A FLEXIBLE TIME-VARYING SPECIFICATION OF THE TECHNICAL INEFFICIENCY EFFECTS MODEL

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The temporal pattern of technical efficiency in the technical inefficiency effects model, as initially modeled by Battese and Coelli (1995), is rather restrictive. Specifically, it a priori imposes a common pattern upon all firms in the sample, which in addition is monotonic over time. Obviously this is an undesirable implication of the model especially when there is evidence of strong firm heterogeneity and/or a long time span. To overcome this shortcoming, the present paper incorporates the Cornwell, Sickless and Schmidt (1990) flexible specification of the temporal pattern of technical efficiency into technical inefficiency effects model. The proposed formulation is then applied to the agricultural sector of the EU and US, during the period 1973-1993. The empirical result support the proposed formulation as quite different temporal patterns of technical efficiency have been found for the ten countries included in the analysis.

Introduction

The technical inefficiency effects model, originally proposed by Kumbhakar, Ghosh and McGuckin (1991) and Reifschneider and Stevenson (1991), is perhaps the most widely used model in the stochastic frontier analysis. Its main advantage is that it can simultaneously (*i*) provide firm-specific estimates of technical efficiency and (*ii*) associate variation in firm performance with variation in exogenous or conditioning variables (e.g., managerial ability, socioeconomic characteristics, ownership form, etc.) characterizing the environment in which production occurs. Another useful aspect of the technical inefficiency effects model, available though only in a panel data setting, is that it permits the identification of the effects of technical change and of time-varying technical efficiency, even if both are modeled via a simple time trend (Battese and Coelli, 1995). This is so as long as the inefficiency effects are stochastic and follow a truncated distribution. Without such a distributional assumption none of the parameters associated with the time trend in the production function and in the one-sided error term capturing technical inefficiency can be identified (Kumbhakar, Heshmati and Hjalmarsson, 1997). And as a result, it is impossible to separate the effects of technical change and of time-varying technical efficiency on productivity changes.[1]

On the other hand, a shortcoming of the technical inefficiency effects model seems to be the rather restrictive specification of the temporal pattern of technical inefficiency, at least as initially modeled by Battese and Coelli (1995). In their set up, the effect of the passage of time on technical inefficiency is necessarily monotonic and whenever is time-varying, it may be either efficiency-enhancing or efficiency-impending, but not both (Wang, 2002). This monotonicity assumption implies further that it would be the same for all observations in the sample. While the assumption that the temporal pattern of technical inefficiency is the same for all firms is quite restrictive, it is not unreasonable for a putty-clay industry (Kumbhakar, Heshmati and Hjalmarsson, 1997). In contrast, in samples with strong firm heterogeneity, it is likely that some firms will tend to improve their technical efficiency scores over time, others will tend to deteriorate them, and some will leave them unaffected. Even though all these outcomes are equally possible at the outset, it is impossible to take them into account appropriately with the specification of the temporal pattern of technical inefficiency used by Battese and Coelli (1995).

Nevertheless, the relative contribution of technical efficiency changes into productivity growth is non-monotonic because of its dependency on an adjustment function (defined as the ratio of the conditional to unconditional variance of the one-sided error term), which differs across observations. That is, the relative importance of technical efficiency changes as a source of growth differs across firms. But since the adjustment function is always positive for the technical inefficiency effects model (Wang, 2002), the effect of technical efficiency changes would be positive or negative according to the sign of the (estimated) time coefficient in the technical inefficiency effect function. And this sign is the same for all observation in the sample. Thus, with the Battese and Coelli (1995) specification of the temporal pattern of technical inefficiency, the effect of technical efficiency changes into productivity growth is qualitatively similar for all firms in the sample but it is quantitatively different.

The objective of this paper is to incorporate a flexible specification of time-varying technical efficiency into the technical inefficiency effect model. For this purpose, the Cornwell, Schmidt and Sickles (1990) specification is used.[2] Its main advantages are that allow for firm-specific patterns of temporal variation in technical efficiency and more importantly, for testing for the existence of a common temporal pattern across firms. Consequently, the Battese and Coelli (1995) specification can be obtained as a special case. Moreover, it allows technical efficiency to vary through time employing a quadratic specification. Thus the proposed formulation attempts to combine the advantages of the Cornwell, Schmidt and Sickles (1990) specification (i.e., analyzing flexible temporal patterns of technical efficiency changes) with those of the technical inefficiency effects model (i.e., explaining efficiency differentials).

The proposed formulation is used to analyze the temporal pattern of technical efficiency for USA and 9 European countries (i.e., Germany, France, Italy, Belgium, Netherlands, UK, Ireland, Denmark and Greece). The empirical results indicate that the evolution of technical efficiency in these countries has been different during the period 1973-1993, and for only two countries (i.e., Denmark and Greece) technical efficiency had been time invariant. This in turn means that technical efficiency cannot be considered as a source of growth for these two countries during the period under consideration. On the other hand, it is found that technical efficiency changes have contributed positively to productivity growth in France, Italy, Ireland and USA and negatively in Germany, Netherlands, Belgium and UK. These quite different temporal patterns of technical efficiency changes could not be captured by the Battese and Coelli (1995) specification.

Empirical Model

Consider the following translog production frontier:

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

where y_{it} is the logarithm of the observed output produced by the ith firm at year t, x_{jit} is the logarithm of the quantity of the jth input used by the ith firm at year t, t is a time index that serves as a proxy for technical change, β is a vector of parameters to be estimated after imposing symmetry (i.e., $\beta_{jk} = \beta_{kj}$), and $e_{it} = v_{it} - u_{it}$ is a stochastic composite error term. The v_{it} term corresponds to statistical noise that is assumed to be independently and identically distributed, and the u_{it} term is a non-negative random variable associated with technical inefficiency. It is further assumed that v_{it} and u_{it} are independently distributed from each other. In the technical inefficiency effects model, u_{it}, could be replaced by a linear function of explanatory variables reflecting firm-and time-specific characteristics. Specifically,

$$\mathrm{u_{it}} = \delta_o + \sum_{m=1}^{M} \delta_m z_{mi} + \omega_{it} \,, \tag{2}$$

where z_{ml} are farm- and time-specific explanatory variables associated with technical inefficiency; δ_0 and δ_m (*m=1,…M*) are parameters to be estimated; and ω_{it} is an independently and identically distributed with $N(0,\sigma_u^2)$ random variable truncated at $-\left(\delta_0 + \sum \delta_m z_{mi}\right)$ from below. The latter implies that $u_{it} \sim N(\delta_0 + \sum \delta_m z_{mi}, \sigma_u^2)$ truncated at zero from below.

For the purposes of this paper, the inefficiency effect model is specified only in terms of a simple time trend, although several demographic, socioeconomic etc. variables could have also been easily included. In particular, following Cornwell, Schmidt and Sickles (1990), (2) is specified as:

$$\mathrm{u_{it}} = \delta_{io} + \delta_{i1} t + \delta_{i2} t^2 + \omega_{it} \tag{3}$$

where δ_{i0}, δ_{i1}, and δ_{i2} (*i=1,…,n*) are firm-specific parameters to be estimated. Thus this specification allows for firm-specific patterns of temporal variation of technical efficiency and captures effects not visible in those models that assume a common pattern of technical efficiency. In addition, we can test (*i*) for the existence of a common temporal pattern for all firms in the sample (i.e., $\delta_{i1} = \delta_1$ and $\delta_{i2} = \delta_2$ for all *i=1,…n*), and (*ii*) the hypothesis of time-varying technical efficiency for all or some of the firms in the sample (i.e., $\delta_{i1} = \delta_{i2} = 0$ for all *i=1,…n*). That is, it is possible to test the hypothesis of time invariant technical efficiency for each firm by performing tests over each of the δ_{i1}, and δ_{i2}. Moreover, the original Battese and Coelli (1995) specification is viewed as a special case in the proposed formulation, which results as a nested model under the hypothesis that $\delta_{i0} = \delta_0$, $\delta_{i1} = \delta_1$ and $\delta_{i2} = \delta_2$ for all *i=1,…n*.

After substituting (3) into (1) the resulting model is estimated by a single-equation estimation procedure using the maximum likelihood method. The variance parameters of the likelihood function are estimated in terms of $\sigma_s^2 = \sigma_v^2 + \sigma^2$ and $\gamma = \sigma^2 / \sigma_s^2$, where σ^2 is the variance of the normal distribution that is truncated at zero to obtain the distribution of u_{it} and the γ-parameter has a value between zero and one. Then, farm-specific estimates of the output-oriented measure of technical efficiency can be obtained from the conditional expectation of $\exp(-u_{it})$ given e_{it} (Battese and Coelli, 1988).

Empirical Results

The empirical results are based on a data set developed recently by Ball *et al*. (2001). This data set contains multilateral data on agricultural output, land, labor, capital, and intermediate inputs for ten countries (Germany, France, Italy, Belgium, Netherlands, UK, Ireland, Denmark, Greece and USA) during the period 1973-1993. Details on data sources, definition and construction of all relevant variables, as well as descriptive statistics are given in Ball *et al*. (2001).

The estimated parameters of the translog production frontier are presented in Table 1. The first-order parameters (β_j) 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 ratio-parameter, γ, is positive and statistically significant at the 5% level of significance, indicating that the technical inefficiency is likely to have an important effect in explaining output variability among farms in the sample. According to the estimated variances, output variability is mainly due to technical inefficiency rather than to statistical noise.

Hypotheses testing regarding model specification are reported on Table 2.[3] The null hypotheses that $\gamma = \delta_{i0} = \delta_{i1} = \delta_{i2} = 0$ and $\gamma = 0$ for all i are both rejected at 5% level of significance indicating respectively that the technical inefficiency effects are in fact present and stochastic in nature.[4] Consequently, most of the countries in the sample operates below the production frontier and thus, a significant part of output variability among them is explained by the existing differences in the degree of technical efficiency. As a result, the traditional average production does not seem to be an adequate representation the production technology. More importantly, rejection of the above hypotheses implies that technical change can be separated from time-varying technical inefficiency even though both are modeled via a simple time trend.

Concerning now the temporal variation of technical efficiency, the results in Table 2 indicate that the common pattern specification (i.e., $\delta_{i1} = \delta_1$ and $\delta_{i2} = \delta_2$ for all i) used in Battese and Coelli (1995) is rejected at 5% level of significance.[5] This implies that the countries considered in the analysis have followed different patterns of temporal variation in technical efficiency. Consequently, the contribution of technical efficiency changes into productivity changes is expected to vary across countries, both in terms of its direction and magnitude. This is an expected result since there is evidence of strong heterogeneity in the sample. Ball *et al*. (2001) have documented substantial differences among the sample countries in output produced, capital-labor and land-labor ratios, as well as changes of input quantities over time. The most remarkable differences are reported for land and the less significant for labor. Furthermore, the patterns of change for labor input bear little resemblance to those of land, capital and intermediate inputs, which increased in both absolute and relative (to US) terms.

The hypothesis of time invariant technical efficiency (i.e., $\delta_{i1} = \delta_{i2} = 0$ for all i) is also rejected at 5% level of significance, when all countries are considered as a whole (see Table 2). However, the picture changes significantly when the relevant test is conducted on a country basis. The results reported in Table 2 indicate that technical efficiency is found to be time invariant for Denmark and Greece, while it is time varying for the rest of the countries in the sample. Thus, for Denmark and Greece, technical efficiency changes cannot be considered as a source of productivity changes. The estimated values of the δ_{i1} and δ_{i2} parameters (see Table 1) imply that technical efficiency changes contributed positively to productivity growth in France, Italy, Ireland and US, whereas they negatively affected productivity in Germany, Netherlands, Belgium and UK. On the other hand, the hypothesis that technical efficiency varies through time (i.e., $\delta_{i2} = 0$ for all i) cannot be rejected at 5% level of significance (see Table 2). From the statistical significance of the estimated δ_{i2} parameters reported in Table 1, it could be seen that, with the exception of Italy, this is true for all countries that exhibited time-varying technical efficiency.

By taking only statistically significant parameters into account and following Battese and Broca (1997), the annual rate of change in technical efficiency may be calculated as:

$$\frac{\partial u_{it}}{\partial t} = -[\delta_{i1} + 2\delta_{i2}t]\left[1 - \frac{1}{\sigma_u}\left\{\frac{\phi\left(\frac{\mu_{it}}{\sigma_u} - \sigma_u\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_u} - \sigma_u\right)} - \frac{\phi\left(\frac{\mu_{it}}{\sigma_u}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)}\right\}\right], \tag{4}$$

where $\phi[\bullet]$ and $\Phi[\bullet]$ represent respectively the density and the cumulative density function of the standard normal random variable. The results are presented in Table 3 along with averages of technical efficiency over the 1973-1993 period. From the countries that exhibited time varying technical efficiency, France achieved the faster improvement in efficiency and Belgium the faster deterioration. The corresponding slower changes in technical efficiency have occurred in the US and the Netherlands. It can also be seen from the results in Table 3 that, with the exception of Ireland, the countries, which on average achieved relatively lower efficiency scores, exhibited either efficiency deterioration or time invariant efficiency. In contrast, with the exception of the Netherlands, the countries that on average achieved relatively higher efficiency scores, exhibited efficiency improvements.

Concluding Remarks

During the last fifteen years or so, an increasing number of empirical studies have considered the effect of technical efficiency changes into productivity growth using either parametric or non-parametric methods. The apparent advantage of employing the parametric approach in such studies is the capability of testing several statistical hypotheses concerning the existence and the magnitude of the various sources of productivity changes. Among other things, there is general cohesion that in samples with strong firm heterogeneity and long time span it is undesirable to model the contribution of technical efficiency changes into productivity changes as being the same across firms and/or invariant over time.

This provided the motivation for incorporating the Cornwell, Schmidt and Sickles (1990) flexible time-varying specification of technical efficiency into the widely used technical inefficiency effects model. In the form used by Battese and Coelli (1995), the technical inefficiency effects models is perhaps the best alterative available for simultaneously explaining efficiency differentials and separating technical change from technical efficiency changes, but it has the disadvantage of imposing the same temporal pattern of technical efficiency for all units in the sample. In contrast, the proposed formulation allows for firm-specific patterns of temporal variation in technical efficiency and more importantly, for testing for the existence of a common temporal pattern across firms and of time invariant technical efficiency. The empirical result presented above support the proposed formulation as quite different temporal patterns of technical efficiency have been found in the agricultural sector of the ten countries included in the analysis. Two of them (i.e., Denmark and Greece) exhibited time invariant technical efficiency; four countries (i.e., France, Italy, Ireland and USA) improved their efficiency over the period 1973-1993, while four other countries (i.e., Germany, Netherlands, Belgium and UK) deteriorated their performance in terms of technical efficiency.

Table1. Parameter Estimates of the Translog Production Frontier

Parameter	Estimate	Std Error	Parameter	Estimate	Std Error
β_0	0.0259	(0.0107)**	ρ_{G0}	-0.3287	(0.1090)*
β_C	0.0342	(0.0323)	ρ_{F0}	-1.6033	(0.1326)*
β_A	0.4337	(0.0777)*	ρ_{I0}	-1.6410	(0.3435)*
β_L	0.1846	(0.0474)*	ρ_{N0}	-1.1570	(0.2743)*
β_E	0.3659	(0.0910)*	ρ_{B0}	-0.2462	(0.0955)*
β_T	0.4218	(0.0183)*	ρ_{K0}	-0.7355	(0.1976)*
β_{CA}	0.2219	(0.0460)*	ρ_{R0}	-0.5868	(0.1600)*
β_{CL}	-0.0999	(0.0470)**	ρ_{D0}	-0.9307	(0.1657)*
β_{CE}	-0.2179	(0.1039)**	ρ_{H0}	-0.1005	(0.0868)
β_{CT}	-0.0136	(0.0192)	ρ_{U0}	-0.9290	(0.1922)*
β_{CC}	-0.0219	(0.0994)	ρ_{G1}	1.1558	(0.1100)*
β_{AL}	-0.0376	(0.0723)	ρ_{F1}	-0.7375	(0.1752)*
β_{AE}	-0.0028	(0.0489)	ρ_{I1}	-0.7260	(0.3417)**
β_{AT}	-0.0350	(0.0148)**	ρ_{N1}	0.5075	(0.2129)**
β_{AA}	-0.0018	(0.0426)	ρ_{B1}	2.1323	(0.1484)*
β_{LE}	-0.0300	(0.0976)	ρ_{K1}	-0.1724	(0.3652)
β_{LT}	0.0282	(0.0137)**	ρ_{R1}	-0.9864	(0.2353)*
β_{LL}	0.1109	(0.0240)*	ρ_{D1}	0.2281	(0.2519)
β_{ET}	0.0969	(0.0211)*	ρ_{H1}	-0.0284	(0.1652)
β_{EE}	0.0537	(0.0230)**	ρ_{U1}	-0.0633	(0.2558)
β_{TT}	0.0837	(0.0050)*	ρ_{G2}	0.2280	(0.0315)*
			ρ_{F2}	-0.2685	(0.0625)*
			ρ_{I2}	-0.0362	(0.1519)
			ρ_{N2}	0.2903	(0.1432)**
			ρ_{B2}	0.7403	(0.0619)*
			ρ_{K2}	-0.2131	(0.0749)*
			ρ_{R2}	0.1901	(0.0863)**
σ^2	0.0456	(0.0053)*	ρ_{D2}	0.0049	(0.1283)
γ	0.9980	(0.0011)*	ρ_{H2}	-0.0213	(0.0779)
$Ln(\theta)$	-357.967		ρ_{U2}	-0.0977	(0.0358)**

Notes: 1. (A) refers to land, (L) to labor, (C) to capital, (E) to intermediate inputs and (T) to time trend.
2. (G) refers to Germany, (F) to France, (I) to Italy, (N) to Netherlands, (B) to Belgium, (K) to UK, (R) to Ireland, (D) to Denmark, (H) to Greece and (U) to USA.
3. *(**) indicates statistical significance at the 1 (5) % level.

Table 2. Model Specification Test

Hypothesis	LR-test	Critical Value (α=0.05)
$\gamma = \delta_{i0} = \delta_{i1} = \delta_{i2} = 0 \;\; \forall i$	369.8	$\chi^2_{(31)} = 43.19^*$
$\gamma = 0$	25.9	$\chi^2_{(4)} = 8.76^*$
$\delta_{i0} = \delta_0 \wedge \delta_{i1} = \delta_1 \;\wedge\; \delta_{i2} = \delta_2 \;\; \forall i$	77.6	$\chi^2_{(30)} = 53.05$
$\delta_{i1} = \delta_1 \;\wedge\; \delta_{i2} = \delta_2 \;\; \forall i$	52.7	$\chi^2_{(20)} = 31.41$
$\delta_{i1} = \delta_{i2} = 0 \;\; \forall i$	42.7	$\chi^2_{(20)} = 31.41$
$\delta_{G1} = \delta_{G2} = 0$	24.6	$\chi^2_{(2)} = 9.63$
$\delta_{F1} = \delta_{F2} = 0$	34.3	$\chi^2_{(2)} = 9.63$
$\delta_{I1} = \delta_{I2} = 0$	26.5	$\chi^2_{(2)} = 9.63$
$\delta_{N1} = \delta_{N2} = 0$	43.5	$\chi^2_{(2)} = 9.63$
$\delta_{B1} = \delta_{B2} = 0$	21.8	$\chi^2_{(2)} = 9.63$
$\delta_{K1} = \delta_{K2} = 0$	18.1	$\chi^2_{(2)} = 9.63$
$\delta_{R1} = \delta_{R2} = 0$	33.1	$\chi^2_{(2)} = 9.63$
$\delta_{D1} = \delta_{D2} = 0$	7.9	$\chi^2_{(2)} = 9.63$
$\delta_{H1} = \delta_{H2} = 0$	0.7	$\chi^2_{(2)} = 9.63$
$\delta_{U1} = \delta_{U2} = 0$	26.6	$\chi^2_{(2)} = 9.63$
$\delta_{i2} = 0 \;\; \forall \mathrm{i}$	30.7	$\chi^2_{(10)} = 24.49$

Notes: 1. (G) refers to Germany, (F) to France, (I) to Italy, (N) to Netherlands, (B) to Belgium, (K) to UK, (R) to Ireland, (D) to Denmark, (H) to Greece and (U) to USA.
2. Critical values with an asterisk are taken from Kodde and Palm (1986, Table 1).

Table 3. Technical Efficiency Scores and Technical Efficiency Change Estimates, 1973-1993 (average values)

Country	Technical Efficiency (Average Value)	Technical Efficiency Change (Average Annual Growth Rate)
Germany	94.5	-1.06
France	97.1	1.65
Italy	95.6	1.28
Netherlands	96.7	-0.13
Belgium	93.8	-1.72
U.K.	95.0	-0.24
Ireland	92.9	0.88
Denmark	90.8	0.00
Greece	93.3	0.00
U.S.A.	95.9	0.18

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Endnotes

[1] Since the pioneering work of Nishimizu and Page (1982), a great number of studies have considered the effect of technical efficiency changes into productivity growth using either the Tornqvist or the Malmquist index (see Kumbhakar and Lovell (2000, pp. 279-309) and Fare, Grosskopf and Roos (1998) for extensive reviews). In that respect, what really matters is not the degree of technical efficiency *per se* but its changes over time. Specifically, if technical efficiency is time invariant it makes no contribution to productivity growth, whereas it is time varying it affects productivity growth positively (negatively) when is associated with movements towards (away from) the production frontier.

[2] We do not use the flexible specification of the temporal pattern proposed by Cuesta (2000) because it is difficult to accommodate it into the technical inefficiency effects model, and in addition, it does not allow for variation of technical efficiency changes over time.

[3] The generalized likelihood-ratio test statistic, $\lambda = -2\{\ln L(H_0) - \ln L(H_1)\}$, is used for these purposes, 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. If the given null hypothesis is true, λ has approximately a chi-square distribution, except cases where the null hypothesis involves also $\gamma = 0$. In this case, the asymptotic distribution of λ is a mixed chi-square and the appropriate critical values are obtained from Kodde and Palm (1986).

[4] In the latter case, the variance of the inefficiency effects is zero and the model reduces to a traditional response function, in which country-specific intercept terms and time variables are included in the production function. Then, the parameters γ and δ_{i0}, δ_{i1} and δ_{i2} for one *i* cannot be identified. In our case, the critical value to test the null hypothesis is obtained from the $\chi^2_{(4)}$-distribution.

[5] In addition, the hypothesis that the sample countries share a common temporal pattern of technical efficiency, along with a common intercept in the inefficient effect model, is rejected at 5% level of significance (see Table 2).