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**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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## 1 Introduction

The loss of environmental quality and of rural landscapes is one of the major challenges for developed countries. Growing demand for environmental quality forces policy-makers to take care of environmental impacts of their political decisions. 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 influence of the CAP on the environment, there is no doubt that the CAP has had a serious impact on 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. This impact has been recently recognized at European level, and common policies have been developed emphasizing countryside management (VAN HUYLENBROECK et al., 1999).

Within the CAP-reform, for the first time policy measures were introduced, which address environmental issues. These so-called 'accompanying measures' aim at stimulating farmers and landowners to implement environmental-friendly agricultural practices. Among the most common tools are compensations for higher costs or lower revenues which arise from maintaining certain land uses and are related to the production of positive externalities or the prevention of negative externalities. The granting of these payments is conditional on the adoption of environmental friendly techniques, the so-called 'eco-conditionality'.

Originally, these policies started with EU Regulation 797/85, permitting member states to pay farmers in return for their adherence to traditional practices in environmental sensitive areas. Regulation 1760/87 provided some opportunities of co-financing actions aiming at the stimulation of positive contributions of agriculture to the conservation of the environment. They became more important under Regulation 2078/92, which is one of the so-called accompanying measures of the 1992 CAP reform. Under the Agenda 2000<sup>4</sup> these policies are reinforced through certain structural policies. Member states were obliged to make proposals for the new generation of agri-environmental measures by the end of 1999.

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, preferences, and resource availability. However, they usually involve voluntary

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<sup>4</sup> The Agenda 2000 is a complex set of policy measures for reforms in European policy, with the ultimate goal of relieving accession of the Central and East European countries.

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

As the objectives of agricultural policy have evolved from increasing agricultural productivity towards enhancing the sustainable development of a competitive agriculture, farms are forced to choose production plans which are the most friendly towards environment but still competitive. That means among many output and pollution emission combinations, those production plans should be favored which maximize 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 not), 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 to develop 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 non-radial and provides an hyperbolic output efficiency measurement, while the second one is radial and uses a directional output distance function. They can be considered as two steps in the transformation process of arable farms. Both of them involve an increase in production and a reduction in pollution, however the intensity of the transformation of the production process involved by the radial approach is higher than the change resulting from the non-radial approach. These measurements are obtained by using both a non-parametric Data Envelopment Analysis (DEA) and a Stochastic Frontier Analysis (SFA) in order to evaluate the impact of agricultural policy changes, both in France and Germany, on the technical and environmental efficiency (with regard to nitrogen surplus) 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 depicted in section 3 which is devoted to the definition of the two different measurements used in this paper: the hyperbolic output efficiency measurement and the directional output distance function. Section 4 describes DEA and SFA models. In section 5 the empirical application follows, using a sample of French and German arable farms drawn from the Farm Accountancy Data Network (FADN). The last section formulates final conclusions.

## 2 Overview 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 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 the Stochastic Frontier Approach (SFA) is that it deals with stochastic noise and permits statistical tests of hypotheses pertaining to the production structure and to the degree of inefficiency. Its main weaknesses are the need to impose an explicit parametric form for the underlying technology and an explicit distributional assumption for the inefficiency term. 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.

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 technical efficiency at micro-economic level. Among the empirical applications, REINHARD et al. (1996) use SFA to construct environmental efficiency indices at farm level while BALL et al. (1994) and TYTECA (1997) adopt 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 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) suggests hyperbolic measurement of technical efficiency which allows for a simultaneous proportional 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 the expansion of desirable and the reduction of undesirable outputs.

The environmental efficiency indices used in this study rely on comparisons of production processes under alternative assumptions on the disposability of pollutants, as in FÄRE et al. (1989). In production theory it is usually assumed that outputs are strongly disposable which implies that the disposal of any output can be achieved without any costs in terms of a 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; therefore, 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 crops' producers to take into account the social cost of their production activities. The output lost due to this transformation determines the environmental efficiency of farms. The hyperbolic and the directional output efficiency approach used in this study allow for an increase in desirable outputs and a decrease in undesirable outputs; technical efficiency of producers is reached when it is possible to maintain competitiveness and to be less pollutant. Moreover, this evolution of the production process is assessed in two steps. The first one is a short or middle term adaptation (non-radial measurement), while the second one can be considered as a long term transformation (radial measurement) since it involves higher changes for producers.<sup>5</sup> Then, the environmental efficiency indices are

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<sup>5</sup> Both measurements evaluate efficiency of producers with an increase in goods and a decrease in bads. However, the hyperbolic efficiency measurement reaches the production frontier through an hyperbolic path which is not the shortest distance onto the frontier. The directional distance function is a radial measurement with the shortest distance. Thus, the former measurement provides lower potential improvements of both competitiveness and environmental impacts than the latter. In a political context, we can consider hyperbolic measurements as the first step of the producers' production transformation process in order to evolve from an agricultural policy searching an increase of productivity to a new political context which promotes competitiveness and environmental-friendly practices. This is a short or middle term adaptation since it involves lower improvements of both production and pollution than the directional efficiency, which can be regarded as a second step in the transformation of the production process with stronger improvements on both production and pollution.

constructed by comparing production processes under alternative assumptions of disposability for pollutants (strong or weak). 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 the reduction of polluting output, 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:

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

The production technology is assumed to satisfy some axioms<sup>6</sup>, i. e., it is allowed to produce nothing with any inputs (inaction is possible) while no positive outputs can be produced without inputs. This implies that the only feasible output vector is zero when no inputs are used. 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 free of charges 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 non-radial and a radial measurement which simultaneously increases the level of desirable outputs and decreases the level of undesirable outputs.

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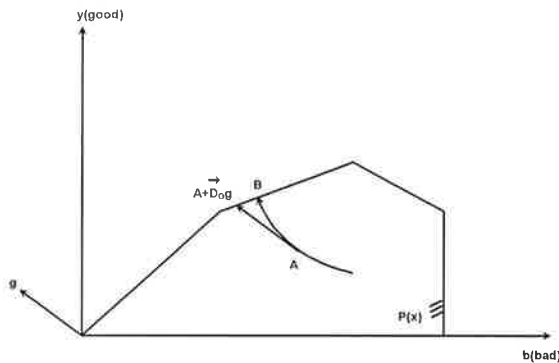
<sup>6</sup> See SHEPHARD (1970) or FÄRE (1988).

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 contraction for the undesirable outputs:

$$HTE_o(x, y, b) = \max\{\theta : (\theta y, \theta^{-1} b) \in P(x)\} \quad (3)$$

The hyperbolic output technical efficiency characterizes a technology by measuring a non-radial expansion of good outputs and a reduction of bad outputs along an hyperbolic path. This measure is not the shortest distance to the production frontier but an hyperbolic distance. As illustrated in figure 1, point A is technically inefficient. Along the hyperbolic path, its performance can be improved by increasing its desirable outputs and decreasing its undesirable outputs as point B.

**Figure 1: Directional and hyperbolic efficiency measurement**



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:

$$\bar{D}_o(x, y, b, g) = \max_{\theta} \{\theta : (y, b) + \theta g \in P(x)\} \quad (4)$$

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



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

The directional output distance function characterizes the 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  $\beta$  such that  $(y, b) + \beta g$  belongs to  $P(x)$ . In figure 1, the performance of point A can be improved by increasing its desirable outputs and decreasing its undesirable outputs along the radial path in the direction of the  $g$  vector, until point  $A + \bar{D}_o g$ .

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.

#### 4 Model Specifications

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

##### 4.1 Non-parametric model for technical and environmental efficiency measurements

For constructing a reference technology from the observed data, a non-parametric DEA approach is used. It requires a set of  $J$  observations of inputs and outputs  $(x_j, y_j, b_j)$ ,  $j=1, \dots, J$ , where  $x_{nj}$ ,  $n=1, \dots, N$  is the  $n^{\text{th}}$  input used by the observation  $j$  in the production of desirable outputs  $y_{mj}$ ,  $m=1, \dots, M$  and undesirable outputs  $b_{sj}$ ,  $s=1, \dots, S$ . 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:

$$P^S(x) = \left\{ (y, b) : \sum_{j=1}^J y_{mj} \lambda_j \geq y_m, m=1, \dots, M; \sum_{j=1}^J b_{sj} \lambda_j \leq b_s, s=1, \dots, S; \right. \\ \left. \sum_{j=1}^J x_{nj} \lambda_j \geq x_n, n=1, \dots, N; \sum_{j=1}^J \lambda_j = 1; \lambda_j \geq 0, j=1, \dots, J \right\} \quad (6)$$

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

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

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 **hyperbolic technical efficiency measure** can be computed for the firm  $k$  as the solution to the following non-linear programming problem:

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

subject to:

$$\begin{aligned} \sum_{j=1}^J y_{mj} \lambda_{jk} &\geq \theta y_{mk} & m = 1, \dots, M \\ \sum_{j=1}^J b_{sj} \lambda_{jk} &\geq \theta^{-1} b_{sk} & s = 1, \dots, S \\ \sum_{j=1}^J x_{nj} \lambda_{jk} &\leq x_{nk} & n = 1, \dots, N \\ \sum_{j=1}^J \lambda_{jk} &= 1 \\ \lambda_{jk} &\geq 0 & j = 1, \dots, J \end{aligned} \quad (8)$$

Before computing, the above non-linear programming problems are converted into linear programs (see appendix A). Then, an hyperbolic environmental efficiency measurement can be obtained for each observation from the ratio of technical efficiency scores under alternative assumptions on pollutant disposability<sup>7</sup> as:

$$HEE_o(x_k, y_k, b_k) = \frac{HTE_0^S(x_k, y_k, b_k)}{HTE_0^W(x_k, y_k, b_k)} \quad (9)$$

This measure takes a value of 1 only for those farms which have the same efficiency score under both assumptions on the disposability of undesirable outputs. In this case, no

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<sup>7</sup> The technical efficiency score  $HTE_0^W(x_k, y_k, b_k)$  is computed for a technology that assumes weak disposability for undesirable outputs and strong disposability for desirable outputs, i.e., where the formula  $\sum_{j=1}^J b_{sj} \lambda_{jk} \geq \theta^{-1} b_{sk}$  of model (8) has been transformed into  $\sum_{j=1}^J b_{sj} \lambda_{jk} = \theta^{-1} b_{sk}$ .

opportunity cost for transforming the production process exists. When technical efficiency scores are different, the hyperbolic 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  $(HEE_o - 1)$ .

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

$$\bar{D}_0^S(x_k, y_k, b_k; y_k, -b_k) = \max_{\beta, \lambda_k} \beta_k$$

subject to:

$$\sum_{j=1}^J y_{mj} \lambda_{jk} \geq (1 + \beta) y_{mk} \quad m = 1, \dots, M$$

$$\sum_{j=1}^J b_{sj} \lambda_{jk} \geq (1 - \beta) b_{sk} \quad s = 1, \dots, S$$

$$\sum_{j=1}^J x_{nj} \lambda_{jk} \leq x_{nk} \quad n = 1, \dots, N$$

$$\sum_{j=1}^J \lambda_{jk} = 1$$

$$\lambda_{jk} \geq 0 \quad j = 1, \dots, J$$

(10)

Then, a directional environmental efficiency measurement can be obtained for each observation from the ratio of technical efficiency scores under alternative assumptions on pollutant disposability<sup>8</sup> as:

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

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<sup>8</sup> The technical efficiency score  $\bar{D}_0^W(x_k, y_k, b_k; y_k, -b_k)$  is computed for a technology that assumes weak disposability for undesirable outputs and strong disposability for desirable outputs, i.e., where the formula  $\sum_{j=1}^J b_{sj} \lambda_{jk} \geq (1 - \beta) b_{sk}$  of model (10) has been transformed into  $\sum_{j=1}^J b_{sj} \lambda_{jk} = (1 - \beta) b_{sk}$ .

As for the hyperbolic 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.

#### 4.2 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 (1999) 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 (12):

$$\begin{aligned} \ln D_H(y, b, x) = & \alpha_0 + \sum_{i=1}^2 \alpha_i \ln y_i + \gamma_1 \ln b + \sum_{i=1}^4 \beta_i \ln x_i + \frac{1}{2} \sum_{i=1}^2 \sum_{j=1}^2 \alpha_{ij} \ln y_i \ln y_j \\ & + \frac{1}{2} \gamma_{11} (\ln b)^2 + \frac{1}{2} \sum_{i=1}^4 \sum_{j=1}^4 \beta_{ij} \ln x_i \ln x_j + \sum_{i=1}^2 \eta_{yi} \ln y_i \ln b \\ & + \sum_{i=1}^2 \sum_{j=1}^4 \delta_{ij} \ln y_i \ln x_j + \sum_{i=1}^4 \eta_{xi} \ln x_i \ln b \end{aligned} \quad (12)$$

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  $k = y_2/y_1$ . Then

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

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 (13):

$$\begin{aligned} \ln y_1 = & \alpha_0 + \alpha_1 \ln \frac{y_2}{y_1} + \sum_{i=1}^4 \beta_i \ln x_i + \gamma_1 \ln(by_1) + \frac{1}{2} \alpha_{11} \ln\left(\frac{y_2}{y_1}\right)^2 + \frac{1}{2} \gamma_{11} \ln(by_1)^2 \\ & + \eta_{y1} \ln \frac{y_2}{y_1} \ln(by_1) + \frac{1}{2} \sum_{i=1}^4 \sum_{j=1}^4 \beta_{ij} \ln x_i \ln x_j + \sum_{i=1}^4 \delta_{1i} \ln \frac{y_2}{y_1} \ln x_i + \sum_{i=1}^4 \eta_{xi} \ln(by_1) \ln x_i - u + v \end{aligned} \quad (13)$$

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  $N(m_u, \sigma_u^2)$  distribution (BATTESE and COELLI 1995),

where  $m_i = Z\rho$  gives the firm-specific mean of the distribution. The  $\rho$  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 measurement.

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<sup>9</sup> 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.

## 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 and consistency. The French sample includes 175 farms and the German sample contains 132 farms. All these farms have a nitrogen surplus and consequently, a potential detrimental impact on environment.

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<sup>9</sup> 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).

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<sup>10</sup> ( $y3$ ). 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.

**Table 1: Description of the Samples of Arable farms**

Variable	Description	Units	France (175 farms)		Germany (132 farms)	
			Mean	Stand. dev.	Mean	Stand. dev.
<i>Outputs</i>						
$y1$	Cereal production	1,000 €	84.36	57.27	70.20	71.14
$y2$	Other productions	1,000 €	54.35	40.97	74.13	70.29
$y3$	Nitrogen surplus	kg (kg/ha) <sup>a</sup>	2862.00 (32.2)	3195.00 (48.1)	7394 (46.97)	8985 (31.1)
<i>Inputs</i>						
$x1$	Land	ha	121.87	78.53	164.49	160.37
$x2$	Labour	AWU <sup>b</sup>	1.37	0.68	2.22	1.52
$x3$	Capital and equipment	1,000 €	13.73	13.65	78.2	60.63
$x4$	Specific variable inputs	1,000 €	33.02	21.70	33.8	33.55
$x5$	Other variable inputs	1,000 €	28.73	23.76	26.1	28.95

<sup>a</sup> Non weighted average

<sup>b</sup> Annual worker units

## 5.2 Empirical results

### 5.2.1 Non-parametric output oriented hyperbolic and directional efficiency measurements

Efficiency indices were obtained by solving program (8) for hyperbolic efficiency measurement and program (10) for the directional distance function under alternative assumptions on the disposability of detrimental outputs. Further, these measurements were

<sup>10</sup> Nitrogen surplus is evaluated based on standard practices.

used to calculate environmental efficiency indices (9) and (11). Means of efficiency are reported in table 2.

For **France**, the average hyperbolic efficiency which is used to describe a middle-term production process transformation equals to 1.055 for the whole sample, under the strong disposal assumption, with 64 farms behaving efficiently (36.6 %). This suggests that French farms could increase production by 5.5 % and simultaneously decrease the by-production of nitrogen surplus by 5.5 % in the middle-term, holding inputs fixed and assuming that a reduction of wastes generates no costs in terms of desirable outputs. The introduction of a regulation on the polluting output, expressed by weak disposability, induces cost in terms of foregone desirable production. The average efficiency index is 1.044, with 75 efficient farms (42.8 %). In this case, farms could increase desirable outputs by 4.4 % and reduce nitrogen surplus by the same amount. The comparison of potential changes in both, desirable and undesirable outputs under the two assumptions of disposability on nitrogen surplus, shows a loss in foregone desirable outputs of 1.1 %. Thus, the hyperbolic environmental efficiency of French farms is on average 1.011 with 98 efficient farms (56 %).

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

Efficiency measurement	<i>France (175 farms)</i>		<i>Germany (132 farms)</i>	
	Mean	Standard deviation	Mean	Standard deviation
<i>Middle term transformation: Hyperbolic output efficiency</i>				
$HTE_o^S$	1.055	0.059	1.044	0.064
$HTE_o^W$	1.044	0.055	1.037	0.060
$HEE_o$	1.011	0.028	1.007	0.020
<i>Long term transformation: Directional output efficiency</i>				
$1 + \bar{D}_o^S$	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

Results provided by the directional output efficiency measurement are higher and describe a longer-term production process transformation. Under strong disposability of nitrogen surplus, the average efficiency is 1.135 with 61 efficient farms (34.8 %), while under weak disposability of nitrogen surplus, it is 1.106 with 70 efficient farms (40 %). Farms could increase desirable outputs and decrease nitrogen surplus by more than 13 % and almost 10 %, respectively.

respectively. Thus, in long-term, higher impacts both on competitiveness and environment can be expected. The average environmental efficiency is 1.027 with 85 efficient farms (48.6 %). The loss in foregone desirable outputs resulting from an environmental regulation is 2.7 % on average. In the long term, the lack of disposability has an higher impact on French farms.

Results for **German** arable farms do not so much differ from the French ones regarding the level of efficiency. Under the assumption of weak disposability the average technical efficiency  $HTE_o^W$  is 1.037 and the hyperbolic environmental efficiency  $HEE_o$  is 1.007, indicating a slightly better technical and environmental efficiency than for French farms. In the middle term, results are better than those provided in long-term. The directional technical efficiency is 1.098, with 74 efficient farms, that is 56 % of the sample. The environmental efficiency is 1.019, with 86 environmentally efficient farms (65 %). Based on these results German arable farms show a slightly better technical and environmental efficiency than the French ones in the long term.

**Table 3: Technical and environmental efficiency measurement by farms size**

Acreage in hectare	France				Germany			
	>100	50-100	<=50	Total	>100	50-100	<=50	Total
#	88	64	23	175	75	46	11	132
<i>Middle term transformation: Hyperbolic output efficiency</i>								
$HTE_o^S$	1.048	1.052	1.085	1.055	1.052	1.046	1.006	1.044
$HTE_o^W$	1.039	1.042	1.065	1.044	1.041	1.032	1.009	1.037
$HEE_o$	1.009	1.010	1.019	1.011	1.003	1.002	1.001	1.007
<i>Long term transformation: Directional output efficiency</i>								
$1 + \vec{D}_o^S$	1.112	1.128	1.241	1.135	1.144	1.111	1.008	1.121
$1 + \vec{D}_o^W$	1.089	1.101	1.185	1.106	1.119	1.086	1.006	1.098
$DEE_o$	1.021	1.025	1.051	1.027	1.020	1.022	1.002	1.019

Efficiency measurements are provided in table 3 by size intervals in terms of total acreage. Regarding **French** farms, efficiency increases with farm size. For instance, in the case of hyperbolic output efficiency under strong disposability of nitrogen surplus ( $HTE_o^S$ ), the average index for farms smaller than 50 hectares is 1.085, while for farms size larger than 100 hectares, it is 1.048.



Opposite to France, **German** small farms show a 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).

*Opportunity costs for environmental regulations*

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

**Table 4: Desirable output loss from imposing weak disposability**

Acreage in hectares	France				Germany			
	>100	50-100	<=50	Total	>100	50-100	<=50	Total
#	88	64	23	175	75	46	11	132
<i>Middle term transformation: Hyperbolic output efficiency</i>								
Desirable output loss (€)	1,356	935	954	1,149	924	820	35	814
Share in total desirable output (%) <sup>a</sup>	0.67	1.09	2.35	0.82	0.47	1.03	0.08	.56
Output loss (€) per kg of nitrogen surplus <sup>b</sup>	0.35	0.44	0.70	0.40	0.95	2.57	0.14	1.19
<i>Long term transformation: Directional output efficiency</i>								
Desirable output loss (€)	3,197	2,269	2,496	2,765	2,820	1,961	69	2,291
Share in total desirable output (%) <sup>a</sup>	1.57	2.64	6.16	1.99	1.42	2.46	0.15	1.59
Output loss (€) per kg of nitrogen surplus <sup>b</sup>	0.84	1.07	1.84	0.97	0.35	2.12	0.29	1.49

<sup>a</sup> weighted by total output

<sup>b</sup> weighted by N-surplus

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 **French** farms would be 1.1 thousand € with the hyperbolic measurement and 2.7 thousand € with the directional measurement. These corresponds to 0.8 and 2 % of total production,

respectively. The amount of desirable output loss is higher for larger farms. However, it represents a lower part of total production than for the other farms. When output loss is expressed by units of nitrogen surplus, the results emphasize higher values for smaller farms than for larger ones; this is true with both efficiency measurements.

Environmental constraints, imposed by the weak disposability restrictions, would induce a lower reduction of desirable outputs in **German** farms than in France; this is true for both measurements. As for France, opportunity costs for the reduction of nitrogen surplus, expressed in output loss per kg of nitrogen surplus, are higher in long term than in middle term, with respectively, 1.19 and 1.49 €/kg for the total of farms. There are significant differences between farm size; the smaller ones show the lowest opportunity costs to reduce nitrogen surplus, while the middle-size farms show the highest.

*Comparison of efficiency levels of farms applying or not agri-environmental (AE) measures*

The following results (tables 5 and 6) are those obtained by farms involved or not in an agri-environmental program. For France, only 4 farms (2.3% of the sample) are concerned by an AE program, while for Germany, the sample includes a larger share of farms applying AE measures (33.3 %); therefore results seem to be better proved with regard to the question of environmental impacts of agri-environmental measures.

**Table 5: Technical and environmental efficiency measurement for farms involved or not in agri-environmental (AE) programs**

	<i>Farms with an AE program</i>		<i>Farms without any AE program</i>	
	<i>France</i>	<i>Germany</i>	<i>France</i>	<i>Germany</i>
#	4	44	171	88
<i>Middle term transformation: Hyperbolic output efficiency</i>				
$HTE_o^S$	1.073	1.065	1.054	1.034
$HTE_o^W$	1.072	1.061	1.043	1.025
$HEE_o$	1.000	1.004	1.011	1.008
<i>Long term transformation: Directional output efficiency</i>				
$1+\bar{D}_o^S$	1.157	1.174	1.135	1.095
$1+\bar{D}_o^W$	1.148	1.149	1.105	1.073
$DEE_o$	1.006	1.018	1.027	1.020

For **France**, average technical efficiency indices for participating farms are higher than for farms without any AE program for both the hyperbolic and directional measurements,

indicating a lower efficiency in middle and long terms. However, environmental efficiency is higher and the loss of desirable output is very small (table 6) since French farms participating in an AE program have already taken into account the cost involved by an environmental regulation.

As for the French sample, **German** farms applying AE measures are less technical efficient and show a better environmental efficiency. This is true for both, the hyperbolic and directional measurements. Opportunity costs for the reduction of nitrogen surplus are considerably lower than in non-participating farms.

**Table 6: Desirable output loss from imposing weak disposability for farms involved or not in agri-environmental (AE) programs**

	<i>Farms with an AE program</i>		<i>Farms without any AE program</i>	
	<i>France</i>	<i>Germany</i>	<i>France</i>	<i>Germany</i>
#	4	44	171	88
<i>Middle term transformation: Hyperbolic output efficiency</i>				
Desirable output loss (€)	31.7	391	1,175	1,026
Share in total desirable output (%) <sup>a</sup>	0.01	0.34	0.86	0.65
Output loss (€) per kg of nitrogen surplus <sup>b</sup>	0.004	0.57	0.42	1.5
<i>Long term transformation: Directional output efficiency</i>				
Desirable output loss (€)	816	1,814	2,811	2,530
Share in total desirable output (%) <sup>a</sup>	0.35	1.58	2.06	1.59
Output loss (€) per kg of nitrogen surplus <sup>b</sup>	0.11	0.74	1.02	2.23

<sup>a</sup> weighted by total output

<sup>b</sup> weighted by N-surplus

### 5.2.2. Parametric hyperbolic efficiency measurement

Point estimates for technical efficiency were obtained by estimating equation (13) using Maximum Likelihood. The outputs included are the same as in the DEA efficiency measurement: two desirable outputs and one bad output (nitrogen). However, on the input side, we chose to use one input category less than in the DEA model. Variables  $x_4$  and  $x_5$  have

been aggregated to a single input which now comprises specific and other variable inputs to avoid multicollinearity and degrees of freedom problems which could otherwise arise.

One advantage of the SFA approach is the possibility to check for various determinants of technical efficiency (*Z*-variables), i.e. those variables which one might suspect to be influential in explaining the observed efficiency differences. Given the focus of our analysis, we modeled the impact of agri-environmental payments by the following variables: (a) the level of payments, (b) a participation dummy which indicates whether a farm participated in agri-environmental programmes or not. Among other socio-economic variables of interest, we checked for the influence of the farmer's age and education.

As outlined above, the models estimations were done under varying restrictions regarding the elasticities of the outputs. For both France and Germany, an unrestricted model run was done as a first step to get an idea of the overall fit of the model. Table 7 gives some indicators for the overall characteristics of the model, while the detailed parameter estimates are left for the interested reader in appendix B.

**Table 7: Summary results SFA (unrestricted models)**

	<i>France (175 farms)</i>	<i>Germany (132 farms)</i>
Log likelihood function	166.58	63.11
Percentage of sig. par's*	43.3%	36.4%
VAR(u)/VAR(Total)	0.001%	60.4%
Test for inefficiency	1.6967	10.56
Average efficiency	0.99	0.86

\* at the 5% level

The results for the two countries are quite different. In France, the econometric approach gives an estimate with a high value for the log-likelihood function (first row) and an acceptable percentage of significant parameters (second row). However, the results clearly show that any observable deviation from the frontier is attributed to unsystematic influences. The variance decomposition (third row) between systematic and unsystematic error terms attaches only 0.001 % of the total variation to inefficiency. This is reflected by the test statistic in the next row as well. The average level of efficiency is virtually equal to one, accordingly. This pattern proved to be very stable across slightly different model formulations. In the light of these results, the further analysis must neglect the French sample because no statistical evidence for non-random deviations from the frontier could be found.

The picture looks different for the German farms. The overall fit of the model is worse than for France, as shown by the figures in rows one and two. The inefficiency term plays an important role here: about 60 % of the total variation originates from systematic influences. The inefficiency model is preferred over the average model since the test statistic in the last but one row is larger than the critical value from the corresponding mixed  $\chi^2$ -distribution of 9.35. The average level of efficiency is 86 percent. This degree of inefficiency is not influenced was found to be unresponsive to the age and the education of the farmer. The impact of the variable *AgEnv* proved to be significant: although participation in the program alone did not have an impact (the dummy variable *D<sub>AgEnv</sub>* is insignificant), higher payments lead to lower efficiency.

For the measurement of environmental efficiency measures, it is important 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 model, we decided to restrict the signs of the distance elasticities: the measure  $HTE_o^S$  is estimated by imposing negative signs on the elasticities of 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 with positive signs of the elasticities of the nitrogen output imposed.

Imposing the restrictions on the elasticities leads to lower likelihood values. However, the drop in the likelihood function is modest: the logarithmic function value drops from 63.1 to 60.8 ( $HTE_o^S$ ) and 60.9 ( $HTE_o^W$ ), respectively. the parameter estimates for the restricted models are given in the appendix B.

The use of two different methods for efficiency measurement allows a comparison between DEA and SFA results (restricted to the German sample because of the statistical insignificance of inefficiency in the French SFA model). Table 8 shows in the average estimates of from SFA and the rank correlation coefficient between SFA and DEA results. The average hyperbolic efficiency level is slightly higher for SFA (1.13 and 1.12) than for DEA (1.05 and 1.04), regardless of the maintained disposability assumptions. This is somewhat surprising since SFA attributes part of the observed deviation to white noise, therefore generally estimating lower inefficiencies compared to the deterministic approaches.

This results is probably influenced by the more restrictive, parametric functional form in SFA, and by the ‘curse of dimensionality’, i.e. the DEA results are based on one additional input category, leading to an higher average efficiency estimate<sup>11</sup>. The environmental efficiency measure  $HEE_o$ , however, is estimated nearly equal by both methods (DEA:1.007, SFA: 1.009). In both cases, we can conclude that the opportunity cost of imposing environmental regulations is not very high. For a comparison of the methods, the relative results are more appropriate since they separate out any level effects. The rank correlation coefficients in the second row of Table 8 indicate that the two models yield similar but not identical rankings for the efficiency measures. This suggests that the differences between the two approaches (modeling of white noise, parametric functional form) have indeed some influence on the efficiency estimates; the main characteristics, however, remain remarkably unchanged.

**Table 8: Efficiency results for German sample**

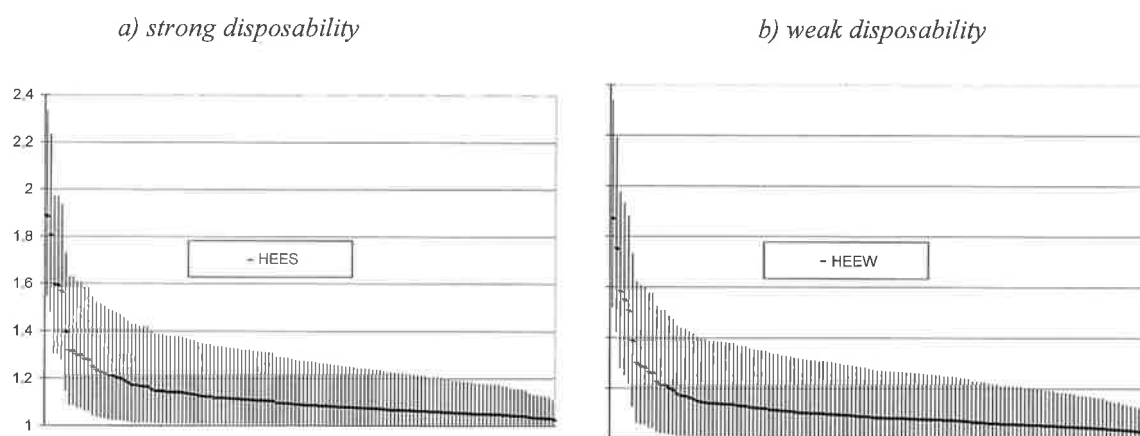
	<i>Germany</i>			
	#	$HTE_o^S$	$HTE_o^W$	$HEE_o$
All farms	132	1.133	1.123	1.009
Rank correlation with DEA		0.56	0.51	0.50
<i>Grouped by farm size</i>				
<=50 ha	11	1.111	1.099	1.011
50-100 ha	46	1.120	1.110	1.010
>100 ha	75	1.143	1.134	1.009
<i>Grouped by AE payments</i>				
Without AE payments	88	1.123	1.111	1.011
With AE payments	44	1.152	1.146	1.006

This line of reasoning is further supported by the grouping results in Table 8 where the average efficiency estimates according to farm size, and receipt of agri-environmental payments, are given. Although slightly different regarding the efficiency level, the results follow the same pattern as for the DEA efficiency estimates: the differences according to farms size are quite small, with larger farmers showing slightly higher technical but marginally lower environmental inefficiency. The German farmers with AE payments are technically more inefficient than their counterparts without these payments. For the environmental efficiency, it is just vice versa.

<sup>11</sup> Further calculations indicated that the use of this additional input category led to a substantial move towards full efficiency.

The overall picture is characterized by small differences in the efficiency estimates. This raises the question, how much of these differences can be regarded as statistically significant? The SFA approach offers the possibility to easily derive confidence intervals for the efficiency estimators (HORRACE and SCHMIDT, 1996). Figure 2 shows the corresponding 95% intervals for the hyperbolic efficiency measures.

**Figure 2: 95% Confidence Intervals for hyperbolic efficiency**



It is obvious that the efficiency levels are estimated with only low precision since the intervals are quite wide. For example, the null hypothesis of full efficiency could not be rejected for most observations. Regarding the environmental efficiency measure, we must conclude that the SFA finds no significant environmental inefficiency. The efficiency confidence intervals for the weakly and the strongly disposable technology overlap to a large extent, suggesting that the environmental efficiency estimate is not significantly different from one. The poor discriminatory power of SFA is common for cross-sectional samples (see e.g., HORRACE and SCHMIDT, 1996). Hence, a possible solution could be the extension of the analysis to panel data.

## 6 Concluding remarks

This paper develops a methodology that deals with desirable and undesirable outputs asymmetrically. First, an hyperbolic output efficiency measurement is used to describe a middle term transformation of production processes where producers try to improve their competitiveness together with a reduction of the negative impact on the environment. Second, a radial efficiency measurement, called directional output distance function, is used to depict a

long-term transformation of the production process which involves a higher reduction of the degree of pollution together with an higher increase in production. Moreover, we calculated an environmental efficiency index which captures the impact of the introduction of an environmental regulation on producers' performance. The index is derived by varying the assumptions regarding the disposability of pollutants between strong and weak disposability. DEA and SFA approaches are used for the quantitative assessment, thus providing the opportunity of a comparison between these methods.

The empirical application uses data on two samples of arable farms in France and Germany. Generally, the level of efficiency is very high for both countries. The small differences revealed the following pattern: French arable farms are less involved in AE programs and are more efficient in middle-term than in the long-term. German farms do have a slightly better technical and environmental efficiency than those of France. Efficiency increases with the size of French farms, while it is the opposite in Germany. However, these results indicate that, while transforming their production processes in order to take environmental considerations into account, competitiveness of farms in both countries can be improved. Moreover, the introduction of an environmental legislation restricting nitrogen surpluses has an higher impact on small-size farms in France and middle-size farms in Germany.

The statistical significance of the observed small differences in efficiency is very low, according to the results from SFA. For France, no inefficiency could be found when allowing for white noise. The farms in Germany were still classified as slightly inefficient; however, the environmental efficiency index no longer signaled significant opportunity costs of environmental regulation when the imprecision of the estimated efficiency scores is taken into account.

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## Appendix A:

For computational purposes, the non-linear programming problem (8) 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:

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

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

## Appendix B:

Table B1: Estimation results unrestricted model: France

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

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

Table B2: Estimation results unrestricted model: Germany

<i>Variable</i>	<i>Coefficient (std.err.)</i>	<i>Variable</i>	<i>Coefficient (std.err.)</i>
<i>Constant</i>	0.196 (0.045) **	<i>Y_oth**land</i>	0.072 (0.112)
<i>Y_oth*</i>	-0.458 (0.039) **	<i>Y_N**lab</i>	-0.022 (0.064)
<i>Y_N*</i>	-0.032 (0.029)	<i>Y_N**cap</i>	0.146 (0.093)
<i>lab</i>	0.120 (0.056) **	<i>Y_N**inter</i>	0.010 (0.070)
<i>cap</i>	0.234 (0.079) **	<i>Y_N**land</i>	-0.104 (0.103)
<i>inter</i>	0.607 (0.079) **	<i>lab*cap</i>	-0.376 (0.174) **
<i>land</i>	0.124 (0.071) *	<i>lab*inter</i>	0.409 (0.186) **
<i>.5*Y_oth*^2</i>	-0.263 (0.124) **	<i>lab*land</i>	0.109 (0.210)
<i>.5*Y_N*^2</i>	-0.013 (0.026)	<i>cap*inter</i>	-0.141 (0.211)
<i>.5*lab^2</i>	-0.185 (0.232)	<i>cap*land</i>	0.109 (0.209)
<i>.5*cap^2</i>	-0.240 (0.219)	<i>inter*land</i>	0.243 (0.242)
<i>.5*inter^2</i>	-0.049 (0.322)	<i>ln{\sigma_v}</i>	-2.339 (0.199) **
<i>.5*land^2</i>	-0.356 (0.366)	<b>Inefficiency model</b>	
<i>Y_oth**Y_N*</i>	0.067 (0.063)	<i>ln{\sigma_u}</i>	-1.622 (0.175) **
<i>Y_oth**lab</i>	0.127 (0.145)	<i>Constant</i>	-4.248 (3.142)
<i>Y_oth**cap</i>	0.202 (0.119) *	<i>AgEnv</i>	0.011 (0.005) **
<i>Y_oth**inter</i>	-0.529 (0.118) **	<i>DAGEnv</i>	-0.154 (0.132)

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

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

	Strong d.	Weak d.		Strong d.	Weak d.
<i>Constant</i>	0.153	0.151	<i>Y_oth**land</i>	0.122	0.128
<i>Y_oth*</i>	-0.464	-0.452	<i>Y_N**lab</i>	-0.007	-0.002
<i>Y_N*</i>	-0.025	0.012	<i>Y_N**cap</i>	0.020	0.021
<i>lab</i>	0.138	0.128	<i>Y_N**inter</i>	0.007	0.001
<i>cap</i>	0.227	0.225	<i>Y_N**land</i>	-0.014	-0.010
<i>inter</i>	0.598	0.541	<i>lab*cap</i>	-0.335	-0.311
<i>land</i>	0.113	0.104	<i>lab*inter</i>	0.431	0.375
<i>.5*Y_oth^2</i>	-0.262	-0.294	<i>lab*land</i>	0.061	0.019
<i>.5*Y_N^2</i>	-0.003	-0.005	<i>cap*inter</i>	-0.045	-0.060
<i>.5*lab^2</i>	-0.243	-0.120	<i>cap*land</i>	0.142	0.158
<i>.5*cap^2</i>	-0.103	-0.098	<i>inter*land</i>	0.222	0.207
<i>.5*inter^2</i>	-0.154	-0.086	<i>ln{\sigma_y}</i>	-2.240	-2.195
<i>.5*land^2</i>	-0.502	-0.501			
<i>Y_oth**Y_N*</i>	0.021	0.003	<b>Inefficiency model</b>		
<i>Y_oth**lab</i>	0.173	0.128	<i>ln{\sigma_u}</i>	-0.354	-0.274
<i>Y_oth**cap</i>	0.206	0.230	<i>Constant</i>	-4.248	-5.509
<i>Y_oth**inter</i>	-0.507	-0.472	<i>AgEnv</i>	0.066	0.087
			<i>D<sub>AgEnv</sub></i>	0.001	0.002