Brümmer, Bernhard; Glauben, Thomas; Thijssen, Geert

Working Paper

Analysis of productivity growth within a distance function approach: An application to European dairy farms

FE Workingpaper / Universität Kiel, Department of Food Economics and Consumption Studies, No. 9903

Provided in cooperation with:

Christian-Albrechts-Universität Kiel (CAU)

Analysis of productivity growth within a distance function approach: An application to European dairy farms

Bernhard Brümmer, Christian-Albrechts-University of Kiel, Germany

Thomas Glauben, Christian-Albrechts-University of Kiel, Germany

Geert Thijssen, Wageningen Agricultural University, The Netherlands

29 October, 1999

Contact address: Bernhard Brümmer
Institut für Agrarökonomie
Christian-Albrechts-Universität Kiel
24098 Kiel
Germany
Tel.: +49 (0) 431 880 4449
Fax.: +49 (0) 431 880 4592
e-mail: bbruemmer@email.uni-kiel.de

* The willingness of the Agricultural Economics research Institute in The Hague to make data available for this study is gratefully acknowledged.

Abstract

A detailed decomposition of the sources of the Total Factor Productivity (TFP) growth index within an output distance function framework was carried out, looking at the following components: technical change, change in technical efficiency, scale component, and violations of the profit maximizing assumption for inputs and outputs. Stochastic translog output distance functions were estimated by using panel data from dairy farms over the period 1991- 1994 for three European regions (northern Germany, the Netherlands, Poland) separately and for all regions together. The decomposition results were then examined , and a detailed comparison of the separate and the common model was made.

Introduction

Until recently, literature on productivity growth measurement has been primarily based on the standard calculation of Total Factor Productivity (TFP). The growth rate of this index is usually interpreted as a measure of technical change (TC). This way of interpretation incorporates several restrictive assumptions such as constant returns to scale and allocative and technical efficiency. To disentangle some of these shortcomings and to identify the components of TFP change, several techniques were developed based on the decomposition of the standard productivity index (TFP).

Nishimizu and Page (1981) showed that, when panel data are available, productivity growth can be estimated as the combination of two components, one at the frontier level (technical change) and the other at the firm level (efficiency change). Morrison (1992), starting from a cost function approach, ignored the efficiency component but took the effect of scale economies, markups of price over marginal costs and also adjustments for capital utilization into account. A decomposition of productivity growth into scale effects, technical change, technical efficiency and price components was carried out by Kumbhakar (1997).

In this article we have extended the line of the Kumbhakar production function approach to a distance function approach. We decomposed the traditional index of TFP growth into the following components: technical change, change in technical efficiency, scale component, and price effects of inputs and outputs. The allocative effects for outputs[1] require the explicit modeling of a multi-input, multi-output technology. Therefore, we used an output distance function approach.[2] Another characteristic of the distance function approach is that no behavioral assumption (cost minimization or profit maximization) is necessary. This might be especially advantageous for the Polish case because of changes in market constellations in a transformation economy. We then applied the analysis to the estimation of productivity growth using panel data from dairy farms over the period 1991-1994 of selected European regions: northern Germany (Schleswig-Holstein), the Netherlands and Poland. While northern Germany and the Netherlands have a similar environment with regard to both natural conditions and agricultural policy regime, Poland as an economy in transformation is clearly a different case. Unlike other central and east European countries, the private farming in Poland has traditionally been much more important than collective (state and cooperative) farming[3]. Hence, the structural transformation of private agriculture in Poland has been smoother than in countries like the Slovak Republic or Hungary. This allowed us to draw more meaningful conclusions from direct comparisons between all three regions. Therefore, we estimated a parametric translog output distance function for each region, and for all regions together[4].

Several approaches to comparing productivity growth have been suggested in literature. The first studies in this field used a one-dimensional scale. For example, Hayami and Ruttan (1970) and Kawagoe, Hayami and Ruttan (1985) used cross-country data to estimate a global production function. An extension of this approach to a two-dimensional approach was accomplished by using panel data from different countries over time (e.g. Binswanger et al. (1987), Morrison (1992) and Färe et al (1994)). In our study we used a three dimensional scale — different farms in different countries in different years. This allowed us to analyse productivity growth for each country separately, but also for them together.

The article is structured as follows. First, we give a short description of the output distance function framework. Using this approach, we then describe the decomposition of the standard measure of TFP growth. In the next section we look at the incorporation of these components into a stochastic translog output distance function. We also show how the discrete nature of data has been taken into account. This is followed by a presentation of the data and the results of the estimation of TFP growth in the regions over the period 1991-1994. We focus especially on the interpretation of the calculated productivity growth components. Finally, we summarize and give our main conclusions.

Theoretical background

One way to define the output distance function is to start from the output correspondence. Consider a farm using a vector of K inputs $x^t = \left(x_1^t, \ldots, x_K^t\right)$ to produce a vector of M outputs $y^t = \left(y_1^t, \ldots, y_M^t\right)$ for each time period $t=1\ldots N$. The output set is defined as the set of all output vectors which can be produced with an arbitrary input vector x^t. This defines the output correspondence which maps each possible vector x^t to an output set $P^t(x^t)$ (see Färe and Primont, p. 11). In terms of the output correspondence, the output distance function is defined as

$$D_o^t\left(x^t, y^t\right) = \inf_{\phi}\left\{\phi > 0: \left(\frac{y^t}{\phi}\right) \in P^t\left(x^t\right)\right\} \textit{ for all } x^t \in \Re_+^K \qquad (1)$$

The distance function is defined as the reciprocal of the maximum proportional expansion of the output vector y^t, given inputs x^t. It characterizes the technology completely. The output distance function is non-decreasing, convex, and linearly homogeneous in outputs. Furthermore, this function is non-increasing and quasiconcave in inputs (see Färe and Primont).

This definition of $D^t_o(x^t,y^t)$ for the case of two outputs y_1 and y_2 is illustrated in Figure 1[5]. The output set $P^t(x^t)$ is determined by a given input vector x^t. For an arbitrarily chosen vector of outputs y^t, the value of $D^t_o(x^t,y^t)$ projects the output vector along the ray from the origin through y^t on the boundary of $P^t\left(x^t\right)$. In this example, y^t is interior of $P^t\left(x^t\right)$ and thus $D^t_o(x^t,y^t) < 1$. The distance function takes a value of one whenever the output vector lies on the outer boundary of the output set. This means that the farm is technically efficient.

Figure 1: Productivity change in a distance function framework

We then used this distance function representation of technology to derive the different components of (observable) productivity change: technical change, change in technical efficiency, scale effect, and price effects of inputs and outputs. Our starting point was provided by the fact that the reciprocal of the distance function is equal to the Farrell-type output orientated measure of technical efficiency TE.[6]

$$D_O(t,x,y) = 1/TE \Leftrightarrow \ln D_O(t,x,y) + TE = 0 \tag{2}$$

This could be rewritten with an exponential non-negative error term *u* that accounts for technical inefficiency.

$$D_o(t,x,y)\exp(u) = 1 \Leftrightarrow \ln D_o(t,x,y) + u = 0 \tag{3}$$

Totally differentiating the latter expression led to

$$\sum_{m=1}^{M} \frac{\partial \ln D_o(.)}{\partial \ln y_m}\dot{y}_m + \sum_{k=1}^{K} \frac{\partial \ln D_o(.)}{\partial \ln x_k}\dot{x}_k + \frac{\partial \ln D_o(.)}{\partial t} + \frac{\partial u}{\partial t} = 0 \tag{4}$$

where a dot over a variable indicates the respective growth rate, e.g., $\dot{y} = dy/y$.

Next, we defined $\frac{\partial \ln D_o(.)}{\partial \ln y_m} = \mu_m$ and $\frac{\partial \ln D_o(.)}{\partial \ln x_k} = -\lambda_k RTS$[7]. Using these definitions and multiplying equation (4) by minus gave

$$-\sum_{m=1}^{M} \mu_m \dot{y}_m + RTS\sum_{k=1}^{K} \lambda_k \dot{x}_k - \frac{\partial \ln D_o(.)}{\partial t} - \frac{\partial u}{\partial t} = 0 \tag{5}$$

The traditional total factor productivity growth measure $T\dot{F}P$ for a multi-output, multi-input setting is defined as $T\dot{F}P = \sum_{m=1}^{M} R_m \dot{y}_m - \sum_{k=1}^{K} S_k \dot{x}_k$, where $R_m = \frac{p_m y_m}{\sum_m p_m y_m}$ is the revenue share of output y_m, $S_k = \frac{w_k x_k}{\sum_k w_k x_k}$ is the cost share of input x_k, and

$p = (p_1, \ldots, p_M)$, $w = (w_1, \ldots, w_K)$ are the price vectors for outputs and inputs, respectively.

Using this definition and equation (5) , we can identify the different components of TFP growth. Summing up equation (5) and the above definition of TFP growth leads to equation (6), the decomposition formula of productivity growth for multiple outputs.

$$\begin{aligned} T\dot{F}P &= \sum_{m=1}^{M} (R_m - \mu_m)\dot{y}_m + \sum_{k=1}^{K} (RTS\lambda_k - S_k)\dot{x}_k - \frac{\partial \ln D_o(.)}{\partial t} - \frac{\partial u}{\partial t} \\ &= \sum_{m=1}^{M} (R_m - \mu_m)\dot{y}_m + \sum_{k=1}^{K} (\lambda_k - S_k)\dot{x}_k + (RTS-1)\sum_{k=1}^{K} \lambda_k \dot{x}_k - \frac{\partial \ln D_o(.)}{\partial t} - \frac{\partial u}{\partial t} \end{aligned} \qquad (6)$$

Observable factor productivity growth is decomposed into an output price effect, an input price effect, a scale effect, a technical change effect, and a technical inefficiency effect[8]. For example, assume constant RTS (= *1*) and allocative inefficiency (see below) on neither the output nor the input side. Equation (6) then collapses to the effect of technical change, $-\frac{\partial \ln D_O}{\partial t}$, and to the effect of change in technical efficiency, $-\frac{\partial u}{\partial t}$. If we have non-constant RTS ($\neq$ 1), but allocative and technical efficiency and no technical change, then the above equation contains the pure scale effect $(RTS-1)\sum_{k=1}^{K} \lambda_k \dot{x}_k$.

These components are also depicted in Figure 1. Technical change leads to a change in the output set from $P^t(x^{t+1})$ to $P^{t+1}(x^{t+1})$. The related change in the distance function is represented by a change from $D^t_o(x^{t+1}, y^{t+1})$ to $D^{t+1}_o(x^{t+1}, y^{t+1})$. Efficiency change measures the producer capacity to improve technical efficiency from period t to period t+1, and is represented by a change from $D^t_o(x^t, y^t)$ to $D^{t+1}_o(x^{t+1}, y^{t+1})$. In Figure 1 there are locally varying returns to scale, because an increase of x^t to x^{t+1} and assuming the same technology P^t does not lead to an equi-proportianate shift in the isoquant.

To gain insights into the price effects for output m (R_m - $\mu_m \neq 0$) and input k (λ_k - $S_k \neq 0$) in Equation (6), we derived the stationary solutions of the following simple profit maximization approach: $\max_{y,x} \sum_m p_m y_m - \sum_k w_k x_k$ subject to $D_o(x, y) - 1 = 0$[9]. The technology restriction ignores technical inefficiency because we were only interested in the pure allocative effects. We derived the M+N+1 first order conditions from the corresponding Lagrangian: $0 = p_m - \theta \frac{\partial D_O}{\partial y_m}\,(\text{i});\; 0 = w_k - \theta \frac{\partial D_O}{\partial x_k}\,(\text{ii});$ and $0 = D_O - 1\,(\text{iii})$.

Summing up the first m equations in (i), and by utilizing Euler's theorem and linear homogeneity in outputs of the distance function, it can be seen that total revenue must be equal to the Lagrange multiplicator θ: $\sum_m p_m y_m = \theta \sum_m \frac{\partial D_O}{\partial y_m} y_m = \theta$. By utilizing this latter identity, we could then express the output share R_m in terms of a logarithmic derivative of the distance function as follows:

$$R_m = \frac{p_m y_m}{\sum_m p_m y_m} = \theta \frac{\partial D_O}{\partial y_m} y_m \frac{1}{\theta} = \frac{\partial \ln D_O}{\partial \ln y_m} \equiv \mu_m$$

From the above, it is clear that the slope of the distance function at the observed output mix must be equal to the price ratio of the output prices (under profit maximization). In Figure 1 this equation does not hold at time t and time t+1 because the assumption of profit maximization is assumed to be violated. We applied a similar procedure to the K first order conditions of inputs (ii). Summing up these K equations and considering the definition of returns to scale (RTS) led to the identity $\sum_k w_k x_k = \theta \sum_k \frac{\partial D_o(.)}{\partial x_k} x_k = -\theta \cdot RTS$.[10] To fulfill the first-order conditions for the inputs, the cost share S_k has to be equal to the negative of the corresponding logarithmic derivative of the distance function divided trough RTS: $-\frac{\partial \ln D_o(.)}{\partial \ln x_k} \Big/ RTS = \lambda_k$.

To summarize, the following is true for the allocative effects regarding output *m* and input *k* in the decomposition formula given in (6):

$$\left.\begin{matrix}(R_m - \mu_m)\\(S_k - \lambda_k)\end{matrix}\right\} =: \begin{cases} = 0 \text{ if no f.o.c. violation for output } m \text{ / input } k; \\ \neq 0 \text{ if f.o.c. violation for output } m \text{ / input } k. \end{cases}$$

Note that these allocative components represent the part of TFP change that is not technologically determined, but is caused by the violation of the first order conditions (for perfect markets). These violations can occur if market imperfections exist (e.g., transaction costs, risk, quantitative restrictions, incomplete information, or mark-ups) or if the behavioral assumptions are inadequate.

These allocative components are somewhat artificial in the sense that they explain the change of a technological productivity measure by utilizing the extent of violation of the first order conditions. Since these effects are caused by the problems with market structure and/or behavioral assumptions, we suggest to contrast the first three components (TC, TEC and scale component) as the "connected to technology" part of TFP change with the allocative components as the "connected to market" part of TFP change.

Empirical Specification

In order to estimate a parametric distance function we first had to choose an appropriate functional form. Coelli and Perelman (1996) enumerated the desirable properties of the functional form for the distance function (flexible; easy to calculate; permits the imposition of homogeneity). The translog form has these properties and that is the reason why it is found in the literature (e.g. Lovell et al. (1994), Grosskopf et al. (1997)). The translog specification for the output distance function, with 2 outputs, 4 inputs and technical change, can be described as

$$\begin{aligned}\ln D_{Oi}^t = {} & \alpha_0 + \sum_{m=1}^{2} \alpha_m \ln y_{im}^t + \sum_{k=1}^{4} \beta_k \ln x_{ik}^t + \delta_0 t \\ & + \frac{1}{2}\sum_{l=1}^{2}\sum_{m=1}^{2} \alpha_{lm} \ln y_{il}^t \ln y_{im}^t + \sum_{m=1}^{2} \delta_{ym} \ln y_{im}^t t \\ & + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln x_{ij}^t \ln x_{ik}^t + \sum_{k=1}^{4} \delta_{xk} \ln x_{ik}^t t \\ & + \frac{1}{2}\sum_{m=1}^{2}\sum_{k=1}^{4} \gamma_{mk} \ln y_{im}^t \ln x_{ik}^t + \frac{1}{2}\delta_{11} t^2\end{aligned} \qquad (7)$$

where, for all farms indexed with a subscript i and for all years indexed with a superscript t,

D^t_{Oi} denotes the output distance function measure,

y^t_i is a vector of outputs (y^t_{i1}= other output; y^t_{i2} = milk),

x^t_i is a vector of inputs (x^t_{i1} = intermediate input, x^t_{i2} = labour, x^t_{i3} = capital, x^t_{i4} = land), and

α, β, γ, δ are parameters to be estimated.

The output distance function is linear homogeneous in outputs. Therefore, a normalization with respect to one of the outputs is admissible (we normalize with output 2)

$$\ln D_O^t\left(\frac{y_i^t}{y_{i2}^t}, x_i^t, t\right) = \ln \frac{1}{y_{i2}^t} D_O^t\left(y_i^t, x_i^t, t\right) \qquad (8)$$

The major problem with econometric estimation of distance functions is that the dependent variable cannot be observed. Using the homogeneity restriction and from equation (5) it follows that ln D^t_{Oi} equals minus - u^t_i. By adding a random error term, the output distance function can be rewritten[11] as:

$$-\ln y_{i2}^t = \alpha_0 + \alpha_1 \ln \frac{y_{i1}^t}{y_{i2}^t} + \sum_{k=1}^{4} \beta_k \ln x_{ik}^t + \delta_0 t + \frac{1}{2}\alpha_{11}\left(\ln \frac{y_{i1}^t}{y_{i2}^t}\right)^2 + \delta_{y1} \ln \frac{y_{i1}^t}{y_{i2}^t} t$$
$$+ \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln x_{ij}^t \ln x_{ik}^t + \sum_{k=1}^{4} \delta_{xk} \ln x_{ik}^t t \qquad (9)$$
$$+ \sum_{k=1}^{K} \gamma_{1k} \ln \frac{y_{i1}^t}{y_{i2}^t} \ln x_{ik}^t + \frac{1}{2}\delta_{11} t^2 + u_i^t + v_i^t$$

where

v^t_i 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^t_i is a non-negative random error term, intended to capture technical inefficiency in outputs, which are assumed to be independently distributed as truncations at zero of the $N(m^t_i,\sigma_u^2)$ distribution, where $m_i^t = \sum_{i=91}^{94} \omega_{Di} D_i$, the D_i variables represent dummies that have a value of one in year i, and ω is a vector to be estimated.[12] For the common country estimation we extended this model by including country-specific binary variables: $m_i^t = \sum_{i=91}^{93} \omega_{Di} D_i + \omega_{DSH} D_{SH} + \omega_{DPO} D_{PO} + \omega_{DNL} D_{NL}$.

This function was slightly adapted for our purposes by transforming the left hand side of the equation to be $\ln y^t_{i2}$ rather than $-\ln y^t_{i2}$. Because of the a minus sign for u^t_i, the resulting function is more comparable to standard production frontier models. We estimated the stochastic translog distance function by using maximum likelihood. The maximum likelihood function of this model was derived and evaluated by Battese and Coelli (1993). We used Gauss to estimate the model and to generate the parameters required for the decomposition in equation (6).

The results given in the previous section can only be applied accurately to data generated continuously. Since our data came only through discrete observations, the variables in Equation (6) had to be approximated. We chose the common approximation to use the arithmetic mean of the shares. We also used the averages of μ's and λ's. For measuring technical change we used the mean of the first derivatives of two subsequent years[13].

Data description

For estimating the translog distance function we had to decide between modeling more technical details by applying more inputs and adding the risk of multicollinearity on the one hand, and aggregating the inputs and sacrificing potentially useful information on the other. In the specification we chose the conventional procedure: inputs were aggregated into four categories (intermediate inputs, labour, capital and land), and the outputs were aggregated into two categories (milk and other outputs, e.g. meat). Where prices at the farm level were available in the data sets, we used them to calculate price indexes. Where price information was not directly available, we took the price indexes from official statistics. The data set contained information on the quantity of milk produced and the value of sales to the milk factory and to other customers. The price that farmers received from the factory depends on the protein and fat content of the milk, and so milk prices reflected differences in quality. Some farmers sold home-made cheese and butter, or sold milk directly to customers. If we had used an index of the quantity of milk produced, the differences in prices between farmers would have been the result of differences in the quality of outputs and in the composition of the components. This price index then would become an endogenous variable. Therefore we preferred using an implicit quantity index. Implicit quantity indexes for the milk output and other outputs were obtained as the ratio of value to the price index. Therefore these variables were in prices of a specific year with 1994 being the base year. The same method was used to aggregate capital stock (buildings, equipment and livestock) and the intermediate inputs (concentrates, roughage, fertilizer and other intermediate inputs). The labor input consisted of total on-farm[14] family labour in hours. For Germany, labour was originally measured in man years and was transformed using the ratio of 2200 hours per man year. The land input was measured in hectares. The characteristics of the sample are summarized in the table below. In the estimation we used the sample mean to normalize all variables. We did this to ensure independence of units of measurement.

The focus of our research is to identify and separate the sources of productivity growth over time. This identification is the more reliable, the longer each farm has been observed. For this reason, we restricted all data sets to balanced sub-samples, i.e. we considered only those farms that were in the sample each year.

For the Netherlands we used data from 141 highly specialized dairy farms that were in the Dutch Farm Accountancy Data Network for 1991-1994. We used the same period for the other countries. During this period, the Dutch and German farmers, as members of the European Union, were confronted by a milk quota system, while the Polish farmers faced a minimum price system. For Germany we utilized data describing the production activities of 34 specialized dairy farms in Schleswig -Holstein for 1991-1994. The selection of farms was done by applying standardized gross margins to every farms factor endowment. The selection criterion was that over 75% of total standardized gross margin stem from dairy production. The same criterion was used for the Dutch data. For Poland, we utilized results from a farm accounting survey in the region around Poznan (Middle West Poland) that had been collected by the Institute for Agriculture and Food Industries (IERiGZ) in Warsaw. We had an unbalanced panel of about 700 farms from 1991 to 1994. We then constructed a balanced sub-sample panel of 50 farms per year. The selection criterion was that farms had to produce at least some milk. These data were the first reliable data sets after transition that are based on individual farm results.

Table 1: Characteristics of the sample

As can be seen from Table 1, the Dutch farms were the most specialized in milk production while farms from Poland were the most diversified. Total production was ranked in the same order across the countries.

Empirical results

Four models are estimated: a separate distance function for each country and one common distance function. The common frontier was motivated by the fact that we were interested to see which country's farms determine the position of this hypothetical frontier. It could be seen as a kind of estimate of the production potential in the regions, if all farms were facing the same environment and had access to the same technology.

Parameter estimates

Before beginning to describe and interpret the main results, namely the development of TFP growth and its components, we use Appendix Table A1 to give an overview of the estimated coefficients of the various distance functions.

We found between 38% and 61% significant parameters, where the "best" results show up for the pooled estimation (61%) and the single country estimation for Poland (56%). The high rate of statistically significant parameters in the common frontier model, despite the differences between the countries, is probably because of the mitigation of multicollinearity problems in the single country models. With panel data, it is possible to test for poolability. In our case, this amounted to checking if the estimated translog parameters of the single country models differed significantly from the common country model. The null hypothesis of poolability across countries was rejected at the 5 % significance level[15].

The statistical significance of the parameter σ_u which measures the relative importance of inefficiency is high in all models except for the Netherlands. Note that we found no significant change in time of the frontier for the Netherlands (Dummy 91 – Dummy 94 are not significant). Most of these parameters can be more easily interpreted by calculating elasticities.

Distance Elasticities

Table 2 gives an overview of the technological properties of the estimated models based on the average elasticities of the distance function with respect to outputs and inputs. For example, the low (high) milk output elasticity in Poland (Netherlands) reflects the low (high) share of milk in production. Because of the homogeneity constraint in outputs, the picture for the elasticity of other output is simply the opposite. There is a common pattern for the input elasticities[16] across all countries: a very low elasticity for labour is found in all three regions, indicating that labor is not the scarcest input in any of them. The most important input is intermediates. Its distance elasticity varies from 0.5 (Netherland) to over 0.7(Poland) in absolute values. Most surprisingly, the value of the distance elasticity of capital for Poland is very low, compared to the results from the other single-country estimations. This feature needs to be explored further. A detailed look at the individual results for Poland reveals a very high variability of this elasticity. The relative coefficient of variation is found to be as high as 56%. The marginal productivity as indicated by the capital distance elasticity varies in the sample, reflecting the effect of restrictions on the capital market.[17] Results for technical change are interesting. While there is a very high rate of technical progress for the German farms (nearly 8% p.a.), the Polish farms seem to have suffered from technical regress (over 9% p.a.). In the Netherlands, there are only modest annual rates of technological progress (0.4%). At the sample mean, increasing returns to scale are realized for the single country estimations as well as for the common country estimation.

Table 2: Average distance elasticities

Technical efficiency

The degree of technical inefficiency in production is documented in Table 3 for every region and year. In general, the coefficients for the single country estimation show the actual opportunities for improvements, while the common frontier estimates give an idea of the potential (especially for Poland) that might be realized by adopting the (purely hypothetical) common best-practice sectoral frontier technology.

The single country estimates show a high level of technical efficiency in the Netherlands as well as in Germany. This also indicates the high degree of similarity of factor endowment and production possibilities between the farms in these countries. In the Netherlands, these results are not surprising because the frontier is not statistically different from the average distance function in any year. Consequently, no specific pattern of temporal change could be identified. In Germany, however, there is a distinct decrease in the efficieny score from 1991 to 1994. Of course, this is partly caused by the rapid technological progress found in this region. The single country results for Poland reveal that the Polish farms were quite efficient in the first year of the observation period. In 1992, there was a decrease in technical efficiency which persisted in 1993. At the end of the sample period, average efficiency again approached the original high level. This latter catching up is not surprising, since the technological regress from 1991 to 1994 should have made it easier for the farmers to reach a point of production close to the frontier.

The common distance function seems to be determined by the Dutch farms, i.e. when measured in relation to the hypothetical common frontier, the farms in the Netherlands are by far the closest to this in every year. The German farms are second closest and greatest deviations from the hypothetical common technology are found for the Polish farms.

The last column of Table 3 shows clearly how the level of technical efficiency changes from the single country estimates to the common country estimates. Although this change is not unexpected, it is nevertheless interesting not only to look at the levels of technical efficiency, but also to compare the relative rankings of the farms in the single country model with those in the common country model. The calculation of rank correlation coefficients shows that rankings remain very stable for the Netherlands (0.95) and Poland (0.89). This indicates that the ranking of farms according to their technical efficiency score is unaffected by the model chosen. For Germany, the rank correlation coefficient is lower (0.58), but this is still indicative of a significant relationship between the results from the alternative model specifications.

Table 3: Average technical efficiency by years and regions

Components of TFP change

We now continue with the description and interpretation of TFP change and the decomposition of its components. Table 4 contains the average results for the decomposition of TFP change over the investigated period (1991-1994) for every single country.

The most rapid change in productivity growth was realized in Schleswig-Holstein with about 6 % per annum. Over the same period, the Polish farms experienced an annual decrease in total factor productivity of about 5 %. In the Netherlands, annual total factor productivity growth in milk production amounted nearly 3 %.

Table 4: Decomposition of TFP change p.a. by regions, 1991-94

The productivity growth in Germany is mainly caused by the high rate of technical change (TC) of about 8 % (0.0782). A slight decrease in the technical efficiency component (TEC) of 2.5 percentage points (-0.025) and in the scale component (RTS) of about 0.5 % (-0.0053) offsets the effect of the fast rate of technical change. When summarizing these three components we noticed the prevalence of these "connected to technology ” elements of productivity change. They add up to about 4.8 % of TFP growth. This is four times as high as the total influence of the components that we classified as "connected to market", which amounts to only 1.2 %. Three quarters of this sum (0.0078) comes from the impact of allocative inefficiencies induced by labor input.

The sharp decrease of total factor productivity in Poland is mainly dominated by the technical change component (TC) with a rate of technological regress of nearly 9 % (-0.0873). One possible hypothesis for this feature could be based on the specific problems that the Polish agriculture faced in the first years of transition. At the beginning, the available technology possibly did not change very much, but the access to inputs was partly restricted. If all farms experienced such a limited access, we could see the contraction of the output set as a technological regress. The small increase of the technical efficiency component (TEC) of about 0.3 percentage points (0.0034) and of the scale component (RTS) with about 0.6 % (0.0058) cannot offset the negative effect of technical change. Again, Table 4 shows a dominance of the elements of productivity change that are "connected to technology". Together, they account for nearly - 8 % of the total change. The "connected to market" change of TFP amounts to about 2.6 % (0.0258). It is obvious how misleading the traditional TFP growth measure, if interpreted as a proxy for technical change can be if these components are ignored. In particular the effect of intermediates with about 4.7 % (0.0467) and the effect of capital with - 1.8 % (0.018) indicate a relatively high degree of distortion that originate either from allocative inefficiencies or market imperfections.

The observed total productivity growth of about 3 % per annum in the Dutch milk industry shown in Table 4 is highly influenced by the components "connected to market". The total technologically-induced productivity change adds up to about 1.4 % (0.0137). If we look at the results in more detail, we see that the rate of technical change is relatively low with about 0.4 % (0.0043), the technical efficiency component (TEC) is slightly higher with 0.7 percentage points (0.007) and the average influence of RTS of about 0.2 % (0.0024) can almost be ignored. The calculated TFP growth is dominated by the ”allocatively induced” elements that amount to about 1.5 %. This means that these components account for about 50 % of total TFP change. Nearly all of this is generally determined by the inputs, while the average output mix seems to be optimal.

Turning to the results of the estimated common distance frontier, a first look at Figure 2 reveals an interesting picture. The overall productivity growth rate increased steadily during the sample period, starting with about -0.5 % in 1991/92 to more than 1 % in 1992/93 and to about 3 % in 1993/94. This amounts to an annual TFP increase of about 1.2 % (0.0126). The largest and the smallest values are also presented in Figure 2, the white area representing the interval between the 25% and 75% quantile. Appendix Table A2 gives the results of the decomposition of this aggregate number for all farms. The interpretation of this decomposition, however, is a difficult issue in this model. In fact, the allocative terms in the decomposition formula always depend on the deviation between the observed shares and the estimated distance elasticities. Consider the case of Poland. If we apply the decomposition to the common frontier model, the Polish farmers are presumed to optimize with respect to some distance elasticities which they are not even able to observe. This underlines the critical impact of the assumption that all farms in a specific model have access to the same technology. However, it is not very realistic to assume that the Polish farms actually had access to the same technology as the German and Dutch farmers during the observation period.

Figure 2

Despite these limitations, the results of technical change and technical efficiency change deserve some consideration. These results show an average technological regress of the frontier of 1 % (- 0.0106) that is almost completely offset by the increase in efficiency of about 0.7 percentage points (0.0072). For the average farm, however, both measures are numerically small. The wide range of all values in Appendix Table A2 suggests that the aggregate picture might hide some further characteristics of this model.

We now proceed with the discussion of the common frontier model with the disaggregated results (see Appendix Table A3), where the detailed results are given per country and year. In the overall frontier framework, the German dairy farms show a rate of technical change of 2% per annum and an improvement of their technical efficiency. The German farmers are not only very good in catching up but are also shown to be innovative. Both components together explain most of the observed TFP growth. The rate of technical change has increased over time, while the movements towards the frontier have become slower, even becoming negative in 1993/94. The Polish farmers face a decrease in technical change of 6% per annum. They also are not able to catch up to the common frontier since their technical efficiency remains virtually unchanged. Most of this negative development occurs in the period 1991/92, while the following years show some signs of improvement. In the overall framework, the Dutch farmers show only a low increase of technical change of 0.3 % per annum for the period 1991/94, and an improvement in technical efficiency.

As shown above, these results should be compared to the single frontier estimates. For the estimates of the technical change component, the results of the common frontier model are clearly influenced by the fact that each of the regions experienced a different development over the sample period. The extreme rates of technical change for Poland and Germany are substantially reduced in magnitude, while the estimate for the Netherlands remains nearly unchanged. The extreme rates of technical change from the single country models are smoothed out in the common frontier framework.

These movements of the frontier also influence the results for the technical efficiency change. For Poland, the single country model gave positive technical efficiency changes. In the common frontier model, this change becomes (modestly) negative. This is because in the single country model, the reference against which efficiency is measured moves strongly downward over time (remember that the technical change for Poland was negative). In the common frontier model, the downward movement of that part of the frontier that is relevant for the Polish farms is smaller (see above). Therefore, more of the deterioration observed can be attributed to efficiency, which leads to a negative change in technical efficiency. Compare this with the picture for the change in technical efficiency for northern Germany. Here the single country efficiency change was estimated negatively. In the common frontier model, we estimate this change positive. Here, the same mechanism is at work in reverse. The previously high estimate of technical change is now lower. Therefore, more of the improved performance of the German farmers can be attributed to efficiency change and less to technical progress.

One last thing should be noted about the common frontier model. Although the interpretation of the allocative components of the decomposition was fraught with difficulties, the general pattern of distortion remained remarkably stable between the models. For Schleswig-Holstein, the overall impact of the 'connected to market' components, i.e. the price effects for inputs and outputs, was relatively small in the single country model, and within these components, distortions caused by the capital input were dominant. The picture remained the same for the common estimation. The relative importance of the labor component was reduced, because the very low value of the distance elasticity for labor from the single country estimation was higher for the common frontier model. The pattern was even more similar for Poland and the Netherlands. In Poland, the intermediate input was the single most important component among the inputs in the single frontier model, and this was the same for the common estimation. The results for the allocative components of TFP growth for the Dutch farms not only showed the same relative importance, but also the same magnitudes. This underlines the stability of these estimates.

Summary

We decomposed the standard measure of productivity growth into four basic components using a distance function framework. The first component, technical change, accounted for in a shift of the production possibilities frontier over time. The second component was the change in the level of outputs in relation to the frontier resulting in a change of technical efficiency. The third was the scale component. The last component (which can be divided into six subgroups since we distinguished two outputs and four inputs) was related to violations of the profit maximizing assumption implicitly made when calculating the standard measure of productivity growth.

By means of the stochastic frontier approach, we estimated a translog output distance function, using data in three dimensions: different farms from different countries (Germany, Poland and the Netherlands) over a period of time (1991-1994). Four models were estimated: a separate distance function for each country and one common distance function.

For the single country estimates the average annual productivity growth in Germany was about 6 %. This was mainly caused by the high rate of technical change. There was a slight decrease in technical efficiency and in the scale component. The violations of the profit maximizing assumption proved to be of minor importance. For Poland, there was a sharp decrease in annual productivity growth of -5% in this transition period. This was clearly dominated by the technical change component . In the Netherlands, the annual productivity growth of about 3% was influenced more by factors related to the violations of the profit maximizing assumption implicitly made in the calculation of the standard TFP measure.

The common distance function estimate was dominated by the Dutch farms. The German farms were the second closest to this hypothetical frontier, but we attributed their high rate of catching up to a different source. There is a shift from the observed technical progress in the single country estimation for Germany towards an improvement in technical efficiency for these farms when measured against the common frontier. The largest distance was found for the the Polish farms. Assuming a common technology for these three countries, then the development in Poland shows a severe deterioration in productivity.

To summarize, the results discussed in this article reveal interesting insights into the components of productivity growth that prove the need for this decomposition procedure. The common frontier results that are based on the assumption of a common technology are consistent with *a priori* expectations.

References

Baltagi, B.H. (1995). *Econometric Analysis of Panel Data.* Chichester: Wiley.

Battese, G.E., T.J. Coelli (1993) "A Stochastic Frontier Production Function Incorporating a Model for Technical Inefficiency Effects." *Working Papers in Econometrics and Applied Statistics* No. 69, Armidale: University of New England.

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

Bauer, P.W. (1990). "Decomposing TFP Growth in the Presence of Cost Inefficiency, Nonconstant Returns to Scale, and Technological Progress." *Journal of Productivity Analysis*, 1:287-299.

Binswanger, H., M. Yang, A. Bowers (1987) "On the Determinants of Cross-Country Aggregate Agricultural Supply." *Journal of Econometrics* 36:111-131.

Caves, D.W., Christensen L.R., Diewert W.E. (1982). "The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity." *Econometrica*, 50:1393-1414.

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

Färe, R. (1988). *Fundamentals of Production Theory*. Berlin: Springer-Verlag.

Färe, R., D. Primont (1995). *Multi-output Production and Duality : Theory and Applications*. Boston: Kluwer Academic Publishers.

Färe R., Grosskopf S., Lovell C.A.K. (1994). *Production Frontiers*. Cambridge: Cambridge University Press.

Färe, R., S. Grosskopf, M. Norris, Z. Zhang (1994) "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries." *American Economic Review* 84:66-83.

Fuentes, H., E. Grifell-Tatjé, S. Perelman (1997). "A Parametric Distance Function Approach for Malmquist Index Estimation: The Case of Spanish Insurance Companies." Paper presented at the Fifth European Workshop on Efficiency and Productivity Analysis, Copenhagen.

Grosskopf, S. (1993). "Efficiency and Productivity". in: H.O. Fried, C. A. K. Lovell and S. S. Schmidt, eds., *The Measurement of Productive Efficiency: Techniques and Applications,* New York: Oxford University Press.

Hayami, Y., V. Ruttan (1970) "Agricultural Productivity Differences Among Countries." *American Economic Review* 60:895-911.

Kawagoe, T., Y. Hayami, V. Ruttan (1985) "The Intercountry Agricultural Production Function and Productivity Differences Among Countries." *Journal of Development Economics* 19:113-132.

Kumbhakar, Subal C. (1997). "Productivity Growth, Efficiency and Technical Change: A Panel Data Approach." Paper presented at the Fifth European Workshop on Efficiency and Productivity Analysis, Copenhagen.

Lovell, C.A.K. (1996). "Applying Efficiency Measurement Techniques to the Measurement of Productivity Change." *Journal of Productivity Analysis,* 7:329-340.

Morrison, C.J. (1988). "Quasi-fixed Inputs in U.S. and Japanse Manufacturing: A Generalized Leontief Restricted Cost Function Approach." *Review of Economics and Statistics* 70:275-287.

Morrison, C.J. (1992) "Unraveling the Productivity Growth Slowdown in the United States, Canada and Japan: The Effects of Subequilibrium, Scale Economics and Markups." *Review of Economics and Statistics* 74:381-393.

Johnston, W.E., C.J. Morrison (1997) "Efficiency in New Zealand Sheep and Cattle Farming: Pre and Post Reform." Paper presented at the Fifth European Workshop on Efficiency and Productivity Analysis, Copenhagen.

Nishimuzu, M., Page, J.M. (1981). "Total Factor Productiviy Growth, Technological Change and Technical Efficiency Change." *The Economic Journal*, 92:920-936.

OECD (1994), *Review of Agricultural Policies: Poland*. Paris: OECD.

Appendix

Calculation of the components of TFP Growth

To decompose TFP growth according to Equation (6), we need the growth rates of inputs and outputs, and the revenue and cost shares *R* and *S*. We also require the parameters μ_m, λ_k, *RTS*, the change in technical efficiency, and the magnitude of technical change. The calculation of the latter parameters is based on the coefficient estimates from the econometric model. According to their definitions, each of these quantities is derived from the corresponding distance function elasticity. Returns to scale are then calculated as the negative sum of distance elasticities with respect to the inputs. The growth rates of inputs and outputs are readily available from the data. We took the difference of the logarithms of the variables from year to year. The shares were calculated using representative price indices from official statistics. Together with the quantities from the data set, we were able to calculate the corresponding shares.

We decided to overcome the problem that we could only observe discretized data by averaging between years for all calculations. For example, the parameter μ_m for the period 1991/92 was calculated as the arithmetic mean of the values in every single year.

Table A1: Parameter estimates

Table A2: Decomposition of TFP change p.a. for all regions, 1991-94

Table A3: Decomposition of TFP change by years and regions

Notes:

[1] Multiple outputs are a common feature of agricultural production. This holds even for specialised dairy farms since they also produce some meat.

[2] This device for efficiency measurement with multiple outputs has already been used by others, see e.g. Coelli and Perelman (1996), Grosskopf et al. (1997), and Morrison and Johnston (1997).

[3] For example, as early as 1989, about 80% of utilized agricultural area in Poland was cultivated by the private farming sector. The transformation process in Polish agriculture is described in detail by OECD (1994).

[4] We have used a parametric approach because it can distinguish the effects of noise from the above mentioned components.

[5] This is an extension of a figure used by Fuentes et al. (1997).

[6] To facilitate the calculation of technical change, the influence of time is considered as an exogenous time variable *t*, so that $D_o^t(x^t,y^t) \rightarrow D_o(t,x,y)$.

[7] Returns to scale (RTS) are defined as in Färe and Primont (1995)

[8] In the case of only one output, equation (6) is identical to the formula Kumbhakar (1997) derived in the context of a production function.

[9] To simplify the exposition, the time regressor *t* has been left out.

[10] Since there are no homogeneity restrictions on inputs, the term with the sum of the partial derivatives does not vanish but is substituted by the expression for the returns to scale.

[11] Coelli and Perelman (1996) discussed the endogeneity problem for outputs in a distance function. We followed their reasoning that the ratios of outputs in the transformed distance function (9) are not endogeneous.

[12] Other explanatory variables can also be included in the equation of m^t_i (Battese and Coelli, 1995). However, as the focus of our research was not efficiency measurement, we chose a simple function which allowed for time varying inefficiency per farm.

[13] The calculation of the parameters is explained in more detail in the appendix.

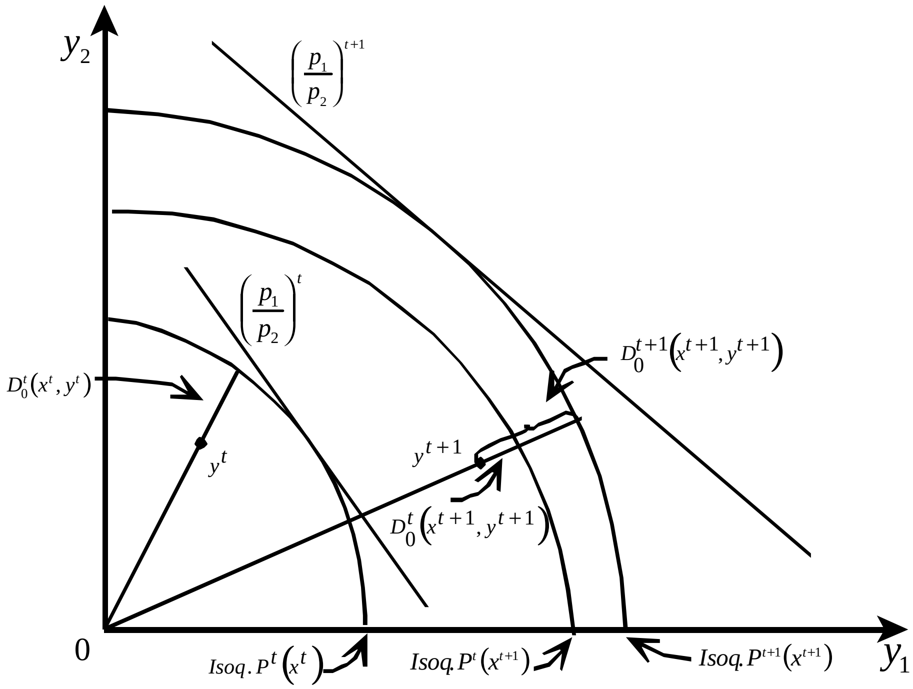
[14] The difference between available family labor and actual on-farm work is important especially for the Polish data. About 25% of total family work time is spent on off-farm activities.

[15] This test can be formulated as a LR-test (see Baltagi (1995), p.53), where the sum of the likelihood values of the single country estimates is compared to the likelihood of the pooled model. This statistic is χ^2(A-1)B distributed, where A is the number of countries and B is the number of parameters in the pooled model. The calculated value of 194.78 exceeds the critical value for 72 df and 5 % significance level (92.81), so that the null of poolability can be rejected.

[16] The distance elasticities for a "well behaved" input must be negative. A positive value for time therefore implies technical regress.

[17] The prevailing restrictions on the capital market in Poland during the observation period mean that the potential marginal productivity of capital could not be fully exploited by each farm. With a functioning market, farmers with higher marginal productivity would have been able to acquire more of this factor. This would have decreased marginal productivity. At the end, the variation of marginal productivity should approach zero, except for quality differences. In this sense, high variability must come either from restrictions on factor markets (e.g., for capital, credit restrictions; for labour, institutional restrictions) or from different factor qualities.

Figure 1: Productivity growth in a distance function framework



Source: Extension of a figure used by Fuentes et al., 1997.

Table 1: Characteristics of the Sample:

Variables	Unit	mean	min.	max.	std. dev.
Germany (128 observations)					
Milk Output	1,000 ‘94DM	138	59	321	48
Other Outputs	1,000 ‘94DM	95	37	208	36
Intermediate Input	1,000 ‘94DM	134	68	351	50
Labour	hours	3,795	2,200	5,940	954
Capital	1,000 ‘94DM	540	238	840	153
Land	hectares	52	28	92	13
Poland (200 observations)					
Milk output	1,000 ‘94DM	2.66	0.02	35.76	4.40
Other Outputs	1,000 ‘94DM	13.35	2.20	48.22	9.69
Intermediate Input	1,000 ‘94DM	9.34	1.67	38.36	6.95
Labour	hours	3,432	1,030	9,030	1,667
Capital	1,000 ‘94DM	52.76	8.80	230.91	44.89
Land	hectares	9.79	1.78	31.45	6.76
Netherlands (564 observations)					
Milk output	1,000 ‘94DM	316	45	919	173
Other Outputs	1,000 ‘94DM	42	4	222	30
Intermediate Input	1,000 ‘94DM	120	18	381	69
Labour	hours	4,315	1,500	11,050	1,455
Capital	1,000 ‘94DM	752	112	1781	378
Land	hectares	40	7	131	20

Source: Own calculations.

Table 2: Average distance elasticities

	SH	PO	NL	TOT
milk	0.5123	0.1681	0.8872	0.6847
other outputs	0.4877	0.8319	0.1128	0.3153
intermediates	-0.5594	-0.7065	-0.4990	-0.5235
labour	-0.0548	-0.1616	-0.0916	-0.1111
capital	-0.2921	-0.0177	-0.1713	-0.1552
land	-0.1866	-0.2119	-0.3293	-0.3197
time	-0.0790	0.0887	-0.0043	0.0106
RTS	1.0929	1.0976	1.0911	1.1095

Source: Own calculations.

Table 3: Average technical efficiency by years and regions

	type of frontier	1991	1992	1993	1994
Schleswig-Holstein	single	0.950	0.992	0.990	0.875
	common	0.489	0.526	0.551	0.537
Poland	single	0.843	0.726	0.725	0.757
	common	0.305	0.292	0.335	0.302
The Netherlands	single	0.882	0.893	0.894	0.903
	common	0.795	0.830	0.834	0.819
overall		0.641	0.666	0.682	0.662

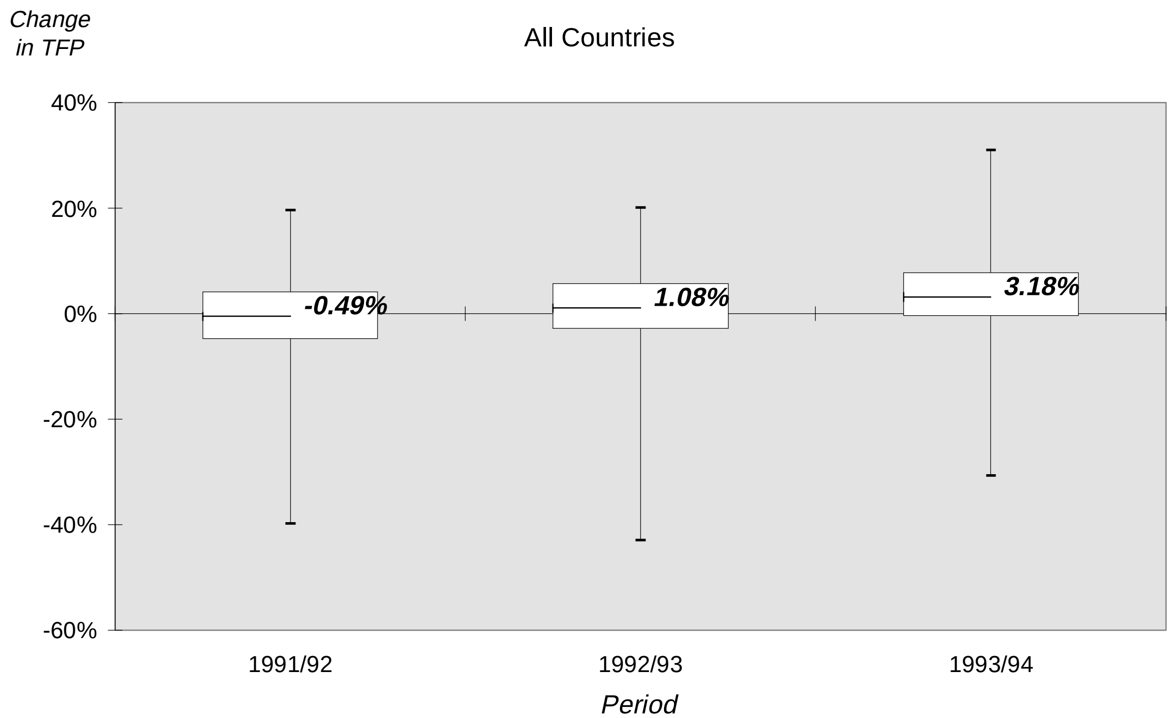
Source: Own calculations.

Table 4: Decomposition of TFP change p.a. by regions, 1991-94

	Mean	Std Dev.	Minimum	Maximum
Schleswig-Holstein				
TFP change	0.0599	0.0537	-0.0596	0.238
milk	0.0038	0.0116	-0.0253	0.0454
other outputs	-0.0025	0.0262	-0.0597	0.1658
Scale effects	-0.0053	0.0472	-0.2719	0.1157
intermediates	0.0013	0.0557	-0.1884	0.1809
labour	0.0078	0.0361	-0.0564	0.2064
capital	-0.0008	0.0191	-0.1066	0.0672
land	0.0023	0.0142	-0.078	0.0712
Technical Change	0.0782	0.0552	-0.0304	0.186
Technical Eff. Change	-0.025	0.0696	-0.1745	0.0999
Poland				
TFP change	-0.0521	0.144	-0.4916	0.3072
milk	-0.0031	0.0308	-0.2601	0.077
other outputs	-0.0009	0.0142	-0.0561	0.0592
Scale effects	0.0058	0.0219	-0.1160	0.1063
intermediates	0.0467	0.084	-0.2487	0.3329
labour	0.002	0.0317	-0.1315	0.2185
capital	-0.018	0.0767	-0.3728	0.2219
land	-0.0009	0.0239	-0.1733	0.1499
Technical Change	-0.0873	0.1961	-0.4213	0.2067
Technical Eff. Change	0.0034	0.1857	-0.4121	0.2999
The Netherlands				
TFP change	0.0287	0.0538	-0.1145	0.2674
milk	0.0003	0.0041	-0.0196	0.0245
other outputs	0	0.0216	-0.1254	0.1378
Scale effects	0.0024	0.0085	-0.0337	0.0587
intermediates	0.0067	0.0233	-0.0823	0.1237
labour	0.0036	0.0289	-0.1706	0.2089
capital	0.0008	0.0129	-0.0904	0.1411
land	0.0036	0.0207	-0.1311	0.0981
Technical Change	0.0043	0.017	-0.0341	0.0447
Technical Eff. Change	0.007	0.0477	-0.1435	0.1933

Remark: Single frontier results;
Source: Own calculations.

Figure 2: Overall TFP change p.a.



Remark: Common frontier results;
Source: Own calculations.

Appendix Table 1: Parameter estimates

Parameters	SH	PO	NL	TOT
Constant β_0	-0.0532 (0.1293)	-0.1051 (0.2036)	0.1554* (0.0574)	0.3987* (0.1186)
milk/other α_1	0.3978* (0.0579)	0.7656* (0.0326)	0.1241* (0.0276)	0.1972* (0.0169)
intermediates β_1	0.1043 (0.1261)	0.0646* (0.0203)	0.1835* (0.0435)	0.1377* (0.0098)
labour β_2	-0.4917* (0.0793)	-0.4857* (0.1180)	-0.4601* (0.0533)	-0.3958* (0.0410)
capital β_3	-0.0163 (0.0954)	-0.3314* (0.0981)	-0.1516* (0.0539)	-0.2098* (0.0408)
land β_4	-0.2270* (0.0896)	0.0348 (0.0604)	-0.1931* (0.0718)	-0.2213* (0.0433)
time δ_0	-0.1761 (0.1166)	-0.3595* (0.0911)	-0.2908* (0.0527)	-0.3139* (0.0421)
α_{11}	0.0761 (0.1205)	-0.5280* (0.1607)	0.0396 (0.0375)	0.1064 (0.0846)
β_{11}	-0.4453* (0.2546)	0.1920 (0.2303)	0.1644* (0.0941)	0.1981* (0.0728)
β_{22}	0.3983* (0.1879)	0.3022* (0.1332)	0.0178 (0.0893)	0.1023* (0.0599)
β_{33}	-0.1187 (0.1906)	-0.0498 (0.1032)	-0.1833* (0.1035)	-0.2562* (0.0624)
β_{44}	0.7059* (0.2960)	-0.4366* (0.2069)	0.0554 (0.0730)	-0.0005 (0.0693)

Appendix Table 1: Parameter estimates

Parameters	SH	PO	NL	TOT
β_{55}	-0.0196 (0.0282)	-0.1059* (0.0378)	-0.0140 (0.0187)	-0.0389* (0.0131)
γ_{11}	-0.3380 (0.2765)	0.0737 (0.1580)	-0.0693 (0.1047)	0.1282* (0.0725)
γ_{12}	-0.4077* (0.2067)	-0.0961 (0.0909)	-0.1871 (0.1197)	-0.0477 (0.0676)
γ_{13}	-0.4564* (0.2161)	-0.0781 (0.1384)	-0.0213 (0.0850)	-0.1073* (0.0589)
γ_{14}	-0.0284 (0.0341)	0.0817* (0.0283)	0.0083 (0.0191)	0.0412* (0.0151)
δ_{y1}	-0.3612 (0.3410)	0.2291* (0.0810)	0.0752 (0.1693)	0.0977 (0.0733)
β_{12}	-0.1585 (0.2471)	-0.0663 (0.0811)	0.1936* (0.1089)	0.1063* (0.0529)
β_{13}	-0.0438 (0.0340)	0.0005 (0.0198)	0.0091 (0.0233)	0.0095 (0.0135)
β_{14}	-0.6201* (0.3441)	0.5588* (0.2045)	-0.1594 (0.1466)	0.0152 (0.0996)
δ_{x1}	-0.0112 (0.0442)	0.0518* (0.0313)	-0.0082 (0.0189)	-0.0051 (0.0143)
β_{23}	-0.0637 (0.0497)	0.2437* (0.0619)	-0.0182 (0.0145)	-0.0438 (0.0299)
β_{24}	-0.1469 (0.1151)	0.0286 (0.0673)	-0.0817 (0.0506)	-0.0805* (0.0197)
δ_{x2}	-0.0025 (0.1230)	-0.0060 (0.0436)	-0.1309* (0.0438)	0.0027 (0.0221)
β_{34}	0.2965* (0.1613)	-0.1176* (0.0336)	0.0808 (0.0504)	-0.0175 (0.0204)
δ_{x3}	-0.0629 (0.1933)	0.0836 (0.0564)	0.0444 (0.0408)	0.0868* (0.0197)
δ_{x4}	0.0370 (0.0271)	0.0175 (0.0120)	-0.0008 (0.0103)	0.0001 (0.0055)
$\ln(\sigma_v)$	-2.4854* (0.1281)	-2.7055* (0.5550)	-2.5949* (0.1415)	-2.9433* (0.5152)
$\ln(\sigma_u)$	-2.7090* (0.6240)	-2.0257* (0.1886)	-0.9826 (0.8917)	-1.9577* (0.0693)
Dummy-SH ω_{DSH}				0.6513* (0.0817)
Dummy-POL ω_{DPO}				1.1902* (0.0849)
Dummy-NL ω_{DNL}				0.1793* (0.0902)
Dummy91 ω_{D91}	-0.0028 (0.1237)	0.1430 (0.1359)	-0.8124 (2.0917)	0.0375 (0.0742)
Dummy92 ω_{D92}	-0.5640 (2.0476)	0.5043* (0.0596)	-0.9565 (2.2523)	0.0036 (0.0504)
Dummy93 ω_{D93}	-0.3995 (0.7902)	0.3320* (0.0595)	-0.9797 (2.3296)	-0.0491 (0.0348)
Dummy94 ω_{D94}	0.1315* (0.0764)	0.1223 (0.0966)	-1.1077 (2.6048)	
% significant parameters	38%	56%	35%	61%

Remark: A star indicates significance on the 5 % level.
Source: Own calculations.

Appendix Table 2: Decomposition of TFP change p.a. for all regions, 1991-94

	Mean	Std Dev	Minimum	Maximum
TFP change	0.0126	0.0802	-0.4289	0.3110
milk	-0.0007	0.0190	-0.3155	0.0502
other outputs	-0.0001	0.0140	-0.0609	0.0494
Scale effects	0.0024	0.0093	-0.0493	0.0630
intermediates	0.0122	0.0435	-0.1935	0.4189
labour	0.0024	0.0250	-0.1820	0.1858
capital	-0.0040	0.0388	-0.3597	0.2313
land	0.0037	0.023	-0.2413	0.1254
Technical Change	-0.0106	0.0519	-0.1515	0.1229
Technical Eff. Change	0.0072	0.0580	-0.1882	0.1868

Remark: Common frontier results;
Source: Own calculations.

Appendix Table 3: Decomposition of TFP change by years and regions

	TFP change	milk	other outputs	Scale effects	inter-mediates	labour	capital	land	Technical Change	Technical Eff. Change
					Schleswig-Holstein					
91/92	0.0147	-0.0014	0.0001	-0.0019	0.0015	0.0035	-0.0024	0.0038	-0.0261	0.0377
92/93	0.0578	-0.0006	0.0088	0.0015	0.0000	0.0039	-0.0005	0.0003	0.0199	0.0245
93/94	0.0436	-0.0030	-0.0029	-0.0013	-0.0014	-0.0024	-0.0016	0.0037	0.0659	-0.0135
p.a.	**0.0387**	**-0.0016**	**0.0020**	**-0.0006**	**0.0000**	**0.0017**	**-0.0015**	**0.0026**	**0.0199**	**0.0162**
					Poland					
91/92	-0.0544	-0.0031	-0.0028	0.0067	0.0783	-0.0012	0.0005	-0.0043	-0.1157	-0.0130
92/93	-0.0568	-0.0006	0.0045	-0.0009	-0.0143	0.0045	-0.0282	0.0026	-0.0681	0.0438
93/94	-0.0300	-0.0104	-0.0013	0.0038	0.0565	-0.0038	-0.0322	0.0118	-0.0210	-0.0335
p.a.	**-0.0471**	**-0.0047**	**0.0001**	**0.0032**	**0.0402**	**-0.0002**	**-0.0200**	**0.0034**	**-0.0682**	**-0.0009**
					The Netherlands					
91/92	0.0082	0.0011	-0.0009	0.0028	0.0032	0.0032	0.0014	0.0055	-0.0432	0.0351
92/93	0.0241	0.0007	-0.0004	0.0029	0.0065	0.0033	0.0019	0.0022	0.0030	0.0041
93/94	0.0510	0.0011	-0.0008	0.0025	0.0057	0.0041	0.0000	0.0047	0.0492	-0.0152
p.a.	**0.0278**	**0.0010**	**-0.0007**	**0.0027**	**0.0051**	**0.0035**	**0.0011**	**0.0041**	**0.0030**	**0.0080**

Remark: Common frontier results;
Source: Own calculations.