Decomposing Partial Factor Productivity in the Presence of Input-Specific Technical Inefficiency: A Self-Dual Stochastic Production Frontier Approach

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Abstract
The present paper provides a theoretical framework for the decomposition of partial factor productivity in the presence of input-specific technical inefficiency. Based on Kuroda’s dual approach and using the theoretical foundations developed by Kopp, we decompose the growth rate of partial factor productivity into five sources, namely, changes in input-specific technical efficiency, substitution effect, technical change, the effect of scale economies and a homotheticity and input biased technological effect. The empirical model is based on a generalized self-dual Cobb-Douglas stochastic production frontier and on the methodological approach for measuring orthogonal input-specific technical efficiency suggested by Reinhard, Lovell and Thijssen. The model is applied to a panel data set of 723 cereal farms in Greece observed during the 1994-2003 cropping period obtained from FADN. The empirical results suggest that the labor productivity of cereal farms has been increased by 2.89 per cent annually. Technical change was found to be the main source of labor productivity (70.4%), while changes in technical efficiency also contributed significantly over the period analyzed (34.7%). On the other hand, substitution effect was found to affect negatively the rate of labor productivity (-14.2%).

Keywords: partial factor productivity, stochastic production frontier, input-specific technical efficiency, Greek cereal farms.

JEL Classification Codes: C23, D24, J24, Q16.

Introduction
The measurement of productivity growth and the identification of the factors that affect, it has been always an aspect of great interest for the economists in both developed and developing countries around the world. Productivity growth is probably the key element that can ensure a continuously economic growth with a relative low cost. This fact is even more evident in the agricultural sector, where production faces many limitations due to the inelastic supply of factors of production (e.g., labor, land). High rates of factor productivity growth in the agricultural sector is a necessary presupposition for a self-sufficient economy. Furthermore, the increase of income in the developed countries in combination with the increase of population requires, necessarily, a growth in agricultural production. Productivity growth is the
most cost effective way towards this direction and therefore its measurement has justifiably captivated the interest of agricultural economists in last decades.

Several methodological advances have been developed that dealt explicitly with the decomposition and measurement of total factor productivity in agriculture using both primal and dual approaches (see for example Bauer, Lovell and Kumbhakar for the most recent contributions in this strand of the literature). Despite of the extensive research in this area, one salient feature stands out: most empirical studies are focused on the decomposition of farm total factor productivity neglecting factor-specific productivity growth. Given the diverse and complexity nature of modern farming technological structures, it would be quite useful from a policy point of view to have specific measures of productivity growth for each factor of farm production separately.

However, despite the importance of partial productivity, past attempts to measuring productivity have focused more on total factor productivity and less on partial factor productivity, using either parametric or non-parametric techniques. The mainly reason that led the majority of the economists to this direction, is that partial factor productivity indices provide unbiased results only in the case of fixed factor proportion production technologies, which corresponds to a Leontief production function. However, Hayami and Ruttan supported that partial factor productivity indices represent significant measures of productivity growth when they refer to the scarce factor of production (i.e. labor and land). Without a complete theoretical framework, agricultural economists interested in partial factor productivity decomposition have been forced to work with highly imperfect, partial productivity measures like “output per labor unit” and “output per acre of land” (Nin et al.).

There are only few studies appearing in the relevant literature that provide a complete theoretical framework for the decomposition of partial factor productivity. By constructing non-parametrical, output-oriented distance functions, Nin et al. estimated a Malmquist index to measure and decompose sub-sector productivity growth in an output specific direction (livestock and crops) in a set of developing and high income countries, without assuming that all inputs are allocated across activities. Using a similar empirical framework and utilizing a Russell-measure of technical efficiency under constant returns to scale and strong disposability of inputs, Oude Lansink and Ondersteijn managed to measure non-parametrically energy productivity growth and to decompose it into an efficiency change effect and technological change
effect. Finally, Henderson and Russell, utilizing nonparametric production frontier methods, provided a decomposition of labor productivity growth for OECD countries taking into account technological catch-up and physical and human capital accumulation as an element of growth process.

Although the use of non-parametric methods for decomposing partial factor productivity can be straightforward implemented, still have two important shortcomings: first, non-parametric techniques are based on strict assumptions attributing all variation in output to technical efficiency which is questionable for modeling farm production that is more vulnerable to exogenous shocks (i.e., environmental and physical conditions) and; second, they fail to identify explicitly the effect of factor price changes on the decomposition of partial factor productivity growth. There is only one study that provides a complete decomposition of partial factor productivity using a parametric approach. Kuroda using a flexible translog cost function provides a dual decomposition of labor productivity in Japanese agriculture. Specifically, labor productivity is attributed into three sources, namely substitution effect, technological change and productivity effect. However, still the theoretical framework is incomplete as it does not take into account changes in labor-specific technical efficiency that certainly affects the level of specific factor productivity.

Along these lines, the objective of this paper is to provide a complete approach for decomposing the growth rate of partial factor productivity and to investigate empirically the factors that affected the labor productivity in the Greek cereal-growing farms during the 1994-2003 cropping period. Specifically, we integrate appropriately Kuroda’s theoretical framework with Kopp’s orthogonal indices of factor-specific technical efficiency enabling thus the decomposition of partial factor productivity by taking into account changes in their efficiency levels. Our approach although is focused on labor productivity can be applied to the case of any other factor of farm production. The proposed model is based on the Generalized Cobb-Douglas (or quasi translog) stochastic production frontier suggested by Fan and Karagiannis and Tzouvelekas and it is applied to sample of 723 cereal farms located in Greece during the period 1994-2003 obtained from Farm Accountancy Data Network (FADN). The advantage of our approach is that it enables to handle separately the effects of technological progress, factor-specific technical efficiency and price changes in decomposition analysis and still relying on the econometric estimation of a production frontier function.
The remaining paper is organized as follows. In the following section, the developed theoretical framework is presented. Next, the empirical model is discussed and described followed by data description. The empirical results born out from our study are discussed in the next section. Finally, the summary of the results and their economic implications follow in the last section.

Theoretical Framework

Let’s assume that farms in period $t$ utilize a vector of inputs $\mathbf{x} = (x_1, x_2, \ldots, x_k) \in \mathbb{R}_+^k$ to produce a single output $y \in \mathbb{R}_+$ through a well behaved technology satisfying all regularity conditions described by $S(t) \equiv \{ (\mathbf{x}, y) | \mathbf{x} \text{ can produce } y \text{ in period } t \}$, where $\mathbb{R}_+$ denotes the nonnegative real numbers. Accordingly, for every $y \in \mathbb{R}_+$ we can define the input correspondence set as all the input combinations capable of producing $y$, i.e.,

$$V(y; t) \equiv \{ \mathbf{x} \in \mathbb{R}_+^k | (\mathbf{x}, y) \in S(t) \}$$

(1)

Similarly, by letting $\mathbf{w} \in \mathbb{R}_+^k$ to denote the vector of positive factor prices, we can define the cost function for all producible $y$ in period $t$, that is, for all $y$ such that $V(y; t) \neq \emptyset$ as:

$$C(\mathbf{w}, y; t) \equiv \min_{\mathbf{x}} \{ \mathbf{w}' \mathbf{x} | \mathbf{x} \in V(y; t) \}$$

(2)

which is the minimum cost of producing output quantities $y$ with period’s $t$ technology, when the factor prices are $\mathbf{w}$. Finally, the production function dual to (2) can be defined as:

$$f(\mathbf{x}; t) \equiv \min_y \{ y | (\mathbf{x}, y) \in S(t) \}$$

(3)

Let’s assume at this point that farms are not utilizing one of the $k$ inputs used in the production process technically efficient, namely labour input, $x_L$. Then it should
holds that $y \leq f(x, x_L; t)$ or equivalently \( y = f(x, \theta_L, x_L; t) \) where $\theta_L$ is an orthogonal measure of labour-specific technical efficiency defined over the range $(0,1]$. Formally, $\theta_L$ is defined according to Kopp’s orthogonal non-radial index of input-specific technical efficiency as:

\[
TE_{KP}^{\theta_L} = \min_{\theta_L} \left\{ \theta_L > 0, f(x, \theta_L, x_L; t) \geq y \right\} \rightarrow (0,1]
\]  

(4)

or in other words under allocative efficiency it is defined as the ratio of optimal over observed labor input use, i.e.,

\[
TE_{KP}^{\theta_L} = \frac{\theta_L x_L}{x_L} = \frac{x^*_L(y, w; t)}{x_L}
\]  

(5)

where $x^*_L(y, w; t)$ is the optimal demand function for labor input obtained through Shephard’s lemma and the cost function in (2), i.e., \( \partial C(y, w; t)/\partial w_L = x^*_L(y, w; t) \).

Graphically, the above definition is presented in figure 1 for the two-input case (i.e., capital, labor). Assuming that individual farmer operates at point $A$ in the graph utilizing $x_L$ quantity from labor and $C$ quantity from capital producing $y$ level of output. Obviously the farm in question is technically inefficient as it is possible to reduce input use moving on the respective isoquant and still being able to produce the same level of output. If inefficiency arises only from labor use then an obvious change would be the movement to point $B$ on the graph, where capital use remains unchanged but labor quantity has been reduced to $x^*_L = \theta_L x_L$. If allocative efficiency is assumed then point $B$ satisfies the cost minimization conditions that is the marginal rate of technical substitution equals with the factor price ratio.

Taking the logarithms on both sides of (5), i.e., \( \ln TE_{KP}^{\theta_L} = \ln x^*_L(y, w; t) - \ln x_L \) and totally differentiating with respect to time we get:

\[
\dot{TE}_{KP}^{\theta_L} = \frac{\partial \ln x^*_L(y, w; t)}{\partial \ln y} \cdot \frac{y}{\sum_j e_{ij}(y, w; t) w_j + \frac{\partial \ln x^*_L(y, w; t)}{\partial t} \cdot x_L}
\]  

(6)
where a dot over a function or a variable indicates its time rate of change, 
\( e_{ij}(y,w;t) = \frac{\partial \ln x^*_{ij}(y,w;t)}{\partial \ln w_j} \) is the cross-price elasticity of labour demand with respect to the price change of the \( j^{th} \) input.

The conventional growth rate of labor productivity can be expressed as the growth rate of farm output minus the growth rate of the labor input, \( i.e., \)

\[
PFP_L = \frac{d \ln (y/x_L)}{dt} = \frac{d \ln y}{dt} - \frac{d \ln x_L}{dt} = y - x_L 
\]

Substituting equation (7) into equation (6) and rearranging terms, we obtain the following:

\[
PFP_L = TE_L^{KP} - \sum_j e_{ij}(y,w;t) w_j + \left[ 1 - \frac{\partial \ln x^*_{ij}(y,w;t)}{\partial \ln y} \right] y - \frac{\partial \ln x^*_{ij}(y,w;t)}{\partial t} 
\]

The above relation shows that the growth rate of the labor input is composed into technical inefficiency effect (first term on the RHS), price effect (second term), output effect (third term) and technological change effect (last term). The last two effects can be further decomposed as follows (Kuroda):

Using the cost share equation of labor input, \( i.e., \)

\[
S_L(y,w,t) = w_L \cdot x^*_L(y,w;t) / C(y,w,t) ,
\]

taking logarithms and slightly rearranging terms we obtain:

\[
\ln x^*_L(y,w;t) = \ln S_L(y,w,t) + \ln C(y,w,t) - \ln w_L
\]

Now, we can derive the last two terms of relation (8), by differentiating equation (9) with respect to output and time, respectively, \( i.e., \)

\[
\frac{\partial \ln x^*_L(y,w;t)}{\partial \ln y} = \frac{\partial \ln S_L(y,w,t)}{\partial \ln y} + \frac{\partial \ln C(y,w;t)}{\partial \ln y} = \frac{1}{S_L(y,w;t)} \frac{\partial S_L(y,w;t)}{\partial \ln y} + \varepsilon_{CT}(y,w;t)
\]

and
\[
\frac{\partial \ln x_t^* (y, w; t)}{\partial t} = \frac{\partial \ln S_y (y, w; t)}{\partial t} + \frac{\partial \ln C (y, w; t)}{\partial t} = \frac{1}{S_L (y, w; t)} \frac{\partial S_L (y, w; t)}{\partial t} - C' (y, w; t)
\]

where \( \varepsilon_{Cy} (y, w; t) = \frac{\partial \ln C (y, w; t)}{\partial \ln y} \) is the output cost elasticity, \( S_L (y, w; t) = \frac{\partial \ln C (y, w; t)}{\partial \ln w_L} \) is the cost share of labor input and \(-C' (y, w; t) = \frac{\partial \ln C (y, w; t)}{\partial t}\) is the rate of cost diminution (i.e., dual rate of technical change). Substituting equations (10) and (11) into (8) results in:

\[
PF_L = T'E_{ KP}^{TE} + \left[ 1 - \varepsilon_{Cy} (y, w; t) \right] y^* - C' (y, w; t) - \sum_j e_{lj} w_j
\]

Equation (12) is the final decomposition formula for labor factor productivity growth. Unlike with Kuroda, in the above equation partial factor productivity has been decomposed into five sources. The first component of the right hand side of (12) indicates changes in labor-specific technical inefficiency. It is positive (negative) as labor technical efficiency increases over time. The second term measures the relative contribution of scale economies to partial productivity growth (Christensen and Greene). This term vanishes under constant returns-to-scale as \( \varepsilon_{Cy} (y, w; t) = 1 \), while it is positive (negative) under increasing (decreasing) returns-to-scale as long as aggregate output increases and vice versa. The third term refers to the dual rate of technical change, which is positive (negative) under progressive (regressive) technical change. The sum of the first three terms using Kuroda’s terminology constitutes the total productivity effect of labor input. The fourth term is substitution effect of the labor demand due to changes in all factor prices. It is positive (negative) only if inputs are complements (substitutes). The substitution effect is zero when input prices change at the same rate. The last term is the sum of the non-homotheticity
effect and technological bias effect. According to Blackorby, Lovell and Thursby and Antle and Capalbo the sum of these two terms is defined as the extended Hicksian biased technological effect. The first part of the last term is different than zero if the underlying technology is non-homothetic, while the second part is negative (positive) and therefore affects positively (negatively) partial factor productivity if technical change is labor saving (using) in the Hicksian sense (it is zero under Hicks-neutral technical change).

**Empirical Model**

To obtain quantitative measures of Kopp’s labor-specific technical efficiency index we need to estimate either an output-distance or a production function. The former is dual to the profit function and thus it does not allow the identification of all other terms appearing in (12). On the other hand, the single equation estimation of a production frontier function although it permits the identification of labor-specific technical efficiency it requires an analytical closed form solution for the corresponding cost frontier in order to identify appropriately the last two terms appearing in (12). This may restrict however the functional specification of the underlying frontier production functions. In the present study, this shortcoming is partially overcame by using a generalized Cobb-Douglas (or quasi translog) frontier production function, proposed by Fan and Karagiannis and Tzouvelekas. This functional specification allows for variable returns to scale, input-biased technical change, and time varying production and substitution elasticities, but it restricts the latter to be unchanged over farms. Nevertheless, it permits statistical tests for the hypotheses of zero rate of technical change and constant returns to scale. Thus, this specification represents a reasonably flexible alternative (Fan and Pardey). When panel data are available it takes the following form:

\[
y_{it} = \beta_0 e^{\beta_1 t + 0.5 \beta_2 t^2} \prod_{j=2}^K x_{jit}^{(\beta_{j1} + \beta_{j1t} t)} x_{lit}^{(\beta_{j1} + \beta_{j1t} t)} e^{v_{it} - u_{it}}
\]

or

\[
\ln y_{it} = \ln \beta_0 + \beta_1 t + 0.5 \beta_2 t^2 + \sum_{j=2}^K \beta_j \ln x_{jit} + \sum_{j=2}^K \beta_{jt} \ln x_{jit} + v_{it} - u_{it}
\]

(13)

(14)
where $i = 1, \ldots, N$ are the farms in the sample, $t = 1, \ldots, T$ are the time periods, $j = 1, \ldots, K - 1$ are the conventional inputs used in the production process, $x_{lit}$ is the quantity of labor use by farm $i$ at year $t$, $\beta$ are the parameters to be estimated, $v_{it} \sim N(0, \sigma_{v}^2)$ is a symmetric and normally distributed error term (i.e., statistical noise) which represents those factors that cannot be controlled by farmers and left-out explanatory variables and, $u_{it} \sim N_{+}(\mu, \sigma_{u}^2)$ is an independently and identically distributed one-sided random error term representing the stochastic shortfall of the $i$th farm output from its production frontier due to the existence of output technical inefficiency. It is further assumed that the two error terms are independently distributed from each other.

The temporal pattern of $u_{it}$ is important in (13) and (14) as the changes in technical efficiency over time rather than the degree of technical efficiency per se matters. For this purpose Battese and Coelli specification is adopted to model the temporal pattern of technical inefficiency, i.e.,

$$u_{it} = \left\{ \exp \left[ -\xi (t - T) \right] \right\} u_i$$

(15)

where $\xi$ captures the temporal variation of individual output-oriented technical efficiency ratings, and $t \in [1, 2, \ldots, T]$. If the parameter $\xi$ is positive (negative), technical efficiency tends to improve (deteriorate) over time. If $\xi = 0$, output-oriented technical efficiency is time-invariant.

The above production frontier function can be estimated by single-equation methods under the assumption of expected profit maximization. The latter implies also cost minimization under price uncertainty and thus allows to go back and forth between the stochastic production and cost frontiers in a theoretically consistent way (Batra and Ullah). Specifically, the dual to (13) cost frontier has the following form:

$$C_{it} = e^{B + \delta_j + \delta_{2it}} y_i \prod_{j=2}^{K} w_{ijit}^{(\delta_j - \delta_{2it})} w_{lit}^{(\delta_j - \delta_{2it})}$$

(16)

or
\[
\ln C_{it} = B + \delta_T t + \delta_{TT} t^2 + \delta_j \ln y + \sum_{j=2}^{K} \delta_j \ln w_{jt} + \\
+ \sum_{j=2}^{K} \delta_{jt} \ln w_{jt} + \delta_L \ln w_{Lt} + \delta_{LT} \ln w_{Lt} t
\]  

(17)

where \( w \) are the factor prices, \( B = \frac{1}{\delta_y} \left( \frac{1}{\delta_B + \delta_{mT}} \right) - \sum_{j=2}^{K} \ln \left( \frac{\delta_j + \delta_{jt} t}{\delta_B + \delta_{mT}} \right) \left( \delta_j + \delta_{jt} t \right) - \delta_0 \)

\( \forall j \neq m \), \( \delta_T = \beta_T \delta_y \), \( \delta_{TT} = \beta_{TT} \delta_y \), \( \delta_j = \beta_j \delta_y \), \( \delta_L = \beta_L \delta_y \), \( \delta_{LT} = \beta_{LT} \delta_y \), \( \delta_0 = \delta_y \ln \beta_0 \) and, \( \delta_y = \frac{1}{\left( \sum_{j} \beta_j + \beta_L \right)} \). Then, through Shephard’s lemma, we can derive the optimal demand functions for both labor input and conventional factors of production using the minimum cost function in (16) and (17) as follows:

\[
x^*_{L i t} = e^{B + \delta_T t + \delta_{TT} t^2} y^{\delta_y} \prod_{j=2}^{K} w_{jt}^{(\delta_j + \delta_{jt} t - 1)} w_{L it}^{(\delta_L + \delta_{LT} t)} \left( \delta_L + \delta_{LT} t \right)
\]  

(18)

and

\[
x^*_{j it} = e^{B + \delta_T t + \delta_{TT} t^2} y^{\delta_y} w_{L it}^{(\delta_L + \delta_{LT} t)} \prod_{m=3}^{K} w_{j m i}^{(\delta_j + \delta_{jt} t - 1)} w_{m i}^{(\delta_j + \delta_{jt} t - 1)} \left( \delta_j + \delta_{jt} t \right)
\]  

(19)

for every \( m \neq j \). From relations (18) and (19) we can derive the labor own- and cross-price elasticities of demand, \( i.e. \)

\[
e_{LL} = \delta_L + \delta_{LT} t - 1
\]  

(20)

\[
e_{lj} = \delta_j + \delta_{jt} t, \hspace{1em} \forall j
\]  

(21)

which are necessary for the estimation of the third term in (12). For the estimation of the scale and the technological change effects we need to compute the output cost elasticity and the rate of cost diminution which under the generalized Cobb-Douglas specification in (17) are obtained from the following:

\[
\epsilon_{Cy} = \frac{\partial \ln C_{it}}{\partial \ln y} = \delta_y
\]  

(22)

and
The hypothesis of constant returns-to-scale can be statistically tested by imposing the necessary restrictions associated with linear homogeneity of the production function in input quantities, i.e., ∑_j β_j + β_L = 1 and ∑_j β_{jt} + β_{LT} = 0. If this hypothesis cannot be rejected then the underlying technology exhibits constant returns-to-scale and the second term in (12) vanishes. Accordingly the hypothesis of Hicks-neutral and zero technical change involves the following parameter restrictions in (13): β_{LT} = β_{jt} = 0 ∀j and β_L = β_{LT} = β_{jt} = 0 ∀j, respectively. If the underlying technology exhibits zero technical change then the last two terms in (12) are zero and labor productivity is affected only from the first three terms. If, however, technical progress is Hicks-neutral then the last term in (12) vanishes.

Next from the labor cost share equation obtained from the minimum cost function we can derive the non-homotheticity and input technological change effects in (12). Specifically,

\[ S_{Lt} = \frac{\partial \ln C_u}{\partial \ln w_{Lt}} = \delta_L + \delta_{LT}t \]

Since the generalized Cobb-Douglas production frontier defined in (13) is homothetic the non-homotheticity effect is zero and therefore it does not contribute in labor factor productivity. On the other hand, the input technological change effect is present if Hicks biased technical change is assumed and it is obtained from:

\[ \frac{1}{S_{Lt}} \frac{\partial S_{Lt}}{\partial t} = \frac{\delta_{LT}}{\delta_L + \delta_{LT}t} \]

If the underlying technology is neutral with respect to labor use, i.e., δ_{LT} = 0, then the above equation is zero and the final term in (12) vanishes. Finally, for the estimation of the first term in (12) we need to compute labor specific technical efficiency. For doing so we use Reinhard, Lovell and Thijssen approach in the
context of the generalized Cobb-Douglas production function. Conceptually, measurement of $TE^{KP}_{Lit}$ requires an estimate for the quantity $x_{Lit}^* = \theta_{Lit} x_{Lit}$ which is not observed. Nevertheless substituting relation (5) into the stochastic production frontier in (13) and by noticing that point $B$ in Figure 1 lies on the frontier, i.e., $u_\mu = 0$, relation (13) may be rewritten as:

$$y_\mu = \beta_0 e^{\beta_0 + \beta_0 t \rho_{\rho_T t}} \prod_{j=1}^{K} x_{j\mu}^{(\beta_j + \rho_{\rho_T t})} x_{Lit}^{(\beta_L + \rho_{\rho_T t})} e^{\nu}$$  \hspace{1cm} (26)$$

Since under weak monotonicity, output technical efficiency should imply and must be implied by input-specific technical efficiency, we can set the input specification in (26) equal to the output-oriented specification in (13). Then using the parameter estimates obtained from the econometric estimation of the stochastic production frontier and solving for $x_{Lit}^*$, we can derive a measure of Kopp’s non-radial labor-specific technical efficiency from the following relation (Reinhard Lovell and Thijssen):

$$TE^{KP}_{Lit} = \exp\left(-\frac{u_\mu}{\beta_L + \rho_{\rho_T t}}\right)$$  \hspace{1cm} (27)$$

which is always different than zero as long as farms are technically inefficient from an output-oriented perspective, i.e., $u_\mu > 0$ and labor is an essential input in farm production, i.e., $\beta_L \neq 0 \land \rho_{\rho_T t} \neq 0$. It is time-invariant if both output-oriented technical efficiency is also time-invariant and biased technical change is labor neutral. In the context of Battese and Coelli model specification this implies the following set of restrictions in the stochastic frontier model in (13): $\xi = 0 \land \beta_{LT} = 0$.

**Data and Empirical Results**
The data for this study are drawn from Farm Accounting Database Network (FADN) database and refer to an unbalanced dataset of 723 Greek crop farms observed during the 1994-2003 period. FADN survey covers only the agricultural holdings, which are of a size allowing them to rank as commercial holdings. Non-farm activities are not
included, while cost expenses refer to the year’s production and not to inputs purchased during the accounting year. The sample includes crop farms that are observed at least six years during the whole period. In the total our sample consists of 5,517 observations. One output and four inputs were distinguished. Output is measured as the total gross revenues arising from crop production (i.e., soft and durum wheat, corn, maize, barley, forage crops, fruits, vegetables) measured in euros. The inputs considered are: (a) total labour, comprising hired (permanent and casual), family and contract labour, measured in working hours; (b) total value of fixed assets including machinery, buildings, equipment and utilized agricultural area in euros; (c) total value of fertilizers including lime, compost, manure etc. in euros; (d) total purchased intermediate inputs, such as seeds, energy, storage, irrigation water measured in euros and; (d) total value of measured also in euros.

Aggregation over the various components of the input and output categories was conducted using Divisia indices with cost or revenue shares serving as weights. Further, in order to avoid problems associated with units of measurement, all variables included in the stochastic Cobb-Douglas production frontier model were converted into indices. The basis for normalization was the farm with the smallest deviation of its output and input levels from the sample means. All variables measured in money terms have been converted into 2000 constant values. Summary statistics of the variables used are given in Table 1. On the average, the total revenues received by Greek crop farms are 28,440 euros ranging from a minimum of 1,664 to a maximum of 154,220 euros. This total value arises from the utilization 2,898 working hours, 2,595 euros of intermediate inputs, 82,260 euros of fixed assets and 2,346 euros of fertilizers.

The maximum likelihood estimates of the generalized stochastic Cobb-Douglas production frontier in (13) and (14) are presented in Table 2. The estimated first-order parameters \( \beta_j \) are having the anticipated sign and magnitude being between zero and one. Hence, the bordered Hessian matrix of first- and second-order partial derivatives is negative semi-definite indicating all that regularity conditions hold at the point of approximation, i.e., sample means. That is marginal products are positive and diminishing an the production frontier is locally quasi-concave. The estimated variance of the one-sided error term, i.e., output technical efficiency, is found to be 0.7045 and statistical significant at the 1 per cent level. Finally, the
variance-parameter $\gamma$ is 0.7484 and also statistical significant at the 1 per cent model, implying that technical inefficiency is likely to be important in explaining output variability among Greek cereal farms.$^{15}$

Several hypotheses concerning model specification have been tested and the results are presented in Table 3.$^{16}$ First, the null hypothesis that the traditional average production function is an adequate representation of the model, i.e., $\gamma = \mu = \xi = 0$ is rejected at the 5 per cent level indicating that technical efficiency is indeed present explaining output variability among Greek crop farms. Moreover, Schmidt and Lin’s test for the skewness of the composed error term also confirms the existence of technical inefficiency.$^{17}$ Second, we tested the proposed formulation against several nested alternatives. In particular, the estimated stochastic frontier model cannot be reduced to that of the Aigner $et \ al.$, regardless whether output technical efficiency is time-invariant ($\mu = \xi = 0$) or time-varying ($\mu = 0$). Under the specific frontier formulation, i.e., Battese and Coelli, technical efficiency is time-varying as the hypothesis that $\xi = 0$ is rejected at the 5 per cent level of significance.

Based on the parameter estimates we computed basic features of the production structure for Greek crop farms, namely returns-to-scale, technical change and output elasticities that are shown in Table 4. All production elasticity estimates are statistical significant$^{18}$ at the 5 per cent level and indicate that labor contributed the most to crop production, followed by fertilizers, capital and intermediate inputs. Specifically the magnitude of output elasticities is 0.6836 for labor, 0.2935 for fertilizers, 0.1359 for capital and 0.1215 for intermediate inputs. These values means that $ceteris \ paribus$, 1 per cent increase in labor, fertilizer, capital and intermediate input use would result in a 0.6836, 0.2935, 0.1359 and 0.1215 per cent increase in marketable output for Greek crop farms, respectively. On the average returns-to-scale were found increasing 1.2346. This means that the average acreage is still below the potential capabilities of the crop production system in Greece. That this the average farm size 45 stremmas (one stremma equals 0.1 ha) is less than the farm size that maximizes the ray average productivity. Further, we have statistically examined the hypothesis of linearly homogeneous frontier production technology ($\sum \beta_j + \beta_L = 1$ and $\sum \beta_{jT} + \beta_{LT} = 0$) which was rejected at the 5 per cent significance level.
indicating non-constant returns-to-scale. Thus, the scale effect is a significant source of labor productivity and should be taken into account in equation (12).

In addition, the hypotheses of no technical change \((i.e., \beta_t = \beta_{TT} = \beta_{LT} = \beta_{JT} = 0 \ \forall j\ \text{for all} \ j)\) as well as that of Hicks-neutral technical change \((i.e., \beta_{LT} = \beta_{JT} = 0 \ \forall j\ \text{for all} \ j)\) are rejected at the 5% significance level. Thus, also technical change has been a significant source of labor productivity and it should be included in decomposition analysis. Specifically, technical change was found to be 1.8845 over the sample period. The neutral component of technical change is found to be progressive at a constant rate as the estimates for the parameters \(\beta_t\) and \(\beta_{TT}\) are both positive and statistically significant at the 5% significance level (see Table 3). On the other hand, the biased component was found to be negative, -0.1509. Regarding technological biases, technical change is found to be fertilizer, labour and intermediate inputs saving and capital-neutral (as the relevant estimated parameter is not statistically different from zero). We have further examined the hypothesis of labour-neutral technical change using the LR-test rejecting the relevant hypothesis. Thus, the labour biased technical change effect, \(i.e., \text{last term in relation (12)}\) is present and it should be taken into consideration in the decomposition analysis.

Given the estimates of the stochastic production frontier we have computed the corresponding cost frontier presented in relation (17) for the whole sample period:

\[
\ln C_t = 12.345 + 0.099t + 0.045t^2 + 0.809 \ln y + 0.572 \ln w_{La} + \\
0.112 \ln w_{Ka} + 0.105 \ln w_{Li} + 0.228 \ln w_{Fi} + 0.085 \ln w_{Li}t \\
+ 0.009 \ln w_{Ka}t + 0.028 \ln w_{Li}t - 0.016 \ln w_{La}t \tag{28}
\]

where \(L\) stands for labor, \(K\) for capital, \(I\) for intermediate inputs and \(F\) for fertilizers. Given (28) we have computed the corresponding factor demand functions through Shephard’s lemma and the subsequent factor demand elasticities which are presented in Table 5. All the own-price factor demand elasticities are negative and statistically significant at the 1 per cent level. The highest value is that for intermediate input (0.9024) followed by capital (0.8900), fertilizers (0.7597) while labor is the less sensitive factor in changes of its own price. Contrary, labor input is the most sensitive factor of production in changes of other factor prices. Specifically, cross-price demand elasticities are all positive indicating substitution among factors of production.
in Greek crop farms. The highest value is for labor (0.5521), followed by fertilizers (0.2403), capital (0.1100) and intermediate inputs (0.0976). All point estimates are statistical significant at least at the 5 per cent level.

Estimates of both labour-specific and output technical efficiency scores in the form of frequency distribution within a decile range are reported in Table 6. Estimated mean output technical efficiency for the period 1994-03 is 64.52 per cent implying that output could have increased approximately by 35 per cent if technical inefficiency was eliminated. The parameter $\xi$ capturing the pattern of time-varying technical inefficiency is positive and statistical significant indicating that farmer’s know-how has been improved over time. Specifically, mean output technical efficiency has been increased since 1994 from 61.3 to 68.1 per cent in 2003. On the other hand, labour-specific technical efficiency was also found to be increasing over time. Statistical testing using LR-test rejects the hypothesis of time-invariant labour technical efficiency pattern ($i.e., \xi = \beta_{LT} = 0$). It’s temporal pattern is different than that of output technical efficiency as the second-order parameter of labor input ($\beta_{LT}$) is statistically different than zero. Mean labor technical efficiency was found to be higher than that of output technical efficiency, 79.3 per cent, ranging from a minimum of 28.7 to a maximum of 98.5 per cent. Concerning it’s temporal pattern it is clearly increasing during the period analyzed. In particular it has been increased from 74.5 per cent in 1994 to 81.6 per cent in 2003.

The decomposition analysis results of labour productivity is presented in Table 7. The average annual rate of change in labour productivity during the period under consideration is reported first, followed by the relative contribution of each effect included in (12). An average annual rate of 2.8925 per cent is observed for labour productivity growth during the 1994-2003 period. Both productivity and labour technological bias effects contributed positively to that productivity growth accounting for the 3.1530 and 0.1509 per cent of its annual rate of change. On the other hand the substitution effect was found to be negative accounting for the 0.4114 per cent of total labour productivity slowdown.

Concerning the productivity effect first, the 34.7 per cent it arises from improvements in labour technical efficiency during the period analyzed. Farmer’s know how has been improved over years utilizing for efficiently labour input in cereal production process. This rather significant figure would have been omitted if labour
technical efficiency was falsely assumed. On the other hand the technological innovations during the sampled period contributed by 1.8845 per cent to total labour productivity growth accounting for the 65.2 per cent of total productivity effect. Besides the negative contribution of the biased component (0.1509), the neutral part is considerably high resulting to a significant contribution of technical progress. Finally, the existence of scale economies accounted for the 9.2 per cent of the total productivity effect as the aggregate output index increased over time. In relative terms, the scale effect is the least important factor influencing productivity effect after technological progress and labour technical efficiency.

Since technological change was found to be labor saving, the technological bias effect was found to be positive accounting for the 5.2 per cent of total labor productivity increase during the 1994-03 period. The bias of technological change towards saving labor is associated with the rising trend of the price of labor during the period analyzed however, this increase in the price of labor was lower than the associated increase in the price of fertilizers and other intermediate inputs during the same period. This implies that the substitution effect due to biased technological change may be regarded, in a broader sense, as part of the substitution effect due to factor price changes.

After the beginning of ‘90s, all factor prices increased sharply. Specifically, the rates of growth of the factor prices were substantial during the 1994-03 period: 11.2, 8.4, 1.09 and 2.34 per cent for fertilizers, other intermediate inputs, capital and labor, respectively. Although the own substitution effect and that with respect to capital that exhibit a low relative increase in it’s price were both found positive (0.0799 and 0.1222 per cent, respectively), they were less than the substitution effects with respect to fertilizers and other intermediate inputs which were found to be -0.4942 and -0.1193 per cent, respectively. Hence, the substitution effects with fertilizers and other intermediate inputs were the major components for the price effect of -0.4114 per cent during the 1994-03 period.

**Summary and Conclusions**

In this article, we develop a tractable dual approach for the decomposition of partial factor productivity in the presence of input-specific technical inefficiency. Based on Kuroda’s methodological approach and using the theoretical foundations developed by Kopp, we decompose the growth rate of partial factor productivity into five
sources, namely, changes in input-specific technical efficiency, substitution effect, technical change, the effect of scale economies and a homotheticity and input biased technological effect. Unlike with Kuroda, input-specific technical efficiency was introduced as a component of the growth rate of partial factor productivity in the context of the well-established stochastic production frontier model. Input-specific technical efficiency was estimated using the methodological framework first developed by Ray and Reinhard, Lovell and Thijssen.

Our model was applied to a unbalanced panel data set of 723 cereal producing farms in Greece during the 1994-03 period. The empirical results suggest that changes in technical efficiency constitute an important source of partial productivity growth which was falsely omitted in previous studies. Specifically, labor productivity grew by 2.8925 per cent annually with the 34.7 per cent of this annual growth arising from improvement in labor technical efficiency. This result implies that much attention must be given in the role of technical efficiency. Still technological progress was found to be the main source of labor productivity growth (65.2 per cent), suggesting that policies aiming at enhancing the adoption of technological innovations and at increasing investments in R&D are significantly effective. Furthermore, the substitution effect were found to cause a 0.4114 per cent slowdown in labor productivity mainly due to the sharp increase of factor prices which was more evident in fertilizers and other intermediate inputs.

Specifically, the increase of labor productivity in Greek crop production requires policies aiming at improving technological change, taking into account the of farmer’s know-how. Contrary, changes in inputs-prices do not seem to have a significant impact on labor productivity. Nevertheless, the empirical results confirm our initial prediction that technical efficiency is a factor of productivity growth that is too important to ignore.
References
Chambers, R. *Applied Production Analysis: A Dual Approach.*


Figure 1. Kopp’s Orthogonal Measure of Labour Technical Efficiency.
Table 1. Descriptive Statistics of the Variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>StDev</th>
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</thead>
<tbody>
<tr>
<td>Output (in euros)</td>
<td>28,440</td>
<td>140</td>
<td>754,220</td>
<td>22,111</td>
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<tr>
<td>Labour (in working hours)</td>
<td>2,898</td>
<td>154</td>
<td>17,200</td>
<td>1,626</td>
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<tr>
<td>Capital (in euros)</td>
<td>82,260</td>
<td>1,750</td>
<td>586,146</td>
<td>68,651</td>
</tr>
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<td>Intermediate Inputs (in euros)</td>
<td>2,595</td>
<td>10</td>
<td>43,866</td>
<td>2,846</td>
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<tr>
<td>Fertilizers (in euros)</td>
<td>2,346</td>
<td>6</td>
<td>35,192</td>
<td>2,602</td>
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<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
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<td>$\beta_0$</td>
<td>0.6957</td>
<td>(0.0390) *</td>
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<tr>
<td>$\beta_L$</td>
<td>0.7067</td>
<td>(0.0245) *</td>
</tr>
<tr>
<td>$\beta_C$</td>
<td>0.1385</td>
<td>(0.0180) *</td>
</tr>
<tr>
<td>$\beta_I$</td>
<td>0.1290</td>
<td>(0.0166) *</td>
</tr>
<tr>
<td>$\beta_F$</td>
<td>0.2817</td>
<td>(0.0136) *</td>
</tr>
<tr>
<td>$\beta_{LT}$</td>
<td>-0.1052</td>
<td>(0.0196) *</td>
</tr>
<tr>
<td>$\beta_{CT}$</td>
<td>0.0119</td>
<td>(0.0176)</td>
</tr>
<tr>
<td>$\beta_{IT}$</td>
<td>-0.0341</td>
<td>(0.0157) **</td>
</tr>
<tr>
<td>$\beta_{FT}$</td>
<td>-0.0539</td>
<td>(0.0136) *</td>
</tr>
<tr>
<td>$\beta_T$</td>
<td>0.1223</td>
<td>(0.0272) *</td>
</tr>
<tr>
<td>$\beta_{TT}$</td>
<td>0.0557</td>
<td>(0.0157) *</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>0.7045</td>
<td>(0.0830) *</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.7484</td>
<td>(0.0287) *</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.6101</td>
<td>(0.1289) *</td>
</tr>
<tr>
<td>$\xi$</td>
<td>0.0228</td>
<td>(0.0050) *</td>
</tr>
</tbody>
</table>

Note: $L$ refers to labour, $C$ to capital, $I$ to intermediate inputs and $F$ to fertilizers. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively.
<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>LR test-statistic</th>
<th>Critical Value ((a=0.05))</th>
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</thead>
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<tr>
<td>Average Production Function, (i.e., \gamma = \mu = \xi = 0)</td>
<td>303.60</td>
<td>(\chi_3^2 = 7.81)</td>
</tr>
<tr>
<td>Aigner et al., (1977) SPF model with time-invariant output technical efficiency, (i.e., \mu = \xi = 0)</td>
<td>29.67</td>
<td>(\chi_2^2 = 5.99)</td>
</tr>
<tr>
<td>Aigner et al., (1977) SPF model with time-varying output technical efficiency, (i.e., \mu = 0)</td>
<td>8.61</td>
<td>(\chi_1^2 = 3.84)</td>
</tr>
<tr>
<td>Time-invariant output technical efficiency, (i.e., \xi = 0)</td>
<td>20.92</td>
<td>(\chi_1^2 = 3.84)</td>
</tr>
<tr>
<td>Constant returns-to-scale, (i.e., \sum_j \beta_j + \beta_L = 1) and (\sum_j \beta_{jT} + \beta_{LT} = 0)</td>
<td>89.00</td>
<td>(\chi_5^2 = 11.1)</td>
</tr>
<tr>
<td>Hicks-neutral technical change, (i.e., \beta_{LT} = \beta_{jT} = 0 \forall j)</td>
<td>55.94</td>
<td>(\chi_4^2 = 9.49)</td>
</tr>
<tr>
<td>Zero-technical change, (i.e., \beta_T = \beta_{jT} = \beta_{LT} = \beta_{jT} = 0 \forall j)</td>
<td>81.54</td>
<td>(\chi_6^2 = 12.6)</td>
</tr>
<tr>
<td>Time-invariant labour specific technical efficiency, (i.e., \xi = \beta_{LT} = 0)</td>
<td>13.41</td>
<td>(\chi_2^2 = 5.99)</td>
</tr>
<tr>
<td>Labour-neutral technical change, (i.e., \beta_{LT} = 0)</td>
<td>9.07</td>
<td>(\chi_1^2 = 3.84)</td>
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Table 4. Output Elasticities, Returns-to-Scale and Technical Change for Greek Cereal Farms.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean Value</th>
<th>Standard Error</th>
</tr>
</thead>
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<tr>
<td><strong>Output elasticities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labour</td>
<td>0.6836</td>
<td>(0.1721)*</td>
</tr>
<tr>
<td>Capital</td>
<td>0.1359</td>
<td>(0.0644)**</td>
</tr>
<tr>
<td>Intermediate inputs</td>
<td>0.1215</td>
<td>(0.0702)**</td>
</tr>
<tr>
<td>Fertilizers</td>
<td>0.2935</td>
<td>(0.0475)*</td>
</tr>
<tr>
<td><strong>Returns-to-Scale</strong></td>
<td>1.2346</td>
<td>(0.1341)*</td>
</tr>
<tr>
<td><strong>Technical Change</strong></td>
<td>1.8845</td>
<td>(0.1458)*</td>
</tr>
<tr>
<td>Autonomous</td>
<td>2.0354</td>
<td>(0.1234)*</td>
</tr>
<tr>
<td>Biased</td>
<td>-0.1509</td>
<td>(0.0675)**</td>
</tr>
</tbody>
</table>

* (**) indicate statistical significance at the 1 (5) percent level, respectively.

Table 5. Own- and Cross-Price Demand Elasticities for Greek Cereal Farms.

<table>
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<tr>
<th></th>
<th>Estimate</th>
<th>StdError</th>
<th></th>
<th>Estimate</th>
<th>StdError</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_{LL}$</td>
<td>-0.4479</td>
<td>(0.0706)*</td>
<td>$e_{jL}$</td>
<td>0.5521</td>
<td>(0.0706)*</td>
</tr>
<tr>
<td>$e_{KK}$</td>
<td>-0.8900</td>
<td>(0.0382)*</td>
<td>$e_{jK}$</td>
<td>0.1100</td>
<td>(0.0382)**</td>
</tr>
<tr>
<td>$e_{II}$</td>
<td>-0.9024</td>
<td>(0.0909)*</td>
<td>$e_{jI}$</td>
<td>0.0976</td>
<td>(0.0509)**</td>
</tr>
<tr>
<td>$e_{FF}$</td>
<td>-0.7597</td>
<td>(0.0402)*</td>
<td>$e_{jF}$</td>
<td>0.2403</td>
<td>(0.0402)*</td>
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* (**) indicate statistical significance at the 1 (5) percent level, respectively.
Table 6. Frequency Distribution of Output and Labour Technical Efficiency for Greek Cereal Farms.

<table>
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<th>(%)</th>
<th>94</th>
<th>95</th>
<th>96</th>
<th>97</th>
<th>98</th>
<th>99</th>
<th>00</th>
<th>01</th>
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<tr>
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</tbody>
</table>
Table 7. Decomposition of Labour Productivity Growth for the Greek Cereal Farms (average values for the 1994-03 period).

<table>
<thead>
<tr>
<th>Category</th>
<th>Average Annual Rate of Change</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labour Factor Productivity</td>
<td>2.8925</td>
<td>(100.0)</td>
</tr>
<tr>
<td>Productivity Effect</td>
<td>3.1530</td>
<td>(109.0)</td>
</tr>
<tr>
<td>Change in Labour Technical Efficiency</td>
<td>1.0023</td>
<td>(34.7)</td>
</tr>
<tr>
<td>Scale Effect</td>
<td>0.2662</td>
<td>(9.2)</td>
</tr>
<tr>
<td>Rate of Technical Change</td>
<td>1.8845</td>
<td>(65.2)</td>
</tr>
<tr>
<td>Autonomous Part</td>
<td>2.0354</td>
<td>(70.4)</td>
</tr>
<tr>
<td>Biased Part</td>
<td>-0.1509</td>
<td>(-5.2)</td>
</tr>
<tr>
<td>Substitution Effect</td>
<td>-0.4114</td>
<td>(-14.2)</td>
</tr>
<tr>
<td>Labour</td>
<td>0.0799</td>
<td>(2.8)</td>
</tr>
<tr>
<td>Capital</td>
<td>0.1222</td>
<td>(4.2)</td>
</tr>
<tr>
<td>Intermediate inputs</td>
<td>-0.1193</td>
<td>(-4.1)</td>
</tr>
<tr>
<td>Fertilizers</td>
<td>-0.4942</td>
<td>(-17.1)</td>
</tr>
<tr>
<td>Labour Biased Technical Change Effect</td>
<td>0.1509</td>
<td>(5.2)</td>
</tr>
</tbody>
</table>
Endnotes

1 Lau and Tamura and Chambers provide a complete characterization of the non-homothetic Leontief technologies in a dual context.

2 Labour-specific technical efficiency as defined in (4) and (5), has an input conserving interpretation, which however cannot be converted into a cost-saving measure due to its orthogonal non-radial nature (Kopp). Akridge based on Kopp’s theoretical framework incorporated factor prices suggesting a single factor technical cost efficiency index which measures the potential cost savings that can be realized by adjusting single factor use.

3 Following Kuroda we assume that the price of labour is fixed and therefore not a function of the quantity produced and technological change.

4 As Kuroda didn’t account for the existence of labour-specific technical efficiency, the first term in the productivity effect was not included in his analysis of Japanese agriculture.

5 Blackorby, Lovell and Thursby demonstrate a technological shift down the expansion path can simultaneously result in the maintenance of the MRTS and non-varying factor shares in a Hicksian sense only if the production technology is homothetic. For a neutral shift of the MRTS along the expansion path of a farm operating with a non-homothetic production process, factor shares would not remain constant.

6 Kuroda under the assumption of technical and allocative efficiency estimated a dual translog cost function identifying thus all terms in his decomposition formula.

7 In the case of unbalanced panels, includes a subset of integers representing the periods for which observations on individual producers are obtained.

8 The hypothesis of time invariant technical efficiency can be tested statistically.

9 Under allocative efficiency it holds that and thus we are justified us to work with observed factor shares to derive the last two terms appearing in (12).

10 Using relation (24) the non-homotheticity effect in the case of generalized Cobb-Douglas production function equals to

11 In fact Ray based on Atkinson and Cornwell’s findings suggested a similar approach with Reinhard et al. for the estimation of input-oriented technical efficiency.
12 For a detailed discussion of the properties of efficiency indices, see Russell (pp. 30-41) and Kumbhakar and Lovell (pp. 44-46).

13 Reinhard, Lovell and Thijssen in developing their approach of measuring Kopp’s orthogonal input-specific technical efficiency correctly argued that under a Cobb-Douglas specification of the production frontier, both indices will exhibit the same ranking for farms in the sample. However, this is not true with the generalized Cobb-Douglas production frontier utilized herein which allows for different temporal patterns among the two efficiency measures. The latter is important in appropriately identifying the sources of labour productivity growth in the surveyed farms.

14 Output technical efficiency was estimated using the predictor suggested by Battese and Coelli which, unlike with that proposed initially by Aigner et al. is based on the ratio parameterization of the variances of the composed error term.

15 For true gamma parameter, see Kumbhakar and Lovell (pp. 82-86): 
\[ V(\varepsilon) = \mu^2 \frac{\alpha}{2} \left(1 - \frac{\alpha}{2}\right) + \frac{\alpha}{2} \left(1 + \frac{\alpha}{\pi}\right) \sigma_u^2 \] 
where \( \alpha = \Phi(-\mu/\sigma_u^2) \) and \( \Phi \) is the normal truncated normal distribution.

16 These tests were conducted using the generalized likelihood-ratio test statistic, 
\[ LR = -2\left\{ \ln \left[ \frac{L(H_0)}{L(H_1)} \right] \right\} \] 
where \( L(H_0) \) and \( L(H_1) \) denote the values of the likelihood function under the null \( (H_0) \) and the alternative \( (H_1) \) hypothesis, respectively. The LR-test statistic follows a \textit{chi-squared} distribution except in the cases that involve testing of the \( \gamma \) parameter where it has a \textit{mixed chi-squared} distribution the appropriate critical values of which are obtained from Kodde and Palm (table 1).

17 The test-statistic computed as \( \sqrt{b_1} = m_3/m_2^{3/2} \) (with \( m_3 \) and \( m_2 \) being the third and second moments of the residuals and \( b_1 \) is the coefficient of skewness) is 2.047, well above the corresponding critical value at the 5% level of significance (0.298).

18 The standard errors reported in Tables 4 and 5 were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks and reestimating the system leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano).