Explaining Output Growth of Sheep Farms in Greece: A Parametric Primal Approach

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This paper provides a parametric decomposition of output growth of sheep farms in Greece using an integrated primal approach, in which output growth is attributed to input growth (size effect), changes in technical efficiency, technical change, and the scale effect. The empirical results indicate that the scale effect, which has not been taken into account by previous studies, has a significant role in explaining output growth and TFP changes. It was found that during the period 1989-92 it caused a 0.61% output slowdown and it was the second main source of TFP changes after technical progress. Consequently, there would have been significant biases in TFP measurement by not accounting for the scale effect.

Introduction

The two sources of output growth are factor accumulation (input growth) and total factor productivity (TFP) changes. During the last decade, considerable effort has been devoted into developing accurate and reliable decomposition of TFP changes within both the parametric and the non-parametric framework. For agriculture in particular, several studies have attempted to explain and to identify the sources of output growth. By using a stochastic production frontier approach and panel data, Fan (1991), Ahmad and Bravo-Ureta (1995), Wu (1995), Kalirajan et al. (1996), Kalirajan and Shand (1997), and Giannakas et al. (2000, 2001) have attributed observed output growth to movements along a path on or beneath the production frontier (input growth), shifts in the production frontier (technical change), and movements towards or away from the production frontier (changes in technical efficiency). Even though such a decomposition of TFP changes goes beyond the conventional Solow’s (1957) residual approach, it implicitly assumes that changes in TFP are attributed to only two sources: namely, technical change and technical efficiency.1

Bauer (1990) and Lovell (1996) have shown that the effect of returns to scale on TFP growth can also be identified within a parametric production function approach as long as allocative efficiency is assumed, without need of information in input prices. Scale economies can stimulate output growth even in the absence of
technical change and improvements in technical efficiency as long as input use increases. Analogously, diseconomies of scale would deteriorate production under similar circumstances. Since the range of scale economies is not known a priori, it seems appropriate to proceed by statistically testing the hypothesis of constant returns to scale. If this hypothesis is rejected, the scale effect is present and should be taken into account. Its relative contribution to output growth depends on both the magnitude of scale economies and the rate of input growth.

Nevertheless, none of the aforementioned studies has considered the impact that returns to scale may have on agricultural output growth. It has been shown that the scale effect can correctly be omitted in the decomposition of TFP growth only in the case of constant returns to scale (Bauer, 1990; Lovell, 1996; Kumbhakar, 2000). Otherwise, TFP growth may be either over- or under-estimated by not accounting for the scale effect. Thus, Fan (1991), Ahmad and Bravo-Ureta (1995), and Giannakas et al. (2001) more probably underestimated the portion of output growth attributed to TFP by omitting the contribution of the scale effect associated with increasing returns to scale in US dairy production, Chinese agriculture, and Saskatchewan wheat farms, respectively. On the other hand, Wu (1995), and Giannakas et al. (2000) more likely overestimated the portion of output growth attributed to TFP due to the presence of decreasing returns to scale in Chinese agriculture and Greek olive oil production, respectively.

The objective of this paper is to provide a parametric decomposition of output growth of sheep farms in Greece using the integrated primal approach developed by Bauer (1990), Lovell (1996) and Kumbhakar (2000). Within this framework, output growth is attributed to input growth, changes in technical efficiency, technical change, and the scale effect. Separate estimates of these effects may be obtained directly from the estimated parameters of the underlying production frontier. The empirical results are obtained by applying Battese and Coelli (1995) inefficiency effects model to a unbalanced panel data set consisting of 51 sheep farms observed during the period 1989-92.

The rest of this paper is organized as follows: the theoretical model based on the primal (i.e., production function) approach is presented in the next section. The empirical model is discussed in the third section, and the data used are described in the forth section. The empirical results are analyzed in the fifth section. Concluding remarks follow in the last section.
Theoretical Framework

Consider that firms use inputs \( x = (x_1, ..., x_j) \) to produce a single output \( y \) through a technology described by a well-behaved production frontier \( f(x;t) \), where \( t \) is a time index that serves as a proxy for technical change. Since firms are not necessarily technically efficient, \( y \leq f(x;t) \). Then, the output-oriented measure of technical efficiency is defined as \( TE^O(x,y;t) = y/ f(x;t) \), where \( 0 < TE^O(x,y;t) \leq 1 \) (see for example Kumbhakar and Lovell, 2000, pp. 46-48). \( TE^O \) relates actual to best practice output in the sense that gives the maximum amount by which output can be increased and still being producible by a given input vector.

After taking the natural log of both sides of the above measure of technical efficiency, and totally differentiating with respect to time results in:

\[
\dot{TE}^O(x,y;t) = y - \sum_{j=1}^{n} \varepsilon_j(x;t)x_j - T_t(x;t),
\]

where a dot over a function or a variable indicates a time rate of change, \( \varepsilon_j(x;t) = \frac{\partial \ln f(x;t)}{\partial \ln x_j} \) is the output elasticity of the \( j^{th} \) input, and \( T_t(x;t) = \frac{\partial \ln f(x;t)}{\partial t} \) is the primal rate of technical change. Substituting the conventional Divisia index of TFP growth, \( \dot{TFP} = y - \sum_{j=1}^{n} s_j x_j \), into (1) yields:

\[
\dot{TFP} = \dot{TE}^O(x,y;t) + T_t(x;t) + \sum_{j=1}^{n} (\varepsilon_j(x;t) - s_j)x_j,
\]

where \( s_j = (w_j x_j)/C \), \( w_j \) is the price of the \( j^{th} \) input and \( C \) is the total cost of production. Equation (2), firstly developed by Bauer (1990), attributes TFP growth to changes in technical efficiency (first term), to technical change (second term), and to a hodgepodge of returns to scale and cost efficiency effects (third term). Alternatively following Kumbhakar (2000), (2) may be written as:

\[
\dot{TFP} = \dot{TE}^O(x,y;t) + T_t(x;t) + (E - 1) \sum_{j=1}^{n} \left( \frac{\varepsilon_j(x;t)}{E} \right)x_j + \sum_{j=1}^{n} \left( \frac{\varepsilon_j(x;t)}{E} - s_j \right)x_j
\]
where \( E = \sum \varepsilon_j(x;t) \) is the scale elasticity that is greater, equal, or less than one under increasing, constant, or decreasing returns to scale, respectively. The last term in (3) captures either deviations of input prices from the value of their marginal products or departures of marginal rate of technical substitution from the ratio of input prices. However, under profit maximization and allocative efficiency \( w_j = p(\partial f(x;t)/\partial x_j) \) and thus \( s_j = \varepsilon_j(x;t)/E \) (Chan and Mountain, 1983). Then, (3) may be rewritten as (Lovell, 1996):

\[
\dot{TFP} = \dot{TE}^o(x,y;t) + T_t(x;t) + (E - 1)\sum_{j=1}^{n} \left( \frac{\varepsilon_j(x;t)}{E} \right) x_j^*,
\]

where the last term refers to the effect returns to scale may have on TFP changes. This term vanishes under constant returns to scale (i.e., \( E = 1 \)) and thus, TFP growth is attributed to changes in technical efficiency and technical change, as in Nishimizu and Page (1982). The scale effect is, however, positive (negative) under increasing (decreasing) returns to scale as long as input use increases and vice versa. Its relative contribution depends on both the magnitude of the scale elasticity and the rate of input quantity changes.

For the purposes of the present study, (4) is converted into an output growth decomposition form by making use of the conventional Divisia index of TFP growth and of \( s_j = \varepsilon_j(x;t)/E \), i.e.,:

\[
\dot{y} = \dot{TE}^o(x,y;t) + T_t(x;t) + (E - 1)\sum_{j=1}^{n} \left( \frac{\varepsilon_j(x;t)}{E} \right) x_j^* + \sum_{j=1}^{n} \left( \frac{\varepsilon_j(x;t)}{E} \right) x_j^*. \tag{5}
\]

In (5), output growth is attributed into four sources: first, into changes in technical efficiency (first term) that contribute positively (negatively) to output growth if they are associated with movements towards (away from) the production frontier. Thus, what really matters is not the degree of technical efficiency itself, but its changes over time.\(^4\) Second, into the technical change effect (second term), which is positive (negative) under progressive (regressive) technical change.\(^5\) Third, into the scale effect (third term), the sign of which depends on both the magnitude of the scale elasticity and the changes of the aggregate input over time. Fourth, into the size effect (fourth term) that captures the contribution of aggregate input growth on output.
changes over time. Output increases (decreases) are associated with increases (decreases) in the aggregate input, *ceteris paribus*. Also, the more essential an input is in the production process the higher its contribution is on the size effect.

A quite different relationship has been used by previous studies to decompose agricultural output growth, namely:

$$ y = T E^o(x, y; t) + T_j(x; t) + \sum_{j=1}^{n} \epsilon_j(x; t) x_j $$

(6)

Despite the fact that the scale effect is neglected in (6), the measurement of the size effect consists another notable difference between (5) and (6). Fan (1991), Ahmad and Bravo-Ureta (1995), and Giannakas *et al.* (2000, 2001) have measured the size effect by the last term in (6), which however is different from the last term in (5). They are equal to each other only under constant returns to scale. Thus, given that Fan (1991), Ahmad and Bravo-Ureta (1995), and Giannakas *et al.* (2000) have reported evidence of increasing returns to scale, they have overestimated the relative contribution of the size effect into output growth, while Giannakas *et al.* (2001) have underestimated it since they have found decreasing returns to scale.

Apparently, (5) and (6) would yield quite different results concerning the sources of output growth. In particular, the relative contribution of TFP changes into output growth is overestimated (underestimated) when (6) is employed and decreasing (increasing) returns to scale prevail, while the opposite is true for the size effect. The two relations will yield exactly the same decomposition of output growth only in the limited case of constant returns to scale. In this case, the third term in (5) vanishes and the last term in (5) and (6) are equal to each other as $E = 1$. Nevertheless, exactly the same portion of observed output growth could be explained by employing either (5) or (6). This is clear by noticing that the sum of the last two terms in (5) is equal to the last term in (6). Then, given that the first two terms in (5) and (6) are identical to each other, the same unexplained residual will result from both relations.
where \( f(\bullet) \) is approximated by a translog function, i.e.,

\[
y_{it} = \beta_0 + \beta_T t + \frac{1}{2} \beta_{TT} t^2 + \sum_{j=1}^{n} \beta_j x_{jit} + \frac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{jk} x_{jit} x_{kit} + \sum_{j=1}^{n} \beta_{jt} x_{jit} t + e_{it},
\]

\( y_{it} \) is the logarithm of the observed output produced by the \( i \)th farm at year \( t \), \( x_{jit} \) is the logarithm of the quantity of the \( j \)th input used by the \( i \)th farm at year \( t \), \( \beta \) is a vector of parameters to be estimated, and \( e_{it} = v_{it} - u_{it} \) is a stochastic composite error term. The \( v_{it} \) depicts a symmetric and normally distributed error term (i.e., statistical noise), which represents those factors that cannot be controlled by farms, such as access to raw material, labor market conflicts, measurement errors in the dependent variable, and left-out explanatory variables. On the other hand, the \( u_{it} \) is a one-sided non-negative error term representing the stochastic shortfall of the \( i \)th farm’s output from its production frontier due to the existence of technical inefficiency. Thus, \( u_{it} \) accounts for the \( i \)th farm degree of technical inefficiency. It is further assumed that \( v_{it} \) and \( u_{it} \) are independently distributed from each other.

Battese and Coelli (1995) suggested that the technical inefficiency effects, \( u_{it} \), in (7) could be replaced by a linear function of explanatory variables reflecting farm-specific characteristics. The technical inefficiency effects are assumed to be independent and non-negative truncations (at zero) of the normal distribution with unknown variance and mean. Specifically,

\[
u_{it} = \delta_0 + \sum_{m=1}^{M} \delta_m z_{mit} + \omega_{it}, \tag{9}
\]

where \( z_{mit} \) are farm- and time-specific explanatory variables associated with technical inefficiencies, \( \delta_0 \) and \( \delta_m \) are parameters to be estimated, and \( \omega_{it} \) is a random variable with zero mean and finite variance \( \sigma^2_{\omega} \) defined by truncating the normal distribution in such a way that \( \omega_{it} \geq -\left( \delta_0 + \sum \delta_m z_{mit} \right) \). This implies that the means,

\[
\mu_{it} = \delta_0 + \sum \delta_m z_{mit},
\]

of the \( u_{it} \) are different among farms but the variance, \( \sigma^2_u \), is assumed to be the same for all of them.

The above formulation of inefficiency effects has three advantages. First, it permits the prediction and explanation of technical inefficiency by using a single-stage estimation procedure, as long as the inefficiency effects in (9) are stochastic.
The two-stage estimation procedure, often used in previous empirical applications, has been recognized as one that is inconsistent with the assumption of identically distributed inefficiency effects in the stochastic frontier. Second, it allows separating time-varying technical efficiency from technical change by using a single-stage estimation procedure, as long as the inefficiency effects are stochastic and follow a specific (i.e., truncated half-normal) distribution. Third, even though the inefficiency effects follow a truncated half-normal distribution, the truncation point is farm-specific determined by the \( z \)-variables. Consequently, the inefficiency effects are farm-specific.

After substituting (8) and (9) into (7) the resulting model is estimated by a single-equation estimation procedure using the maximum likelihood method and the FRONTIER (version 4.1) computer program developed by Coelli (1992). The variance parameters of the likelihood function are estimated in terms of \( \sigma^2 = \sigma_v^2 + \sigma_u^2 \) and \( \gamma = \sigma_u^2 / \sigma^2 \), where the \( \gamma \)-parameter has a value between zero and one. The closer the estimated value of the \( \gamma \)-parameter to one is, the higher the probability that the technical inefficiency effect is significant in the stochastic frontier model, and in such a case the average response production function is not an adequate representation of the farms’ technology.

Several hypotheses can be tested by using the generalized likelihood-ratio statistic, \( \lambda = -2 \{ \ln L(H_0) - \ln L(H_1) \} \), 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. First, if \( \gamma = 0 \) technical inefficiency effects are non-stochastic and (7) reduces to the average response function in which the explanatory variables in the technical inefficiency model are also included in the production function. Second, if \( \gamma = \delta_0 = \delta_m = 0 \) for all \( m \), the inefficiency effects are not present. Consequently, each farm in the sample operates at the frontier and thus, the systematic and random technical inefficiency effects are zero. Third, if \( \delta_m = 0 \) for all \( m \), the explanatory variables in the model for the technical inefficiency effects have zero coefficients. In this case, farm-specific factors do not influence technical inefficiency and (7) reduces to Stevenson’s (1980) specification, where \( u_{it} \) follow a truncated normal distribution. Fourth, if \( \delta_0 = \delta_m = 0 \) the original Aigner et al. (1977) specification is obtained, where \( u_{it} \) follow a half-normal distribution.
Farm-specific estimates of the output-oriented measure of technical efficiency are obtained directly from the estimated mean and variance of $u_{it}$. Specifically,

$$TE_{it}^O = \exp(-u_{it}) = \exp\left(-\delta_0 - \sum_{m=1}^{M} \delta_m z_{mit} - \omega_{it}\right).$$  \hspace{1cm} (10)

Thus, the output-oriented measure of technical efficiency is inversely related to the inefficiency effects. Following Battese and Coelli (1988), $TE_{it}^O$ is predicted using the conditional expectation of $\exp(-u_{it})$ given $\varepsilon_{it}$:

$$TE_{it}^O = E\left\{\exp(-u_{it})|\varepsilon_{it}\right\} = \exp(-\mu_{it}^0 + 0.5\sigma_o^2)\Phi\left[\left(\frac{\mu_{it}^0}{\sigma_o}\right) - \sigma_o\right] - \Phi\left[\left(\frac{\mu_{it}^0}{\sigma_o}\right)\right]^{-1},$$  \hspace{1cm} (11)

where $\mu_{it}^0 = \frac{\sigma_v^2(\delta_0 + \sum_{m=1}^{M} \delta_m z_{mit}) - \sigma_u^2 \varepsilon_{it}}{\sigma_v^2 + \sigma_u^2}$, $\sigma_o^2 = \frac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + \sigma_u^2}$, $\Phi[\bullet]$ represents the cumulative density function of the standard normal random variable, and $E$ is the expectation operator.

In the context of this paper, the temporal pattern of technical efficiency is modeled with time dummies $D_t$, i.e., $A(t) = \sum_{t=1}^{T} \delta_t D_t$, which are directly incorporated in the inefficiency effect model (9). Then, based on previous results by Battese and Broca (1997), the annual rate of change in output-oriented technical efficiency may be calculated as follows:

$$TE_{it}^O = -[A(t) - A(t-1)]\left[1 - \frac{1}{\sigma_u}\left\{\frac{\phi\left(\frac{\mu_{it}}{\sigma_u} - \sigma_u\right) - \phi\left(\frac{\mu_{it}}{\sigma_u}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_u} - \sigma_u\right) - \Phi\left(\frac{\mu_{it}}{\sigma_u}\right)}\right\}\right],$$  \hspace{1cm} (12)

where $\phi[\bullet]$ represents the density function of the standard normal random variable.

On the other hand, given (8), the rate of technical change is measured as:

$$T_{it}(x_t; t) = \beta_T + \beta_{TT} t + \sum_{j=1}^{n} \beta_{j} x_{jt},$$  \hspace{1cm} (13)

and the scale elasticity is calculated as follows:
\[ E_{it} = \sum_{j=1}^{n} e_{jit} = \sum_{j=1}^{n} \left( \beta_j + \sum_{k=1}^{n} \beta_{jk} x_{kit} + \beta_{jt}^t \right). \]  

(14)

The above three relationships are used to implement the decomposition of output growth through (5).

**Data Description**

The data used in this study were extracted from a survey undertaken by the Institute of Agricultural Economics and Rural Sociology of the National Agricultural Research Foundation of Greece. Our analysis is based on a total of 51 sheep farms observed for varying numbers of years between 1989-92. The unbalanced panel data set consists of 178 observations, which in turn implies that on the average each farm is observed 3 to 4 times during the period under consideration. As sheep are classified those farms on which sheep meat, milk and wool products accounts for more than 95% of their total revenue.

The dependent variable is the annual revenue from farm produce (meat, milk and wool) measured in drachmas and the inputs considered are: first, total labor cost consisting of hired (permanent and casual), family and contract labor, measured in drachmas. Second, herd size measured by the number of animals. Third, cost of feeding stuff measured in drachmas; and fourth, other cost expenses, consisting of fuel and electric power, depreciation, interest payments, veterinary expenses, fixed assets interest, taxes and other miscellaneous expenses, measured in drachmas.

The following variables have been included in the inefficiency effect model: first, farmer’s age and its square measured in years. Second, farmer’s education measured in years of schooling. Third, a dummy variable determining the location of sheep farms, which takes the value of one if the farm locates in less-favored area and zero otherwise. Fourth, a dummy variable related with the existence of family successors in farming, which takes the value of one if there is a family member that is willing to continue farming and zero otherwise. Fifth, a dummy variable indicating the existence of an improvement plans taking place in the farm, which takes the value of one if such a plan is in order and zero otherwise. Sixth, total direct income payments received by farmers measured in drachmas. Seventh, time dummies to capture the temporal pattern of technical inefficiency.
Empirical Results

The estimated parameters of the stochastic translog production frontier function are presented in Table 1. The first-order parameters ($\beta_i$) have the anticipated (positive) sign and magnitude (being between zero and one), and the bordered Hessian matrix of the first- and second-order partial derivatives is negative semi-definite indicating that all regularity conditions (namely, positive and diminishing marginal products) are valid at the point of approximation (i.e., the sample mean). On the other hand, the estimated variance of the one-side error term is found to be $\sigma_u^2 = 0.017$ and that of the statistical noise $\sigma_v^2 = 0.007$. Finally, the log of the likelihood function indicates a good fit for the stochastic frontier model.

Hypotheses testing concerning model representation are reported on Table 2. The null hypotheses that $\gamma = 0$ and $\gamma = \delta_0 = \delta_m = 0$ for all $m$ are both rejected at 5% level of significance indicating respectively that the technical inefficiency effects are in fact stochastic and present in the model. Thus, the majority of farms in the sample operates below the technically efficient frontier and a significant part of output variability among farms is explained by the existing differences in the degree of technical efficiency. Consequently, the traditional average production does not represent adequately the production structure of sheep farms in the sample. This is also evident from the statistical significance of the $\gamma$ parameter (see Table 1).

As far as the distribution of the technical inefficiency effects is concerned, our empirical results (see Table 2) indicate that (7) cannot be reduced to Aigner et al. (1977) model (in which the technical inefficiency effects have a half-normal distribution) as the null hypothesis of $\delta_0 = \delta_m = 0$ for all $m$ is rejected at 5% level of significance. Furthermore, (7) cannot be reduced to Stevenson’s (1980) model (in which the technical inefficiency effects have the same truncated-normal distribution with mean equal to $\delta_0$) as the null hypothesis of $\delta_m = 0$ for all $m$ is rejected at 5% level of significance (see Table 2). The latter also implies that the explanatory variables included in (9) contribute significantly to the explanation of technical inefficiency differences among sheep farms in the sample.

In particular, the age of the farmer, as a proxy of experience and learning-by-doing, is one of the factors enhancing technical efficiency, while the positive sign of
the squared term supports the hypothesis of decreasing returns to experience (see Table 1). That is, young farmers are becoming relatively more efficient over time by improving learning-by-doing, but this would continue until the relationship levelled off and it is expected to decline as farmer approaches the retirement age (Makary and Rees, 1981; Tauer, 1995). Education has also a positive and significant role to play in determining efficiency differentials among sheep farmers in Greece. This finding is in accordance with Welch’s (1970) “worker effect”, stating that education leads to better utilization of given inputs and thus, is related with greater technical efficiency. Schooling helps farmers to use production information efficiently as a more educated farmer acquires more information. On the other hand, as was expected, the placement of farms in less favoured areas affect negatively their degree of technical efficiency, while the existence of improvement plan within the farm affect technical efficiency positively. It was also found that direct income payments affect technical efficiency negatively whereas the existence of family successors in farming does not seem to have a statistically significant effect on technical efficiency.

Estimates of technical efficiency in the form of frequency distribution within a decile range are reported on Table 3. During the period 1989-92, the estimated mean output-oriented technical efficiency is found to be 80.31% implying that output could have increased on average by 19.69% if technical inefficiency was eliminated. This can be achieved by using the same technology and employing the same level of inputs. Mean technical efficiency lies on the interval 63.99% to 93.96%. However, most farms in the sample (83%) have achieved technical efficiency between 70% and 100%. This means that only a small portion of the farms in the sample faces severe technical inefficiency problems.

As far as the structure of production technology is concerned, the hypothesis that the production frontier has a Cobb-Douglas form (i.e., $\beta_{jk} = 0$) is rejected at the 5% level of significance (see Table 2). More importantly, the null hypothesis of a linearly homogeneous production technology (i.e., $\sum \beta_j = 1$ and $\sum \beta_{jk} = \sum \beta_{ij} = 0$) is also rejected at the 5% level of significance (see Table 2) implying the existence of non-constant returns to scale. Thus, the scale effect is a significant source of output growth and it should be taken into account in (5). According to our empirical results, production was characterized by decreasing returns to scale, which on average was 0.812 during the period 1989-92. Most likely this finding reflects the small size of
sheep farms. Moreover, returns to scale were following a declining trend over time (see Table 4). At 1989 the relevant estimate of returns to scale was 0.848, while at 1992 it decreased to 0.758.

By rejecting the hypothesis that \( \gamma = 0 \) it is evidence that the inefficiency effects in (9) are in fact stochastic and thus, the effect of technical change on output growth can be separated from the effect of time-varying technical inefficiency (Battese and Coelli, 1995). However, before we proceed further, the hypotheses of zero technical change and/or of time-invariant technical efficiency should be tested. In fact, the hypotheses of zero technical change (i.e., \( \beta_T = \beta_{TT} = \beta_{ij} = 0 \) for \( j = 1, \ldots, 4 \)) and of time-invariant technical inefficiency (i.e., \( \delta_{90} = \delta_{91} = \delta_{92} = 0 \)) are both rejected at the 5% level of significance (see Table 2). In addition, the joint hypothesis of time-invariant technical inefficiency and of zero technical change (i.e., \( \delta_{90} = \delta_{91} = \delta_{92} = \beta_T = \beta_{TT} = \beta_{ij} = 0 \) for \( j = 1, \ldots, 4 \)) is also rejected at the 5% level of significance (see Table 2).

The above results indicate that both technical change and time-varying technical efficiency have been significant sources of output growth and thus they should be taken into account in (5). Specifically, a positive effect of technical change on output growth is found as the estimated parameters \( b_T \) and \( b_{TT} \) are both positive, with the latter being statistically insignificant at the 5% level of significance (see Table 1). This indicates that technical change is found to be progressive at a constant rate. On the other hand, technical inefficiency followed a less smooth temporal pattern as it decreased during the period 1989-91 and increased at 1992 (see Table 3). This temporal pattern is also consistently depicted by the sign of the estimated parameters of time dummies reported in Table 1. Based on these results, it can be argued that on average the pattern of efficiency indicates movements towards the production frontier over time for most farms in the sample. Thus, a positive effect of technical efficiency on output growth is found.

The decomposition analysis results are presented on Table 5. Those reported in the first two columns are based on (5) while those reported in the last two columns are based on (6). In each case, the magnitude of the average annual rate of change during the period under consideration is reported first and the relative contribution of the corresponding effect is the presented next. The empirical results in Table 5 indicate that (5) and (6) yield quite different results concerning the sources of output growth.
This is rather expected as the hypothesis of constant returns to scale has been rejected (see Table 2). Since evidence of decreasing returns to scale has been found (see Table 4), the relative contribution of TFP into output growth is overestimated when (6) is employed, while the opposite is true for the size effect. Thus, part of output growth is falsely attributed to TFP changes whereas is in fact associated with increased input use. As a result, the estimated rate of TFP changes is greater when (6) is employed. Nevertheless, exactly the same portion of unexplained residual (5.8%) is obtained by employing either (5) or (6).

Given that the hypothesis of constant returns to scale has been rejected (see Table 2), we proceed the decomposition analysis of output growth based on (5). An average annual output growth of 3.94% is observed during the period 1989-92 (see Table 5). Our empirical results indicate that a greater part of output growth (69.5%) is attributed to the size effect while a smaller portion (24.7%) is explained by TFP growth. Specifically, 2.74% of the observed output growth is attributed to the size effect while the average annual rate of TFP change is estimated at 0.97%. Most of the aggregated input growth is associated with feeding stuff whereas a smaller portion is due to herd size, labor and other cost. Given the estimated production elasticities reported in Table 4, the former is most probably due to the increasing cost of feeding stuff.

Technical change is found to be the main source of TFP growth. This result is in accordance with previous empirical findings reported by Fan (1991), Ahmad and Bravo-Ureta (1995), Wu (1995), Kalirajan et al. (1996), Kalirajan and Shand (1997), and Giannakas et al. (2000, 2001). The average annual rate of technical change is estimated at 1.33% and accounts for 33.9% of the observed output growth. On the other hand, changes in technical efficiency have on average affected positively both TFP and output growth. However, its relative contribution was small compared to technical change and the scale effect. In particular, during the period 1989-92, 25.8% of TFP growth and only 6.3% of output growth have been attributed to changes in technical efficiency.

The scale effect is negative as sheep farms in the sample exhibited decreasing returns to scale and aggregate input increased over time. During the period 1989-92, diseconomies of scale have slowed down annual output growth by an average rate of 0.61%. This is a rather significant figure that would have been omitted if constant returns to scale were falsely assumed. In such a case, TFP growth would have been
overestimated. Specifically, the estimated average annual rate of TFP growth would have been 1.58% instead of 0.97%. Consequently, there would have been significant differences in TFP growth by not accounting simultaneously for the scale effect.

**Concluding Remarks**

This paper uses an integrated approach, developed by Bauer (1990), Lovell (1996) and Kumbhakar (2000) for explaining output growth based on decomposition analysis and the primal approach. Output growth is decomposed into input growth (size effect), technical change, and the effect of returns to scale. This methodology is applied to an unbalanced panel data set of sheep farms in Greece during the period 1989-92. Empirical findings indicate that the scale effect, which has not been analyzed in previous studies, had a significant role in explaining output growth; it was found that, on average, it caused a 0.61% output slowdown annually. Consequently, there would have been significant differences in TFP growth by not accounting simultaneously for the scale effect. Further, despite of any errors that may arise by not accounting for the scale effect when parametrically measuring TFP growth, misconceptions also arise concerning the potential sources of TFP and output growth.

Even though the decomposition analysis of output growth used in this study is more complete than those used previously, a portion of the observed annual output growth still remains unexplained. In the present case, this unexplained residual refers, on average, to 0.23% of annual output growth. This may be due to the assumption of allocative efficiency. Unfortunately, within the primal framework it is impossible to separate the scale from the allocative efficiency effect without information on input prices. A potential alternative could be to use a system-wide approach (Kumbhakar, 1996), but at the cost of complicating the estimation procedure and by needing input price data. Another potential alternative could be the use of dual approach with similar complications.
Table 1: Parameter Estimates of the Translog Production Frontier for a Sample of Sheep Farms in Greece, 1989-1992.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Std Error</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stochastic Frontier Model</strong></td>
<td></td>
<td></td>
<td><strong>Inefficiency Effects Model</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>0.1963 (0.0669)*</td>
<td></td>
<td>$\delta_0$</td>
<td>-0.4016 (0.1237)*</td>
<td></td>
</tr>
<tr>
<td>$\beta_H$</td>
<td>0.4149 (0.0537)*</td>
<td>$\beta_{LL}$</td>
<td>0.1079 (0.0469)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_L$</td>
<td>0.0867 (0.0356)**</td>
<td>$\beta_{FC}$</td>
<td>-0.0856 (0.0349)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_F$</td>
<td>0.1229 (0.0454)*</td>
<td>$\beta_{FF}$</td>
<td>0.0716 (0.0241)*</td>
<td></td>
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<tr>
<td>$\beta_C$</td>
<td>0.1055 (0.0336)*</td>
<td>$\beta_{CC}$</td>
<td>0.0142 (0.0239)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{HL}$</td>
<td>-0.1506 (0.0702)**</td>
<td>$\beta_T$</td>
<td>0.0489 (0.0077)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{HF}$</td>
<td>-0.1490 (0.0691)**</td>
<td>$\beta_{TT}$</td>
<td>0.0338 (0.0314)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{HC}$</td>
<td>0.0095 (0.0685)</td>
<td>$\beta_{TH}$</td>
<td>0.0459 (0.0210)**</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: (1) H stands for herd size, L for labor, F for feeding stuff, C for other cost, T for time, AGE for farmer's age, AGE2 for farmer's age squared, EDU for farmer's education, LFA for farms location in less-favored areas, IMP for the existence of improvement plan in the farm, SUC for the existence of successor, DIP direct income payments and T90-T92 for time dummies. (2) (*) and (**) denote statistical significance at the 1% and 5% level, respectively.
**Table 2: Model Specification Tests**

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Calculated $\chi^2$ Statistic</th>
<th>Critical Value ($\alpha=0.05$)</th>
</tr>
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<tbody>
<tr>
<td>$\gamma = 0$</td>
<td>22.58</td>
<td>$\chi^2_5 = 10.37^*$</td>
</tr>
<tr>
<td>$\gamma = \delta_0 = \delta_m = 0 \quad m = 1,\ldots,10$</td>
<td>36.58</td>
<td>$\chi^2_{12} = 20.41^*$</td>
</tr>
<tr>
<td>$\delta_0 = \delta_m = 0 \quad m = 1,\ldots,10$</td>
<td>33.58</td>
<td>$\chi^2_{11} = 19.05$</td>
</tr>
<tr>
<td>$\delta_m = 0 \quad m = 1,\ldots,10$</td>
<td>24.31</td>
<td>$\chi^2_2 = 18.30$</td>
</tr>
<tr>
<td>$\beta_{jk} = 0 \quad j,k = 1,\ldots,4$</td>
<td>33.45</td>
<td>$\chi^2_{10} = 18.30$</td>
</tr>
<tr>
<td>$\sum \beta_j = 1, \sum \beta_{jk} = \sum \beta_{ij} = 0 \quad j,k = 1,\ldots,4$</td>
<td>28.44</td>
<td>$\chi^2_6 = 12.59$</td>
</tr>
<tr>
<td>$\beta_T = \beta_{TT} = \beta_{ij} = 0 \quad j = 1,\ldots,4$</td>
<td>20.17</td>
<td>$\chi^2_{6} = 12.59$</td>
</tr>
<tr>
<td>$\beta_{jk} = \beta_T = \beta_{TT} = \beta_{ij} = 0 \quad j,k = 1,\ldots,4$</td>
<td>40.58</td>
<td>$\chi^2_{4} = 23.69$</td>
</tr>
<tr>
<td>$\delta_{g0} = \delta_{g1} = \delta_{g2} = 0$</td>
<td>15.32</td>
<td>$\chi^2_{5} = 7.81$</td>
</tr>
<tr>
<td>$\beta_T = \beta_{TT} = \beta_{ij} = \delta_{g0} = \delta_{g1} = \delta_{g2} = 0 \quad j = 1,\ldots,4$</td>
<td>42.31</td>
<td>$\chi^2_{9} = 16.92$</td>
</tr>
<tr>
<td>$\beta_{ij} = 0 \quad j = 1,\ldots,4$</td>
<td>19.31</td>
<td>$\chi^2_{4} = 9.49$</td>
</tr>
</tbody>
</table>

*Note: Critical values with an asterisk are taken from Kodde and Palm (1986, Table 1).*

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<th></th>
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<td>&lt;40</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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<tr>
<td>40-50</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>50-60</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>2</td>
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<tr>
<td>60-70</td>
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<td>70-80</td>
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<tr>
<td>80-90</td>
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<td>18</td>
<td>7</td>
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<tr>
<td>90-100</td>
<td>8</td>
<td>10</td>
<td>16</td>
<td>2</td>
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<tr>
<td>N</td>
<td>42</td>
<td>51</td>
<td>35</td>
<td>50</td>
</tr>
<tr>
<td>Mean</td>
<td>78.71</td>
<td>80.44</td>
<td>82.80</td>
<td>80.56</td>
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<tr>
<td>Maximum</td>
<td>97.69</td>
<td>97.56</td>
<td>92.53</td>
<td>90.34</td>
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<tr>
<td>Minimum</td>
<td>47.87</td>
<td>50.48</td>
<td>59.76</td>
<td>57.70</td>
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</table>

<table>
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<th></th>
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<tbody>
<tr>
<td><strong>Production Elasticities</strong></td>
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</tr>
<tr>
<td>Herd</td>
<td>0.521</td>
<td>0.476</td>
<td>0.433</td>
<td>0.418</td>
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<tr>
<td>Labor</td>
<td>0.059</td>
<td>0.078</td>
<td>0.104</td>
<td>0.090</td>
</tr>
<tr>
<td>Feeding Stuff</td>
<td>0.116</td>
<td>0.139</td>
<td>0.162</td>
<td>0.138</td>
</tr>
<tr>
<td>Other Cost</td>
<td>0.152</td>
<td>0.131</td>
<td>0.119</td>
<td>0.111</td>
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<tr>
<td><strong>Returns to Scale</strong></td>
<td>0.848</td>
<td>0.824</td>
<td>0.819</td>
<td>0.758</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Based on (5)</th>
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<th>Based on (6)</th>
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<tbody>
<tr>
<td><strong>Output Growth</strong></td>
<td>3.94 (100)</td>
<td>3.94 (100)</td>
<td></td>
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<tr>
<td><strong>Size Effect:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herd</td>
<td>0.75 (18.9)</td>
<td>0.53 (13.6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor</td>
<td>0.29 (7.3)</td>
<td>0.23 (5.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feeding Stuff</td>
<td>1.28 (32.5)</td>
<td>1.03 (26.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other Cost</td>
<td>0.42 (10.8)</td>
<td>0.33 (8.4)</td>
<td></td>
<td></td>
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<tr>
<td><strong>TFP Growth:</strong></td>
<td>0.97 (24.7)</td>
<td>1.58 (40.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technical Change</td>
<td>1.33 (33.9)</td>
<td>1.33 (33.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changes in Technical Efficiency</td>
<td>0.25 (6.3)</td>
<td>0.25 (6.3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale Effect</td>
<td>-0.61 (-15.5)</td>
<td>-</td>
<td>-</td>
<td></td>
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<tr>
<td><strong>Unexplained Residuals</strong></td>
<td>0.23 (5.8)</td>
<td>0.23 (5.8)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
References


Endnotes

1 A notable exception is a recent study by Karagiannis and Tzouvelekas (2001) that takes into account the effects of returns to scale and of allocative inefficiency, but at the cost of relying on self-dual (i.e., Cobb-Douglas) production frontiers.

2 Park and Kwon (1995), for example, provided such empirical evidence for the manufacturing sector in Korea during the period 1967-89. They found that rapid growth of output is possible with little or no technical change.

3 For simplicity, the ‘it’ subscripts referring to the $i^{th}$ firm at period $t$, are omitted in this section.

4 That is, even at low levels of technical efficiency, output gains may be achieved by improving resource use. However, it is difficult to achieve substantial output growth gains at very high levels of technical efficiency. This is expected during the catching-up process.

5 Fan (1991) has calculated the effect of technical change residually. In such a case, the contribution of technical change on TFP growth is overestimated (underestimated) in the presence of increasing (decreasing) returns to scale.

6 On the other hand, if the size effect is measured residually, as in Kalirajan et al. (1996) and Kalirajan and Shand (1997), its relative contribution to output growth is incorrectly calculated in the absence of constant returns to scale.

7 Biased estimates of $\delta_m$ parameters may be obtained by not including an intercept parameter $\delta_0$ in the mean, $\mu_t$, and in such a case the shape of the distribution of the inefficiency effects is unnecessarily restricted (Battese and Coelli, 1995).

8 The two-stage estimation approach proceeds as follows. The first stage involves the specification and estimation of the stochastic production frontier function and the prediction of technical inefficiency under the assumption of identically distributed one-side error term. The second stage involves the specification of a regression model for explaining the predicted technical inefficiency, which however contradicts with the assumption of an identically distributed one-side error term in the stochastic frontier (Kumbhakar et al., 1991; Reifsneider and Stevenson, 1991; Battese and Coelli, 1995).

9 If the given null hypothesis is true, the generalized likelihood-ratio statistic has approximately a $\chi^2$ distribution, except the case where the null hypothesis involves
also \( \gamma = 0 \). In this case, the asymptotic distribution of \( \lambda \) is a mixed \( \chi^2 \) (Coelli, 1995) and the appropriate critical values are obtained from Kodde and Palm (1986).

10 This consists another notable difference with previous studies, which computed the annual rate of change in technical efficiency as the average of the differences of farm-specific estimates between sequential periods.

11 It is debatable whether education should be considered as an input to be included in the production function or as human capital that increases technical efficiency. Following Kumbhakar et al. (1991), among others, we adopted the latter view for the purposes of the present study.

12 In this case, the parameters \( \gamma, \delta_0 \) and those associated with the temporal pattern of technical efficiency can not been identified. In our case, the critical value to test the null hypothesis is obtained from the \( \chi^2 \) distribution.

13 Notice that the probability of the technical inefficiency effect to be significant in the stochastic frontier model is high since the estimated value of the \( \gamma \)-parameter is close to one (see Table 1).

14 The hypothesis of a zero technical change has also been tested in the presence of a Cobb-Douglas production frontier. This hypothesis (i.e., \( \beta_{jk} = \beta_T = \beta_{TT} = \beta_{ij} = 0 \), \( j,k = 1,...,4 \)) is also rejected at the 5% level of significance (see Table 2).

15 Also the hypothesis of Hicks-neutral technical change (i.e., \( \beta_{ij} = 0 \), \( j = 1,...,4 \)) is rejected at the 5% level of significance (see Table 2). Technical change is found to be saving towards feeding stuff, herd-using and neutral with respect to labor and other cost as the relevant estimated parameters are not statistically different than zero (see Table 1).