SEPARATING TECHNICAL CHANGE FROM TIME-VARYING TECHNICAL INEFFICIENCY IN THE ABSENCE OF DISTRIBUTIONAL ASSUMPTIONS

G. Karagiannis
Department of Economics, University of Crete &
Institute of Agricultural Economics and Rural Sociology,
National Agricultural Research Foundation, Greece

P. Midmore
Institute of Rural Studies, University of Wales, UK

V. Tzouvelekas
Institute of Agricultural Economics and Rural Sociology,
National Agricultural Research Foundation, Greece

Paper presented in the IX European Congress of Agricultural Economists, "European Agriculture Facing the 21st Century in a Global Context"
Warsaw, Poland, August 24-28, 1999

Correspondence Address:
G. Karagiannis, Institute of Agricultural Economics & Rural Sociology, National Agricultural Research Foundation, 184c, Kifisias Av. 14562 Kifisia, Athens, Greece. Tel. 001-30-1-8010816; fax 001-30-1-8088947; e-mail igeke@compulink.gr.
Authors' names are in alphabetical order.

SEPARATING TECHNICAL CHANGE FROM TIME-VARYING TECHNICAL INEFFICIENCY IN THE ABSENCE OF DISTRIBUTIONAL ASSUMPTIONS

This paper proposes an alternative approach for separating technical change from time-varying technical inefficiency. The approach uses the general index, developed by Baltagi and Griffin (1988), to model technical change along the production function, and a quadratic function of time trend, as in Cornwell, Schmidt and Sickles (1990), to capture the temporal pattern of technical inefficiency. In such a setting, all parameters associated with the rate of technical change and the temporal pattern of technical inefficiency are identified separately. Moreover, the proposed approach is independent of any distributional assumption concerning the one-sided error term associated with technical inefficiency, and can easily be estimated using FGLS. Comparative empirical results based on a translog production frontier function, and estimates of technical inefficiency and technical change are presented for the UK dairy sector over the period 1982-1992.

1. Introduction

Both technical change and efficiency are important components of total factor productivity (TFP). In a primal setting, technical change is defined, after Solow's (1957) seminal work, as a shift in the production function with all input quantities held constant. This shift may be outward (technical progress) or inward toward the origin (technical regress). Technical progress (regress) results in TFP growth (slowdown). On the other hand, TFP growth is not affected by the presence of (technical) inefficiency, if the latter is time-invariant. It has been argued elsewhere that the improvement of efficiency over time, rather than the degree of inefficiency, really matters in TFP changes. Improvements in (technical) efficiency result in TFP growth, and *vice versa*. For a theoretical model that decomposes TFP growth into technical change and technical efficiency change effects, see Bauer (1990) and also Lovell (1996).

In empirical modelling, the specification of time-varying (technical) efficiency and technical change is a crucial issue. Both technical change and time-varying inefficiency have usually been modelled via a simple time trend, as part of the econometric estimation of the production frontier function. In such cases, none of the parameters associated with the time trend in the production function or the one-sided error term capturing technical inefficiency can be identified, because the time trend appears (in a linear fashion) as a regressor in both the production function and the one-sided error term. In particular, identification of the separate effects of neutral technical change, which is common to all producing units, and technical efficiency change, which is also common to all firms, would be problematic (Lovell, 1996). It is therefore not possible to separate the effects of technical change and of changes in technical efficiency without further complicating the estimation process.

Several approaches, discussed in detail in the next section, have been proposed to overcome this shortcoming. All involve provision of an alternative to the simple time trend specification of the temporal pattern of technical inefficiency, based on particular distributional assumptions for the one-side error term associated with technical inefficiency. These attempts comprise either *(i)* positing a non-linear specification of time trend in the function identifying the temporal pattern of technical inefficiency (i.e., Kumbhakar (1990), Battese and Coelli (1992)); or *(ii)* using time dummies to capture the temporal pattern of technical inefficiency (Lee and Schmidt, 1993); or *(iii)* defining a technical inefficiency effects function, within which the time trend is one of the explanatory variables (Battese and Coelli, 1995); or *(iv)* measuring time-varying technical inefficiency residually from producer-specific persistent technical efficiency (Kumbhakar and Hesmati, 1995). Each of these alternatives involves a certain loss of realism, through particular distributional assumptions for the one-sided error term associated with technical inefficiency.

The objective of this paper is to propose an alternative approach for separating the effect technical change and technical inefficiency may have into TFP changes, involving a radical departure from previous attempts. Notably, rather than focusing on the specification of the temporal pattern of technical inefficiency, technical change is modelled differently, avoiding the use of a simple time trend. Specifically, the proposed approach uses the general index, developed by Baltagi and Griffin (1988), to model technical change along the production function, and a quadratic function of time trend, as in Cornwell, Schmidt and Sickles (1990), to capture the temporal pattern of technical inefficiency. In such a setting, all parameters associated with the rate of technical change and the temporal pattern of technical inefficiency are identified separately. More importantly, the proposed approach is independent of any distributional assumption concerning the one-sided error term associated with technical inefficiency, and can easily be estimated econometrically using a feasible generalised least squares (FGLS) approach.

The remainder of this paper is organised as follows: the various approaches used to model technical change and time-varying technical inefficiency within panel data are reviewed in the next section, followed by a development of our proposed alternative. The data and the estimations are discussed in the third section. Comparative empirical results, based on translog production frontier functions and estimated for the UK dairy sector, are presented in the fourth section. Concluding remarks form the final section.

2. Methodology

The stochastic production frontier model with panel data is given as

$$\mathrm{Y}_{it} = x_{it}'\beta + \varepsilon_{it} \tag{1}$$

where Y_{it} is the output of the ith firm (i = 1,...,n) at time t ($t = 1,...,T$), X_{it} is the corresponding matrix of κ inputs and the state of technology R, and $ß$ is a $(\kappa+1)x1$ vector of unknown parameters to be estimated. The error term is specified as $\varepsilon_{it} = v_{it} - u_{it}$, where v_{it} are statistical noise and are assumed to be independently and identically distributed, and $u_{it} > 0$ represents technical inefficiency. Technical inefficiency is defined, according to Timmer (1971), in an output-based manner as the discrepancy between a firm's actual output and its potential output, using the same amount of inputs employed with the frontier technology. That is, a firm's degree of technical inefficiency in each year is derived from $TE_{it} = \exp(-u_{it})$.

In order to keep the structure of technology in production frontier function as general as possible, a flexible functional form is used to approximate the underlying frontier function. For the purpose of the present study, a translog specification has been chosen as follows:

$$\ln Y_{it} = \alpha_0 + \sum_j a_j \ln x_{jit} + a_1 R + \frac{1}{2}\sum_j \sum_\kappa a_{jk} \ln x_{jit} \ln x_{kit} + \frac{1}{2}\beta_2 R^2 + \sum_j \gamma_j \ln x_{jit} R$$

(2)

It is well known that translog functional form does not impose any *a priori* restrictions on the structure of production and, in consequence many hypotheses, such as constant returns to scale, separability, Cobb-Douglas, neutral technical change, can be statistically tested.

2.1. Models of Technical Change

Beginning with Tinbergen (1942), technical change has been described through the inclusion of a simple time trend, as part of the production function. Thereafter, quadratic terms in time and interactions of the time trend with input quantities were introduced to account for increases at a non-constant rate and for non-neutral technical change. Empirically, first- and second-order time terms were found to be dominant, suggesting a smooth and slowly changing pattern of technical change at a constant rate. That is, the model yields a smooth index of technical change driven by the passage of time, but is constrained from describing bursts of rapid technical change and periods of stagnation.

By replacing R and R^2 with t and t^2 into (2), the standard time trend model is obtained. Then, the primal rate of technical change is defined as

$$T_p = \frac{\partial \ln Y_{it}}{\partial t} = \beta_1 + \beta_2 t + \sum_j \gamma_{ij} \ln x_{jit} \tag{3}$$

The rate of technical change can be decomposed into two components: *(i)* effects due to pure technical change $(ß_1+ß_2t)$ and *(ii)* effects due to non-neutral technical change $\left(\sum \gamma_{ij} \ln x_{jit}\right)$. Pure technical change will be constant, increasing or decreasing at a constant rate, according to whether β_2 is zero, positive or negative, respectively. More importantly, pure technical change is common to all firms. In contrast, non-neutral technical change is firm-specific. Further, the non-neutral component is independent of the neutral one and thus, even for unchanged input quantities, there could still be an impact on the rate of technical change.

On the other hand, the general index of technical change, developed by Baltagi and Griffin (1988), can be obtained by replacing R and R^2 into (2) with $A(t)$, where

$$A(t) = \sum_{t=1}^{T} \beta_t D_t \tag{4}$$

and D_t is the time dummy for year t.[1] Notice that $A(t)$ is not constrained to obey a given functional form. Moreover, since $A^2(t)$ is the same as $A(t)$, (2) does not have the squared D_t term, which is the same as D_t. However, given that time dummies appear interactively with input quantities, the estimated model is non-linear in parameters, and capable of describing complex and sometime erratic patterns of technical change. $A(t)$ can be calculated only when the initial year is taken as base (i.e., $A(1) = 0$), which allows relevant parameters to be identified.

In the general index model, the rate of technical change is defined as

$$T_p = (A(t) - A(t-1)\left(1 + \sum_j \gamma_j \ln x_{jit}\right) \tag{5}$$

As in the case of a simple time trend, the rate of technical change can be decomposed into a pure technical change effect ($A(t)$-$A(t$-$1)$) and a non-neutral component $\left(A(t) - A(t-1)\sum \gamma_j \ln x_{jit}\right)$, which is firm-specific. In this case, however, the non-neutral component depends on the neutral component. That is, the non-neutral component is different from zero only if the neutral component is different from zero (Baltagi and Griffin, 1988). As a result, if $A(t)$ is unchanged, changes in input quantities have no effect on the rate of technical change.

A hydrid model has recently proposed by Hesmati (1996), in which pure technical change is captured in a manner similar to Baltagi and Griffin (1988), and the non-neutral component is modelled with a simple time trend. The main advantage of this model is its linearity with regard to estimated parameters. In particular, R is defined as $D_s t$, where D_s is a time dummy representing the time interval s of unspecified length, in the pure technical change effect, and as t in the non-neutral component.

2.2 Models of Time-Varying Technical Efficiency

Models of time-varying technical efficiency can be divided in two categories, depending on whether distributional assumptions are imposed on the temporal patterns of efficiency. Within the first category, where no distributional assumptions are made, Cornwell, Schmidt and Sickles (1990) modelled the temporal pattern of inefficiency through a quadratic function of time (*t*),

$$u_{it} = \delta_{1i} + \delta_{2i} t + \delta_{3i} t^2 \tag{6}$$

where $\delta_{1i}, \delta_{2i}, \delta_{3i}$ ($i = 1,...,n$) are the firm-specific parameters to be estimated.[2] The main advantages of this specification are that it is flexible, and it allows inefficiency to vary across firms and time. That is, (6) represents firm-specific levels of technical inefficiency, as well as over time. But, since time appears in a linear fashion as a regressor in both the production frontier (2) as well as in u_{it}, not all parameters associated with the simple time trend can be identified. Consequently, it is not possible to separate technical change from improvements in technical efficiency over time.

Within the second category, where no functional specification of the temporal pattern is assumed, distributional assumptions about u_{it} are made and/or non-linear formulations are used to separate the time (trend) effect into technical change and improvements in technical efficiency. Without these distributional assumptions the two effects cannot be individually identified. Several models have been developed in this direction:[3] *first*, Kumbhakar (1990) suggested that

$$u_{it} = \left[1 + \exp(\delta_1 t + \delta_2 t^2)\right]^{-1} u_i \tag{7}$$

where u_i is assumed to have a half normal distribution, and δ_1 and δ_2 are parameters to be estimated.[4] *Second*, Battese and Coelli (1992) modelled the temporal pattern of inefficiency as an exponential function of time, i.e.,

$$u_{it} = u_i \exp(-\delta(t - T_i)) \tag{8}$$

where u_i is assumed to be independently and identically distributed as a truncated normal distribution and δ is a parameter to be estimated.[5] Technical efficiency increases, remains constant, or decreases overtime when δ is greater, equal to or less than zero. *Third*, Lee and Schmidt (1993) proposed that

$$u_{it} = u_i \delta_t \tag{9}$$

where δ_t are time-effects, represented by time dummies. Despite its non-linearity, this specification is attractive as it does not impose any functional specification on the temporal pattern of inefficiency and it is reasonable when the number of time periods (T) is small. *Fourth*, Kumbhakar and Hesmati (1995) included a firm-specific error component within the one-side error term, to capture time-invariant persistent technical inefficiency.[6] That is,

$$u_{it} = \mu_i + \tau_{it} \tag{10}$$

where μ_i is the persistent component, which is only firm-specific, and τ_{it} is the component that is both firm- and time-specific.[7] Within this approach, time-varying technical inefficiency is measured residually. Nevertheless, separate measures of persistent and time-varying technical inefficiency require distributional assumptions about both of them. Despite these distributional assumptions, a further disadvantage of this specification is that if there is any persistent time-specific inefficiency, it is masked in technical change (Kumbhakar and Hesmati, 1995).[8]

One common disadvantage of (7), (8) and (9) is that the temporal pattern of inefficiency, not the magnitude, is assumed to be the same for all firms.[9] However, a model proposed by Battese and Coelli (1995) overcomes this shortcoming. They assumed that

$$u_{it} = \sum \delta_l z_{lit} + \mu_{it} \tag{11}$$

where z_{it} is an ($lx1$) vector of firm characteristics explaining technical inefficiency and μ_{it} is defined by the truncation of the normal distribution with zero mean, such that the point of truncation is $-\sum \delta_l z_{lit}$.[10] The simple time trend can be included as part of the z_{it} vector and it can be interpreted as the change (in a linear fashion) in technical inefficiency over time. The stochastic nature of and the distributional assumptions on the inefficiency effects in (11) permit the effect of technical change and time-varying behaviour of inefficiency to be identified, even though both are modelled via a simple time trend.

This specification may also be extended to the case of a non-neutral stochastic frontier (see Huang and Liu) by incorporating interaction terms between firm-specific variables (z_{it}) and input quantities into (11). In this case, (11) may be reformulated, following Battese and Broca (1997), as:

$$u_{it} = \sum \delta_l z_{lit} + \sum \vartheta_l z^*_{lit} + \mu_{it} \tag{12}$$

where ϑ_l are parameters to be estimated and z^*_{lit} are appropriate interactions between firm-specific variables (z_{it}) and input quantities x_{it}. Notice that, in this case, time-varying technical inefficiency also depends on the levels of inputs used, as the frontier of each firm shifts differently over time.

2.3. Proposed Formulation

A suitable, easy to implement, and distribution-free model of time-varying technical inefficiency may be obtained by incorporating the general index of technical inefficiency into the Cornwell, Schmidt and Sickles (1990) setting. The general index, given by (4), is used to model technical change along the production frontier function, and a quadratic function of time trend, given by (6), is used to capture the temporal pattern of technical inefficiency. This formulation has all the advantages associated with modelling technical change with the general index, but at the same time circumvents the need for distributional assumptions regarding the one-sided error term. The proposed model may be estimated in two stages (Neogh and Ghosh, 1994; Ahmad and Bravo-Ureta, 1996). In the first stage, (1), with the specification of (2), is estimated, as a random effect model, using feasible generalised least squares (FGLS), making no distributional assumption about the one-side error term. Then, the temporal pattern of technical inefficiency is estimated in the second stage through (6).

More importantly, as technical change and the temporal pattern of technical inefficiency are each captured through different variables, the identification problem inherent in the Cornwell, Schmidt and Sickles (1990) approach is eliminated. That is, all parameters associated with the rate of technical change and the temporal pattern of technical inefficiency are identified separately. Then, the rate of technical change is measured by (5) and the changes in technical inefficiency are obtained by using (6). As a result, firm-specific TFP changes can be attributed to the effect of technical change, the effect of changes in technical inefficiency, and to economies of scale.

In addition, there is no inconsistency in this two-stage approach, as in the second stage predicted inefficiency is not regressed on a number of firm-specific factors, but on a variable (time trend) identically distributed among firms. This is consistent with the first-stage assumption of independently and identically distributed inefficiency effects in the stochastic frontier. The only complexity remains the non-linearity in parameters in the first-stage, but the model can easily become linear by assuming Hicks-neutral technical change.

To compare relative performance, the Cornwell, Schmidt and Sickles (1990) time-varying efficiency model is estimated with three variants of technical change: *first*, with a simple time trend; *second*, with the general index of technical change assuming Hicks-neutrality; and *third*, by allowing for non-neutral technical change. The second variant may also be viewed as a special case of multiple time trend model (Hesmati, 1996), with time intervals specified to be equal to one. In each case, measures of the rate of technical change and of temporal variation in technical inefficiency are obtained and compared to each other, using an unbalanced panel data set for UK dairy sector over the period 1982-1992.

3. Data and Estimation Procedure

Financial data from dairy farm accounts are drawn from the *Farm Business Survey* (FBS) for England and Wales (MAFF, 1994a).[11] The FBS is an annual survey covering about 3,000 farms in England and Wales, selected from a random sample of census data that is stratified according to region, economic size of farm and type of farming. From this sample 242 dairy farms, defined as those where 60 per cent or more of their total revenue is derived from milk or milk products, observed for varying numbers of years, were extracted to form an unbalanced panel. The final panel data set consists of 2,147 observations, which in turn implies that on the average each farm is observed almost 9 times during the 1982-92 period.

Dairy farms were chosen in the present analysis because they are the most widely represented farm-type in the FBS, both in terms of geographical distribution and in the total number surveyed. Milk is relatively important in the agricultural economy of the U.K., accounting on aggregate for 34 per cent of all livestock output, and just over 20 per cent of the gross output of the industry as a whole (MAFF, 1994b). It also provides relatively high incomes: in 1992-1993, 47 per cent of English dairy farms in the FBS sample had an occupier's net income of more than £30,000, whereas overall only 29 per cent of farms achieved such a performance. The corresponding figures for Wales were 58 and 25 per cent, respectively (MAFF, 1994b).

Over the period of the analysis, the structure of the industry has undergone significant change, both in terms of the policy environment, industry structure and technological enhancement. Milk quotas were introduced in 1984 and tightened in 1988, and in 1992 legislation was initiated to liberalise the milk market; import competition also became more vigorous, especially in the milk product sector. In 1982, 51 per cent of dairy herds had fewer than 50 cows, whereas by 1992 this had fallen to 45 per cent; over the same period, the number of herds with 100 cows or more rose from 15 to 19 per cent (MAFF, 1982, 1992). Dairy cow numbers fell by 19 per cent, although as average yields rose from 5085 to 5250 litres per cow, marketed output decreased considerably less (MMB). Innovative approaches to fertility and genetic improvement, enhanced grassland productivity, labour-efficient milking and greater enterprise specialisation combined with the market, policy and sector organisational changes to provide a challenging environment for analysis of technical change and efficiency. Finally, as milk is a relatively homogeneous product, generally accounting for a high proportion of farm revenue, aggregation problems are minimised.

The dependent variable in the translog production frontier (2), is total annual *milk products* in hectolitres of milk equivalent. The aggregate inputs included as explanatory variables are: (a) total agricultural *land* in hectares; (b) total *labour*, comprising hired (permanent and casual), family and contract labour, measured in working hours; (c) number of dairy *cows*; (d) purchased dairy concentrated feed, coarse fodder and other livestock expenses (such as veterinary and medicine costs) measured in pounds sterling (constant 1992 prices). Summary statistics for these variables are provided in Table 1.

To reduce the number of parameters to be estimated, the random effect specification is used in all models. Since the first two models are linear in parameters, they can be estimated using the FGLS procedure, as the variance of the error term in (1) is unknown. The variance of statistical noise σ_v^2 is estimated from the mean sum of squared errors from the within regression, and the variance of the one-sided error term σ_u^2 is estimated as $1/T\left((1/T(N-1))\sum_i\left(\sum_i \varepsilon_i\right)^2-\sigma_v^2\right)$, where e_{it} are the residuals of the OLS model. Then FGLS estimates can be obtained by using OLS into a transformed model, which arises by multiplying both sides of (2) by a and then subtracting their means, where $a=1-\left(\sigma_v^2/\left(\sigma_v^2+T\sigma_u^2\right)\right)^{1/2}$.

For the third model, which is non-linear, we follow the procedure proposed by Kumbhakar and Hjalmarson (1995). In this case, $\sigma_v^2=1/N(T-1)\sum\sum(e_{it}-\bar{e}_i)^2$ and $\sigma_u^2=1/T\left(1/T(N-1)\sum\left(\sum e_i\right)^2-\sigma_v^2\right)$, where e_{it} are the residuals of the non-linear OLS model and $\bar{e}_i=\sum e_{it}/T$. Then, (2) is transformed as previously, using the new values of a, and non-linear OLS is used to estimate all relevant parameters.

4. Empirical Results

The estimated parameters of the translog production frontier function for the variants of technical change are reported on Table 2. All models predict positive marginal products for inputs, but only the last two have positive semi-definite Hessian matrices, indicating quasi-concave production frontier functions. The simple time trend model fails to satisfy curvature conditions. In addition, all models predicted a similar production structure (see Table 3).[12] There are, however, some differences in estimated marginal products (see Table 4) as well as in returns to scale, which range from 0.86 in the simple time trend model to 0.94 in the general index model.

Much more significant differences are found for the estimated rate of technical change (see Table 5). These differences are both qualitative and quantitative. Even though all models rejected the hypothesis of zero technical change and of Hicks-neutrality, the average estimated rate of technical change differs significantly among the three models. During the period 1982-1992, the average annual rate of technical change is estimated at 1.25 per cent with the simple time trend model and at 0.31 per cent with the multiple time trend model, while the general index model indicates a technological regress of 0.03 per cent. Moreover, the pure technical change effect was found to be dominant in the multi time trend and the general index model, while the opposite is true for the single time trend model.

The temporal pattern of technical change is depicted in Figure 1. The simple time trend model (upper panel) indicates a progressive slowdown in the rate of technical change over time, which became much more significant since 1987 when the non-neutral component started also declining. In 1982, the annual rate of technical change was 1.91 per cent, it declined to 1.55 per cent by 1987, and even further to 0.23 per cent in 1992. This was mainly due to the declining contribution of the pure technical change effect. It is also worth noticing that the non- neutral effect has dominated the neutral component since 1986. This is in contrast with previous empirical findings supporting the entire dominance of the pure technical change effect and it may be due to the violation of curvature conditions in this model.

A quite different pattern of technical change is indicated by the multiple time trend model (middle panel of Figure 1). Two sub-periods were found with technical progress (1984-1987 and 1991-1992) combined with a sub-period (1988-1990) of technical regress. In the two sub-periods of technical regress, the rate of technical change increased initially, and fell afterwards. The opposite pattern was observed during the technical regress sub-period. During the entire period under consideration, except 1991-1992, the pure technical change effect was dominant in determining both the direction and the magnitude of the rate of technical change. Notice though, that the non-neutral component was also progressive in nature for the entire period.

A similar temporal pattern of technical change is indicated by the general index model (see lower panel of Figure 1), although with significant qualitative differences with respect to the components of technical change. Specifically, for the period of technical progress (1983-1987 and 1991-1992) the pure effect is positive but the non-neutral component is negative, indicating a slowdown into the rate of technical change. The opposite occurred during the technical regress period (1988-1990). In addition, the general index model predicted the smallest, in absolute terms, contribution of the non-neutral component among the competing models. Finally, as expected, this model predicted much more volatile technical change than the other two, contributing to a smaller rate of change on average.

Frequency distributions of technical efficiency for the three alternative models are reported on Table 6. It seems that the multiple time trend and the general index models predicted a lower degree of technical inefficiency, which were very similar to each other. During the period 1982-1992, technical inefficiency was found, on average, to be 63.07 per cent in the single time trend model, 76.05 per cent in the multiple time trend model, and 76.30 per cent in the general index model. In the multiple time trend and the general index model, there were only a limited number of firms with lower than 50 per cent degree of technical efficiency.

The multiple time trend and the general index models show a very similar temporal pattern of technical inefficiency, except for the period 1983-1984, while a different pattern is depicted by the single time trend model. In addition, the multiple time trend and the general index models predicted a slow improvement of technical efficiency over time, while the single trend model indicated a period (1985-1986) of efficiency deterioration (see also Figure 2). Thus, it seems that the temporal pattern of technical inefficiency is affected by the way of modelling technical change in the production frontier.

In England and Wales, the imposition of milk quotas in 1984 forced additional culling, improving the genetic merit of the aggregate herd, which is captured correctly in the evolution of estimated technical change in the multiple time trend model, and adequately in the general index model. Further external corroboration of pressures causing the pattern of technical change may be gleaned from the average cost-output ratio (MMB; see also Mukhtar and Dawson, 1990). As Figure 3 indicates, this fell in the early years of the period of the analysis, from 1.30 in 1982-1983 to 1.16 in 1984-1985, before rising to another peak of 1.37 in 1988-1989, and falling back to 1.22 by 1992-1993. The technical regress clearly estimated by both the multiple time trend and general index models after 1989 reflects a shift from concentrate to grass feed, motivated by this cost price squeeze. The efficiency estimates also behave, to some extent, inversely in relation to the cost-price ratio.

When compared with similar recent studies of temperate dairy production (e.g. Kumbhakar and Heshmati, 1995; Ahmad and Bravo-Ureta, 1995, 1996; Heshmati, 1998), the technical change and efficiency measures are broadly concordant. The approach used here, however, allows investigation of firm-specific measures that may be of significantly greater use in terms of policy development at farm level, as improving efficiency will become increasingly important. Fewer public resources are being devoted to agricultural research and development and, depending on market conditions (especially increased concentration on the purchasing side), this may not always have an impact on farming prosperity (Dryburgh and Doyle, 1995).

Additionally, the pace and direction of technical progress may be increasingly constrained by environmental legislation, especially in the dairy sector (where grassland monocultures and water pollution hazard are increasingly common; Rigby and Young, 1996), leaving efficiency improvement the only option for achieving productivity gains.

5. Conclusion

This paper proposes an alternative approach for separating the effects of technical change and of technical inefficiency into TFP changes, involving a radical departure from previous analyses. Notably, rather than focusing on the specification of the temporal pattern of technical inefficiency, technical change is modeled differently, avoiding the use of a simple time trend. The general index, developed by Baltagi and Griffin (1988), models technical change along the production function, and a quadratic function of time trend, as in Cornwell, Schmidt and Sickles (1990), captures the temporal pattern of technical inefficiency.

This approach has several advantages: *first*, it captures more complicated patterns of technical change than the simple time trend. *Second*, it has no need for distributional assumptions as far as the one-sided error term is concerned, since it is estimated with FGLS. *Third*, there is no inconsistency between the two stages of estimation, as inefficiency predicted in the second stage is not regressed on a number of firm-specific factors, but on a variable (time trend), identically distributed among firms. *Fourth*, both the effects of technical change and of changes in technical inefficiency can be clearly interpreted. The only remaining complexity of the model is in the non-linearity of parameters at the first-stage of estimation.

Table 1

Summary Statistics of the Variables

Variable	Mean	Std Deviation	Min	Max
Output (hectolitres)	4,436	2,757	320	18,685
Area (ha)	58	31	12	205
Labour (hours)	5,902	2,539	1,600	23,929
Herd Size (No of Cows)	145	86	19	564
Feeding Stuff and Livestock Expenses (£)	31,350	21,638	996	213,719

Table 2

Parameter Estimates of the Translog Production Frontiers for the Single, Multiple and General Index Time Trend Model

Parameter	Single TT		Multiple TT		General Index TT	
	Estimate	*Std Error*	*Estimate*	*Std Error*	*Estimate*	*Std Error*
$ß_0$	-0.007	(0.002)	0.009	(0.002)	0.017	(0.005)
$ß_H$	0.188	(0.038)	0.168	(0.038)	0.332	(0.083)
$ß_L$	0.122	(0.037)	0.108	(0.037)	0.063	(0.017)
$ß_A$	0.276	(0.036)	0.272	(0.037)	0.070	(0.026)
$ß_F$	0.377	(0.025)	0.420	(0.026)	0.521	(0.050)
$ß_{HL}$	0.301	(0.081)	0.276	(0.080)	0.104	(0.072)
$ß_{HA}$	0.161	(0.087)	0.162	(0.086)	0.644	(0.093)
$ß_{HF}$	0.186	(0.059)	0.167	(0.059)	0.171	(0.071)
$ß_{HH}$	-0.286	(0.063)	-0.273	(0.062)	-0.447	(0.072)
$ß_{LA}$	-0.046	(0.062)	-0.039	(0.061)	0.148	(0.063)
$ß_{LF}$	-0.194	(0.047)	-0.189	(0.046)	0.005	(0.052)
$ß_{LL}$	-0.036	(0.048)	-0.025	(0.047)	-0.158	(0.053)
$ß_{AF}$	0.006	(0.051)	0.013	(0.050)	-0.122	(0.050)
$ß_{AA}$	-0.116	(0.049)	-0.120	(0.049)	-0.342	(0.042)
$ß_{FF}$	-0.026	(0.011)	-0.016	(0.018)	-0.025	(0.012)
$ß_T$	0.019	(0.008)	-	-	-	-
$ß_{TT}$	-0.008	(0.004)	-	-	-	-
$ß_{HT}$	0.019	(0.004)	0.019	(0.004)	0.031	(0.013)
$ß_{LT}$	-0.016	(0.019)	-0.016	(0.018)	-0.028	(0.069)
$ß_{AT}$	-0.017	(0.014)	-0.014	(0.014)	0.073	(0.058)
$ß_{FT}$	-0.031	(0.011)	-0.029	(0.011)	-0.032	(0.014)
d_{83}	-	-	-0.037	(0.013)	0.002	(0.015)
d_{84}	-	-	-0.027	(0.013)	0.030	(0.015)
d_{85}	-	-	0.004	(0.013)	0.060	(0.015)
d_{86}	-	-	0.016	(0.010)	0.069	(0.015)
d_{87}	-	-	0.026	(0.013)	0.094	(0.015)
d_{88}	-	-	0.015	(0.008)	0.076	(0.015)
d_{89}	-	-	-0.026	(0.013)	0.017	(0.015)
d_{90}	-	-	-0.041	(0.015)	0.014	(0.008)
d_{91}	-	-	-0.034	(0.017)	0.018	(0.022)
d_{92}	-	-	-0.033	(0.018)	0.005	(0.023)
$\overline{R}^2$	0.966		0.906		0.891	

Where, H: herd size, L: labour, A: area, F: feeding stuff and livestock expenses and T: time.

Table 3

Hypothesis Test for the Production Technology

Hypothesis	Calculated Chi-Square statistic			Tabulated
	STT	MTT	GITT	(α=0.05)
Homotheticity	23.58	21.19	17.11	$\chi^2_{(4)} = 9.49$
Homogeneity	28.12	24.82	19.12	$\chi^2_{(5)} = 11.1$
Linear Homogeneity	36.76	32.04	73.92	$\chi^2_{(6)} = 12.6$
Additive Separability	33.56	31.29	15.23	$\chi^2_{(6)} = 12.6$
Strong Separability	41.32	39.42	53.98	$\chi^2_{(10)} = 18.3$
Zero TC	34.62*	94.30	39.30	$\chi^2_{(14)} = 23.7$
Hicks-Neutral TC	29.62	29.17	16.14	$\chi^2_{(4)} = 9.49$

* in the single time trend model the hypothesis of zero technical change involves only six restrictions.

Table 4

Estimates of Output Elasticities and Returns to Scale

	STT	MTT	GITT
Herd Size	0.200	0.180	0.317
Labour	0.097	0.083	0.040
Grazing Area	0.244	0.245	0.074
Feed and Livestock Costs	0.323	0.370	0.505
RTS	0.864	0.877	0.936

Table 5

Estimates of Technical Change

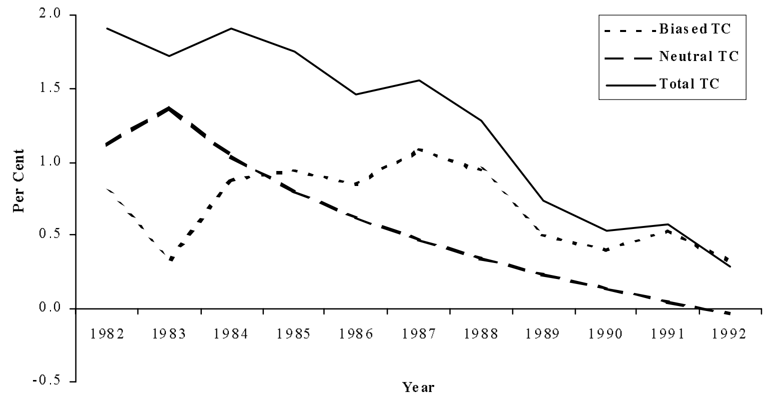
Year	Total Technical Change			Neutral TC			Biased TC		
	STT	MTT	GITT	STT	MTT	GITT	STT	MTT	GITT
1982	1.910	-	-	1.122	-	-	0.788	-	-
1983	1.720	-3.038	0.146	1.376	-3.706	0.171	0.345	0.668	-0.025
1984	1.914	1.280	2.412	1.041	1.012	2.850	0.873	0.268	-0.437
1985	1.745	3.847	2.797	0.804	3.080	3.024	0.942	0.767	-0.227
1986	1.461	2.098	0.784	0.619	1.262	0.829	0.842	0.835	-0.045
1987	1.551	1.692	2.407	0.469	0.947	2.564	1.083	0.745	-0.156
1988	1.281	-0.100	-1.811	0.342	-1.072	-1.849	0.939	0.973	0.038
1989	0.739	-3.305	-5.688	0.232	-4.149	-5.845	0.508	0.844	0.157
1990	0.526	-0.979	-0.337	0.134	-1.429	-0.353	0.392	0.450	0.015
1991	0.574	1.000	0.363	0.047	0.641	0.425	0.527	0.358	-0.062
1992	0.290	0.639	-1.409	-0.031	0.151	-1.360	0.321	0.488	-0.049
Mean	1.247	0.312	-0.034	0.559	-0.326	0.045	0.687	0.609	-0.079

Table 6

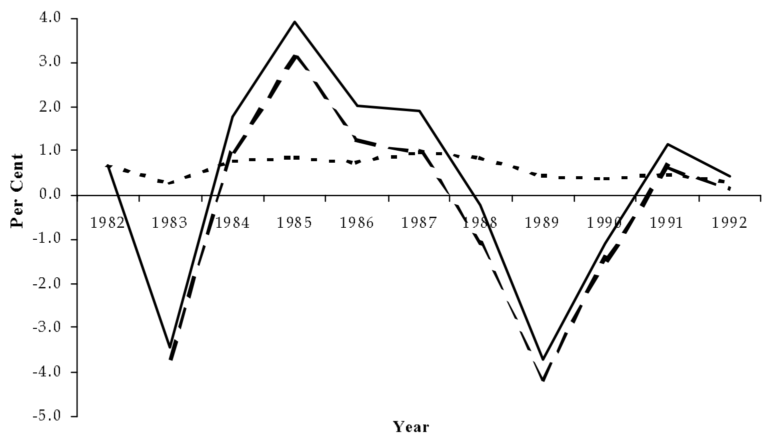
Frequency Distribution of Technical Efficiencies

%	82	83	84	85	86	87	88	89	90	91	92
Single Time Trend Model											
<40	0	1	0	0	3	3	1	0	3	2	2
40-50	0	2	3	3	3	65	58	4	0	2	2
50-60	47	70	12	43	37	157	157	62	19	21	14
60-70	101	118	83	158	159	11	19	114	85	65	39
70-80	43	22	114	30	33	1	1	26	33	43	25
80-90	5	4	10	5	2	2	1	3	10	2	3
>90	1	1	1	1	1	1	1	1	1	1	1
Mean	*65.3*	*62.6*	*70.3*	*64.7*	*64.5*	*52.9*	*53.6*	*63.4*	*66.4*	*63.7*	*66.5*
Multiple Time Trend Model											
<40	0	0	0	0	0	0	0	0	0	0	0
40-50	0	2	0	0	0	0	0	0	1	1	0
50-60	17	77	0	3	1	1	0	2	1	4	3
60-70	108	131	20	52	4	1	3	15	6	26	3
70-80	63	6	168	175	189	106	40	139	63	66	36
80-90	8	1	32	9	42	129	180	51	74	7	36
>90	1	1	3	1	2	3	15	3	6	2	8
Mean	*68.5*	*61.6*	*76.2*	*72.2*	*77.9*	*80.3*	*82.9*	*77.5*	*79.9*	*72.5*	*80.1*
General Index Model											
<40	0	0	0	0	0	0	0	0	0	0	0
40-50	0	1	0	0	0	0	0	0	1	1	0
50-60	2	12	0	3	1	1	0	2	1	3	3
60-70	61	53	22	41	1	1	3	36	5	8	20
70-80	106	131	173	186	191	85	89	152	55	79	42
80-90	25	18	24	8	44	150	138	18	78	13	15
>90	3	3	4	2	1	3	8	2	11	2	6
Mean	*72.8*	*72.5*	*75.4*	*72.5*	*78.3*	*80.9*	*80.9*	*73.9*	*81.0*	*75.2*	*75.8*
N	197	218	223	240	238	240	238	210	151	106	86

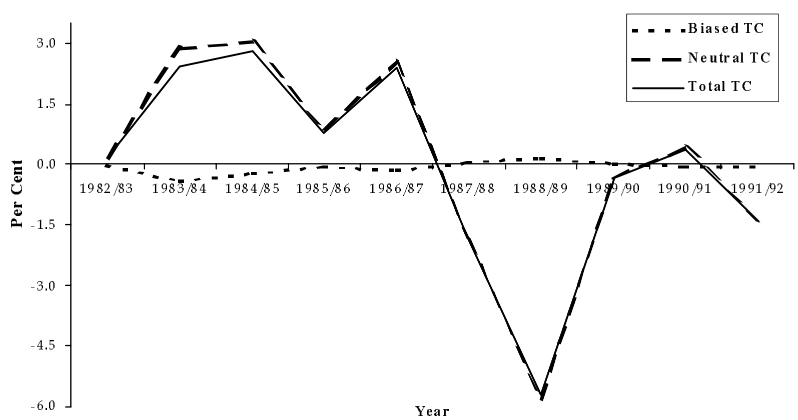
Figure 1



Development of Technical Change in the Single Time Trend Model



Development of Technical Change in the Multiple Time Trend Model



Development of Technical Change in the General Index Time Trend Model

Figure 2

Development of Mean Technical Efficiencies over Time

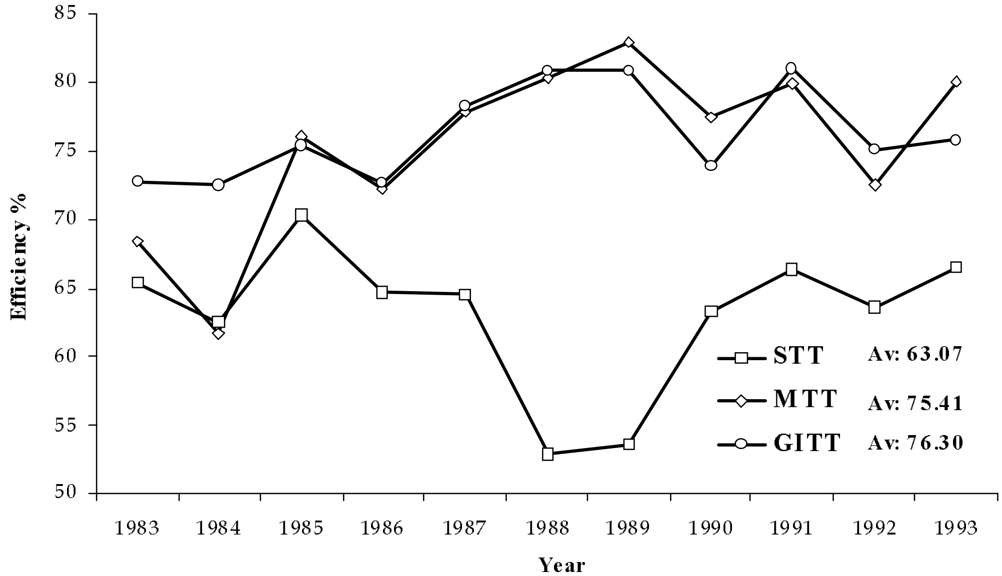
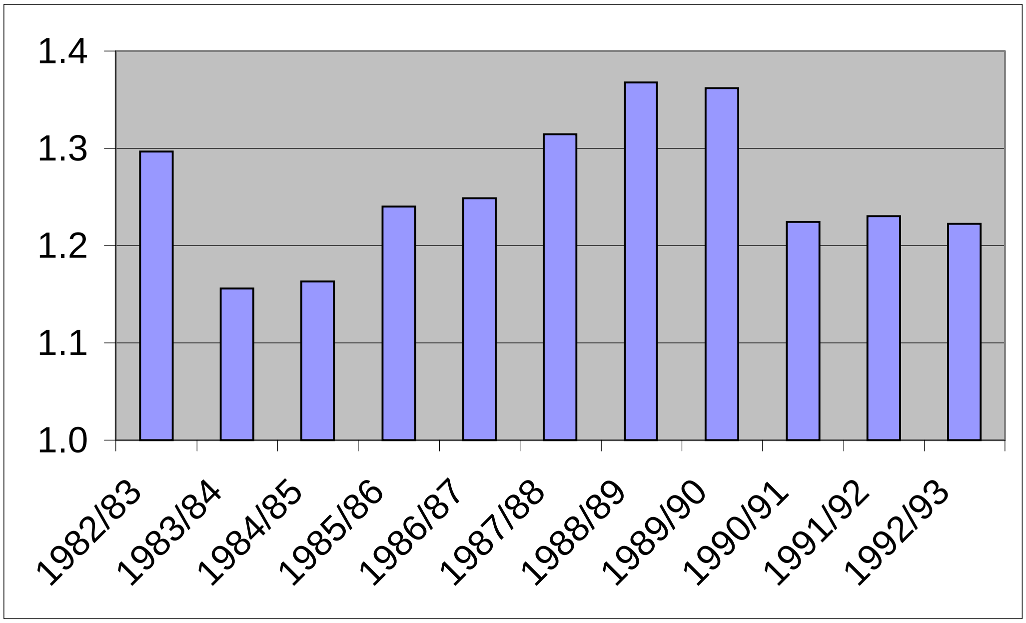


Figure 3

Average Output-Cost Ratios over Time, England and Wales Dairy Farms



References

Agriculture Departments, *Digest of Agricultural Census Statistics*, 1992, London: HMSO.

Agriculture Departments, *United Kingdom Agricultural Statistics*, 1982, London: HMSO.

Ahmad, M. and B.E. Bravo-Ureta. An Econometric Decomposition of Dairy Output Growth, *American Journal of Agricultural Economics*, 1995, 414-421.

Ahmad, M. and B.E. Bravo-Ureta. Technical Efficiency Measures for Dairy Farms using Panel Data: a Comparison of Alternative Model Specifications, *Journal of Productivity Analysis*, 1996, 7, 399-415.

Baltagi, B.H. and J.M. Griffin. A General Index of Technical Change, *Journal of Political Economy*, 1988, 96, 20-41.

Baltagi, B.H., Griffin, J.M. and D.P. Rich. Airline Deregulation: The Cost Pieces of the Puzzle, *International Economic Review*, 1995, 36, 245-258.

Baltagi, B.H., Griffin, J.M. and D.P. Rich. The Measurement of Firm-specific Indexes of Technical Change, *Review of Economics and Statistics*, 1995, 77, 654-663.

Battese, G.E. and S.S. Broca. Functional Forms of Stochastic Frontier Production Functions and Models for Technical Inefficiency Effects: A Comparative Study for wheat Farmers in Pakistan, *Journal of Productivity Analysis*, 1997, 8, 395-414.

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

Battese, G.E. and T.J. Coelli. Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India, *Journal of Productivity Analysis*, 1992, 3, 153-169.

Battese, G.E. and G. Tessama. Estimation of Stochastic Frontier Production Function with Time-varying Parameters and Technical Efficiencies Using Panel Data from Indian Villages, *Agricultural Economics*, 1993, 9, 313-333.

Battese, G.E., Malik, S.J. and M.A. Gill. An Investigation of Technical Inefficiencies of Production of Wheat Farmers in Four Districts of Pakistan, *Journal of Agricultural Economics*, 1996, 47, 37-49.

Battese, G.E., Malik, S.J. and S.S. Broca. Production Frontier for Wheat Farmers in Selected Districts of Pakistan: An Application of a Stochastic Frontier Production Function with Time-varying Inefficiency Effects, *Pakistan Development Reviews*, 1993, 32, 233-268.

Coelli, T.J. and G.E. Battese. Identification of Factors which Influence the Technical Inefficiency of Indian Farmers, *Australian Journal of Agricultural Economics,* 1996, 40, 103-128.

Cornwell, C., Schmidt, P. and R.C. Sickles. Production Frontiers with Cross-sectional and Time-series Variation in Efficiency Levels, *Journal of Econometrics*, 1990, 46, 185-200.

Dryburgh, C.R. and C.J. Doyle, Distribution of Research Gains under Different Market Structures: the Impact of Technological Change within the UK Dairy Industry, *Journal of Agricultural Economics,* 1995, 46, 80-96.

Fecher, F. and P. Pestieau. Efficiency and Competition in OECD Financial Services, in Fried, H., Lovell, C.A.K. and S.S. Schmidt (eds), *The Measurement of Productive Efficiency: Techniques and Applications.* Oxford University Press, 1993, pp.374-385.

Heshmati, A. Efficiency Measurement in Rotating Panel Data, *Applied Economics*, 1998, 30, 919-930.

Hesmati, A. On the Single and Multiple Time Trends Representation of Technical Change, *Applied Economics Letters*, 1996, 3, 495-499.

Hesmati, A. and S.C. Kumbhakar. Estimation of Technical Efficiency in Swedish Crop Farms: A Pseudo Panel Data Approach, *Journal of Agricultural Economics*, 1997, 48, 22-37.

Huang, C.J. and J.T. Liu. Estimation of a Non-Neutral Stochastic Frontier Production Function, *Journal of Productivity Analysis*, 1994, 5, 171-180.

Kim, H.Y. The Translog Production Function and Variable Returns to Scale, *Review of Economics and Statistics*, 1992, 74, 546-552.

Kumbhakar, S.C. and A. Hesmati. Technical Change and Total Factor Productivity Growth in Swedish Manufacturing Industries, *Econometric Reviews*, 1996, 15, 275-298.

Kumbhakar, S.C. and A. Heshmati. Efficiency Measurement in Swedish Dairy Farms: An Application of Rotating Panel Data, 1976-88, *American Journal of Agricultural Economics*, 1995, 77, 660-674.

Kumbhakar, S.C. and L. Hjalmarsson. Decomposing Technical Change with Panel Data: An Application to the Public Sector, *Scandinavian Journal of Economics*, 1995, 97, 309-323.

Kumbhakar, S.C. Production Frontiers, Panel Data, and Time-varying Technical Inefficiency, *Journal of Econometrics,* 1990, 46, 201-212.

Kumbhakar, S.C., Hesmati, A. and L. Hjalmarsson. Temporal Patterns of Technical Efficiency: Results from Competing Models, *International Journal of Industrial Organisation*, 1997

Lee, Y.H. and P. Schmidt. A Production Frontier Model with Flexible Temporal Variation in Technical Efficiency, in Fried, H., Lovell, C.A.K. and S.S. Schmidt (eds), *The Measurement of Productive Efficiency: Techniques and Applications*. Oxford University Press, 1993, pp. 237-255.

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

Milk Marketing Boards, *Dairy Facts and Figures*, various years, 1983-1994, Thames Ditton: United Kingdom Federation of Milk Marketing Boards.

Ministry of Agriculture, Fisheries and Food Economic Division, Welsh Office, *Farm Business Survey 1982-1993*, 1994a, Colchester: ESRC Data Archive

Ministry of Agriculture, Fisheries and Food, *Agriculture in the United Kingdom*, 1994b, London: HMSO.

Mukhtar, S.M. and P.J. Dawson. Herd Size and Unit Costs of Production in the England and Wales Dairy Sector, *Journal of Agricultural Economics*, 1990, 41, 9-20.

Neogh, C. and B. Ghosh. Intertemporal Efficiency Variations in Indian Manufacturing Industries, *Journal of Productivity Analysis*, 1994, 5, 301-324.

Rigby, D. and T. Young, European Environmental Regulations to Reduce Water Pollution: an Analysis of Their Impact on UK Dairy Farms, *European Review of Agricultural Economics*, 1996, 23, 59-78.

Solow, R.M. Technical Change and the Aggregate Production Function, *Review of Economics and Statistics*, 1957, 39, 312-320.

Timmer, C.P. Using a Probabilistic Frontier Function to Measure Technical Efficiency, *Journal of Political Economy*, 1971, 79, 776-794.

Tinbergen, J. Zur Theorie der Iangfristigen Wirtschaftentwicklung, *Weltwirtschaftliches Archiv*, 1942, 55, 511-549.

Tran, S., Coelli, T. and E. Fleming. Analysis of the Technical Efficiency of State Rubber Farms in Vietnam, *Agricultural Economics*, 1993, 9, 183-207.

Yao, S. and Z. Liu. Determinants of Grain Production and Technical Efficiency in China, *Journal of Agricultural Economics*, 1998, 49, 171-184.

Endnotes

1 For previous empirical applications see Baltagi, Griffin and Rich (1995); Kumbhakar and Hjalmarsson (1996); Kumbhakar and Hesmati (1997).

2 Estimation is carried out with FGLS. Examples of empirical applications include Fecher and Pestieau (1993), Ahmad and Bravo-Ureta (1995); Neogi and Ghosh (1994).

3 The first two models are estimated with maximum likelihood while the third one could be estimated with FGLS.

4 To the best of our knowledge there is not an empirical application of Kumbhakar (1990) model.

5 Examples of empirical applications include Battese and Tessema (1993), Battese, Malik and Broca (1993) and Tran, Coelli and Fleming (1993).

6 For previous applications of this model see Kumbhakar and Hesmati (1995), Hesmati and Kumbhakar (1997), and Hesmati (1998). This model is estimated in two steps: the first consists of estimating the frontier with FGLS and the second measuring the persistent and the time-varying inefficiency by using either maximum likelihood (Kumbhakar and Hesmati (1995), Hesmati and Kumbhakar (1997)) or the method of moments (Hesmati, 1998).

7 Persistent technical inefficiency is closely related to government policy and firm-ownership, while the residual time-varying technical inefficiency is due to temporary factors (Kumbhakar and Hesmati, 1995). In the extreme case of $\mu_i = 0$, technical inefficiency varies randomly across firms as well as over time.

8 This may be case with changes in governmental policy. Lovell (1996) also raised the concern of whether is possible to distinguish the effect of firm-specific persistent technical inefficiency from that of quasi-fixed inputs, which also vary across firms but not through time.

9 This assumption is quite restrictive, but not unreasonable for a putty-clay industry (see Kumbhakar, Hesmati and Hjlmarsson, 1997).

10 This model is also estimated with maximum likelihood. Examples of empirical applications include Coelli and Battese (1996); Battese (1996); Battese, Malik and Gill (1996); Yao and Liu (1998).

[11] Grateful acknowledgement is made to MAFF, for permission to use data from the Farm Business Survey, provided through the ESRC Data Archive at the University of Essex.

[12] All relevant parameter restrictions for the structure of production technology are given in detail by Kim (1992).