disposability for pollutants (strong or weak), and by using a directional and an hyperbolic output efficiency approach. It allows us to measure the opportunity cost of transforming the production process from one where producers do not incur any cost due to emissions of pollutants, to one where producers incur some losses in terms of foregone desirable outputs.

3. Hyperbolic and Directional Efficiency Measurements

The production technology provides all the relationships between inputs and outputs which are technologically feasible. It shows how factors of production are transformed into outputs. Let us denote good and bad outputs by $y \in R_+^M$ and $b \in R_+^S$, respectively and inputs by $x \in R_+^N$. The production possibility-set T can be defined by:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\} \quad (1)$$

As we focus on production improvement jointly with pollutant output reduction, i.e., on the output substitutability between good and bad outputs, we model technology by an output set $P(x)$ that specifies the output vectors which can be produced with a given input vector:

$$P(x) = \{(y,b) : (x,y,b) \in T\} \tag{2}$$

The production technology is assumed to satisfy some axioms[1] which are that it is allowed to produce nothing with any inputs, i.e. inaction is possible, while no positive outputs can be produced with no inputs. This implies that the only feasible output vector is zero when no inputs are employed. Moreover, $P(x)$ is a convex compact set and inputs are freely disposable, i.e., increasing inputs do not reduce outputs. On the output side, we consider different disposability assumptions between good and bad outputs. Pollutants are assumed to be only weakly disposable to incorporate the ideas that their reduction is not costless and that a decrease of pollutants has to be accompanied by a proportionate decrease of good outputs. Desirable outputs are assumed to be strongly disposable in the sense that a smaller amount of these outputs can also be produced for a given level of inputs and bad outputs.

An efficiency measure is an index that characterizes how closely a firm operates from the frontier of the technology set. In order to treat undesirable outputs differently from desirable outputs, we used a radial and a non-radial measurement which simultaneously increases the level of desirable outputs and decreases the level of undesirable outputs.

The radial measurement is provided by using a "directional output distance function" (CHUNG, 1996) which is a generalization of the usual output distance function in presence of undesirable output:

$$\vec{D}_o(x,y,b,g) = \max_{\beta}\{\beta : (y,b) + \beta g \in P(x)\} \tag{4}$$

where g is the reference vector. For $g = (y,-b)$, the directional output distance function measures the maximum expansion of goods and the contraction of bads by the same proportion β as:

$$\vec{D}_o(x,y,b;y,-b) = \max_{\beta}\{\beta : (x,(1+\beta)y,(1-\beta)b) \in P(x)\} \tag{5}$$

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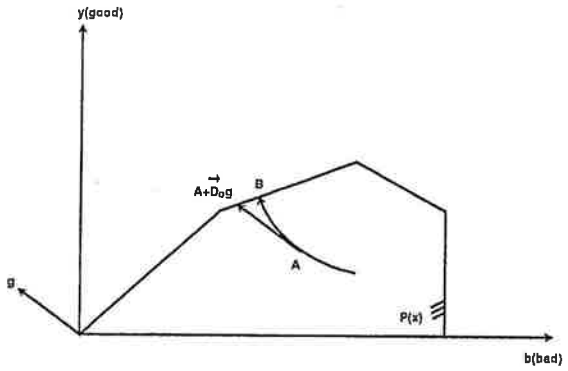
[1] See SHEPHARD (1970) or FÄRE (1988).

The non-radial measurement is provided by using an "hyperbolic technical efficiency measure" (FÄRE et al., 1989) which seeks the maximum simultaneous equiproportionate expansion for the desirable outputs and the contraction for the undesirable outputs:

$$HTE_{\eta}(x,y,b) = \max\{\theta : (\theta y, \theta^{-1} b) \in P(x)\} \qquad (6)$$

This measure is not the shortest distance to the production frontier but an hyperbolic distance as illustrated in figure 1.

Figure 1: Directional and hyperbolic efficiency measurement



The directional output distance function characterizes technology by measuring a radial expansion of outputs in the direction of the g vector which defines a radial path to the production frontier. To obtain this measure, we add $\beta\, g$ to (y,b) until we find the largest β such that $(y,b)+\beta\, g$ belongs to $P(x)$. The hyperbolic output technical efficiency characterizes technology by measuring a non-radial expansion of goods outputs and contraction of bad outputs along an hyperbolic path.

When $g=(y,-b)$, these measures can be compared. As noticed in Chung (1996, p. 37), the directional distance function is a linear approximation of the hyperbolic efficiency measurement:

$$HTE_{\eta}(x,y,b) \approx 1 + \vec{D}_0(x,y,b;y,-b)$$

4.1. Model Specifications

For constructing a reference technology from the observed data, two methods are available: the parametric and non-parametric approaches.

4.1.1. Non-parametric model for technical and environmental efficiency measurements

The non-parametric approach requires a set of J observations of inputs and outputs (x_j, y_j, b_j), $j=1,...,J$, where x_{nj}, $n=1,...,N$ is the n^{th} input used by the observation j in the production of desirable outputs y_{mj}, $m=1,...,M$ and undesirable outputs b_{sj}, $s=1,...,S$. In order to construct the reference technology, each observation is considered as a feasible production activity and an intensity vector $\lambda \in R_+^J$ is used to combine several observations to form new activities. Based on the various assumptions made on the technology, the production possibilities set can be written as:

$$P^S(x) = \{(y,b) : \sum_{j=1}^{J} y_{mj}\lambda_j \geq y_m, m = 1,...,M; \sum_{j=1}^{J} b_{sj}\lambda_j \leq b_s, s = 1,...,S; \sum_{j=1}^{J} x_{nj}\lambda_j \geq x_n, n = 1,...,N; \sum_{j=1}^{J} \lambda_j = 1; \lambda_j \geq 0, j = 1,...,J\} \quad (7)$$

when all outputs are strongly disposable and when the production technology exhibits variable returns to scale (VRS) and as:

$$P^W(x) = \{(y,b) : \sum_{j=1}^{J} y_{mj}\lambda_j \geq y_m, m = 1,...,M; \sum_{j=1}^{J} b_{sj}\lambda_j = b_s, s = 1,...,S; \sum_{j=1}^{J} x_{nj}\lambda_j \geq x_n, n = 1,...,N; \sum_{j=1}^{J} \lambda_j = 1; \lambda_j \geq 0, j = 1,...,J\} \quad (8)$$

when the assumption of weak disposability of undesirable outputs is introduced by the means of an equality constraint.

Under strong disposability of bad outputs, the directional distance function with the g vector $(y,-b)$ is computed for an observation k, $(k=1,...,J)$ as the solution to the following linear program:

$$\vec{D}_0^S(x_k, y_k, b_k; y_k, -b_k) = \max_{\beta_k \lambda} \beta_k$$

subject to:

$$\sum_{j=1}^{J} y_{mj}\lambda_j \geq (1+\beta)y_{mk} \qquad m=1,...,M$$
$$\sum_{j=1}^{J} b_{sj}\lambda_j \geq (1-\beta)b_{sk} \qquad s=1,...,S$$
$$\sum_{j=1}^{J} x_{nj}\lambda_j \leq x_{ik} \qquad n=1,...,N \tag{9}$$
$$\sum_{j=1}^{J} \lambda_j = 1$$
$$\lambda_j \geq 0 \qquad j=1,...,J$$

For a technology that assumes weak disposability for undesirable outputs and strong disposability for desirable outputs, the following linear programming problem is computed:

$$\vec{D}_0^W(x_k, y_k, b_k; y_k, -b_k) = \max_{\beta_k \lambda} \beta_k$$

subject to:

$$\sum_{j=1}^{J} y_{mj}\lambda_j \geq (1+\beta)y_{mk} \qquad m=1,...,M$$
$$\sum_{j=1}^{J} b_{sj}\lambda_j = (1-\beta)b_{sk} \qquad s=1,...,S$$
$$\sum_{j=1}^{J} x_{nj}\lambda_j \leq x_{iik} \qquad n=1,...,N \tag{10}$$
$$\sum_{j=1}^{J} \lambda_j = 1$$
$$\lambda_j \geq 0 \qquad j=1,...,J$$

Then, a directional environmental efficiency measurement can be obtained for each observation from the ratio of these two technical efficiency scores as:

$$DEE_o(x_k, y_k, b_k) = \frac{1+\vec{D}_0^S(x_k, y_k, b_k; y_k, -b_k)}{1+\vec{D}_0^W(x_k, y_k, b_k; y_k, -b_k)} \tag{11}$$

This measure takes a value of 1 only for those firms which have the same efficiency score under both assumptions on the disposability of undesirable outputs. In this case, no opportunity cost for transforming the production process exists. When technical efficiency scores are different, the directional environmental efficiency index is larger than unity. There are opportunity costs existing due to the transformation of the production process, expressed

in terms of percentage of desirable outputs given up due to the reduced disposability of undesirable outputs and measured as $(DEE_o - 1)$.

Under strong disposability of bad outputs, the hyperbolic technical efficiency measure can be computed for the firm k as the solution to the following non-linear programming problem:

$$HTE_0^S(x_k, y_k, b_k) = \max_{\theta_k \lambda} \theta_k$$

subject to:

$$\begin{aligned}
&\sum_{j=1}^{J} y_{mj}\lambda_j \geq \theta\, y_{mk} \qquad m = 1,\ldots,M \\
&\sum_{j=1}^{J} b_{sj}\lambda_j \geq \theta^{-1} b_{sk} \qquad s = 1,\ldots,S \\
&\sum_{j=1}^{J} x_{nj}\lambda_j \leq x_{ik} \qquad n = 1,\ldots,N \\
&\sum_{j=1}^{J} \lambda_j = 1 \\
&\lambda_j \geq 0 \qquad j = 1,\ldots,J
\end{aligned} \tag{12}$$

For a technology that assumes weak disposability for undesirable outputs and strong disposability for desirable outputs, the following non-linear programming problem is computed:

$$HTE_0^W(x_k, y_k, b_k) = \max_{\theta_k \lambda} \theta_k$$

subject to:

$$\begin{aligned}
&\sum_{j=1}^{J} y_{mj}\lambda_j \geq \theta\, y_{mk} \qquad m = 1,\ldots,M \\
&\sum_{j=1}^{J} b_{sj}\lambda_j = \theta^{-1} b_{sk} \qquad s = 1,\ldots,S \\
&\sum_{j=1}^{J} x_{nj}\lambda_j \leq x_{ik} \qquad n = 1,\ldots,N \\
&\sum_{j=1}^{J} \lambda_j = 1 \\
&\lambda_j \geq 0 \qquad j = 1,\ldots,J
\end{aligned} \tag{13}$$

Before computing, the above non-linear programming problems (12) and (13) are converted into linear programs (see appendix).

Then, an hyperbolic environmental efficiency measurement can be obtained for each observation from the ratio of these two technical efficiency scores as:

$$HEE_o(x_k, y_k, b_k) = \frac{HTE_0^S(x_k, y_k, b_k)}{HTE_0^W(x_k, y_k, b_k)} \tag{14}$$

As for the directional environmental efficiency, this measurement evaluates an opportunity cost due to a production process transformation involved in the reduction of undesirable output disposability and measured in terms of losses in foregone desirable outputs.

4.1.2. Parametric model for technical and environmental efficiency measurements

In order to estimate a parametric hyperbolic distance function we first had to choose an appropriate functional form. Coelli and Perelman (1996) enumerated the desirable properties of the functional form for the distance function (flexible; easy to calculate; permit the imposition of theoretical constraints). Assume the following flexible translog form for the hyperbolic output distance function defined in (15):

$$\begin{aligned}\ln D_H(y,b,x) = \alpha_0 &+ \sum_{i=1}^{2}\alpha_i \ln y_i + \gamma_1 \ln b + \sum_{i=1}^{4}\beta_i \ln x_i + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2}\alpha_{ij} \ln y_i \ln y_j \\ &+ \frac{1}{2}\gamma_{11}(\ln b)^2 + \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4}\beta_{ij} \ln x_i \ln x_j + \sum_{i=1}^{2}\eta_{yi} \ln y_i \ln b \\ &+ \sum_{i=1}^{2}\sum_{j=1}^{4}\delta_{ij} \ln y_i \ln x_j + \sum_{i=1}^{4}\eta_{xi} \ln x_i \ln b\end{aligned} \tag{15}$$

Chung (1996) noticed that the following 'almost homogeneity' condition holds for a hyperbolic distance function: $HTE_o(x,ky,k^{-1}b) = k^{-1}HTE_o(x,y,b)$ for any $k>0$. This may be exploited to estimate the model by Maximum Likelihood (ML) techniques. Let $k = 1/y_1$. Then

$D_H\left(\frac{y_2}{y_1}, by_1, x\right) = y_1 D_H(y,b,x)$, or equivalently, $\ln D_H(\frac{y_2}{y_1}, by_1, x) = \ln D_H(y,b,x) + \ln y_1$.

Noting that hyperbolic distance measure will always be larger or equal than one, we can substitute the unobservable value of $\ln D_H(y,b,x)$ with a non-negative random variable u, and, after rearranging, we get the following equation (16):

$$\begin{aligned}\ln y_1 = \alpha_0 &+ \alpha_1 \ln\frac{y_2}{y_1} + \sum_{i=1}^{4}\beta_i \ln x_i + \gamma_1 \ln(by_1) + \frac{1}{2}\alpha_{11}\ln\left(\frac{y_2}{y_1}\right)^2 + \frac{1}{2}\gamma_{11}\ln(by_1)^2 \\ &+ \eta_{y1}\ln\frac{y_2}{y_1}\ln(by_1) + \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4}\beta_{ij}\ln x_i \ln x_j + \sum_{i=1}^{4}\delta_{1i}\ln\frac{y_2}{y_1}\ln x_i + \sum_{i=1}^{4}\eta_{xi}\ln(by_1)\ln x_i - u + v\end{aligned}$$

where v is a random error term, independently and identically distributed as $N(0,\sigma_v^2)$,

intended to capture events beyond the control of farmers, and

u is a non-negative random error term, intended to capture technical inefficiency in outputs, which is assumed to be independently distributed as truncations from below at zero of the $N(m_i,\sigma_u^2)$ distribution (Battese and Coelli 1995), where $m_i = Z\rho$ gives the firm-specific mean of the distribution. The ρ coefficients measure the impact of the exogenous Z variables on inefficiency; a positive coefficient implies that the corresponding variable has a negative impact on the efficiency measure.

Several remarks should be added. First, the advantage of this model specification is that the participation in agri-environmental programs is explicitly considered as a possible determinant of inefficiency. Second, one drawback of this formulation is that it does not necessarily fulfill monotonicity and curvature restrictions. Third, the above specification might well suffer from simultaneity bias because transformations of the dependent variable are used as regressors.

This function may be estimated directly by ML. The hyperbolic distance function measure can then be obtained by using the conditional expectation[2] of *exp(u)* given *(v-u)*.

The above formulation does neither impose restrictive scale assumptions nor does it impose strong disposability. The imposition of strong disposability in the SFA context can be achieved by using restrictions on the logarithmic derivatives of the hyperbolic efficiency measurement. Strong disposability requires that the hyperbolic efficiency measure is decreasing in the strongly disposable output. Lack of strong and prevalence of weak disposability, on the other hand, requires that the shadow prices of the output under consideration are non-negative. The HTE_o measure is declining in strongly disposable outputs and increasing in weakly disposable outputs. In terms of monotonicity conditions, strong disposability of outputs implies negative elasticities, while weak disposability require the opposite sign.

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[2] For reasons of convenience, the measure is calculated as *1/E[exp(-u)|(u-v)]*. The denominator is calculated as the standard predictor for technical efficiency in the cross-sectional case (JONDROW *et al.*, 1982).

5. Empirical application to French and German arable farms

5.1. Data and variables

Data used in this paper were drawn from the Farm Accountancy Data Network (FADN) both in France and Germany for the year 1998. Arable farms were selected referring to criteria of homogeneity, consistency and permanence over time[3]. The French sample includes 175 farms with 4 applying agri-environmental (AE) measures. The German sample contains 132 farms with 44 applying AE measures. All these farms have a nitrogen surplus and consequently, a potential detrimental impact on environment. In France, farms taking part in the AE programs received subsidies of € 24.7 per hectare, on average, for the implementation of more environmental friendly practices while in Germany, they received, on average € 47.9 per hectare. The rather large deviation indicates the high degree of variations, depending on the regional specification of these AE programs and the application of specific measures of the programs[4].

Table 1: Description of the Samples of Arable farms

		France (175 farms)			*Germany (132 farms)*		
Variable	Description	Units	Mean	Stand. dev.	Units	Mean	Stand. dev.
y1	Cereal production	1,000 €	84.36	57.27	1,000 €	70.20	71.14
y2	Other productions	1,000 €	54.35	40.97	1,000 €	74.13	70.29
y3	Nitrogen surplus	kg	2862.30	3195.07	kg	7394	8985
		[kg/ha][a]	[32.2]	[48.1]	[kg/ha][a]	[46.97]	[31.1]
x1	Land	ha	121.87	78.53	ha	164.49	160.37
x2	Labour	AWU[b]	1.37	0.68	AWU[b]	2.22	1.52
x3	Capital and equipment	1,000 €	13.73	13.65	1,000 €	78.2	60.63
x4	Specific variable inputs	1,000 €	33.02	21.70	1,000 €	33.8	33.55
x5	Other variable inputs	1,000 €	28.73	23.76	1,000 €	26.1	28.95

[a] non weighted average [b] Annual worker units

[3] Arable farms over a 4-years period.

[4] Organic farms are not included in these samples.

We assume that all these farms apply the same production process, characterized by the production of two desirable outputs: cereals ($y1$) and other products ($y2$), jointly with the production of one detrimental output, nitrogen surplus[5] ($y3$). They use five inputs: land ($x1$), labour ($x2$), capital and equipment ($x3$), specific variable inputs for crop production as fertilizers and pesticides ($x4$) and other variable inputs ($x5$). Descriptive statistics of the data are presented in table 1. Average figures of the farm samples of both countries indicate that the total output is almost the same, while farm size, capital and equipment and nitrogen surpluses are considerably higher in Germany.

5.2. Empirical results

5.2.1. Non-parametric output oriented directional and hyperbolic efficiency measurement

Efficiency indices were obtained by solving programs (9) and (10) for directional efficiency measurement and programs (A1) and (A2) for hyperbolic efficiency measurement under alternative assumptions on the disposability of detrimental outputs. Further, these measurements were used to calculate environmental efficiency indices (11) and (14). Means of efficiency are reported in table 2.

For **France,** under weak disposability of bad outputs, the average directional efficiency for the whole sample equals 1.106, with 70 farms behaving efficiently (40 %). This suggests that French farms could increase production by almost 10 %, holding inputs fixed and assuming that a reduction of wastes generates costs in terms of nitrogen surplus. Without regulations on polluting output, a reduction of nitrogen surplus does not generate any costs in terms of desirable production and the average efficiency index is 1.135, with 61 efficient farms (34.8 %). In this case, farms could increase desirable outputs by more than 13 %. Thus, with the directional output distance function, the average environmental efficiency of French farms is 1.027 with 85 efficient farms (48.6 %). The introduction of a regulation of the detrimental output could involve a loss of 2.7 % of desirable outputs on average. Results provided by the hyperbolic output efficiency measurement are lower. Under weak disposability conditions for nitrogen surplus, the average efficiency is 1.044 with 75 efficient farms, while under strong disposability of nitrogen surplus, it is 1.055 with 64 efficient farms (36.6 %). Farms could increase desirable outputs of 4 % and 5 %, respectively. The average environmental efficiency

[5] Nitrogen surplus is evaluated based on standard practices.

is 1.011 with 98 efficient farms (56 %). The loss in desirable outputs resulting from a environmental regulation is on average 1.1 %.

Table 2: Means of technical and environmental efficiency measurements in France and Germany.

Efficiency measurement	*France (175 farms)*		*Germany (132 farms)*	
	Mean	Standard deviation	Mean	Standard deviation
$1+\bar{D}_o^S$	1.135	0.151	1.121	0.188
$1+\bar{D}_o^W$	1.106	0.140	1.098	0.161
DEE_o	1.027	0.063	1.019	0.047
HTE_o^S	1.055	0.059	1.094	0.141
HTE_o^W	1.044	0.055	1.079	0.132
HEE_o	1.011	0.028	1.014	0.041

Efficiency measurements are provided in table 3 by size intervals in terms of total acreage. Regarding French farms, efficiency increases with firm size. For instance, in the case of output directional distance function under strong disposability of nitrogen surplus ($1+\bar{D}_o^S$), the average index for farms smaller than 50 hectares is 1.241, while for farms size larger than 100 hectares, it is 1.112.

Results for **German** arable farms do not so much differ from the French ones regarding the level of efficiency; they mainly deviate between farm sizes and between the directional and hyperbolic measures. Under the assumption of weak disposability the average directional efficiency is 1.098 and 74 farms, that is 56 % of the sample, are efficient. The environmental efficiency is 1.019, that means that 86 farms, that is 65 %, are environmentally efficient. Based on these results German arable farms show a slightly better technical and environmental efficiency than the French ones. But this is not true with regard to the hyperbolic efficiency indicators. The hyperbolic efficiency HTE_o^W is 1.079 and HEE_o is 1.014, indicating a better technical efficiency than with the directional distance function and an environmental efficiency which is a little bit less than for French farms. Further, there are also significant differences between the farm sizes. Opposite to France small farms show a much better efficiency than the larger ones. The main reason might be that large arable farms are mainly located in Eastern Germany often working under less favorable natural conditions (low yields due to sandy soils and low rainfall).

Table 3: Efficiency measurement by farms size

Acreage in hectares	#	$1+\bar{D}_o^S$	$1+\bar{D}_o^W$	DEE_o	HTE_o^S	HTE_o^W	HEE_o
				France			
>100	88	1.112	1.089	1.021	1.048	1.039	1.009
50-100	64	1.128	1.101	1.025	1.052	1.042	1.010
<=50	23	1.241	1.185	1.051	1.085	1.065	1.019
Total	175	1.135	1.106	1.027	1.055	1.044	1.011
				Germany			
>100	75	1.144	1.119	1.020	1.112	1.098	1.013
50-100	46	1.111	1.086	1.022	1.088	1.067	1.019
<=50	11	1.008	1.006	1.002	1.006	1.005	1.002
Total	132	1.121	1.098	1.019	1.094	1.079	1.014

Opportunity costs for environmental regulations

To investigate the opportunity cost of transforming the production process from one with all outputs being freely disposable to one with pollution emissions being costly to dispose, the desirable output loss is calculated as $(DEE_0 - 1) * y$ for the directional measurement or as $(HEE_0 - 1) * y$ for the hyperbolic measurement. The results are provided in table 4 on average over the two samples and by farm size in terms of total acreage.

If weak disposability for nitrogen surplus was strictly imposed as the result of an environmental regulation, the average value of production loss for the whole sample of **France** would be 2.7 thousand € with the directional measurement and 1.1 thousand € with the hyperbolic measurement. These corresponds to 2 and 0.8 % of the total production, respectively. The amount of desirable output loss is higher for larger and smaller farms. However, it represents a larger part of total production as farm size decreases. When output loss is expressed by units of nitrogen surpluses, the results emphasize higher values for smaller farms than for larger ones; this is true for both efficiency measurements.

Environmental constraints, imposed by the weak disposability restrictions, would induce a lower reduction of desirable outputs in **Germany** than in France with the directional distance function while the opposite is observed with the hyperbolic efficiency measurement. Opportunity costs for the reduction of nitrogen surpluses, expressed in output loss per kg of nitrogen surplus in environmental inefficient farms, are 1.5 and 2.45 €/kg on the average for the directional and the hyperbolic measurements, respectively. There are significant

differences between farm size; the smaller ones show the lowest opportunity costs to reduce nitrogen surplus.

Table 4: Desirable output loss from imposing weak disposability

Acreage in hectares	Desirable output loss (€)	Share in total Desirable output (%)[a]	Output loss (€) per kg of Nitrogen surplus
		France	
Directional measurement			
>100	3,197	1.57	0.84
50-100	2,269	2.64	1.07
<=50	2,496	6.16	1.84
Total	2,765	1.99	0.97
Hyperbolic measurement			
>100	1,356	0.67	0.35
50-100	935	1.09	0.44
<=50	954	2.35	0.70
Total	1,149	0.82	0.40
		Germany	
Directional measurement			
>100	2,820	1.42	1.34
50-100	1,961	2.46	2.12
<=50	69	0.15	0.29
Total	2,291	1.59	1.49
Hyperbolic measurement			
>100	1,896	0.96	1.94
50-100	1,706	2.14	5.35
<=50	69	0.15	0.29
Total	1,678	1.16	2.45

[a] weighted by total output [b] weighted by N-surplus

Comparison of efficiency levels of farms applying agri-environmental (AE) measures

The following results (table 5) are those obtained by farms involved in an agri-environmental programs in each sample. For **France**, it concerns only 4 farms (2.3%) of the sample. For the directional and the hyperbolic measurement, the average technical efficiency indices are larger than for the non-participating farms, indicating a lower efficiency. However, environmental efficiency is higher. The loss of desirable output is 0.3 and 0.8 % respectively, with only a loss in terms of foregone production per kg of detrimental output when the directional distance function is applied.

The **German** sample includes a larger share of farms applying AE measures than the French one; therefore results seem to be better proved with regard to the question of environmental

impacts of agri-environmental measures. Farms applying AE measures are less technical efficient and they show a better environmental efficiency (like for French farms). This is true for both, the directional and the hyperbolic measure. Opportunity costs for the reduction of nitrogen surpluses are considerably lower than in other farms.

Table 5: Desirable output loss from imposing weak disposability for farms in agri-environmental programs

	France		*Germany*	
Efficiency Measurements	participating (n=4)	not participating (n=171)	participating (n=44)	not participating (n=88)
Directional measurement				
$1+\bar{D}_n^S$	1.157	1.135	1.174	1.095
$1+\bar{D}_n^W$	1.148	1.105	1.149	1.073
DEE_n	1.006	1.027	1.018	1.020
Desirable output loss (€)	816	2,811	1,814	2,530
Share in total desirable output (%)	0.35	2.06	1.58	1.59
Output loss (€) per kg of nitrogen surplus	0.11	1.018	0.74	2.23
Hyperbolic measurement				
HTE_n^S	1.073	1.054	1.140	1.071
HTE_n^W	1.072	1.043	1.132	1.053
HEE_n	1.000	1.011	1.008	1.017
Desirable output loss (€)	31.7	1,175	800	2,117
Share in total desirable output (%)	0.01	0.86	0.7	1.33
Output loss (€) per kg of nitrogen surplus	0.004	0.42	1.16	3.10

5.2.2. Parametric directional and hyperbolic efficiency measurement

The model in Equation (16) was estimated in three different variants[6]. For all specifications, we used 2 desirable outputs, one undesirable output, and 4 inputs in the basic specification. Two possible determinants of efficiency were tested as *Z*-variables: Amount of payments received from agri-environmental programs (*AgEnv*), and the age of the farmer (*Age*). This basic model was estimated (a) without any additional restrictions, (b) with negative monotonicity imposed for all outputs, thus implying strong disposability for all outputs, and (c) with negative monotonicity imposed for the desirable outputs and positive monotonicity for the nitrogen output, thus implying weak disposability for the undesirable output while maintaining the strong disposability assumption for the desirable outputs.

Under these settings, the estimation results for the French farms showed no significant inefficiency. This result proved to be stable under all three model specifications[7]. We have to conclude that the SFA approach is not able to identify any systematic hyperbolic inefficiency for France. Therefore, the following discussion must be restricted to the results for Germany.

The unrestricted model should be viewed as the best model in terms of fitting the data. In this model, the determinants of inefficiency turned out to be significant for the German data. The impact of the variable *AgEnv* proved to be significant: Higher payments lead to lower efficiency. The influence of farmer's age was not significantly different from zero. For the purpose of our study, however, it is crucial that the disposability assumptions are modeled correctly in terms of appropriate signs of the logarithmic derivatives. The analysis of the distance elasticities of the output showed that about 9 % of all farms showed violations of monotonicity for the variable other outputs. For nitrogen surplus, only 79 observations showed negative distance elasticities. To get results compatible to the theoretical models, we restricted the signs of the distance elasticities: The measure HTE_o^S is estimated from imposing negative elasticities on both desirable outputs and the nitrogen surplus, while HTE_o^W is based on a model run with unchanged restrictions for the desirable outputs but imposing positive signs on the elasticities of the nitrogen output.

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[6] All estimations were carried out using Ox 2.20 (DOORNIK 1996).

[7] This result remains unchanged even if additional socio-economic and geographic variables were used as possible determinants of inefficiency. Specifically, the influence of education and regional dummies has been tested for.

Both restricted models perform poorly in terms of convergence of the optimization algorithm: The likelihood function drops sharply from 48.6 to 29.5 (HTE_o^S) and 29.2 (HTE_o^W), respectively. The parameter estimates for all three models are given in the appendix.

Efficiency measurement

Table 6 shows the results of the hyperbolic efficiency estimation for Germany. Under the assumption of strong disposability of outputs, the potential for expanding desirable outputs while simultaneously reducing the level of undesirable output is substantial. The HTE^S measure has a value of 1.42, accordingly. However, the picture changes when regulations on nitrogen are taken into account: HTE^W is estimated on average at 1.19. Therefore, the *HEE* measure indicates a substantial opportunity cost of environmental adjustment. Its average value is 1.18, and for only two farms, the point estimate is slightly lower than one[8]. The maximum score is found to be 1.53. In terms of foregone profit, these estimates are signaling a substantial adjustment pressure. Compared to the non-parametric results, the level of efficiency is considerably lower.

Table 6: Technical and environmental efficiency measurements in Germany (SFA)

Efficiency Measurement	*Germany* (132 farms)	
	Mean	Stand. Dev.
HTE_o^S	1.415	0.300
HTE_o^W	1.181	0.160
HEE_o	1.190	0.117

The analysis by farm size shows that larger farms tend to be more technically efficient than smaller ones (columns 3 and 4 in Table 7). This pattern is contrary to the non-parametric results for Germany. Accordingly, the rank correlation between the efficiency scores from both approaches are quite low.

[8] The implementation of models (7) and (8) in SFA does not necessarily lead to the deterministic condition that the HEE_o measure is larger than one. Depending on the estimated ratio of systematic and unsystematic error terms, numerical values smaller than one may occur.

Although the values for the technical efficiency scores still indicate some similarity between the approaches, the rank correlation for HEE_o is not significantly different from zero. These large differences between the two models are somewhat surprising. Maybe the functional form plays the most important role in this context. Given that a translog functional form was used for SFA, and this functional form had to be restricted regarding its first derivatives, it is quite likely that some of the flexibility of the translog has been lost. However, we could also argue that the SFA approach identifies more noisy components in the deviations of the observed data from the estimated frontier, and that this random part of the deviations is more important for the larger farms.

Table 7: Efficiency measurement by farms size in Germany (SFA)

Acreage in hectares	#	HTE_o^S	HTE_o^W	HEE_o
		Germany		
>100	75	1.390	1.166	1.185
50-100	46	1.450	1.194	1.207
<=50	11	1.443	1.233	1.149
Total	132	1.415	1.181	1.190
Rank correlation with DEA		0.311	0.347	0.035

Opportunity costs for environmental regulations

The above results lead to the following interpretation in opportunity costs, i.e. in terms of foregone profit. The desirable output loss is substantially larger than in the non-parametric models. On average, it amounts to € 27,000 with the highest value for the larger farms and the lowest for the farms smaller than 50 ha. The weighted mean of the share of the desirable output loss compared to total desirable output shows little differences between the groups of the large and the medium-sized farms. Both would be confronted with a loss of approximately 20% of their revenue. In the last column of Table 8, it becomes clear that the loss per kg N is the smallest for the farms above 100 ha size.

Table 8: Desirable output loss from imposing weak disposability (SFA - Hyperbolic Measurement)

Acreage in hectares	Desirable output loss (€)	Share in total Desirable output (%)[a]	Output loss (€) per kg of Nitrogen surplus[b]
		Germany	
>100	37,244	19.06	3.52
50-100	16,138	20.61	4.57
<=50	7,242	16.12	4.11
Total	27,389	19.28	3.70

[a] weighted by total output [b] weighted by N-surplus

A more detailed look at the results for the farms that are participating in agri-environmental programs is given in table 9. Since the amount of payments from these programs were identified as a positive determinant of inefficiency, it is evident that the efficiency scores for the participating farms are slightly worse than for the non-participating farms. However, in terms of adjustment pressure from environmental regulation, the participating farms show little difference to the others with an HEE_o point estimate of 1.18 for participating farms compared to 1.19 for non-participating farms. Because the participating farms are generally smaller in terms of output and factor endowment, this efficiency difference leads to a smaller desirable output loss for the participating farms. The share of this loss compared to the total desirable output is again similar for the groups. The last indicator, the output loss divided by the amount nitrogen surplus, shows that the participating would experience a lower output loss per kg of nitrogen surplus.

Table 9: Desirable output loss from imposing weak disposability for farms in agri-environmental programs (SFA - Hyperbolic Measurement)

Efficiency Measurements	*Germany*	
	With AEP (n=44)	Without AE (n=88)
HTE_o^S	1.201	1.171
HTE_o^W	1.434	1.406
HEE_o	1.182	1.193
Desirable output loss (€)	18,453	31,857
Share in total desirable output (%)	17.08	20.02
Output loss (€) per kg of nitrogen surplus	3.03	3.96

The large difference and ambiguities between the results from linear programming and stochastic frontier analysis raises the question on the statistical significance of the results.

The analysis of confidence intervals (Horrace and Schmidt, 1996) for the efficiency measures can provide valuable information in this context. Figure 2 shows that only about 15 farms reveal significant inefficiencies for the HTE_o^W model[9]. The average efficiency is very high, about 0.9. The HTE_o^S model in figure 3, however, shows a different picture for the efficiency measures. Average efficiency is only 0.7 in this case, and the confidence intervals signal that substantial differences prevail in the German sample.

[9] Note that these figures depict $1/HTE_o$ rather than HTE_o.

Figure 2: Distribution and confidence intervals for HTE^W

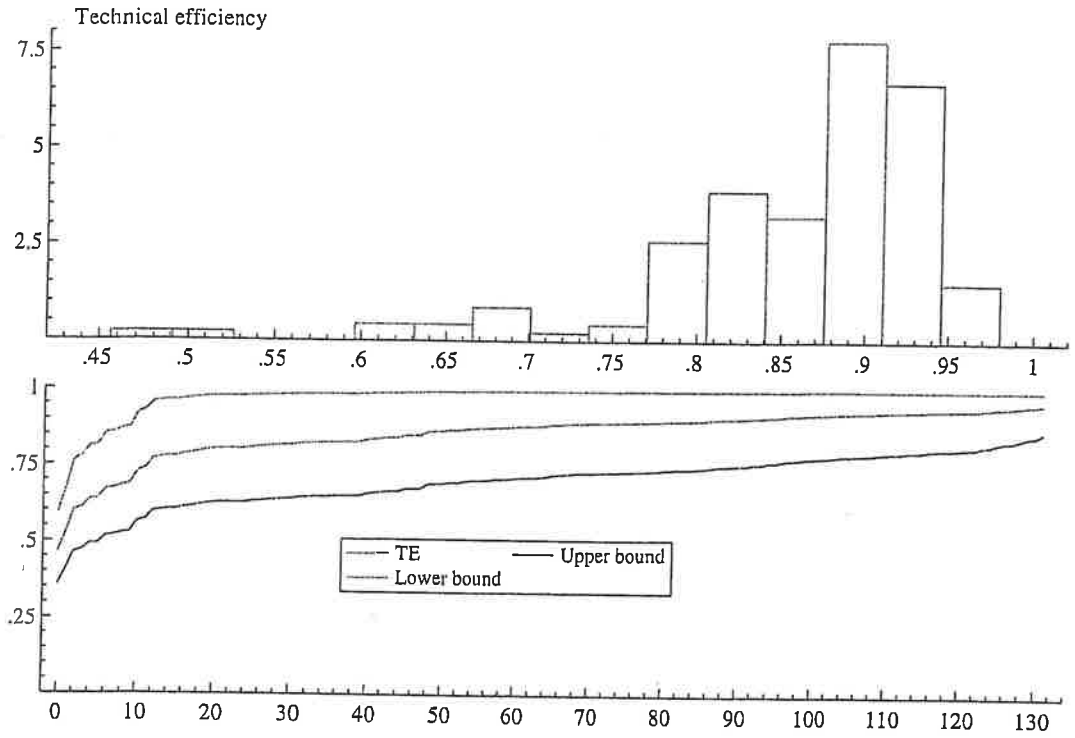
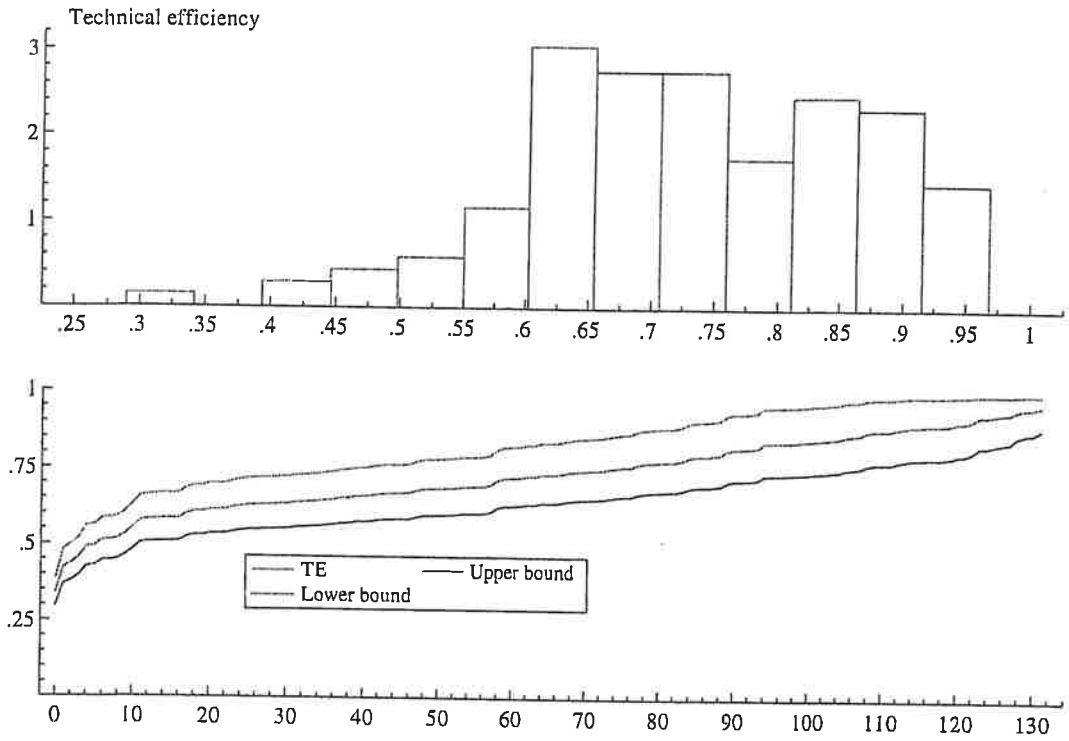


Figure 3: Distribution and confidence intervals for HTE^S



6. References

AIGNER D.; LOVELL C.A.K.; SCHMIDT P. (1977): Formulation and estimation of stochastic frontier production function models, *Journal of Economics*, 6, 21-37.

BALL V. E.; LOVELL C.A.K.; NEHRING R.F.; SOMWARU A. (1994): Incorporating undesirable outputs into models of production: an application to the US agriculture, *Cahiers d'Economie et Sociologie Rurales*, 31, 60-74.

BANKER R.D.; CHARNES A.; COOPER W.W. (1984): Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, 30, 1078-1092.

BATTESE G.E.; COELLI T.J. (1995): A model for technical inefficiency effects in a stochastic frontier production function for panel data, *Empirical Economics*, 20, 325-332.

BATTESE, G.E., T.J. COELLI (1995) "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics* 20:325-332.

CHARNES A.; COOPER W.W.; RHODES E. (1978): Measuring the efficiency of decision making units, European *Journal of Operational Research*, 2, 429-444.

CHUNG Y. (1996): *Directional distance functions and undesirable outputs*, PhDissertaion, Carbondale, Southern Illinois University.

COELLI T.J. (1995): Recent developments in frontier modeling and efficiency measurement, *Australian Journal of Agricultural Economics*, 39, 219-245.Färe R., Grosskopf S., Lovell C.A.K. (1994), *Production Frontiers*, Cambridge University Press.

COELLI, T.J. and S. PERELMAN (1996). "Efficiency Measurement, Multiple-Output Technologies and Distance Functions: With Applications to European Railways." CREPP, Université de Liège.

DOORNIK, J.A. (1999). Object-Oriented Matrix Programming Using Ox, 3rd ed. London: Timberlake Consultants Press and Oxford: www.nuff.ox.ac.uk/Users/Doornik.

FÄRE R. (1988): *Fundamentals of production theory*, Berlin: Springer-Verlag.

FÄRE R.; GROSSKOPF S.; LOVELL C.A.K. (1985): *The measurement of efficiency of production*, Boston, Kluwer-Nijhoff.

FÄRE R.; GROSSKOPF S.; LOVELL C.A.K.; PASURKA C. (1989): Multilateral productivity comparisons when some outputs are undesirable, *The Review of Economics and Statistics*, 71, 90-98.

FÄRE R.; GROSSKOPF S.; TYTECA D. (1996): An activity analysis model of the environmental performance of firms – application to fossil-fuel-fired electric utilities, *Ecological Economics*, 18, 161-175.

FÄRE, R., S. GROSSKOPF, C.A.K. LOVELL and S. YAISAWARNG (1993). "Derivation of shadow prices for undesirable outputs: A distance function approach". *The Review of Economics and Statistics* 75:374:380.

FARRELL M.J. (1957): The measurement of productive efficiency, *Journal of the Royal Statistical Society* A, 120(III), 253-281.

FERRIER G.D.; LOVELL C.A.K. (1990): Measuring cost efficiency in banking: econometric and linear programming evidence, *Journal of Economics*, 46, 229, 245.

HJALMARSSON L.; KUMBHAKAR S.C.; HESHMATI A. (1996): DEA, DFA and SFA: a comparison, Journal of Productivity Analysis, 7, 303-327.

MEEUSEN W.; VAN DEN BROECK J. (1977): Efficiency estimation from Cobb-Douglas production functions with composite error, *International Economic Review*, 18, 435-444.

REINHARD S.; LOVELL C.A.K.; THIJSEN G.J. (1996): Econometric estimation of technical and environmental efficiency: an application to Dutch Dairy Farms, *American Journal of Agricultural Economics*, 81, 44-60.

SHARMA K.R.; LEUNG P.; ZALESKI H.M. (1999): Technical, allocative and economic efficiencies in swine production in Hawaii: a comparison of parametric and non-parametric approaches, *Agricultural Economics*, 20, 23-35.

SHEPHARD R.W. (1970): *Theory of cost and production functions*, Princeton: Princeton University Press.

TYTECA D. (1997): Linear programming modeles for the measurement of environmental performance of firms – conepts and empirical results, *Journal of Productivity Analysis*, 8, 183-198.

VAN HUYLENBROECK G.; WHITBY M. (1999): *Countryside Stewardship: Farmers, Policies and Markets*, Elsevier Sicence Ltd.

Appendix A:

For computational purposes, the non-linear programming problem (12) is converted into the following linear programming problem (Färe *et al.*, 1985):

$$HTE_0^S(x_k, y_k, b_k) = \max_{\delta,\lambda} \delta$$

subject to:

$$\begin{aligned}
&\sum_{j=1}^{J} y_{mj} z_j \geq \delta\, y_{mk} \qquad m = 1,\ldots,M \\
&\sum_{j=1}^{J} b_{sj} z_j \geq b_{sk} \qquad s = 1,\ldots,S \\
&\sum_{j=1}^{J} x_{nj} z_j \leq x_{ik} \qquad n = 1,\ldots,N \\
&\sum_{j=1}^{J} z_j = 1 \\
&z_j \geq 0 \qquad j = 1,\ldots,J
\end{aligned} \tag{A1}$$

where $\delta = \theta^2$ and $z = \theta\lambda$. Thus, $\theta = \sqrt{\delta}$ and $\lambda = \frac{z}{\theta}$.

and the non-linear programming problem (13) is converted into the following linear programming problem:

$$HTE_0^W(x_k, y_k, b_k) = \max_{\delta,\lambda} \delta$$

subject to:

$$\begin{aligned}
&\sum_{j=1}^{J} y_{mj} z_j \geq \delta\, y_{mk} \qquad m = 1,\ldots,M \\
&\sum_{j=1}^{J} b_{sj} z_j = b_{sk} \qquad s = 1,\ldots,S \\
&\sum_{j=1}^{J} x_{nj} z_j \leq x_{ik} \qquad n = 1,\ldots,N \\
&\sum_{j=1}^{J} z_j = 1 \\
&z_j \geq 0 \qquad j = 1,\ldots,J
\end{aligned} \tag{A2}$$

where $\theta = \sqrt{\delta}$ and $\lambda = \frac{z}{\theta}$.

Appendix B:

Table B1: Estimation results unrestricted model: France

Variable	Coefficient (std.err.)	***Variable***	Coefficient (std.err.)
Constant	-0.002 (0.116)	**Y_oth**cap**	-0.037 (0.034)
*Y_oth**	-0.576** (0.035)	*Y_oth**inter*	0.455** (0.119)
*Y_N**	-0.029** (0.012)	*Y_oth**land*	-0.379** (0.117)
lab	0.117** (0.037)	*Y_N**lab*	0.031 (0.023)
cap	0.015 (0.023)	*Y_N**cap*	-0.020 (0.015)
inter	0.460** (0.047)	*Y_N**inter*	0.074** (0.034)
land	0.551** (0.049)	*Y_N**land*	-0.039 (0.032)
*.5*Y_oth*^2*	0.568** (0.116)	*lab*cap*	-0.082 (0.062)
*.5*Y_N*^2*	-0.009 (0.008)	*lab*inter*	0.112 (0.132)
*.5*lab^2*	-0.271 (0.168)	*lab*land*	0.013 (0.116)
*.5*cap^2*	-0.097** (0.021)	*cap*inter*	0.144* (0.080)
*.5*inter^2*	-0.088 (0.229)	*cap*land*	0.126* (0.065)
*.5*land^2*	0.620** (0.282)	*inter*land*	-0.607** (0.221)
*Y_oth**Y_N**	-0.040 (0.027)	*ln{\sigma_v}*	-2.366** (0.053)
*Y_oth**lab*	0.049 (0.087)	*ln{\sigma_u}*	-8.144 (49.50)

Note: *: significant at 10 %, **: at 5 %

Table B2: Estimation results unrestricted model: Germany

Variable	Coefficient (std.err.)	***Variable***	Coefficient (std.err.)
Constant	0.130** (0.056)	*Y_oth**land*	0.012 (0.043)
*Y_oth**	-0.225** (0.021)	*Y_N**lab*	0.032 (0.067)
*Y_N**	-0.031 (0.035)	*Y_N**cap*	0.167* (0.091)
lab	0.108 (0.078)	*Y_N**inter*	-0.006 (0.082)
cap	0.362** (0.091)	*Y_N**land*	-0.179* (0.104)
inter	0.549** (0.091)	*lab*cap*	-0.173 (0.212)
land	0.003 (0.090)	*lab*inter*	0.271 (0.196)
*.5*Y_oth*^2*	-0.047** (0.006)	*lab*land*	-0.070 (0.227)
*.5*Y_N*^2*	-0.012 (0.029)	*cap*inter*	-0.548** (0.235)
*.5*lab^2*	0.148 (0.273)	*cap*land*	0.308 (0.239)
*.5*cap^2*	-0.149 (0.262)	*inter*land*	0.552** (0.274)
*.5*inter^2*	0.302 (0.367)	*ln{\sigma_v}*	-2.316** (0.238)
*.5*land^2*	-0.781* (0.399)	*ln{\sigma_u}*	-1.518** (0.282)
*Y_oth**Y_N**	0.009 (0.016)	*Constant*	0.424* (0.231)
*Y_oth**lab*	-0.105** (0.040)	*AgEnv*	0.013** (0.006)
*Y_oth**cap*	0.072 (0.044)	*Age*	-0.009 (0.006)
*Y_oth**inter*	-0.114** (0.044)	*LLF*	47.68

Note: *: significant at 10 %, **: at 5 %

Table B3: Parameter estimates for strong and weak disposability: Germany

	Strong d.	Weak d.		Strong d.	Weak d.
Constant	0.235	0.077	*Y_oth**land*	0.050	0.086
*Y_oth**	-0.138	-0.127	*Y_N**lab*	-0.001	0.019
*Y_N**	-0.023	0.036	*Y_N**cap*	0.011	0.033
lab	0.058	0.089	*Y_N**inter*	0.007	-0.011
cap	0.226	0.173	*Y_N**land*	-0.020	-0.046
inter	0.482	0.438	*lab*cap*	-0.484	-0.432
land	0.206	0.169	*lab*inter*	0.416	0.311
*.5*Y_oth*^2*	-0.014	-0.012	*lab*land*	0.123	0.005
*.5*Y_N*^2*	-0.004	0.006	*cap*inter*	-0.351	-0.131
*.5*lab^2*	0.041	0.272	*cap*land*	0.359	0.091
*.5*cap^2*	-0.112	-0.073	*inter*land*	0.268	0.247
*.5*inter^2*	0.287	0.124	*ln{\sigma_v}*	-2.636	-1.937
*.5*land^2*	-0.785	-0.419	*ln{\sigma_u}*	-1.497	-1.264
*Y_oth**Y_N**	0.006	0.002	*Constant*	0.525	-0.183
*Y_oth**lab*	-0.073	-0.048	*AgEnv*	0.010	0.019
*Y_oth**cap*	0.064	0.043	*Age*	-0.006	-0.003
*Y_oth**inter*	-0.114	-0.122	*LLF*	29.247	29.531