PRICES AND SPECIES DIVERSITY –

STOCHASTIC EFFICIENCY MODELLING

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ABSTRACT

In recent decades a significant amount of literature has been produced concerned with establishing a link between production efficiency and environmental efficiency with respect to quantitative modelling. This has been mainly addressed by focusing on the incorporation of undesirable outputs or the incorporation of environmentally detrimental inputs. However, while the debate with respect to linear programming based DEA modelling is already at an advanced stage the corresponding one with respect to stochastic frontier modelling still needs considerable efforts. This contribution focuses on the case of biodiversity and the appropriate incorporation in stochastic frontier models to achieve more realistic measures of production efficiency. We use the empirical example of tobacco production drawing from as well as affecting species diversity in the surrounding forests. We apply a shadow profit distance function approach as well as a fixed effects non-radial technique to reveal input specific allocative and output oriented technical efficiency measures as well as measures of environmental efficiency. We also consider functional consistency by imposing convexity on the translog profit function model. Based on a biologically defined species diversity index we incorporate biodiversity either as a desirable output or biodiversity loss as a detrimental input. Beside quantitative shadow price measures the main contribution of the work is the evidence that parametric scores of environmental efficiency are not sensitive to the modelling approach chosen but to the imposition of theoretical consistency on the estimation model. In contrast to earlier stochastic approaches on the producer level our approach can be applied by using any first or second order flexible functional form.

JEL Q12, Q32, Q57

KEYWORDS Environmental Efficiency, Species Diversity, Stochastic Frontier

1. Introduction

It is well known that agricultural production has environmental impacts, both adverse and beneficial ones. In recent decades a significant amount of literature has been produced concerned with establishing a link between production efficiency and environmental efficiency with respect to quantitative modelling. This has been mainly addressed by focusing on the incorporation of undesirable outputs (e.g. polluting emissions) or the incorporation of environmentally detrimental inputs (as e.g. nitrogen surplus). However, while the debate with respect to linear programming based DEA modelling is already at an advanced stage (see Färe et al. 1989, Ball et al. 1994, Scheel 2001, Hailu and Veeman 2001 or Kuosmanen, 2005) the corresponding one with respect to stochastic frontier modelling has been initially started by Reinhard et al. 1999 and 2002 but still needs considerable efforts. Neglecting stochastic influences the former approach seems to be less appropriate with respect to the stochastic nature of agricultural production. Existing stochastic modelling approaches nevertheless show methodical shortcomings with respect to the choice of the functional form (estimates of environmental efficiency are restricted to a certain parameter range as well as functional flexibility) as well as exclusively consider environmentally detrimental inputs.

This contribution focuses on the case of biodiversity and the appropriate incorporation in stochastic frontier models to achieve more realistic measures of production efficiency and reveal relative measures of environmental efficiency. We use the empirical example of tobacco production in a developing country drawing from as well as affecting species diversity in the surrounding forests. Tobacco production in Tanzania is largely characterised by traditional technology with respect to plant growing and curing. Consequently the crop has remained one of the most input intensive agricultural activity which seems to contrast the fundamental goal of sustainable development. We apply a shadow profit distance function approach as well as a fixed-effects non-radial technique to reveal input and output allocative as well as output oriented technical efficiency measures. We also consider functional consistency by imposing convexity on the translog profit distance function model. Based on a biologically defined species diversity index we incorporate (i) biodiversity as a production influencing factor, (ii) as a desirable output, or (iii) biodiversity loss as a detrimental input. In contrast to earlier stochastic approaches on the producer level our approach can be applied by using any first or second order flexible functional form.

Section 2 gives a brief summary of the current state of the discussion on quantitative efficiency measurement and the consideration of environmental efficiency. Based on this section 3 makes some general analytical considerations on the concept of environmental efficiency in a profit frontier framework. Subsequently section 4 introduces the shadow price approach as well as the fixed effects based non-radial model of stochastic efficiency analysis whereas section 5 discusses different perspectives on biodiversity (i.e. species diversity) in a production context and the evaluation of relative scarcity. Section 6 develops the different estimation models and outlines the estimation procedure applied. Finally section 7 discusses the empirical results and possible modelling and policy implications, section 8 concludes.

2. The Measurement of Environmental Efficiency

During the last 15 years the notion that realistic efficiency measures require the incorporation of environmentally relevant variables into analytical models of efficiency measurement has been prevailed. The literature on the measurement of environmental efficiency can be basically distinguished by the analytic approach chosen: non-parametric mathematical programming versus parametric econometric techniques.

Non-Parametric Approach

The former approach is usually modeled by using data envelopment analysis which builds on linear programming. One strand of DEA modelling defines negative environmental effects as undesirable outputs (Färe et al. 1989, Chung et al. 1997). Such measures commonly assume a weak disposable technology with respect to the detrimental outputs i.e. that the disposition of such outputs involves costs for the producer. Weak-disposable best-practice production frontiers are then calculated and the relative performance of the individual production unit is measured with respect to this environmental efficiency frontier (see also Yaisawarng/Klein 1994, Zofio/Prieto, 1996). Another deterministic modelling strand calculates beside relative efficiency scores also corresponding shadow prices with respect to the undesirable output (Ball et al. 1989, Färe et al. 1993). However, the issue of modelling undesirable outputs within a deterministic framework has not been satisfactorily solved at an applied level yet (see Scheel 2001, Agrell/Bogetoft 2004 and Kuosmanen 2005): The hypothesis of weak disposability implies that if a production unit is on the revealed efficiency frontier, a second unit showing more desirable and less undesirable output cannot be part of the same production set (Shepherd 1970, Chambers et al. 1996). The linear programming procedure further removes the slacks of the undesirable outputs implying that inefficient units are part of the frontier (Scheel 2001).

Following earlier studies on polluting emissions (see e.g. Pittman 1981) Hailu and Veeman (2001) suggested to treat the undesirable output as an input which is, however, physically problematic as this implies that an infinite amount of desirable output could be produced by an infinite amount of detrimental input (i.e. undesirable output, see Färe and Grosskopf 2004). Scheel (2001) suggests to use a monotonic decreasing transformation function to transform the undesirable ouput into an ordinary output which is then maximized by programming techniques. This approach has the shortcoming of considering inefficient production units as efficient and following this idea Färe and Grosskopf (2004) introduce the use of a directional distance function consisting of the directional vector (1, -1) with respect to the desirable and the undesirable output respectively. Other most recent studies finally point to the fact that such a directional vector qualifies some inefficient units as being efficient depending on the slope of the frontier and alternatively apply a vector consisting of the relative observation values.

Parametric Approach

The measurement of environmental efficiency by parametric econometric techniques still needs considerable analytical efforts. Pittman (1983) estimated the shadow price of a single undesirable output for a sample of US mills to develop an adjusted Törnqvist productivity index assuming a weak disposability of the undesirable output biochemical oxygen demand. The same strategy was basically followed by Hetemäki (1996) who estimated a translog output distance function by revealing technical efficiency scores as well as shadow prices for the environmental 'bad'. The general strategy of such studies has been to include environmental effects in the output vector of a stochastic distance function to obtain inclusive measures of technical efficiency and occasionally measures of productivity change over time. Reinhard et al. (1999 and 2002) formulate a single output translog production frontier model to relate the environmental performance of individual farms to the best practice of environment friendly farming. Here the environmental effect is modelled as a conventional input rather than an undesirable output as in earlier studies and consequently output-oriented technical as well as input-oriented environmental efficiency measures are obtained. Based on this mixed approach Reinhard et al. (2002) further stochastically investigate the variation of environmental efficiency with respect to different factors. The modelling approach chosen is quite appealing as it approaches the connection between an output- and an input-oriented efficiency measure in one stochastic framework. However, this approach shows severe shortcomings from a modelling perspective: The introduced measure of environmental efficiency is restricted to the choice of the underlying functional form as it is built on a mathematical formula only valid as the discriminant included takes a nonnegative value. This finally implies the restriction of some parameter values to a certain functional range.[1] As a consequence the Cobb-Douglas representation of technology can not be applied as here the measure for environmental efficiency would collapse to the one measuring technical efficiency. In the case of the translog representation the two measures can differ. However, as the required negative or zero value of the second own derivative with respect to the environmentally detrimental input is not guaranteed and hence has to be imposed over the whole range of the functional form, the latter is no longer globally flexible. Hence, from the perspective of a theoretically consistent econometric modelling approach also the translog specification is ruled out and consequently a globally flexible and consistent functional form other than the translog has to be chosen. Unfortunately the translog specification can be expected to show the best empirical performance of all second order flexible functional forms currently available as different applications have previously shown (Sauer 2006). Hence, this means a severe restriction for empirical work. In addition, the approach chosen by Reinhard et. al. do not consider allocative considerations by solely focusing on technical and environmental performance. Nevertheless, producer decisions are also driven by allocative considerations with respect to the relative price ratios of the inputs used. The two stage frontier model used in Reinhard et al. (2002) to subsequently regress the estimates for environmental efficiency gained by the first stage frontier on different explanatory factors by using a second frontier technique is inconsistent with respect to the econometric specification (see Kumbhakar/Lovell 2001 chapter 7). However, this approach further lacks consistency with respect to the underlying production theory of the frontier specification as the latter is not based on a proper definition of an 'environmental' production function (i.e. relating output to inputs by an assumed technology) as required to consider the resulting functional estimates as defining a best practice frontier. The chosen approach simply regresses scores of environmental efficiency on arbitrarily chosen explanatory variables and subsequently corrects for best

[1] See Reinhard et al. (1999) equation (10) as well as footnote 7.

practice. The most current empirical application in the literature by Omer et al. (2005) uses a Cobb Douglas frontier framework and defines biodiversity as a productive – i.e. desirable – input to cereal production on the farm level. While the definition of diversity as a conducive input to farm production is convincing no price ratios and related to that no allocative considerations are done. Further the whole approach focuses on technical and not on environmental efficiency and finally suffers from an econometric inconsistency with respect to the inefficiency variation regression as here the inputs for the frontier are again used as explanatory factors and so the error term adheres not to the iid assumption. Finally, the application of a rather limited first order Cobb-Douglas approximation has to be mentioned.

This contribution follows the econometric strand of efficiency measurement and builds on a second order flexible translog functional form. By combining the shadow price approach with a fixed-effects non-radial model we are able to measure beside technical and environmental efficiency also allocative efficiency. This is reached by applying a profit function approach either in a single output specification or a multi-output distance function specification. In the first case the environmentally relevant variable is incorporated as a simple invariant control variable or a group-wise profit shifter or as a detrimental input. In the second case it is incorporated as a desirable output. With respect to the control variable approach the non-environmental production output is maximised and consequently estimates of systematic output oriented technical efficiency and systematic input and output allocative efficiency (model 1) or systematic output oriented technical efficiency and systematic input and output allocative efficiency as well as environmentally conditional group-wise profit efficiency and environmentally conditional group-wise input allocative efficiency (model 2) are obtained. The input approach (model 3) enables the measurement of systematic output oriented technical efficiency as well as that of systematic input and output allocative efficiency and systematic input environmental efficiency by minimizing the use of the detrimental input. Finally the output approach (model 4) delivers estimates of systematic output oriented technical efficiency, of systematic input and output allocative efficiency and finally such of systematic output environmental efficiency. We estimate all models in an unconstrained as well as a curvature constraint (i.e. convexity) specification and compare the results. By this modelling approach we try to overcome some of the shortcomings of earlier empirical attempts with respect to functional consistency and flexibility, allocative considerations as well as the accurate treatment of the environmental variable.

3. Allocative, Technical and Environmental Efficiency in a Profit Frontier Framework

Before we describe the modelling approaches in more detail it seems appropriate to briefly review the different economic concepts of efficiency used. As we basically apply a profit frontier framework to capture allocative issues we assume that producers face output prices $p \in R_{++}^{M}$ and input prices $w \in R_{++}^{N}$. They maximize the profit $\left(p^{T} y - w^{T} x\right)$ gained by employing $x \in R_{+}^{N}$ to produce $y \in R_{+}^{M}$. A measure of profit efficiency πE can be denoted by a function

$$\pi E_{i}\left(y, x, p, w\right) = \left(p^{T} y - w^{T} x\right) / \pi_{i}\left(p, w\right) \qquad [1]$$

where i denotes the production unit and $\pi\left(p, w\right) > 0$ holds. πE must satisfy the following properties:

(i) $\pi E\left(y, x, p, w\right) \leq 1$, with $\pi E\left(y, x, p, w\right) = 1 \Leftrightarrow y = y\left(p, w\right), x = x\left(p, w\right)$ so that $\left(p^{T} y - w^{T} x\right) = \pi\left(p, w\right)$

(ii) $\pi E\left(\lambda y, x, p, w\right) \geq \pi E\left(y, x, p, w\right), \lambda \geq 1$

(iii) $\pi E\left(y, \lambda x, p, w\right) \leq \pi E\left(y, x, p, w\right), \lambda \geq 1$

(iv) $\pi E\left(y,x,\lambda p,\lambda w\right)=\pi E\left(y,x,p,w\right),\lambda>0$.

Unlike measures of cost or revenue efficiency, profit efficiency is not bounded below by zero, since negative actual profit is possible. πE is further nondecreasing in y, nonincreasing in x, and homogeneous of degree 0 in output prices and input prices collectively. By assuming an output orientation for technical efficiency πE can be decomposed as follows

$$\pi E_i\left(y,x,p,w\right)=\begin{Bmatrix} TE_{i^O}\left(x,y\right)*AE_{i^O}\left(x,y,p\right)*\left[\mathrm{r}\left(x,p\right)/p^T y\left(p,w\right)\right]*p^T y\left(p,w\right) \\ -\left[AE_{i^I}\left(x,y,w\right)\right]^{-1}*\left[\mathrm{c}\left(y/TE_{i^O}\left(x,y\right),w\right)/w^T x\left(p,w\right)\right]*w^T x\left(p,w\right)\end{Bmatrix}/\pi\left(p,w\right) \quad [2]$$

where the Debreu-Farrell measure of output oriented technical efficiency is formulated as the function TE satsifying $TE_{i^O}\left(x,y\right)=\left[\max\left\{\phi:\phi y_i\in F\left(\mathrm{x}\right)\right\}\right]^{-1}$, $AE_{i^O}\left(x,y,p\right)$ denotes output allocative efficiency satisfying $AE_{i^O}\left(x,y,p\right)=RE_i\left(x,y,p\right)/TE_{i^O}\left(x,y\right)$ with RE as revenue efficiency, $\mathrm{r}\left(x,p\right)/p^T y\left(p,w\right)$ is the ratio of maximum revenue r to observed revenue, $\left[AE_{i^I}\left(x,y,w\right)\right]^{-1}$ is input allocative efficiency and r denotes the total revenue and c the total costs of production unit i.

$\pi E_i\left(y,x,p,w\right)=\left[p^T y\left(p,w\right)-w^T x\left(p,w\right)\right]/\pi_i\left(p,w\right)=1$ if, and only if, all five terms in equation [2] are unity. In other words, to achieve full efficiency with respect to the profit frontier the production unit is required to reach either input-oriented or output-oriented technical efficiency and both input and output allocative efficiency as well as scale efficiency.

As shown by the previous section environmental efficiency (EE) can be economically defined in various ways. The following single output and distance function modelling approaches make either use of an input or an output related measure of EE. Following the stochastic modelling strang which considers the environmentally relevant effect as a detrimental input z to the production of a single output y, a profit function based measure of input environmental efficiency is provided by

$$EE_{i^I}\left(z,y,w_z\right)=CE_i(y,x,z,w_x,w_z)/\left[TE_{i^I}(y,x,z)*AE_{i^I}(x,y,w_x)\right] \qquad [3]$$

where CE denotes the cost efficiency or economic efficiency of production unit i. EE_{i^I} has to satisfy the following properties:

(v) $0<EE_{i^I}\left(z,y,w_z\right)\le 1$

(vi) $EE_{i^I}\left(z,y,w_z\right)=1\Leftrightarrow\lambda\le 1$ so that $\lambda z=z(y,w_z)$

(vii) $EE_{i^I}\left(\lambda z,y,w_z\right)=EE_{i^I}\left(z,y,w_z\right)$ for $\lambda>0$

(viii) $EE_{i^I}\left(z,y,\lambda w_z\right)=EE_{i^I}\left(z,y,w_z\right)$ for $\lambda>0$. Consequently EE_{i^I} is bounded between zero and unity, and homogeneous of degree 0 in input prices and quantities. Decomposing profit efficiency given by equation [2] to get input environmental efficiency would deliver

$$EE_{i^I}\left(x,z,y,w_x,w_z\right)=\left\{\begin{array}{l}\left[\mathrm{c}\left(y/TE_{i^O}\left(x,z,y\right),w_x,w_z\right)/\left(\left(w_x{}^T x\left(p,w_x\right)\right)*\left(w_z{}^T z\left(p,w_z\right)\right)\right)\right] \\ /\left[\begin{array}{l}TE_{i^O}\left(x,z,y\right)*AE_{i^O}\left(x,z,y,p\right)*\left(\mathrm{r}\left(x,z,p\right)/p^T y\left(p,w_x,w_z\right)\right) \\ *p^T y\left(p,w_x,w_z\right)-\pi E_i\left(y,x,z,p,w_x,w_z\right)*\pi\left(p,w_x,w_z\right)\end{array}\right]\end{array}\right\} \\ /AE_{i^I}\left(x,z,y,w_x,w_z\right) \qquad [4]$$

By considering on the other side the environmentally relevant effect as an undesirable output y_u in a multi-output production context based on an output distance function $D_i\left(x,y\right)$, a measure of output environmental efficiency is provided after transforming it into a desirable output y_d by using an arbitrary directional vetor (Färe/Grosskopf 2004)

$$P_i\left(x\right)=\left\{y':D_i(x,y')\le 1\right\} \text{ where } y'=y\,v=\left[y_{d_1},y_u\right]\left[1,-\varphi\right]=\left[y_{d_1},y_{d_2}\right] \qquad [5]$$

with y as the output and v as the directional vector resulting in the new output vector $\left[y_{d_1},y_{d_2}\right]$, by

$$EE_{i^O}\left(x,y_{d_2},p_{d_2}\right)=RE_i\left(x,y_{d_1},p_{d_1},y_{d_2},p_{d_2}\right)/\left[TE_{i^O}\left(x,y\right)*AE_{i^O}\left(x,y_{d_1},p_{d_1}\right)\right] \qquad [6]$$

EE_{i^O} has to satisfy the following properties:

(ix) $0 < EE_{i^O}\left(x, y_{d_2}, p_{d_2}\right) \leq 1$

(x) $EE_{i^O}\left(x, y_{d_2}, p_{d_2}\right) = 1 \Leftrightarrow \lambda \geq 1$ so that $\lambda y_{d_2} = y_{d_2}(x, p_{d_2})$

(xi) $EE_{i^O}\left(x, \lambda y_{d_2}, p_{d_2}\right) \leq EE_{i^O}\left(x, y_{d_2}, p_{d_2}\right)$ for $\lambda > 0$

(xii) $EE_{i^O}\left(x, y_{d_2}, \lambda p_{d_2}\right) = EE_{i^O}\left(x, y_{d_2}, p_{d_2}\right)$ for $\lambda > 0$.

Consequently EE_{i^O} is bounded between zero and unity, and homogeneous of degree 0 in output prices and quantities. Decomposing finally profit efficiency given by equation [2] to obtain output environmental efficiency would deliver

$$EE_{i^O}\left(x, y_{d_2}, p_{d_2}\right) = \begin{bmatrix} \pi E_i\left(y_{d_1}, y_{d_2}, x, p_{d_1}, p_{d_2}, w\right) * \pi\left(p_{d_1}, p_{d_2}, w\right) + \left(1 / AE_{i^I}\left(x, y_{d_1}, w\right)\right) * \\ \left(\mathrm{c}\left(y / TE_{i^O}\left(x, y_{d_1}\right), w\right) / w^T x\left(p_{d_1}, p_{d_2}, w\right)\right) * w^T x\left(p_{d_1}, p_{d_2}, w\right) \end{bmatrix}$$
$$/\left[\left(TE_{i^O}\left(x, y\right) * AE_{i^O}\left(x, y, p\right) * \left(\mathrm{r}\left(x, p_{d_1}, p_{d_2}\right) / p^T y\left(p_{d_1}, p_{d_2}, w\right)\right) * p^T y\left(p_{d_1}, p_{d_2}, w\right)\right)\right] \quad [7]$$

4. Shadow Prices and Non-Radial Fixed Effects – The Basic Model

Due to the vast literature on shadow prices (see for an overview e.g. Khumbhakar/Lovell 2000) non-observable shadow price ratios have to be considered as the relevant ones for producer decisions in distorted as well as developing agricultural markets. The divergence between the analysed (i.e. estimated) shadow prices and the observed market prices can be interpreted as the sum of allocative inefficiency due to the prevalence of various market constraints as well as optimization failure by the management of the respective production unit. Different approaches to model this divergence can be found in the literature: The usual method consists of additively translating observed prices to create shadow prices. Alternatively shadow prices can be modeled by multiplicatively scaling observed prices into shadow ones (Lau/Yotopoulos 1971). We follow the latter approach here and define the relationship between the normalized shadow input and output prices w^*, p^* and the normalized market prices w, p as

$$w^*_j = \theta_j w_j \qquad p^*_k = \kappa_k p_k \qquad [8]$$

where θ_j, κ_k are (non-negative) price efficiency parameters and j, k indicate input j and output k respectively. If no bending market restrictions are the case then θ_i, κ_k equal unity, if market distortions restrict optimizing behaviour then $\theta \geq 0 \wedge \theta \neq 1,\ \kappa \geq 0 \wedge \kappa \neq 1$. Consequently, a production unit can be regarded as allocatively efficient with respect to observed market prices only if observed market prices reflect the management's opportunity cost with respect to inputs and outputs. It has to be considered that the price efficiency parameters θ_j, κ_k may reflect both effects of market distortions as well as optimization errors.

A Shadow Profit Distance Model

Following an output oriented approach with respect to the measurement of technical efficiency, observed normalized profit is

$$\frac{\pi}{p_1} = y_1 + \sum_{m>1}\left(\frac{p_m}{p_1}\right)y_m - \sum_n\left(\frac{w_n}{p_1}\right)x_n = \phi\pi\left[(p,w)^*;\beta\right]\left\{1 + \sum_m\left(\frac{1-\kappa_m}{\kappa_m}\right)R^*_m + \sum_n\left(\frac{1-\theta_n}{\theta_n}\right)S^*_n\right\} \qquad [9]$$

where $\pi\left[(p,w)^*;\beta\right]$ is the normalized shadow profit function, $(p,w)^* = \left[\kappa_m\left(\frac{p_m}{p_1}\right), \left(\frac{\theta_n}{\phi}\right)\left(\frac{w_n}{p_1}\right)\right]$ is a normalized shadow price vector incorporating output oriented technical inefficiency $0 < \phi \leq 1$ and systematic allocative inefficiency (κ_m, m = 2, …, M and θ_n, n = 1, …, N). The corresponding output and input shadow profit shares are respectively[2]

$$R_m^* = \frac{\partial \ln \pi\left[(p,w)^*;\beta\right]}{\partial \ln p^*_m},\ \text{m} = 2, ..., \text{M} \qquad [10]$$

[2] Estimation could be also based on the system of observed output supply and input demand equations.

$$S_n * = \frac{\partial \ln \pi\left[(p,w)*;\beta\right]}{\partial \ln w*_m}, \text{ n = 1, ..., M} \qquad [11]$$

Observed normalized profit is related to shadow normalized profit by

$$\ln \frac{\pi}{p_1} = \ln \pi\left[(p,w)*;\beta\right] + \ln H + \ln \phi \qquad [12]$$

where

$$H = \left\{1 + \sum_m \left(\frac{1-\kappa_m}{\kappa_m}\right) R*_m + \sum_n \left(\frac{1-\theta_n}{\theta_n}\right) S*_n\right\} \qquad [13]$$

and the observed proft shares can be related to the shadow profit shares simply by

$$R_m = \frac{p_m y_m}{\pi} = \frac{1}{H} * \frac{1}{\kappa_m} R_m *, m = 2,...,M \qquad [14]$$

$$S_n = \frac{w_n x_n}{\pi} = -\frac{1}{H} * \frac{1}{\theta_\mathrm{n}} \mathrm{S_n} *, n = 1, ..., N \qquad [15]$$

In the case of a single output equation [9] collapses to

$$\frac{\pi}{p} = y - \sum_n \left(\frac{w}{p}\right) x_n = \kappa\pi\left[\left(\frac{w}{p}\right)*;\beta\right] + \kappa \sum_n \frac{1-\theta_n}{\theta_n}\left(\frac{w}{p}\right)_n \frac{\partial \pi\left[\left(\frac{w}{p}\right)*;\beta\right]}{\partial \left(\frac{w}{p}\right)_n} \qquad [16]$$

Well known for its empirical accuracy as well as functional flexibility the translog functional form is used here. A translog normalized shadow profit function is given by

$$\ln \pi\left[(p,w)*;\beta\right] = \beta_0 + \sum_m \beta_m \ln p_m * + \sum_n \gamma_n \ln w_n * + \frac{1}{2}\sum_j \sum_m \beta_{jm} \ln p_j * \ln p_m * + \frac{1}{2}\sum_k \sum_n \gamma_{kn} \ln w_k * \ln w_n * + \sum_m \sum_n \delta_{mn} \ln p_m * \ln w_n * \qquad [17]$$

and the associated shadow profit shares can be written as

$$R_m * = \beta_m + \sum_j \beta_{jm} \ln p_j * + \sum_n \delta_{mn} \ln w_n *, \; m = 2, ..., M \qquad [18]$$

$$S_n{}^* = \gamma_n + \sum_k \gamma_{kn} \ln w_k{}^* + \sum_m \delta_{mn} \ln p_m{}^*, \; n = 1, \ldots, N \qquad [19]$$

This system of equations to be estimated consists then of

$$\ln \frac{\pi}{p_1} = \ln \pi\left[\left(p, w\right)^*; \beta\right] + \ln H + \ln \phi \qquad [20]$$

$$R_m = \frac{R_m{}^*}{H^* \kappa_m}, m = 2, \ldots, M \qquad [21]$$

$$S_n = \frac{-S_n{}^*}{H^* \theta_n}, n = 1, \ldots, N \qquad [22]$$

by simply using equations [17], [13], [18] and [19].

Fixed Effects Non-Radial Model

By linking this shadow price approach to a fixed effects non-radial model (see e.g. Kumbhakar 1989, Greene 2005 or Sauer/Frohberg 2006) we are able to measure also group-wise environmentally conditional profit efficiency and group-wise environmentally conditional allocative efficiency. Hereby we are able to model the change in relative profit and allocative efficiency as the environment of a production unit would change. The outlined translog normalized shadow profit system in equation [17] to [19] is reformulated by incorporating b_q as a binary dummy variable for q different groups of producers in the sample classified along different criteria depending on the underlying research question

$$\begin{aligned}\ln \pi\left[\left(p, w\right)^*; \beta\right] = {} & \beta_0 + \sum_m \beta_m \ln p_m{}^* + \sum_n \gamma_n \ln w_n{}^* + \frac{1}{2} \sum_j \sum_m \beta_{jm} \ln p_j{}^* \ln p_m{}^* + \\ & \frac{1}{2} \sum_k \sum_n \gamma_{kn} \ln w_k{}^* \ln w_n{}^* + \sum_m \sum_n \delta_{mn} \ln p_m{}^* \ln w_n{}^* + \sum_q \zeta_q \ln b_q\end{aligned} \qquad [23]$$

$$R_m{}^* = \beta_m + \sum_j \beta_{jm} \ln p_j{}^* + \sum_n \delta_{mn} \ln w_n{}^* + \sum_{q_m} \zeta_{q_m} \ln b_{q_m}, \; m = 2, \ldots, M \qquad [24]$$

$$S_n{}^* = \gamma_n + \sum_k \gamma_{kn} \ln w_k{}^* + \sum_m \delta_{mn} \ln p_m{}^* + \sum_{q_n} \zeta_{q_n} \ln b_{q_n}, \; n = 1, \ldots, N \qquad [25]$$

where symmetry ($\beta_{jm} = \beta_{mj}, \gamma_{kn} = \gamma_{nk}$) holds as usual. The dummy variable B is used here for determining efficiency and ζ denotes the parameters with respect to the efficiency variable. With respect to the cross-sectional context the subscript q, with q = 1, …, Q indicates a group of producers due to a specific classification. This classification is necessary with respect to degrees of freedom problems. If panel data were available this procedure could be avoided and efficiency estimates are obtained for every producer. The profit function system in [23] to [25] is 'corrected' with respect to the 'best' group of households by calculating the inefficiency τ_{ik}

$$\tau_q = \zeta_q - \min_q(\zeta_q) \qquad [26]$$

$$\tau_{q_m} = \zeta_{q_m} - \min_{q_m}(\zeta_{q_m}) \qquad [27]$$

$$\tau_{q_n} = \zeta_{q_n} - \min_{q_n}(\zeta_{q_n}) \qquad [28]$$

τ_q represents overall profit inefficiency of the q^{th} group and can be interpreted as the amount by which the profit could be increased by radially reducing the use of all inputs and/or by radially increasing the production of all outputs ceteris paribus. τ_{q_m} represents output specific allocative inefficiency of the q^{th} group with respect to output m and can be interpreted as the amount by which the profit could be increased by increasing the production of output m ceteris paribus. Finally, τ_{q_n} represents input specific profit inefficiency of the q^{th} group with respect to input n and can be interpreted as the amount by which the profit could be increased by reducing the use of input n ceteris paribus. If $\tau_q = 0$ or $\tau_{q_m} = 0$ and $\tau_{q_n} = 0$ the specific group of producers is on the stochastic frontier and can be considered as fully profit efficient or allocative efficient respectively. E.g. profit efficiency for group q is therefore obtained by

$$\pi E_q = \pi_q^* / \pi_q = 1 + (\tau_q / \pi_q) \qquad [29]$$

with subscripts as explained above and π_q as the maximum profit attainable by producing a given mix and level of outputs by a given mix and level of inputs. However, as is the case with every approach attempting to measure efficiency some drawbacks with respect to the described approach have to be mentioned: If ‘only’ cross-sectional data is available, with respect to the number of observations as well as the number of regressors a classification of groups of observations is necessary to maintain sufficient degrees of freedom. Such a classification is always subject to arbitrariness by the researcher due to the decision about the classifying criteria. As a consequence inefficiency does not vary over producers in a particular group of producers. Efficiency measures are always relative to the ‘best’ group of producers in the sample producing on the stochastic frontier. By correcting an average function this approach implies that the structure of ‘best practice’ production technology is the same as the structure of the ‘central tendency’ production technology. On the other side, the approach applied here requires no special distributional assumptions for the efficiency containing parameters. It is also not necessary to assume their independence from other regressors of the profit function as is the case for the ‘mainstream’ error components approach (see also Kumbhakar 1989). Furthermore, the underlying technology can be specified by a particular functional form adhering to theoretical consistency, global curvature correctness as well as flexibility.

Curvature Correct Modelling

Different recent contributions point to the crucial importance of considering the consistency of the estimated frontier with basic microeconomic requirements, i.e. monotonicity with respect to input prices as well as convexity of the function in a profit maximizing context (see e.g. Ryan/Wales 1998 and Sauer 2006). Monotonicity of the estimated profit function – i.e. positive first derivatives with respect to all input prices - holds as all variable inputs are positive for all observations in the sample. The necessary and sufficient condition for a specific curvature consists in the definiteness of the bordered Hessian matrix as the Jacobian of the derivatives $\partial\Pi/\partial w_n$ with respect to w_n and $\partial\Pi/\partial p_m$ with respect to p_m: if $\nabla\Pi^2(p,w)$ is positive semidefinite, Π is convex, where ∇^2 denotes the matrix of second order partial derivatives with respect to the shadow translog profit model defined by [17] and [23] respectively. The Hessian matrix is positive semidefinite at every unconstrained local maximum. Hence, the underlying function is convex and an interior extreme point will be a global maximum. The condition of convexity is related to the fact that this property implies a concave cost function, a quasi-concave production function, and consequently a convex input requirement set (see in detail e.g. Chambers 1988). Hence, a point on the isoquant is tested, i.e. the properties of the corresponding production function are evaluated subject to the condition that the amount of production remains constant. With respect to the translog shadow profit function model curvature depends on the specific variable input price and output price bundle, as the corresponding Hessian **H** for a 2 input, 2 output case shows

$$H = \begin{pmatrix} \beta_{11} + \beta_1^2 - \beta_1 & \beta_{12} + \beta_1\beta_2 & \delta_{11} + \beta_1\gamma_1 & \delta_{12} + \beta_1\gamma_2 \\ \beta_{12} + \beta_1\beta_2 & \beta_{22} + \beta_2^2 - \beta_2 & \delta_{21} + \beta_2\gamma_1 & \delta_{22} + \beta_2\gamma_2 \\ \delta_{11} + \beta_1\gamma_1 & \delta_{21} + \beta_2\gamma_1 & \gamma_{11} + \gamma_1^2 - \gamma_1 & \gamma_{12} + \gamma_1\gamma_2 \\ \delta_{12} + \beta_1\gamma_2 & \delta_{22} + \beta_2\gamma_2 & \gamma_{12} + \gamma_1\gamma_2 & \gamma_{22} + \gamma_2^2 - \gamma_2 \end{pmatrix} \qquad [30]$$

Given a point x^0, necessary and sufficient for curvature correctness is that at this point $v'Hv \leq 0$ and $\mathbf{v's} = 0$ where $\mathbf{v}$ denotes the direction of change. For some input and output price bundles convexity may be satisfied but for others not and hence what can be expected is that the condition of positive semidefiniteness of the Hessian is met only locally or with respect to a range of input bundles. The respective Hessian is positive semidefinite if the determinants of all of its principal submatrices are positive in sign (i.e. $D_j > 0$ where D is the determinant of the leading principal minors and j = 1, 2, …, n). Hence, with respect to our translog shadow profit model it has to be checked a posteriori for every input and output bundle that monotonicity and convexity hold. If these theoretical criteria are jointly fulfilled the obtained estimates are consistent with microeconomic theory and consequently can serve as empirical evidence for possible policy measures. Convexity can be imposed on our translog shadow profit model at a reference point (usually at the sample mean) following Jorgenson and Fraumeni (1981) and Ryan and Wales (1998). By this procedure the bordered Hessian in [30] is replaced by the product of a lower triangular matrix **Δ** times its transpose **Δ'**. Imposing curvature at the sample mean is then attained by simply setting

$$\beta(\gamma)_{rs} = (\Delta\Delta')_{rs} + \beta(\gamma,\delta)_{rs}\lambda_{rs} + \beta(\gamma)_r \beta(\gamma)_s \qquad [31]$$

where r = j, k and s = n, m and λ_{rs} = 1 if r = s and 0 otherwise and $(\Delta\Delta')_{rs}$ as the rs-th element of ΔΔ' with Δ as a lower triangular matrix. As our point of approximation is the sample mean all data points are divided by their mean transferring the approximation point to an (n + 1)-dimensional vector of ones. At this point the elements of **H** do not depend on the specific input and output price bundle. The estimation model of the normalized translog shadow profit frontier given in [23] to [25] is then simply reformulated as follows

$$\ln\pi\left[\left(p,w\right)^{*};\beta\right] = \beta_0 + \sum_m \beta_m \ln p_m^{\ *} + \sum_n \gamma_n \ln w_n^{\ *} + \frac{1}{2}\sum_j\sum_m \left(h_{jm} + \beta_{jm}\lambda_{jm} + \beta_j\beta_m\right)\ln p_j^{\ *}\ln p_m^{\ *} + \frac{1}{2}\sum_k\sum_n \left(h_{kn} + \beta_{kn}\lambda_{kn} + \gamma_k\gamma_n\right)\ln w_k^{\ *}\ln w_n^{\ *} + \sum_m\sum_n \left(h_{mn} + \delta_{mn}\lambda_{mn} + \beta_m\gamma_n\right)\ln p_m^{\ *}\ln w_n^{\ *} + \sum_q \zeta_q \ln b_q \qquad [32]$$

$$R_m{}^* = \beta_m + \sum_j \left(h_{jm} + \beta_{jm}\lambda_{jm} + \beta_j\beta_m\right)\ln p_j{}^* + \sum_n \left(h_{mn} + \delta_{mn}\lambda_{mn} + \beta_m\gamma_n\right)\ln w_n{}^* + \sum_{q_m} \zeta_{q_m} \ln b_{q_m},\ m = 2, \ldots, M \qquad [33]$$

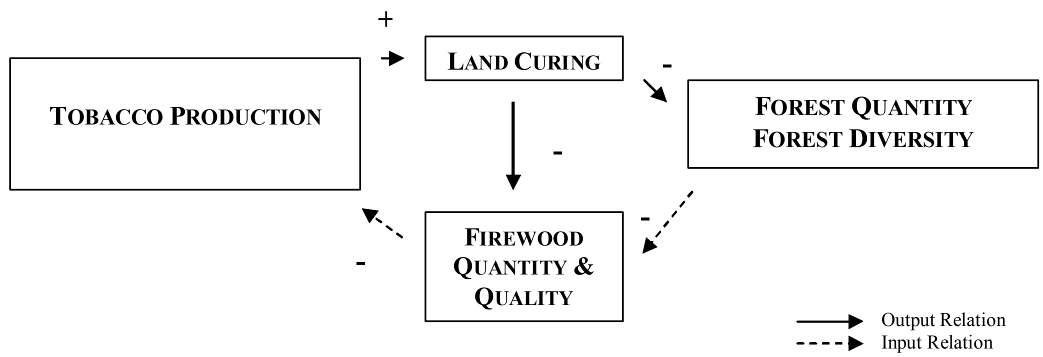
$$S_n{}^* = \gamma_n + \sum_k \left(h_{kn} + \beta_{kn}\lambda_{kn} + \gamma_k\gamma_n\right)\ln w_k{}^* + \sum_m \left(h_{mn} + \delta_{mn}\lambda_{mn} + \beta_m\gamma_n\right)\ln p_m{}^* + \sum_{q_n} \zeta_{q_n} \ln b_{q_n},\ n = 1, \ldots, N \qquad [34]$$

However, the elements of **Δ** are nonlinear functions of the decomposed Hessian, and consequently the resulting normalized translog model becomes nonlinear in parameters. Hence, linear estimation algorithms are ruled out even if the original function is linear in parameters. By this "local" procedure a satisfaction of consistency at most or even all data points in the sample can be reached. The transformation in [31] moves the observations towards the approximation point and thus increases the likelihood of getting theoretically consistent results at least for a range of observations (see Ryan/Wales 2000). However, by imposing global consistency on the translog functional form Diewert and Wales (1987) note that the parameter matrix is restricted leading to seriously biased elasticity estimates. Hence, the translog function would lose its flexibility. By a second analytical step we finally (a posteriori) check the theoretical consistency of our estimated model by verifying that the Hessian is positive semidefinite (i.e. functional convexity). The detailed estimation models are shown in section 6.

5. Empirical Context: Tobacco and Forest - The Price of Species Diversity

For the empirical application we refer to the case of highly resource intensive small-scale tobacco production in the Iringa region of Tanzania. As the use of advanced inputs (e.g. power driven equipments, fertilizers and sustainable crop processing technologies) is beyond the reach for the majority of those farmers an expansion in production is only possible by clearing more forest land. In combination with uncoordinated sectoral policies, high agricultural input prices and ineffective market reforms this has been resulted in environmental degradation and a loss of biodiversity in the form of a decreasing number of tree species. Tobacco curing is the process that causes the destruction of the tobacco plants' chlorophyll giving the tobacco leaves a yellow appearance by converting starch into sugar and removing the moisture in the plants. By this procedure the aroma and flavor of each tobacco variety is brought out. The efficiency of this curing process is mainly due to the barn technology as well as the variety of different kinds of firewood used i.e. the mixture of tree species (Eucalyptus and Miombo woodlands). The firewood is collected in the surrounding forest areas (see Monela/Abdallah 2005, Sauer/Abdallah 2006). Figure 1 gives an illustration of the basic interrelations between tobacco production and forest species diversity

FIGURE 1: TOBACCO PRODUCTION AND FOREST DIVERSITY



Species Diversity

In general biodiversity can be considered at different levels: genetic diversity, species diversity as well as ecosystem diversity. Whereas genetic diversity refers to the diversity between and within populations (Norse et al. 1986), species diversity focuses the variety of species found, i.e. the number of different species existing in a biome, taxonomic grouping or a geographically defined area (Magurran 1988). Ecosystem diversity finally refers to the diversity between and within ecosystems. The following considerations solely focus on species diversity with respect to trees. The question of how many different species exist in a particular environment is central to the understanding of why it is important to promote and preserve species diversity. A uniform population of a single species of plants adapted to a particular environment is more at risk if environmental changes occur. A more diverse population consisting of many species of plants has a better chance of including individuals that might be able to adapt to changes in the environment. Hence, species diversity identifies and characterizes the biological community and the functional conditions of a habitat as well as the overall ecosystem (Kenchington et al. 2003). However, estimates of precise loss rates with respect to biological diversity are hampered by the absence of any baseline measurement (Pearce/Moran 1994). Different biodiversity indices - Simpson's Diversity

Index, Species Richness Index, Shannon Weaver Index, Patil and Taillie Index, Modified Hill's Ratio - have been applied to mathematically combine the effects of species' richness and eveness. Each has its merits putting more or less emphasis upon richness or eveness. The Shannon Weaver Diversity Index (H′, also called the Shannon Index or the Shannon-Wiener Index) as the most widely used shows the relative advantage of correcting for the "abundance" of species and can be mathematically described by

$$H^{'} = -\sum_{i=1}^{s} \rho_i \log_e \rho_i \qquad [35]$$

where p_i as the proportion of each species in the sample (relative abundance), log_e as the natural log of p_i, and s denotes the number of species in the community (species richness). The minimum value of 0 for H′ denotes a community consisting of only one species and is increasing as the number of species increases and the relative abundance becomes more even (see also Kindt et al., 2002). By a survey in 2003/2004 131 species have been found for the Miombo woodlands' forest in Tanzania: *Brachystegia boehmii Taub.* contributed about 10% to the total number of stems *Brachystegia spiciformis Benth.* about 7% and *Vitex payos (lour.) Merr.* about 5%. With respect to the family managed forests the most dominant species were found to be *Combretum zeyheri Sond* (about 20%), *Vitex paro (lour.) Merr.* (19%) *Markhamia obtusifolia (Bak.) Sprague* (18%) and *Lannea humilis (Oliv.) Engl.* (8%). With respect to the forest reserves the main dominant species are *Brachystegia boehmii Taub.* (12%), *Diplorhynchus condylocarpon (Muell. Arg.) Pichon* (8%), *Acacia tortilis (Forsk.) Hayne* (7%). 90% of the tobacco farmers interviewed named these species as being normally used for tobacco curing. The Shannon-Weaver Index calculated consequently ranges from 1.41 to 3.46 over the sample.

Data

Table 1 contains a descriptive statistic for the variables used, the number of cross-sectional observations are 110:

TABLE 1: DESCRIPTIVE STATISTICS

VARIABLE (UNIT)	MEAN	STDEV	MIN	MAX
TOTAL PROFIT/LOSS (USD)	649.977	161.484	-1101.352	3957.45
TOBACCO OUTPUT (KG)	935.329	913.937	165	6780
PRICE OF TOBACCO (USD/KG)	0.808	0.152	0.470	1.190
LABOR (MAN-DAYS)	353.494	242.219	23	1250
FIREWOOD (M^3)	4.073	2.086	1	12
LAND (HA)	0.971	0.754	0.202	4.856
FERTILIZER (50 KG BAGS)	10.298	8.528	2	60
PRICE OF LABOR (USD/MD)	1.599	0.717	0.67	2.74
PRICE OF FIREWOOD (USD/M^3)	16.017	6.244	2	28.32
PRICE OF LAND (USD/HA)	3.049	0.562	1.89	3.49
PRICE OF FERTILIZER (USD/BAG)	16.415	0.750	15.77	17.28
TOTAL COSTS (USD)	782.084	562.960	144.75	4106.36
DIVERSITY INDEX	1.928	0.696	1.46	3.41
COSTS OF SISALTWINE (USD/YEAR)	1.070	0.879	0	5.030
JUTETWINE (KG/YEAR)	2.766	2.552	0	16
LOAN (USD/YEAR)	86.141	80.262	0	556.02
LAND CLEARED (HA)	0.418	0.495	0	1
EXPERIENCE (YEARS)	21.418	14.109	4	44
BARN DESIGN	0.327	0.471	0	1
DISTANCE (KM)	6.300	3.779	0.5	20
EDUCATION (YEARS)	5.691	3.55	0	11
VILLAGE	2.909	1.351	1	5
SEX	1.818	0.387	1	2
AGE (YEARS)	43.3	12.688	20	78
SOURCE OF FIREWOOD	0.345	0.478	0	1

The total quantity of tobacco produced varies quite a bit over the sample and accordingly also the total profit made in the reference period (2003). Some farms even showed a net loss in the period. As inputs (family/hired) labour, firewood, land and fertilizer are used in the analysis. The quantity of labour used was calculated by summing up the man-days for family and hired labour with respect to the following operations: nursery, land clearing and tilling, transplanting, weeding, fertilizer application, pesticides spraying, topping and desuckering, harvesting, curing, grading and bailing. The price of labour was obtained by applying the opportunity costs of labour equaling the price for labour by the 'second-best' usage. As firewood is freely collected in the forests, the costs for firewood are obtained by considering the acquisition costs with respect to firewood cutting, loading, unloading as well as transport. The price of firewood is simply total costs for firewood divided by the sum of the firewood used in the curing cycles. The price of fertilizer was obtained from the dealers' records. As finally there are no prices for agricultural land in the majority of regions in Tanzania, the opportunity cost approach was again used by considering the rental rate for land with respect to the different villages in the sample. Total costs of tobacco production are obtained as the sum of all input cost items. The *diversity index* denotes the species diversity index on the base of the Shannon Weaver formula. As additional control variables influencing the profitability of tobacco production on the farm level the following variables are considered in the analysis according to data availability: the *costs of sisaltwine* used in production, the quantity of *jutetwine* used, and the total *loan* amount received in the production year. Further, the decision of the farmers to use already cultivated or newly *cleared land* is reflected by a binary variable denoting the land type used – newly cured forest land or already cultivated tobacco land. *Experience* denotes the farming experience of the respective household head whereas *barn design* is a binary proxy for the different tobacco curing technologies applied in the form of an improved furnace or a more traditional one. The level of education of the household head is reflected by the proxy variable *education* as the number of years of formal schooling received. The distance (in km) from the location of the farm to the edge of the next forest is considered by *distance*, *source of firewood* as a binary dummy variable reflects if the firewood used for tobacco curing was obtained from woodlands managed under community based arrangements or from woodlands managed by other forms of arrangements (i.e. open access or family based management). *Sex* finally refers to the gender of the farm head and *age* gives the age of the same. The variable *village* is incorporated to control for possible effects by the institutional setting of the village.

The Price of Diversity

As a profit maximisation framework is used in this study prices are the relevant categories with respect to the empirical analysis. However, from a production analysis point of view there are basically three different perspectives on biodiversity (i.e. species diversity, see also section 3):

> *Proposition 1*: The diversity of species found in the surrounding forests influences the level of profit made on the individual farm level.

Hence, *DI* (for diversity index, with $\mathrm{DI} \in \mathbb{R}_{+}^{U}$) controls for negative and/or positive effects on the profit frontier $\Pi^{'}$, and consequently the measure for environmentally conditional profit efficiency is

$$\pi E_E\left(y,x,DI,p,w\right)=\left[\left(p^T y-w^T x\right)/\pi\left(p,w\right)\right]:\left(y,x,DI\right)\in\Pi^{'} \qquad [36]$$

where πE_E has to satisfy the properties

(i) $\pi E_E\left(y,x,DI,p,w\right)\le 1$, with $\pi E_E\left(y,x,DI,p,w\right)=1 \Leftrightarrow y=y\left(p,w\right),x,DI=x\left(p,w\right)$ so that $\left(p^T y-w^T x\right)=\pi\left(p,w\right)$

(ii) $\pi E_E\left(\lambda y,x,DI,p,w\right)\ge\pi E_E\left(y,x,DI,p,w\right),\lambda\ge 1$

(iii) $\pi E_E\left(y,\lambda x,DI,p,w\right)\le\pi E_E\left(y,x,DI,p,w\right),\lambda\ge 1$

(iv) $\pi E_E\left(y,x,DI,\lambda p,\lambda w\right)=\pi E_E\left(y,x,DI,p,w\right),\lambda>0$.

Following proposition 1 a construction of a diversity price vector is not necessary as species diversity enters the empirical model additively as a control variable by simply using the relative index numbers constructed by the Shannon-Weaver Diversity Index H'.

Proposition 2: The loss of diverse tree species in the surrounding forests as a consequence of increased land clearing and use of firewood can be considered as a detrimental input to production beside the ordinary inputs labour, land, firewood, and fertilizer.

It is assumed that the lower the diversity index in the surrounding forest area (i.e. the higher the scarcity of variety), the higher the price for using it as an input to production. Hence, w_{DI} (as the price of diversity, with $w_{DI} \in \mathbb{R}_{++}^{U}$) is incorporated in the profit function as follows

$$\Pi\left(y, x, x_{DI}, p, w, w_{DI}\right) = \left[\left(p^{T} y - w^{T} x - w_{DI} x_{DI}\right) / \pi\left(p, w, w_{DI}\right)\right] \qquad [37]$$

and consequently the measure for input environmental efficiency is

$$EE_{I_{DI}}\left(x_{DI}, y, w_{DI}\right) = CE(y, x, x_{DI}, w_{x}, w_{DI}) / \left[TE_{I}(y, x, x_{DI}) * AE_{I}(x, y, w_{x})\right] \qquad [38]$$

where $EE_{I_{DI}}$ has to satisfy the properties:

(v) $0 < EE_{I_{DI}}\left(x_{DI}, y, w_{DI}\right) \leq 1$

(vi) $EE_{I_{DI}}\left(x_{DI}, y, w_{z}\right) = 1 \Leftrightarrow \lambda \leq 1$ so that $\lambda x_{DI} = x_{DI}(y, w_{DI})$

(vii) $EE_{I_{DI}}\left(\lambda x_{DI}, y, w_{DI}\right) = EE_{I_{DI}}\left(x_{DI}, y, w_{DI}\right)$ for $\lambda > 0$

(viii) $EE_{I_{DI}}\left(x_{DI}, y, \lambda w_{DI}\right) = EE_{I_{DI}}\left(x_{DI}, y, w_{DI}\right)$ for $\lambda > 0$.

Proposition 3: The diversity of species found in the surrounding forests can be regarded as a desirable output of production beside the ordinary output tobacco produced.

It is assumed that the lower the diversity index in the surrounding area, the higher the value of the output species diversity (i.e. the value of creating less diversity loss) for the adjacent livelihoods, and consequently the higher its price. Hence, p_{DI} (as the price of diversity, with $p_{DI} \in \mathbb{R}_{++}^{S}$) can be incorporated in the profit function as follows

$$\Pi\left(y, y_{DI}, x, p, p_{DI}, w\right) = \left[\left(p^{T} y + p_{DI} y_{DI} - w^{T} x\right) / \pi\left(p, p_{DI}, w, w_{DI}\right)\right] \qquad [39]$$

and consequently the measure for output environmental efficiency is

$$EE_{o_{DI}}\left(x, y_{DI}, p_{DI}\right) = RE\left(x, y, p, y_{DI}, p_{DI}\right) / \left[TE_o\left(x, y\right) * AE_{o_{DI}}\left(x, y_{DI}, p_{DI}\right)\right] \qquad [40]$$

and $EE_{o_{DI}}$ has to satisfy the following properties

(ix) $0 < EE_{o\,DI}\left(x, y_{DI}, p_{DI}\right) \leq 1$

(x) $EE_{o_{DI}}\left(x, y_{DI}, p_{DI}\right) = 1 \Leftrightarrow \lambda \geq 1$ so that $\lambda y_{DI} = y_{DI}(x, p_{DI})$

(xi) $EE_{o_{DI}}\left(x, \lambda y_{DI}, p_{DI}\right) = EE_{o_{DI}}\left(x, y_{DI}, p_{DI}\right)$ for $\lambda > 0$

(xii) $EE_{o_{DI}}\left(x, y_{DI}, \lambda p_{DI}\right) = EE_{o\,DI}\left(x, y_{DI}, p_{DI}\right)$ for $\lambda > 0$.

Following proposition 2 or proposition 3 a price vector for the detrimental input species diversity or the desirable output species diversity respectively can be constructed by using the diversity scale found in the sample following

$$w_{DI_f} = w_{DI_{f-1}} - \left(H'_f - H'_{f-1}\right) \qquad [41]$$

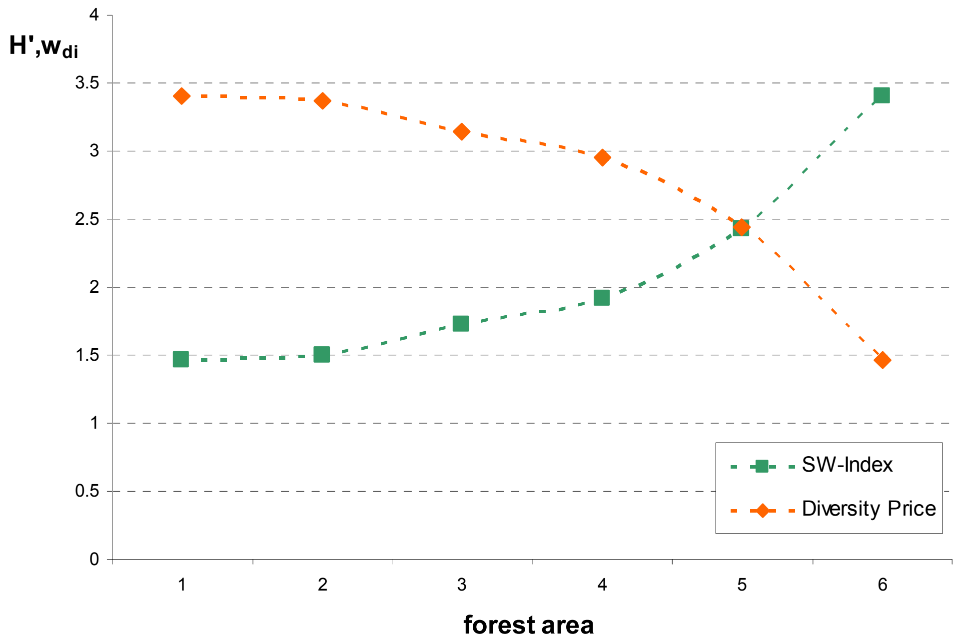
where f = 1, …, 6 and $w_{DI_f} = \max(H')$ for f = 1. Such a simple price vector would be consistent with the individual index relations, i.e. the higher H' the lower the relative scarcity in this forest area *f* and the lower consequently the price w_{DI_f} for using it or for producing it. Table 2 summarizes the generated price vector w_{DI_f}:

TABLE 2: A PRICE OF SPECIES DIVERSITY

Forest Area *f*	1	2	3	4	5	6
SW-Index (*H'*)	1.46	1.5	1.73	1.92	2.43	3.41
w_{DI_f}	3.41	3.37	3.14	2.95	2.44	1.46

This can be illustrated by figure 2:

FIGURE 2: SPECIES DIVERSITY – INDEXED BASED PRICE AND QUANTITY



6. DIFFERENT STOCHASTIC ESTIMATION MODELS

As briefly outlined in section 2 this contribution tries to combine the shadow price approach with a fixed effects non-radial model by using a translog functional form. Whereas model 1 to 3 use a single ouput profit frontier approach model 4 is built on a multi output distance function specification.

Model I – Invariant Controling for Diversity

Species diversity is incorporated as a simple control variable DI_i invariant over the sample of producers. Using the output tobacco produced and the inputs fertilizer, firewood, labour and land where the output price serves as a numeraire the translog shadow profit system in equations [23] to [25] is then reformulated and estimated following [20] to [22] as

$$\ln \pi = \beta_0 + \sum_n \gamma_n \ln\left(\frac{\theta_n w_n}{\kappa p}\right) + \frac{1}{2}\sum_n \gamma_{nn}\left[\ln\left(\frac{\theta_n w_n}{\kappa p}\right)\right]^2 + \sum_k \sum_n \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right)\ln\left(\frac{\theta_n w_n}{\kappa p}\right) + \sum_o \varsigma_o \ln C_o$$
$$+\zeta_{DI} \ln DI + \ln\left\{1 + \left(\frac{1-\kappa_m}{\kappa_m}\right)R_m * + \left(\frac{1-\theta_n}{\theta_n}\right)S_n *\right\} + \ln \phi$$

[42]

$$S_n = \frac{-\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right)\right)}{\left[1 + \left(\frac{1-\kappa_m}{\kappa_m}\right)\left(\sum_n \delta_{mn} \ln\left(\frac{\theta_n w_n}{\kappa p}\right)\right) + \left(\frac{1-\theta_n}{\theta_n}\right)\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right)\right)\right]\theta_n} \qquad [43]$$

where k, n = fertilizer, firewood, labour, land and m = tobacco. Classical error terms are appended and one share equation is deleted, the remaining system of 5 equations is estimated by using iterated seemingly unrelated regression (ITSUR). By following the procedure shown in [30] to [34] convexity is imposed on model I (model IB).

Model II – Group-Wise Controling for Diversity

As in model I species diversity is incorporated as a simple control variable DI_q, but different from model I it varies over groups of tobacco producers defined along the diversity index H' found in the surrounding forest areas. Using the output tobacco produced and the inputs fertilizer, firewood, labour and land where the output price serves as a numeraire the translog shadow profit system becomes now

$$\ln \pi = \beta_0 + \sum_n \gamma_n \ln\left(\frac{\theta_n w_n}{\kappa p}\right) + \frac{1}{2}\sum_n \gamma_{nn}\left[\ln\left(\frac{\theta_n w_n}{\kappa p}\right)\right]^2 + \sum_k \sum_n \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right)\ln\left(\frac{\theta_n w_n}{\kappa p}\right) + \sum_o \varsigma_o \ln C_o$$
$$+\zeta_q \ln DI_q + \ln\left\{1 + \left(\frac{1-\kappa_m}{\kappa_m}\right)R_m * + \left(\frac{1-\theta_n}{\theta_n}\right)S_n *\right\} + \ln \phi$$

[44]

$$S_n = \frac{-\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right) + \zeta_q \ln DI_q\right)}{\left[1 + \left(\frac{1-\kappa_m}{\kappa_m}\right)\left(\sum_n \delta_{mn} \ln\left(\frac{\theta_n w_n}{\kappa p}\right) + \zeta_q \ln DI_q\right) + \left(\frac{1-\theta_n}{\theta_n}\right)\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right) + \zeta_q \ln DI_q\right)\right]\theta_n}$$

[45]

where k, n = fertilizer, firewood, labour, land and m = tobacco. Classical error terms are appended and one share equation is deleted, the remaining system of 5 equations is again estimated by using ITSUR. By following the procedure shown in [30] to [34] convexity is imposed on model II (model IIB).

Model III – Diversity as an Input

Species diversity is now incorporated as an input for production x_{di} varying over the sample of producers. The system of equations to estimate is then

$$\ln \pi = \beta_0 + \sum_n \gamma_n \ln\left(\frac{\theta_n w_n}{\kappa p}\right) + \frac{1}{2}\sum_n \gamma_{nn}\left[\ln\left(\frac{\theta_n w_n}{\kappa p}\right)\right]^2 + \sum_k \sum_n \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right)\ln\left(\frac{\theta_n w_n}{\kappa p}\right)$$
$$+ \sum_o \varsigma_o \ln C_o + \ln\left\{1 + \left(\frac{1-\kappa_m}{\kappa_m}\right)R_m{*} + \left(\frac{1-\theta_n}{\theta_n}\right)S_n{*}\right\} + \ln\phi \qquad [46]$$

$$S_n = \frac{-\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right)\right)}{\left[1 + \left(\frac{1-\kappa_m}{\kappa_m}\right)\left(\sum_n \delta_{mn} \ln\left(\frac{\theta_n w_n}{\kappa p}\right)\right) + \left(\frac{1-\theta_n}{\theta_n}\right)\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa p}\right)\right)\right]\theta_n} \qquad [47]$$

where now k, n = fertilizer, firewood, labour, land as well as species diversity and m = tobacco. The estimation procedure follows the one applied before. Again following the matrix procedure shown in [30] to [34] convexity is further imposed on model 3 (model IIIB).

Model IV – Diversity as an Output

Species diversity is now incorporated as an output of production y_{di} varying over the sample of producers. The system of equations to estimate is then

$$
\begin{aligned}
\ln \pi = {} & \beta_0 + \beta_{di} \ln\left(\frac{\kappa_{di} p_{di}}{\kappa_{tob} p_{tob}}\right) + \sum_n \gamma_n \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{ob}}\right) + \frac{1}{2}\sum_n \gamma_{nn} \left[\ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right)\right]^2 + \frac{1}{2}\beta_{didi}\left[\ln\left(\frac{\kappa_{di} p_{di}}{\kappa_{tob} p_{tob}}\right)\right]^2 \\
& + \sum_k \sum_n \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa_{tob} p_{ob}}\right) \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right) + \sum_n \delta_{din} \ln\left(\frac{\kappa_{di} p_{di}}{\kappa_{tob} p_{ob}}\right) \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right) + \\
& + \sum_o \varsigma_o \ln C_o + \ln\left\{1 + \left(\frac{1-\kappa_{di}}{\kappa_{di}}\right) R_{di}* + \left(\frac{1-\kappa_{tob}}{\kappa_{tob}}\right) R_{tob}* + \left(\frac{1-\theta_n}{\theta_n}\right) S_n*\right\} + \ln \phi
\end{aligned}
$$

[48]

$$
R_{di} = \frac{\left(\beta_{di} + \sum_n \delta_{din} \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right)\right)}{\left[\begin{array}{l}\left[1 + \left(\frac{1-\kappa_{di}}{\kappa_{di}}\right)\left(\sum_n \delta_{din} \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right)\right)\right] + \left[1 + \left(\frac{1-\kappa_{tob}}{\kappa_{tob}}\right)\left(\sum_n \delta_{tobn} \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right)\right)\right] \\ + \left(\frac{1-\theta_n}{\theta_n}\right)\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa_{tob} p_{tob}}\right)\right)\end{array}\right]\kappa_{di}}
$$

[49]

$$
S_n = \frac{-\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa_{tob} p_{tob}}\right) + \sum_n \delta_{din} \ln\left(\frac{\kappa_{di} p_{di}}{\kappa_{tob} p_{ob}}\right)\right)}{\left[\begin{array}{l}\left[1 + \left(\frac{1-\kappa_{di}}{\kappa_{di}}\right)\left(\sum_n \delta_{din} \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right)\right)\right] + \left[1 + \left(\frac{1-\kappa_{tob}}{\kappa_{tob}}\right)\left(\sum_n \delta_{tobn} \ln\left(\frac{\theta_n w_n}{\kappa_{tob} p_{tob}}\right)\right)\right] \\ + \left(\frac{1-\theta_n}{\theta_n}\right)\left(\gamma_n + \sum_k \gamma_{kn} \ln\left(\frac{\theta_k w_k}{\kappa_{tob} p_{tob}}\right) + \sum_n \delta_{din} \ln\left(\frac{\kappa_{di} p_{di}}{\kappa_{tob} p_{ob}}\right)\right)\end{array}\right]\theta_n}
$$

[50]

where k, n = fertilizer, firewood, labour, land and m = tobacco as well as species diversity. The estimation procedure follows again the one applied before and convexity is also imposed on model IV (model IVB) following [30] to [34]. Hence, in total 8 different model specifications as well as the corresponding efficiency measures are estimated.

7. RESULTS AND IMPLICATIONS

The estimations reveal a relatively good overall model fit of model IA, model IIIA, and model IVB (see table 3). This implies that for the cross-sectional data set used the modelling options of controling for diversity (I), incorporating diversity as an input (III), and incorporating diversity as an output (IV) in a constrained specification are superior to the modelling option of controling for group-wise diversity by fixed effects (II). More than 90% of all individual parameter estimates over all estimation models are statistically significant (the more than 450 parameter estimates can be obtained from the author). Imposing curvature correctness on the translog profit system (i.e. convexity of the profit function) led to an improvement in theoretical consistency of up to 412% (model III). However, from a theoretical point of view this seems not very convincing as the different models still violate curvature at least for 50% of the observations in the sample.

TABLE 3: MODEL STATISTICS

MODEL	I		II		III		IV	
	A	B	A	B	A	B	A	B
ADJ R^2 (PROFIT SYSTEM)	0.954	0.651	0.590	0.239	0.829	0.599	0.389	0.326
F-VALUE	5.5E+03	1.2E+03	7.1E+03	9.7E+02	2.8E+03	3.6E+03	4.8E+03	3.6E+03
P>|F|	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CONVEXITY (%)	20.91	50.91	34.54	40.1	7.27	30.1	16.4	30.91

A: unconstrained specification, B: constrained specification

Table 4 summarizes the different efficiency scores with respect to the various model specifications estimated:

TABLE 4: SYSTEMATIC EFFICIENCY SCORES

MODEL	I		II		III		IV	
	A	B	A	B	A	B	A	B
ALLOCATIVE EFFICIENCY								
syst. output AE	0.292***	0.555***	0.803***	0.826***	0.342***	0.873***	0.171***	0.458***
syst. input AE fertilizer	0.131***	0.667***	0.027***	0.003***	0.760***	0.319***	0.074***	0.328***
syst. input AE firewood	0.735***	0.619***	0.899***	0.782***	0.950***	0.908***	0.245***	0.769***
syst. input AE labour	0.025***	0.787***	0.470***	0.835***	0.405***	0.360***	0.105***	0.730***
syst. input AE land	0.813***	0.842***	0.980***	0.565***	0.462***	0.375***	0.066***	0.557***

TECHNICAL EFFICIENCY								
syst. output-oriented TE	0.476	0.100	0.823	0.706	0.603***	0.564	0.165***	0.507***
ENVIRONMENTAL EFFICIENCY								
syst. input EE	-	-	-	-	0.182***	0.214***	-	-
syst. output EE	-	-	-	-	-	-	0.174***	0.135***

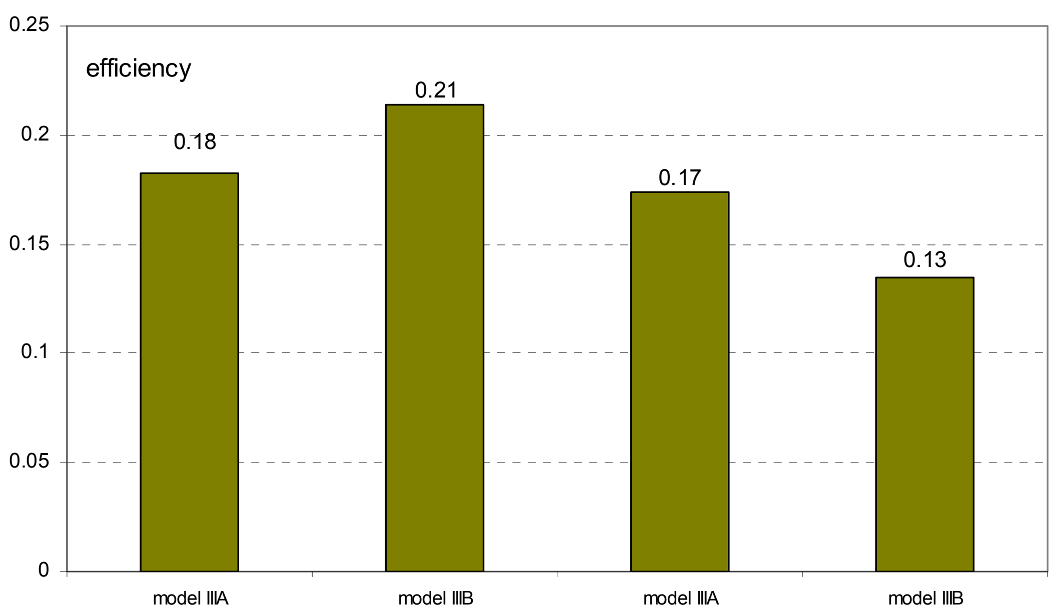
A: unconstrained specification, B: constrained specification
AE: allocative efficiency, TE: technical efficiency, PE: profit efficiency, EE: environmental efficiency
*,**,***: significance at 10, 5, and 1 % -level respectively

Systematic allocative efficiency varies quite a bit over the different models estimated. Controling for species diversity (model I) delivered relatively high values for allocative efficiency with respect to the input land and the input firewood. Mixed evidence was found for the inputs ferilizer and labour as well as the output tobacco. The fixed effects based model (model II) showed high values for output allocative efficiency as well as for input allocative efficiency with respect to firewood. The opposite was found for the input fertilizer. Mixed evidence can be reported for labour and land. Modelling species diversity as an input to tobacco production (model III) delivered for both specifications a high allocative efficiency with respect to the use of the input firewood and a relatively modest allocative efficiency for the use of the inputs labour and land. As for model I mixed evidence was found for the input fertilizer and the output tobacco. Finally modelling species diversity as an output of a joint production structure (model IV) resulted in mixed evidence with respect to all forms of systematic allocative efficiency investigated. Whereas the unconstrained model specification showed low values for almost all inputs and the output tobacco, the constrained one resulted in a relatively high efficiency with respect to land, labour as well as fertilizer and a relatively modest efficiency for fertilizer and tobacco. Comparing the allocative efficiency values over all unconstrained specifications (model IA to IVA) gives (more or less) consistent levels of efficiency for the inputs fertilizer, firewood and labour for at least 3 out of 4 models. Focusing on the other side the allocative efficiency values over all constrained specifications (model IB to IVB) gives (more or less) consistent levels of efficiency with respect to the output tobacco and the inputs firewood, labour and land for at least 3 out of 4 models.

Systematic output-oriented technical efficiency was found to be relatively high following model II and model III whereas mixed evidence has to be reported for model I and model IV. However, comparing again technical efficiency over all unconstrained specifications (model IA to IVA) gives consistent levels of efficiency for at least 3 out of 4 models. The same holds for the comparison with respect to the constrained specifications (model IB to IVB). It has to be noted that not all technical efficiency estimates were found to be statistically significant.

Environmental efficiency was estimated in a systematic input related (model III) as well as a systematic output related specification (model IV). Nevertheless, both model assumptions led to a relatively low level of environmental efficiency (0.135 to 0.214) with respect to species diversity. As figure 3 illustrates these findings are confirmed by the unconstrained and the constrained model case (model IIIB and IVB).

FIGURE 3: ENVIRONMENTAL EFFICIENCY



Environmentally conditional efficiency was estimated by applying a fixed effects model approach and controlling for different levels of species diversity (H') in the surrounding forest areas (model II). Table 5 summarizes the empirical findings for each of the 5 groups of tobacco producers by input and model specification:

TABLE 5: ENVIRONMENTALLY CONDITIONAL EFFICIENCY (MODEL II)

Group of Producers	Profit Efficiency		Input AE Fertilizer		Input AE Firewood		Input AE Labour		Input AE Land	
Model Specification	A	B	A	B	A	B	A	B	A	B
1 (H' = 3.41)	1	1***	1***	0.609***	0.686	1***	0.345***	1**	1***	1***
2 (H' = 2.43)	0.558	0.584	0.885	0.850	1	0.966	1***	0.518	0.231	0.237
3 (H' = 1.73)	0.276	0.599	0.899	0.879	0.689	0.665	0.816	0.606	0.214	0.238
4 (H' = 1.5)	0.777	0.728	0.254	0.517**	0.300*	0.979	0.884	0.271***	0.503	0.685*
5 (H' = 1.46)	0.362	0.652***	0.725***	1***	0.896***	0.963***	0.293***	0.792*	0.291***	0.174***

A: unconstrained specification, B: constrained specification
AE: allocative efficiency. By definition one group of producers is on the frontier, i. e. shows a relative efficiency score of 1.
*,**,***: significance at 10, 5, and 1 % -level respectively.

Overall environmentally conditional profit efficiency was found to be the highest for producers of group 1 followed by those in group 4. This was obtained by both model specifications. The same was revealed for environmentally conditional allocative efficiency with respect to land. However, for the inputs fertilizer, firewood and labour the group-wise efficiency estimates differ to some extent between the unconstrained and constrained model. A significant correlation between the ranking of the producer groups (i.e. species diversity index) and the ranking of the environmentally conditional efficiency estimates could only be confirmed for the allocative efficiency with respect to the use of fertilizer (see table 6): the higher the diversity index H' the higher the allocative efficiency with respect to fertilizer.

TABLE 6: SPEARMAN'S RANK CORRELATION (MODEL II)

Species Diversity	Profit Efficiency		Input AE Fertilizer		Input AE Firewood		Input AE Labour		Input AE Land	
Model Specification	A	B	A	B	A	B	A	B	A	B
H'	0.5	0.1	0.8*	-0.4	0.0	0.5	0.3	0.3	0.2	0.6

A: unconstrained specification, B: constrained specification; *: significance at 10 %-level respectively.

From a policy point of view the following implications have to be noted: The relative modest level of allocative efficiency with respect to the use of labour and land as well as the relative low level of allocative efficiency with respect to the use of fertilizer point to market distortions in the rural agricultural input markets. Structural measures targeting the allocation of these inputs due to their relative price ratios could lead to an improvement in the efficiency of small-scale tobacco production. The modest allocative efficiency of the output related production decisions further highlight existing scope for policy actions aiming to influence the farmers' production decisions with respect to scarcity considerations. Improvements in technical efficiency are possible by targeting the education of the farmers and/or facilitating the choice of more modern technology, e.g. by fostering the modernisation of the barn design and/or strengthening agricultural consulting services. The rather low level of environmental efficiency on farm level with respect to species diversity in the surrounding forest areas impressively point to the need for policy measures aiming at reducing the negative impacts of tobacco production on biodiversity in rural areas of Tanzania. One option could be to establish a system of compensation payments for using firewood of predefined species which are not endangered by species loss. In addition a diversification of small-scale agricultural production towards less environmentally detrimental (as well as more allocatively efficient) crops could lead to an increase in environmental efficiency of tobacco producing farms. The significant positive correlation of the group-wise species diversity index and allocative efficiency with respect to the use of fertilizer for tobacco cultivation finally delivers empirical evidence for the crucial role of chemical fertilizers for the biological and geophysical processes with respect to forest trees (see e.g. Geist 1999). This implies that the environmental efficiency of tobacco producing farms can be increased by enhancing the allocative efficiency of fertilizer use.

From a modelling point of view the empirical results deliver evidence with respect to the following points: The clear deviation of the constrained efficiency estimates from the unconstrained efficiency estimates shows that stochastic performance scores are very sensitive with respect to the underlying functional form and its correct curvature (see also Sauer 2006). However, the effect of the underlying modelling assumption – i.e. controling for diversity, group-wise environmentally fixed effects, diversity as an input or output – was found to be not that crucial as initially assumed: controling for diversity (I), incorporating diversity as an input (III), and incorporating diversity as an output (IV) in a constrained specification showed to be superior specifications compared to the group-wise fixed effects model approach (II). Hence, the underlying modelling proposition 1, proposition 2 as well as proposition 3 formulated in section 5 are proved to be empirically valid with respect to the different efficiency measures analysed. Focusing the stochastic measurement of environmental efficiency it became clear that from an empirical point of view a flexible shadow profit function approach incorporating diversity as a productive input to production as well as a flexible shadow profit function approach incorporating diversity as a desirable output of production should be chosen.

8. Conclusions

The preceeding analysis attempts the stochastic modelling of efficiency frontiers considering also environmental efficiency. As an empirical example the case of small-scale tobacco production and its links to species diversity in surrounding forest areas were used. Four different modelling approaches were chosen based on three underlying propositions with respect to the incorporation of species diversity. The current discussion on the effects of theoretical consistency and functional flexibility on stochastic efficiency measures was considered by estimating all efficiency models in an unconstrained as well as a constrained specification.

The empirical results revealed that the underlying modelling assumption is not essential with respect to the statistical validity and empirical consistency of the efficiency estimates. From an empirical point of view a flexible shadow profit function approach incorporating biodiversity as a productive input to production as well as a flexible shadow profit function approach incorporating biodiversity as a desirable output of production showed to be superior. As previous investigations revealed: stochastic performance measures are very sensitive with respect to the theoretical consistency of the underlying functional form. With respect to the accuracy of the econometric results the latter point seems to be more crucial than the underlying proposition with respect to the appropriate incorporation of the environment related variable. Hence, this study contributes to the ongoing discussion on the stochastic modelling of environmental efficiency by empirically verifying the concern for theoretical consistency of the econometric model beside the need for statistical significance.

The empirical results finally point to the need for policy actions to increase the allocative efficiency of agricultural input markets as well as the technical and environmental efficiency of small-scale tobacco farms. Future research should focus on the analysis of the dynamics of environmetal efficiency.

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