# ESTIMATING TECHNICAL INEFFICIENCY: AN EMPIRICAL APPROACH TO EU INDUSTRIES

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**Abstract:**
*This paper estimates, incorporating a Transcendental Logarithmic Production Function, the technical efficiency level of different industries in selected E.U. countries. The paper considers panel data for inefficiency effects in stochastic production frontier based on Battese and Coelli (1995), providing translog effects, as well as industry effects. The empirical model accommodates not only heteroscedasticity but also allows the possibility that an industry may not always produce the maximum possible output, given the inputs. Unlike most studies, the paper estimates time – varying technical efficiencies (incorporating 'learning – by doing' behaviour) as industry-specific fixed effects. Furthermore, the model decomposes total factor productivity (TFP) growth into two components: technological growth (essentially, a shift of production possibility frontier, set by best-practice enterprises) and inefficiency changes (i.e., deviations of actual output level from the production possibility frontier).*

**Key Words**: Efficiency, Technical Inefficiency, Stochastic Frontier Model

## 1. Introduction

The main core of modern economic theory is based on the assumption of optimising behaviour, either from a producer or a consumer approach. As far as producer behaviour is concerned, economic theory assumes that producers optimise both from a technical and economic perspective:

1. From a technical perspective, producers optimise by not wasting productive resources.
2. From an economic perspective producers optimise by solving allocation problems involving prices.

However, not all producers succeed in solving both types of optimisation problem under all circumstances. For this reason it is important to analyse the degree to which producers fail to optimise and the extent of any resulting distances from the frontier of full technical and economic efficiency. Based on this assumption, one of the main analytical approaches to efficiency measurement is the analysis of production frontiers. This chapter presents an empirical model application dealing with productive efficiency estimation. This paper has four distinct goals:

1. develop a model of efficient producer behaviour and investigate possible types of departure from full technical efficiency level
2. develop an analytical econometric technique for examining the above
3. analyze the level and the development of an industry's productive efficiency along with the determining factors
4. to demonstrate the obtained results and come to safe conclusions as far as modelling producer behaviour at industry level (applied production analysis) is concerned.

The main research questions arising could be summarized into what are the reasons for diverging efficiency in a production industry, which factors contribute to production industries

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efficiency differences, and finally, how the efficiency of a production industry evolves over time, with respect to technical progress and other related determining environmental factors.

## 2. Stochastic Frontier Production Function

Our research approach is based on the framework of a stochastic frontier model [as firstly independently proposed by Aigner et al. (1977) and van den Broeck (1977)]. As described in Movshuk (2004), while early stochastic frontier models were mainly implemented with cross – sectional data, Battese and Coelli (1995) model is formulated for panel data (which may also be unbalanced). Moreover, the model not only estimates inefficiency levels of particular industries, but also explains their inefficiency in terms of potentially important explanatory variables. The model decomposes TFP growth into two components: technological growth: a shift of production possibility frontier set by best – practice industries, and inefficiency changes: deviations of actual output level form the production possibility frontier.

In our model analysis, we follow the approach of modelling both the stochastic and the technical inefficiency effects in the frontier, in terms of observable variables, and estimating all parameters by the method of maximum likelihood, in a one - step analysis[1]. Thus, we undertake an (one – step) estimation of the stochastic frontier model in conjunction with the parameters of the variables included to explain efficiency effects, as developed by Battese and Coelli (1992, 1995)[2]. The model is a time – varying stochastic frontier model given a sample of *N* industries for *t* time periods[3]. The industries are assumed to produce a single output ($x_{i,t}$) from inputs of capital ($K_{i,t}$) and labor ($L_{i,t}$). The basic specification is of a flexible (second – order) transcendental logarithmic (translog) production function model (Kumbhakar, 1989, 2000)[4] with time variable included in the stochastic production function:

$$\ln Y_{it} = \alpha_0 + \sum_j a_j \ln X_{jit} + \alpha_t t + \frac{1}{2}\sum_j \sum_k \alpha_{jk} \ln X_{jit} \ln X_{kit} + \frac{1}{2}\alpha_{tt} t^2 + \sum_j \alpha_{jt} \ln X_{jit} t + v_{it} - u_{it}$$

In this model:

- $Y_i$ is the production (or the logarithm of the production ) of the $i^{th}$ industry
- $x_i$ is a k×1 vector of input quantities of the $i^{th}$ industry

[1] Battese and Coelli (1995) suggested that under the assumption of truncated normal one-sided error term, the mean of the truncated normal distribution could be expressed as a function of certain covariates, a closed form likelihood function can be derived, and the method of maximum likelihood may be used to obtain parameter estimates, and provide inefficiency measures.

[2] When employing regression analysis in the second step to explain the variation of the efficiency scores, it is likely that the included explanatory variables fail to explain the entire variation in the calculated efficiencies and the unexplained variation mixes with the regression residuals, adversely affecting statistical inference. The use of a stochastic frontier regression model allows for the decomposition of the variation of the calculated efficiencies into a systematic component and a random component.

[3] Finally, our model employs panel data set. In contrast to other stochastic frontier specifications, the major advantage of this approach is that it does not require any *a priori* assumption regarding the distribution of efficiency across decision making units (Stephan et al., 2008).

[4] As far as the functional form of the stochastic production Function is concerned, estimation of the Stochastic Production Function requires a particular functional form of the production function to be imposed. A range of functional forms for the production function frontier are available, with the most frequently used being a translog function, which is a second order (all cross-terms included) log-linear form. As broadly described in Khalil (2005), the translog function is an attractive flexible function. This function has both linear and quadratic terms with the ability of using more than two factor inputs. Moreover, this is a relatively flexible functional form, as it does not impose assumptions about constant elasticities of production nor elasticities of substitution between inputs. It thus allows the data to indicate the actual curvature of the function, rather than imposing *a priori* assumptions.

- $t$ is a time – specific effect
- $ln$ represents the natural logarithm
- the subscript $i$ represents the $i^{th}$ industry
- $\beta$ is a vector of unknown parameters
- $V_i$ are the random variables which are assumed to be iid. $N(0, \sigma_v^2)$ and independent of the $U_i$ which are non – negative random variables, accounting for technical inefficiency in production, and assumed to be iid. $N(0, \sigma_U^2)$.

As a double - log form model (where both the dependent and explanatory variables are in natural logs), the estimated coefficients show elasticities between dependent and explanatory variables, relaxing the restrictions on demand elasticities and elasticities on substitution Fried (2008)[5]. The stochastic frontier production function and the technical inefficiency models are jointly estimated by the maximum-likelihood method.

## 3. Model Description

To investigate the determinants of the productive efficiency, we distinguish between two variable groups used in the econometric analysis:

1. First, variables internal to the industry, representing industry - type effects
2. Second, variables external to the industry, namely environmental variables, representing country – type effects

As far as the industry – specific variables are concerned, following a value added approach, and the analysis comprises:

1. Output (in Gross value added, volume indices, 1995 = 100)
2. Labour input (in Labour services, volume indices, 1995 = 100
3. Capital input (in Capital services, volume indices, 1995 = 100)
4. Moreover, the model includes a time variable to capture the effect of technical progress, namely representing technical efficiency across countries in the years 1980 - 2005.

For this analysis, the output is the dependent variable while the explanatory variables are the factors of production which are inputs into the production process. However, as an innovative approach, our analysis includes time as a specific variable, in order to capture evolution and differences in technical progress. Technical progress is a major value added determinant as new technologies allow the automation of production processes which lead to many new and improved products, allow for better and closer links between industries, and can help improve information flows and organization of production. At the same time, technical progress can be embodied in new equipment and trained workers may only be fully productive if there is the appropriate equipment with which to work. Increases in physical capital are clearly necessary as there are spillovers from capital investment to productivity growth. Generally, it is the combination of these three factors and the way in which they are organized and managed within the industry which determines the extent of productivity growth.

[5] However, the generality of the functional form produces a side effect: they are not monotonic or globally convex, as in the Cobb – Douglas model.

Maximum likelihood techniques are used to estimate the frontier and the inefficiency parameters. We adopt the standard flexible translog functional form to represent the technology, including the time variable *time* in order to account for technical change effects. More specifically, in our model, the three - input translog production function presenting both linear and quandratic terms and it may be written as follows:

$$\ln va = \alpha_0 + \beta_K \ln cap + \beta_L \ln lab + \beta_T time + \tfrac{1}{2}\beta_{KK} \ln cap^2 + \tfrac{1}{2}\beta_{LL} \ln lab^2 + \tfrac{1}{2}\beta_{TT} time^2 +$$

$$\beta_{KL} \ln cap \ln lab + \beta_{KT} \ln captime + \beta_{LT} \ln labtime + (v_{it} - u_{it})$$

where, $\alpha_0$ is the intercept of the constant term, $\beta_K, \beta_L, \beta_T$ are first derivatives, $\beta_{KK}, \beta_{LL}, \beta_{TT}$ are own second derivatives and $\beta_{KL}, \beta_{KT}, \beta_{LT}$ are cross second derivatives

## 4. Parameter Estimation

The parameters of the stochastic frontier model and the inefficiency effects model are estimated using maximum likelihood estimation (MLE), which is the preferred estimation technique whenever possible (Coelli, Rao and Battese 1998, Battese and Coelli, 1993)[6]. The parameters estimated include $\beta$, $\lambda$ and $\sigma^2$ where $\lambda = (\sigma_u / \sigma_v)$ and $\sigma^2 = (\sigma_u^2 + {}_v^2)$. Moreover, the model estimation results provide the joint probability density function (pdf) also known as the likelihood function. The likelihood function expresses the likelihood of observing the sample observations as a function of the unknown parameters $\beta$ and $\sigma^2$. The maximum likelihood (ML) estimator of β is obtained by maximizing this function with respect to $\beta$[7]. Specifically, the maximum likelihood estimator can be shown to be consistent and asymptotically normally distributed with variances that are no larger than the variances of any other consistent and asymptotically normally distributed estimator (i.e. the ML estimator is asymptotically efficient).

### 4.1 Existence of Technical Efficiency: The parameter λ

A main instrument to measure the inefficiency component of the model is the parameter $\lambda = \frac{\sigma_u^2}{\sigma_v^2}$. The statistical significance of $\lambda$ obtained from the ML estimates indicates the existence of a stochastic frontier function (Schmidt and Lin, 1984)[8]. If $\lambda$ is statistically different from zero, it implies that the difference between the observed and the frontier production is dominated by technical inefficiency[9]. If $\lambda$ is not statistically significant from zero, it implies that any difference in the production is attributed solely to symmetric random errors. In other words, industries operating on the frontier are accepted to be technically efficient and except for random disturbances, are receiving maximum output response for the combinations of the inputs used.

[6] According to Battese and Coelli (1995), the explanatory variables can include intercept terms or any variables in both the frontier and the model for the inefficiency effects, provided the inefficiency effects are stochastic.

[7] Thus, in the special case of the classical linear regression model with normally distributed errors, the ML estimator for β is identical to the OLS estimator.

[8] If the parameter $\lambda$ is significant, this indicates that the use of the frontier production function is appropriate.

[9] The parameter $\lambda$ is an indication that the one sided error term u dominates the symmetric error v, so variation in actual production comes from differences in industries management practice rather than random variability.

### 4.2 Measurement of Technical Efficiency: The parameter γ

Technical efficiency can be measured using a variance ratio parameter denoted by $\gamma$ as follows (Battese and Corra, 1977): $\gamma = \frac{\sigma_u^2}{\sigma^2}$, where $\sigma^2 = \sigma_u^2 + \sigma_v^2$ , $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$ and $0 \le \gamma \le 1$. Using the composed error terms of the stochastic frontier model, $\gamma$ defines the total variation in output from the frontier level of output attributed to technical efficiency[10] indicating the ratio of the unexplained error and the total error of the regression (Aigner, Lovell, Schmidt, 1977). The variance parameter $\gamma$ captures the total output effect of technical efficiency, suggesting the percentage (%) of the residual which is due to inefficiency. Considering the variance parameter $\gamma$ lies on the interval [0,1], if the estimate is close to 1 and significant, this indicates that most of the total variation in output is attributable to technical efficiency.

### 4.3 Measurement of Technical Efficiency: The LR – test parameter

Before proceeding with the estimation of the SF models, it is important to ascertain statistically whether technical inefficiency effects are indeed present in the model. The model for inefficiency effects can only be estimated if the inefficiency effects are stochastic and have a particular distributional specification. Hence, there is growing interest to test the null hypotheses that the inefficiency effects are not stochastic; the inefficiency effects are not present and the coefficients of the variables in the model for the inefficiency effects are zero. These null hypotheses are tested through imposing restrictions on the model and using using the generalized likelihood ratio statistic (LR - test) to determine the significance each of the restrictions (Greene, 2003, Coelli, 1998). The generalized likelihood ratio statistic (LR - test) is given by: $LR - test = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} = -2\ln\left[\frac{L(H_0)}{L(H_1)}\right]$, where $\ln[L(H_0)]$ and $\ln[L(H_1)]$ are the values of the log-likelihood function for the frontier model under the null and alternative hypotheses[11]. The LR - test indicates the ratio of standard deviation attributable to inefficiency relative to the standard deviation due to random noise. A straightforward implication of LR - test $\to 0$ is that either $\sigma_u^2$ goes to zero or $\sigma_v^2$ goes to infinity. Hence, no inefficiency exists and all deviations are due to random noise. Likewise, for LR - test $\to \infty$ we note that either $\sigma_u^2 \to \infty$ or $\sigma_v^2 \to 0$, which implies that all deviation are explained by inefficiency. Then, inefficiency is deterministic and resembles approaches excluding random noise[12], such as DEA (Koetter, 2006).

### 5. Empirical Implementation: Data Sources

Our analysis is based on estimating efficiencies as industry - specific fixed - effects at industry level of selected countries within European Union, during 1980 – 2005, employing the econometric software program LIMDEP 9.0. The countries selected to be included in the model are: Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, and United Kingdom, in order to create a data set including both countries with strong industrial productive base, such as Germany and France, as well as countries with low industrial productive base, such as Spain. The data used come from the EU KLEMS data base of sectoral accounts for productivity analysis (O' Mahony et al., 2008). We use the EU KLEMS sectoral classification,

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[10] A value of $\gamma = 0.12$ implies that 12% of the discrepancies between the observed and frontier values of output is due to technical inefficiencies.

[11] Various tests of null hypotheses for the parameters in the frontier production functions and in the inefficiency models are performed using the generalised likelihood-ratio test statistic.

[12] An insignificant estimate of LR - test means that no inefficiency prevails and all of the error is due to random noise and specification of a stochastic frontier model is inappropriate.

NACE 2 – digit level of industry disaggregating, comprising 13 manufacturing sectors: Electrical and optical equipment (30 - 33), Food products, beverages and tobacco (15 - 16), Textiles, textile products, leather and footwear (17 - 19), Manufacturing nec; Recycling (36 - 37), Wood and products of wood and cork (20), Pulp, paper, paper products, printing and publishing (21 - 22), Coke, refined petroleum products and nuclear fuel (23), Chemicals and chemical products(24), Rubber and plastics products (25), Other non-metallic mineral products (26), Basic metals and fabricated metal products (27 - 28), Machinery, nec (29), Transport equipment (34 - 35).

## 6. Description of the Variables

The model variables are transformed into natural logarithm forms, as presented in the table below. The depended variable is the natural logarithm of the product *(lnva)*, namely, value added. The independent variables are set to be the labour *(lab)* and capital services *(cap)*, along with time *(time)*, denoting technical progress. Employing the model data set, we form the logarithmic variables:

**Table 1:** Description of Variables

| Variable | Notation |
|---|---|
| Gross value added, volume indices, 1995 = 100 | va |
| Labour services, volume indices, 1995 = 100 | lab |
| Capital services, volume indices, 1995 = 100 | cap |
| Natural logarithm of VA | lnva |
| Natural logarithm of LAB | lnlab |
| Natural logarithm of CAP | lncap |
| 0.5 * (Natural logarithm of LAB * Natural logarithm of LAB) | lab2 |
| 0.5 * (Natural logarithm of CAP * Natural logarithm of CAP) | cap2 |
| 0.5 * (Time *Time) | time2 |
| Natural logarithm of LAB * Natural logarithm of CAP | labcap |
| Natural logarithm of LAB * Time | labtime |
| Natural logarithm of CAP * Time | captime |

Source: Own estimation

Furthermore, the industry dummy variables for the 13 industries (*ind1 – ind13*), as well as the industry composite dummy variables (denoting industry – specific effects) are created. In the first empirical analysis phase, all countries and sectors are included in the model simultaneously (composite dummies) to allow for technology differences, creating a dataset of 2704 observations. However, due to data - set irregularities, we exclude countries 1 and 2, as well as sector 7 from our current sample and also skip any missing values, resulting into o sample of 1872 observations – cases. Then we form the panel data set specification, for fixed – effects model, and proceed to estimation.

## 7. Empirical Model: Extended Translog Frontier Model

The analysis so far provides a solid background for further development of the model. Moreover, since any industrial sector may have in principle a different production function we add to the specification *m-1* intercept dummies for the industries aggregated. More specifically the model is extended in order to include industry specific effects (by employing industry composite dummies), so as to examine differences in efficiency level among different industries. For this reason, our model is estimated including the industry – specific composite dummies, as created above:

$$Y_{it} = \alpha_0 + \sum_{j=1}^{m-1} \alpha_j * Ind_j + \beta_1 K_{it} + \beta_2 L_{it} + \beta_3 T_{it} + v_{it} - u_{it}$$

However, this solution is not completely satisfactory as industry production functions may also differ in input marginal productivities. We therefore estimate the model including the cross products of industry dummies, as well as the first input products with the industry dummies. So the model becomes:

$$Y_{it} = \alpha_0 + \sum_{j=1}^{m-1} \alpha_j * Ind_j \sum_{j=1}^{m-1} \alpha j * Ind * input + \beta_1 K_{it} + \beta_2 L_{it} + \beta_3 T_{it} + v_{it} - u_{it}$$

We multiply the first and the cross – products by the industry dummies. In order to allow for industry – specific effects in the computation of the output elasticity for inputs, we have provided for the industry dummies to interact with the first – order terms. Two goals, first to account for different industry production function (*ind1 – ind12*), and second to account for different marginal input productivities (cross – products with industry dummies). The *ind 1 – ind12* dummies actually enter the equation by multiplying *lncap* to *time* by these variables and then entering these composite dummies to investigate whether factor inputs differ by industry.

Furthermore, one of the underlying objectives is to examine how environmental performance of the industries has an impact on the industry's technical efficiency. It is therefore important to explore what happens to the estimated model in the presence of environmental performance dummy variables. In order to analyze the determinants of productive efficiency, we relate the estimated productive efficiency to a number of explanatory variables and this is achieved when environmental performance dummy variables are included in the estimation. Under this model specification, we estimate different variations, so to investigate alternative model specifications. In this translog function we estimate the frontier model incorporating the industry dummies, as well as the industry - specific cross products, considering the variable *time* as explanatory variables in the inefficiency term. The results are as follows:

**Table 2:** Limited Dependent Variable Model

| **Limited Dependent Variable Model - FRONTIER** | |
|---|---|
| Dependent variable | LNVA |
| Number of observations | 1872 |
| Log likelihood function | 1748.065 |
| Number of parameters | 57 |
| Info. Criterion: AIC | -1.80669 |
| Finite Sample: AIC | -1.80475 |
| Info. Criterion: BIC | -1.63817 |
| Info. Criterion:HQIC | -1.74461 |
| Variances: Sigma-squared(v) | .00782 |
| Sigma-squared(u) | .35681 |
| Sigma(v) | .08845 |
| Sigma(u) | .59734 |
| Sigma | .60385 |

Source: Own estimation

The model is a frontier model estimated with panel data. The Stochastic Production Frontier is denoted as: e=v-u, whereas the time varying efficiency is denoted as: u(i,t)=exp[eta*z(i,t)]*|U(i)|. Table (3) presents the empirical results.

**Table 3:** Empirical Results

| Variable | Coefficient | Standard Error | b/St.Er. | P[\|Z\|>z] | Mean of X |
|---|---|---|---|---|---|
| Maximum Likelihood Estimates | | | | | |
| Constant | .61231161 | 2.76463153 | .221 | .8247 | |
| LNCAP | -1.53590514 | 1.04912420 | -1.464 | .1432 | 4.53813827 |
| LNLAB | 2.24809667 | .88569539 | 2.538 | .0111 | 4.64818191 |
| TIME | .07787319 | .04320160 | 1.803 | .0715 | 13.5000000 |
| LAB2 | -.41749862 | .26931712 | -1.550 | .1211 | 10.8158946 |
| CAP2 | .21626666 | .24352679 | .888 | .3745 | 10.3307444 |
| TIME2 | .00145739 | .00037297 | 3.908 | .0001 | 119.250000 |
| LABCAP | .12750300 | .19718155 | .647 | .5179 | 21.0930324 |
| LABTIME | -.00546179 | .00876350 | -.623 | .5331 | 62.3692144 |
| CAPTIME | -.01178820 | .00890251 | -1.324 | .1855 | 62.8256562 |
| IND1 | 1.59124129 | .55315646 | 2.877 | .0040 | .08333333 |
| IND2 | 1.20735416 | 2.65524722 | .455 | .6493 | .08333333 |
| IND3 | 2.82617018 | .84863628 | 3.330 | .0009 | .08333333 |
| IND4 | .49870893 | .50758200 | .983 | .3258 | .08333333 |
| IND5 | 1.65176018 | .60937735 | 2.711 | .0067 | .08333333 |
| IND6 | -.18807742 | 1.30616174 | -.144 | .8855 | .08333333 |
| IND8 | 2.62893768 | .65304159 | 4.026 | .0001 | .08333333 |
| IND9 | -2.31829478 | .56257237 | -4.121 | .0000 | .08333333 |
| IND10 | -.99593474 | 1.17762351 | -.846 | .3977 | .08333333 |
| IND11 | 1.10415113 | 1.26767380 | .871 | .3838 | .08333333 |
| IND12 | -.96021987 | .66428505 | -1.445 | .1483 | .08333333 |
| LNCAPD1 | -.25021330 | .09739517 | -2.569 | .0102 | .37753423 |
| LNLABD1 | -.14431649 | .09532048 | -1.514 | .1300 | .38837574 |
| TIMED1 | .01855404 | .00354949 | 5.227 | .0000 | 1.12500000 |
| LNCAPD2 | .30373226 | .37146868 | .818 | .4136 | .37617450 |
| LNLABD2 | -.47188219 | .26791478 | -1.761 | .0782 | .38535840 |
| TIMED2 | -.02662133 | .00444067 | -5.995 | .0000 | 1.12500000 |
| LNCAPD3 | -.28758516 | .17536909 | -1.640 | .1010 | .38133607 |
| LNLABD3 | -.23098084 | .11656763 | -1.982 | .0475 | .38972613 |
| TIMED3 | -.02452837 | .00503878 | -4.868 | .0000 | 1.12500000 |
| LNCAPD4 | -.38220997 | .11930744 | -3.204 | .0014 | .37960654 |
| LNLABD4 | .29580579 | .11590306 | 2.552 | .0107 | .38383682 |
| TIMED4 | -.00401915 | .00261014 | -1.540 | .1236 | 1.12500000 |
| LNCAPD5 | .32260660 | .17165433 | 1.879 | .0602 | .38112430 |
| LNLABD5 | -.61467125 | .14258846 | -4.311 | .0000 | .38450072 |
| TIMED5 | -.01679339 | .00765052 | -2.195 | .0282 | 1.12500000 |
| LNCAPD6 | .32297109 | .16440959 | 1.964 | .0495 | .37286709 |
| LNLABD6 | -.19233467 | .17343394 | -1.109 | .2674 | .38400415 |
| TIMED6 | -.02393778 | .00417977 | -5.727 | .0000 | 1.12500000 |
| LNCAPD8 | .00766992 | .09123279 | .084 | .9330 | .38079571 |
| LNLABD8 | -.54236140 | .11041434 | -4.912 | .0000 | .39087342 |
| TIMED8 | -.00717799 | .00280822 | -2.556 | .0106 | 1.12500000 |
| LNCAPD9 | 1.81865666 | .32534989 | 5.590 | .0000 | .37480414 |
| LNLABD9 | -1.13731518 | .32313174 | -3.520 | .0004 | .38228242 |
| TIMED9 | -.04895054 | .01447722 | -3.381 | .0007 | 1.12500000 |
| LNCAPD10 | .64598592 | .23494940 | 2.749 | .0060 | .37896495 |
| LNLABD10 | -.35734708 | .09825019 | -3.637 | .0003 | .38765447 |
| TIMED10 | -.02114090 | .00258184 | -8.188 | .0000 | 1.12500000 |
| LNCAPD11 | -.01068996 | .24513770 | -.044 | .9652 | .38435061 |
| LNLABD11 | -.12634486 | .10583010 | -1.194 | .2325 | .38898708 |
| TIMED11 | -.02512525 | .00451094 | -5.570 | .0000 | 1.12500000 |
| LNCAPD12 | .76113424 | .14608294 | 5.210 | .0000 | .38044290 |
| LNLABD12 | -.47142583 | .10465387 | -4.505 | .0000 | .38900706 |
| TIMED12 | -.02449134 | .00546854 | -4.479 | .0000 | 1.12500000 |
| Variance parameters for compound error | | | | | |
| Lambda | 6.75335710 | .03861506 | 174.889 | .0000 | |
| Sigma(u) | .59733899 | .05726644 | 10.431 | .0000 | |
| Coefficients in u(i,t)=[exp{eta*z(i,t)}]*\|U(i)\| | | | | | |
| TIME | -.13299303 | .00663005 | -20.059 | .0000 | |

Source: Own estimation

The log – likelihood value (1748.065) shows that the translog function provides good fit. However, only a number of the estimated coefficients are statistically significant for the two equations. The variance parameters $\lambda$ and $\sigma_u$ are both statistically significant, then there is evidence of technical inefficiency in the data. The variance parameter, $\gamma$, is approximately 0.97. This implies that of the total variation captured by sigma squared, 97% is as a result of the technical inefficiency in production processes while 3% could be attributed to other stochastic errors. The negative sign in the time trend means that overall technical inefficiency tends to decrease, since there is technical progress which decreases the inefficiency level.

## 8. Concluding remarks

This paper discusses the empirical findings of the technical and environmental efficiency of European Union industries in selected member - countries. The paper begins with a description of the model used, the data set used in the analysis and the definition of the variables. Then the empirical model is formed with estimation results. The results include reporting the estimated technical efficiency and the related explanatory variables. The paper provides the industry -level estimates of technical efficiency using the time-varying inefficiency model within a composite error framework.

From the analysis, it is evident that industries in the sample are far from being efficient. There is evidence that industries could improve their technical efficiency by being more technical efficient which entails choosing inputs and use them efficiently. Even though there is a notable improvement in technical efficiency after accounting for variations, technical inefficiency remains significant which calls for further investigation of the variations regarding to the alternative explanatory variables.

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