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TECHNICAL EFFICIENCY DETERMINANTS OF THE TUNISIAN MANUFACTURING INDUSTRY: STOCHASTIC PRODUCTION FRONTIERS ESTIMATES ON PANEL DATA

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In this paper, we analyze the development of technical efficiency in the Tunisian manufacturing sector using advanced analysis methods. The technical efficiency of the industrial sectors is measured on the basis of panel data through the bias of a classical approach and a Bayesian one, which makes the inefficiency terms change over time. This exercise helps to assess the robustness of the estimated technical efficiency compared to the choice of the estimation technique. The mean efficiency score is found to be of 77 percent and there is no evidence of a continuous increase in efficiency.

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JEL classification: C13, C15, D24, L6

1. INTRODUCTION

As defined by the pioneering work of Farrell (1957), the total efficiency is the ability to produce a given level of output at the lowest cost. According to Farrell, total efficiency can be decomposed into Technical Efficiency (TE) and Allocative Efficiency (AE). Technical efficiency is defined as the ratio of output to maximum output that can be produced from a given set of inputs. Allocative efficiency is defined as the efficiency measured in the context of using several inputs in optimal proportions, given the input and output prices (Shekhar, 2009). Economic Efficiency (EE) combines both of allocative and technical efficiencies. It is achieved when the producer combines resources to generating a maximum output (technical) and ensuring the least cost to obtain maximum revenue (allocative). This study aims at estimating the technical, allocative and economic efficiencies.

* All remaining errors are our own.

The efficiency of a firm or a sector can be measured through some parametric and nonparametric approaches which differ primarily in the assumptions concerning the residues. A production frontier will be deterministic if we impose a deterministic functional form (Cobb-Douglass, Translog, CES, etc.) and suppose that any gap between the estimated function and the observations is considered as coming from the producer's inefficiency. It is considered stochastic if the gaps are explained by both the producer's inefficiency and some random elements which are not under the owner's control. The parametric approaches impose a functional form that presupposes the frontier one, whereas the nonparametric approaches impose less structure on the frontier but suppose the absence of random errors.

The most often used parametric methods of estimation are the Ordinary Least Squares (OLS), the Corrected Ordinary Least Squares (COLS) and the Stochastic Frontier analysis (SFA). The main difference between these models is that the COLS attribute all the deviations to inefficiency, while the SFA model attributes a part of the deviations to inefficiency and the other part to the random noise. In other words, the SFA models take into account both of the inefficiency and the random noise. The most used stochastic frontier models include the stochastic production frontier, the stochastic cost frontier and the stochastic distance function models. Before choosing a specific model, analysts have to choose between the two most commonly used functional forms: the Cobb-Douglas and the Translog functions.

Van den Broeck *et al*. (1994) were the first to apply the Bayesian procedures for the estimation of the stochastic frontiers. They reported that these procedures provide accurate inferences about the scores of technical efficiency when the samples are small, incorporate the experts' opinions via the prior distributions, and easily incorporate restrictions, such as the regularity conditions. The estimation of the stochastic frontier models using the Bayesian approach requires the application of numerical integration methods. In this context, the Monte Carlo Markov Chain "MCMC" is the most appropriate method of Griffin and Steel (2005). It was used by Koop *et al*. (1995) and adopted by Kurkalova and Carriquiry (2002), Huang (2004) and Kumbhakar and Tsionas (2005). Kim and Schmidt (2000) compared the estimates of the stochastic and Bayesian approaches in the context of panel data. To deal with the requirements of the applied research on the stochastic frontier via the Bayesian approach models, Griffin and Steel (2005) developed a reliable and user-friendly software called "WinBUGS" that helps apply the MCMC method.

The objective of this paper was to identify the explanatory factors of technical, economic and allocative efficiencies in the Tunisian manufacturing industry. In a specific way, we would like to analyze the production organization and determine the level of the sector's efficiencies in manufacturing production. The answer to these questions will allow us to identify the sources and determinants of the Tunisian manufacturing efficiency or inefficiency.

Referring to the work of Djokoto (2012), Lin *et al*. (2012), Iain *et al*. (2006) and Inoni (2007), we applied the Bayesian approach of the stochastic production frontier models related to the linear and nonlinear regression models to the panel data models, to the variance components, to the random coefficients, and in general, to the models with unobserved heterogeneity. Indeed, we used the annual time series for the period 1961-2010 built by the Tunisian Institute of Competitiveness and Quantitative Studies for the Tunisian manufacturing sector (TICQS) such as: Agricultural & Food Industries (AFI); Building Materials, Ceramics & Glass (BMCG); Mechanical & Electric Industries (MEI); Chemical Industries (CHI); Textiles, Clothing & Leather (TCL) and Various Manufacturing Industries (VMI). We considered production technology of a single output and three inputs where the output is measured by the Gross Domestic Product (GDP). The inputs are labor (L), capital (K) and energy (E). All the inputs are measured by the appropriate amounts. We dealt with the capital as the only quasi-fixed input in the short run.

The rest of this work is organised as follows: in a second section, we presented the methodology of the classical and Bayesian stochastic frontier. The results of the first approach were shown in the third section, whereas those of the second approach were presented in the fourth section. Finally, the main findings were discussed in the last section.

2. METHODOLOGY

2.1. The Classic Approach

For a classical stochastic frontier model, we took into account a model with a variable term inefficiency over time:

$$y_{it} = X'_{it}\beta + v_{it} - u_{it}, \quad i = 1,...,N \quad \text{and} \quad t = 1,...,T, \tag{1}$$

where for firm *i* at time *t*, y_{it} denotes the logarithm of the output, X_{it} is an logarithm vector of *k* inputs, β is a vector of $[(k+l)\times 1]$ parameters to be estimated, v_{it} is the error term of normal distribution $\aleph(0,\sigma_v^2)$ which is, by hypothesis, independently and identically distributed (*i.i.d.*) and independent from u_{it}, and u_{it} is a non-negative term which represents the time-variable technical inefficiency. In this model, the technical efficiency is therefore defined by $TE = e^{-u_{it}}$, we also have $\varepsilon_{it} = v_{it} - u_{it}$ which shows the compound error term and $\varepsilon_i = (\varepsilon_{i1},...,\varepsilon_{iT})'$.

Equation (1) defines a general model of the parametric stochastic frontier which is consistent with several functional forms. The form of the production Translog function is:

$$y_{it} = \beta_0 + \sum_{l=1}^{k} \beta_l x_{l,it} + 0.5 \times \sum_{m \le l} \sum_{l=1}^{k} \beta_{ml} x_{m,it} x_{l,it} + v_{it} - u_{it} \,, \tag{2}$$

where $x_l, l = 1,...,k$ are the input logarithms, and k is the total number of inputs in the production process. In this case, we have $1 + k + k(k+1)/2$ parameters to be estimated. If $\beta_{ml} = 0, \ \forall \ m,l$, specification (**2**) becomes a Cobb-Douglas function.

The objective is attained by estimating the technical, economic and allocative efficiencies using a Translog stochastic production frontier function. Farrell (1957) provided the impetus for developing the literature on empirical estimation of these three efficiencies. The first objective is attained by estimating the technical efficiency. Therefore, the allocative efficiency is estimated following the physical production relationships derived from the Translog production function of Equation (2).

The technical efficiency is know to vary with time. Therefore, being considered constant, it can be a strong assumption that can be justified when the data do not cover long periods. In a competitive environment, Kumbhakar and Lovell (2000) recommend dropping this hypothesis even if this implies additional parameters to be estimated. Therefore we can replace the term u_i "*time invarying TE*" with u_{it}, which is called "*time varying TE*". Kumbhakar *et al*. (1991) were the first to suggest this refinement which represents an estimation problem since it involves estimating parameters $(N \times T + k + 1)$ with only $(N \times T)$ observations.

An alternative formulation suggested by Lee and Schmidt (1993) specifies $u_{it} = \beta(t) u_i$, where $\beta(t)$ is a monotonous function located between 0 and 1. For example, when $\beta = \beta(t)$, there is a set of binary time variables. This formulation seems to be more flexible than the first in that the effect in time is not necessarily monotonous. However, $\beta(t)$ temporal pattern is forced to remain the same for all the firms. This formulation is suitable in cases where T is not great, since $T - 1$ additional coefficients should be estimated. On the other hand, Kumbhakar (1990) proposed the $\beta(t) = [1 + \exp(\gamma.t + \delta.t^2)]^{-1}$ specification which requires the estimation of only two additional parameters γ and δ. Battese and Coelli (1992) suggested the $\beta(t) = \exp[-\gamma(t - T)]$ wording which requires the estimation of a single additional parameter.

We consider two specifications to model the time dependence for the technical inefficiency term. First, as it was proposed by Battese and Coelli (1992), we specify:

$$u_{it} = \eta_t . u_i \,, \tag{3}$$

where

$$\eta_t = e^{-\eta_0 (t - T)} \,. \tag{4}$$

Alternatively, we specify:

$$\eta_t = 1 + \eta_1(t - T) + \eta_2(t - T)^2, \tag{5}$$

where η_0, η_1 and η_2 are unknown parameters to be estimated and are non-negative *i.i.d.* truncations which follow a normal distribution $\aleph(\mu, \sigma_u^2)$ representing the firm's effect. This distribution of the firm's effect is a generalization of the semi-normal distribution proposed by Jondrow *et al*. (1982). It emphasized that the technical efficiency is affected by the sign and magnitude as long as it increases. The u_{it} value remains constant but decreases or increases when $\eta_0 = 0$, $\eta_0 > 0$ or $\eta_0 < 0$ respectively. This specification imposes the monotonicity of the technical efficiency over time, that is to say, it can only increase, decrease or remain constant. Polynomial specification (5) is less restrictive since it allows for quadratic effects. The main result of Battese and Coelli (1992) focuses on the conditional expectation of $e^{-u_{it}}$ which is derived from Equations (1)-(5) and represented by:

$$TE = E(e^{-u_{it}} | \varepsilon_i) = \left(\frac{1 - \Phi\left(\eta_t \sigma_i^* - \left(\mu_i^* / \sigma_i^*\right)\right)}{1 - \Phi\left(-\mu_i^* / \sigma_i^*\right)} \right) e^{-\eta_t \mu_i^* + \frac{1}{2}\eta_t^2 \sigma_i^{*2}}, \tag{6}$$

where $E(.|\varepsilon_i)$ is the operator of conditional expectation given that ε_i, $\Phi(.)$ is the cumulative distribution function of the normal standard, and

$$\mu_i^* = \frac{\mu \sigma_v^2 - V'_{\eta_t} \varepsilon_i \sigma_u^2}{\sigma_v^2 + V'_{\eta_t} V_{\eta_t} \sigma_u^2}, \text{ and } \sigma_i^{*2} = \frac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + V'_{\eta_t} V_{\eta_t} \sigma_u^2}. \tag{7}$$

V_{η_t} is a vector $(T \times 1)$ and all its elements are equal to η_t. The second result is the firms' average technical efficiency in each period:

$$TE_t = E(e^{-\eta_t u_i}), \tag{8}$$

where u_i is defined by (3) and given by (4) or (5). This is equivalent to:

$$TE_t = \left(\frac{1 - \Phi\left(\eta_t \sigma_u - \left(\mu / \sigma_u\right)\right)}{1 - \Phi\left(-\mu / \sigma_u\right)} \right) e^{-\eta_t \mu_i^* + \frac{1}{2}\eta_t^2 \sigma_i^{*2}}. \tag{9}$$

The empirical implementation of Equations (6) and (8), through the conventional statistical methods, is obtained by substituting the model parameters with the estimated coefficients by maximizing the likelihood function. Our empirical application was carried out with the "Stata 11.2" software.

The second specification used for the time dependence of technical inefficiency is the one developed by Battese and Coelli (1995), which allows for a decomposition of inefficiency in terms of macroeconomic variables. The non-negative terms u_{it}, and *i.i.d.* are obtained by zero truncations of the distribution $\aleph(0,\sigma_u^2)$ with average $Z_{it}\delta$ and a variance $\sigma_{u,r}^2$, where Z_{it} is a $(1\times m)$ vector of the variables conditioning the firms' technical inefficiency whereas δ is a $(1\times m)$ vector of the parameters to be estimated. Specifically, we would have:

$$u_{it} = Z_{it}\delta = \delta_0 + \sum_{j=1}^{m-1}\delta_j Z_{jit} + w_{it}\,, \tag{10}$$

where w_{it} is a normal random variable with zero mean and a truncated variance $\sigma_{u,r}^2$ such that for any combination *i*, *t* on a $w_{it} \geq -(\delta_0 + \sum_{j=1}^{m-1}\delta_j Z_{jit})$. This specification is similar but less restrictive than the one discussed by Reifschneider and Stevenson (1991). The model defined by Equations (1) and (10) can be estimated by the maximum likelihood method.

Following Chukwuji *et al.* (2006) and Inoni (2007), the allocative efficiency (AE) analysis is achieved by estimating a Translog production function. It is followed by computing the value of the marginal product (VMP_j) for each factor of production, which then is compared with the marginal input cost (MIC_j). Results from (2) give Beta (β_j):

$$\frac{\partial LnY}{\partial Ln X_j} = \frac{\partial y}{\partial x_j} = \frac{X_j}{Y}.\frac{\partial Y}{\partial X_j} = \beta_j + \beta_{jj}.x_j + \beta_{jl}.x_l\,. \tag{11}$$

Using the coefficient estimates from (11), the marginal product of the *j*th factor *X* is calculated as:

$$MP_j = \frac{\partial Y}{\partial X_j} = \left(\beta_j + \beta_{jj}.x_j + \beta_{jl}.x_l\right)\frac{Y}{X_j}\,, \tag{12}$$

where $AP_j = \dfrac{Y}{X_j}$ is the average product of the *j*th factor *X*.

The value of the marginal product of input $j(VMP_j)$ can be obtained by multiplying the marginal physical product (MP_j) by the price of output (p_y). Thus,

$$VMP_j = MP_j \times p_y . \tag{13}$$

The allocative Efficiency (AE) is defined as:

$$AE = \frac{VMP_j}{p_j}, \tag{14}$$

where p_j is the marginal cost of the of the *j*th input.

The allocative efficiency is determined by comparing the value of the marginal product of input $j(VMP_j)$ with the marginal factor cost (MIC_j). Since firms are price takers in the input market, the marginal cost of input *j* approximates the price of the factor *j*, p_{xj} (Grazhdaninova and Lerman, 2005). Hence, if $VMP_j > p_{xj}$, the input is underused and firm profit can be raised by increasing the use of this input. Conversely, if $VMP_j < p_{xj}$, the input is overused and to raise firm profits its use should be reduced. The point of allocative efficiency (maximum profit) is reached when $VMP_j = p_{xj}$ (Chavas *et al*., 2005).

Hence, a measure of firm specific economic efficiency (EE) is thus obtained from the estimated technical and allocative efficiencies as:

$$EE = TE \times AE . \tag{15}$$

That is $0 < EE < 1$ (Martin and Taylor, 2003).

2.2. The Bayesian Approach

Concerning the Bayesian stochastic frontier model, we provided the details of the Bayesian approach in terms of inference on both the technical efficiency scores obtained by (6) and (9) in the model context defined by Equations (1) and (3) and the evaluation of the effects of the explanatory variables on the technical efficiency on the basis of the model defined by Equations (1) and (10). We would discuss the Bayesian approach applied to the stochastic frontier model with an inefficiency term varying in time. We, first, described a general Bayesian approach and then discussed our application more specifically.

Let $\mathrm{Y} \equiv (y_1, y_2, ..., y_N)$ be a set of *N* observations of variable *Y* and $\theta \in \Theta$ a vector of unknown and unobservable parameters. Typically, classical inference procedures assume that θ is a vector of unknown and constant parameters to be estimated. The Bayesian approach considers that Y and θ are random variables either of which is characterized by a distribution. Conditional density $p(Y|\theta)$ defines the likelihood of the model in the classical meaning of the term. The density of the marginal distribution of θ, $p(\theta)$ is the ex ante density. One can now use the information contained in the sample of Y data to review the expected distribution for θ, and obtain its posteriori density:

$$p(\theta|Y) \propto p(\theta)\, p(Y|\theta)\,. \tag{16}$$

Inference on θ parameter distribution or any transformation of these parameters is based on the ex post $p(\theta|Y)$ distribution. As a result, the ex ante density of θ, $p(\theta)$, and the $p(Y|\theta)$ conditional density are combined to make the inference about the unobservable parameters θ.

The ex ante marginal density of each element of θ involves the evaluation of multiple integrals which are impossible to be analytically calculated. Numerical integration methods are very useful to overcome this problem. Intuitively, they proceed as follows: (*i*) draw-downs are carried out on the basis of the a posteriori $p(\theta|Y)$ distribution using the Monte Carlo method; (*ii*) these draw-downs can be seen as random samples derived from the a posteriori marginal distribution; (*iii*) the random samples are used to make statistical inferences about each parameter. Koop *et al*. (1995) argue that the Markov Chain Monte Carlo (MCMC) ensures more flexibility in the model specification. Like Griffin and Steel (2005), we use the WinBUGS software to use the MCMC technique in the estimation of a stochastic frontier. The ex ante and the different estimated models are specified as follows:

As for the β parameters of the production stochastic frontier of model (1), an ex ante normal multivariate distribution is assigned:

$$\beta \to \aleph(0, \textstyle\sum_{\beta}), \text{ where } \Sigma_{\beta} = diag(10^{-3})\,. \tag{17}$$

For the inefficiency term, as specified in Equations (3) and (4), we choose

$$\eta_t \to \aleph(0,1)\,, \tag{18}$$

which reflects the fact that, a priori, it is unclear the whether technical efficiency increases or decreases. For specification (3), we consider three possible distributions for the effect of firm u_i:

(a) $u_i \rightarrow Exp(\varpi)$ is an exponential distribution with an average of $1/\varpi$, where the ex ante of ϖ is also an exponential distribution of an average of $-1/(\ln\omega^*)$, which means that the median of the firm effect is equal to ω^*;

(b) $u_i \rightarrow Ga(\rho_1, \rho_2)$, as specified by Greene (1990) for the term of the technical inefficiency in the context of cross-sectional data. The ex ante of ρ_1 is such that $\rho_1 \rightarrow Ga(d_1, d_2)$ where $Ga(d_1, d_2)$ denotes the gamma distribution with the parameter shaped d_1 and with an average d_1/d_2. According to Griffin and Steel (2004), d_1 and d_2 are arbitrary real numbers; so, ρ_2 is given the value $-\ln\omega^*$, where ω^* is the ex ante median of the firm effect;

(c) $u_i \rightarrow \aleph^+(\xi, \kappa^2)$, is a truncated normal distribution with a positive value in which ξ is assigned a normal distribution with mean zero and variance 10^{-3}; the a priori of κ^2 is such that $\kappa^2 \rightarrow Ga(d_0, d_1)$, where $d_0 = d_1 = 10^{-3}$.

The effects of the explanatory variables are assigned independent normal a priori distribution, such as $\delta_k \rightarrow \aleph(0, 10^{-3})$ where $k = 0, 1, ..., m-1$. Two distributions are also taken into account for the error term v_{it} : (i) $v_{it} \rightarrow N(0, \sigma_v^2)$, $\sigma_v^{-2} \rightarrow Ga(d_0, d_1)$, where $d_0 = d_1 = 10^{-3}$; (ii) to take into account a tail possible effect that can impact the distributions of the stochastic frontier, v_{it} is specified as a student-t distribution with τ degrees of freedom, in which τ is assigned an exponential mean a priori and a standard deviation equal to 4.

Graphical representations of the posterior distribution can indicate problems with the performance of the MCMC algorithm. More sophisticated methods for convergence detection are implemented in the Convergence Diagnostic and Output Analysis (CODA) software. The WinBUGS produces an output formatted for direct use with these programs and allows the behaviour of the chain to be investigated using some popular statistical tests.

The various models of the stochastic frontier, which are obtained by making different combinations of the error terms and of inefficiency, are estimated and compared through the Bayesian criterion of deviation “DIC”.

The WinBUGS automatically implements the DIC (Spiegelhalter *et al*., 2002) model comparison criterion. This is a portable information criterion quantity that trades off goodness-of-fit against a model complexity penalty. In hierarchical models, deciding the model complexity may be difficult and the method estimates the “effective number of parameters” denoted here by p_D. $\overline{D}$ is the posterior mean of the deviance and $\hat{D}$ is a *plug-in* estimate of the latter based on the posterior mean of the parameters. The DIC is computed as $DIC = \overline{D} + p_D = \hat{D} + 2p_D$. Lower values of the criterion indicate better fitting models.

3. ESTIMATES OF THE STOCHASTIC PRODUCTION FRONTIER MODELS AND THE EFFICIENCY COMPONENTS

The parametric approach of the production frontier and the efficiency measures depend on the estimation of a production function. Fixing the functional form of technology is of course a restrictive step. The efficiency measures are related to empirical observations and have no relationship with the production possibilities frontier in the context of the neoclassical theory. This problem is worsened by the fact that any measure is conditioned by a single productive combination obtained by translating the production function to the point of tangency of the highest curve. In contrast, the estimation of a production function helps to correct the technical efficiency degrees of the structural impact of the exogenous variables on the internal management.

In our empirical analysis, we consider two stochastic production frontier models with variable inefficiency term: the Cobb-Douglass and Translog models. The parameters of our stochastic frontiers are estimated using the maximum likelihood. Thus, the Cobb-Douglas production frontier with variable returns to scale (*VRS*) can be written as follows:

$$\begin{aligned} LnY_{it} &= \beta_0 + \beta_K LnK_{it} + \beta_L LnL_{it} + \beta_E LnE_{it} + \beta_t t + \beta_{tK} tLnK_{it} + \beta_{tL} tLnL_{it} \\ &\quad + \beta_{tE} tLnE_{it} + v_{it} - u_{it}, \end{aligned} \tag{19}$$

where t is the observation period ($t = 1,...,T$) of sector i ($i = 1,...,N$). The u_{it} have a positive value that represents the technical inefficiency of sector i at time t, and are supposed to be independently distributed. They are obtained by the truncated normal distribution (in zero) with $\aleph(m_{it};\sigma_u^2)$ distribution. In reference to Helali and Kalai (2015), the Translog production frontier with *VRS* is written as follows:

$$\begin{aligned} LnY_{it} &= \beta_0 + \beta_K LnK_{it} + \beta_L LnL_{it} + \beta_E LnE_{it} + \beta_t t + 0.5\beta_{KK}(LnK)_{it}^2 \\ &\quad + 0.5\beta_{LL}(LnL)_{it}^2 + 0.5\beta_{EE}(LnE)_{it}^2 + 0.5\beta_{tt}t^2 + \rho_{KL} LnK_{it}.LnL_{it} \\ &\quad + \rho_{KE} LnK_{it}.LnE_{it} + \rho_{LE} LnL_{it}.LnE_{it} + \beta_{tK}\, tLnK_{it} + \beta_{tL}\, tLnL_{it} \\ &\quad + \beta_{tE}\, tLnE_{it} + v_{it} - u_{it}, \end{aligned} \tag{20}$$

where the time variable t is introduced to take into account any technological change in the production function, which would have been adopted by all the producers.

To check if the Cobb-Douglas production function can advantageously substitute the Translog specification, we use the likelihood ratio test (LR) to prove whether the Translog general functional form, as specified, dominates the Cobb-Douglas functional form. Thus, we denote the Cobb-Douglas model by M1 and the Translog specification by M2. The specification of the technological change lies in M1 and M2 since it is obtained it by neutralizing the quadratic and the cross-effect coefficients of the logarithms of inputs and time variables. The third model, which is denoted by M3, corresponds to the M1 model with technological change restrictions. This implies that there is no technological change in the production process. Finally, the last model, which is denoted by M4, corresponds to the M2 model with restrictions involving the absence of technological change in the production process. M4 is a Translog model with neutral technological change, that is to say, it does not promote the use of certain inputs to the detriment of others.

Table 1. Estimates of Cobb-Douglas and Translog Production Functions

Variables	Cobb-Douglas		Translog	
	M1	M3	M2	M4
β_K	0.212***	0.028	0.683**	-0.107
β_L	0.117*	0.369***	1.189***	-0.46
β_E	0.904***	0.098**	0.097**	0.619
β_t	-0.180***	0.013***	0.083**	-0.019
β_{KK}	-	-	0.194***	-0.040
β_{LL}	-	-	-0.075	0.043
β_{EE}	-	-	0.364***	0.442***
β_{tt}	-	-	-0.0002	0.0004
β_{KL}	-	-	0.085***	0.128***
β_{KE}	-	-	-0.185***	-0.172***
β_{LE}	-	-	0.029	0.122**
β_{tK}	0.006***	-	-0.025***	-
β_{tL}	0.012***	-	0.014***	-
β_{tE}	0.023***	-	0.014***	-
Constant	10.79***	5.102***	6.08***	7.50***
σ_u^2	0.007	0.012	0.040	0.024
σ_v^2	0.034	0.047	0.024	0.027
σ^2	0.041	0.060	0.063	0.051
γ	0.174***	0.218***	0.629***	0.469***
η	0.062***	0.050***	0.044***	0.045***
μ	0.151***	0.217***	0.218	0.460***
Log Likelihood	61.28	16.14	116.19	94.46
Wald Test	955.1(7)	766.62(4)	875.6(14)	389.95(11)

Note: ***, ** and *: significant at 1%, 5% and 10%.

We assume that the error terms v_{it} are independent and identically distributed according to $\aleph(0;\sigma_v^2)$. The technical inefficiency is assumed to vary according to the specification of Equation (10). Moreover, it seems that the technical inefficiency can be written as $u_{it} = z_{it}\delta + w_{it}$, where the random variable is defined by a truncated normal distribution of zero mean and variance σ_u^2 (the truncation point being $-z_{it}\delta$). Similarly, we assume that w_{it} is independent from v_{it}. The error terms are assumed to be independent from each other and from the input. The parameters associated with v_{it} and u_{it} are $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2 / \sigma_u^2 + \sigma_v^2$.

Based on the specifications of v_{it} and u_{it}, we have estimated the models by the maximum likelihood method. Table 1 reports the estimating results of the parameters of the stochastic production frontier models and the associated significance. Since M1, M3 and M4 models are nested in M2, the LR test is used to check the plausibility of the imposed restrictions. The results are reported in Table 2. It appears, from this table, that all the imposed restrictions on M3 or M4 models are rejected at a 5% threshold. Thus, the dominant specification is the general specification of the Translog production frontier where the technical efficiency varies according to the selected model.

Table 2. Hypotheses Tests of Cobb-Douglas and Translog Functions

Tests	Null Hypothesis	Degree of Freedom	Statistics Test	Critical value at 5%
Cobb-Douglas : Neutral Technical Progress	$\beta_{tK} = \beta_{tL} = \beta_{tE} = 0$ M1 vs M3	3	90.272	7.815
Translog : Neutral Technical Progress	$\beta_{tK} = \beta_{tL} = \beta_{tE} = 0$ M2 vs M4	3	43.458	7.815
Cobb-Douglas vs Translog	$\beta_{KK} = \beta_{LL} = \beta_{EE} = \beta_{tt} = \beta_{KL} = \beta_{KE} = \beta_{LE} = 0$ M1 vs M2	7	109.824	14.067

In the previous models, the part of the inefficiency term in the total variance, which is estimated by the ratio $\gamma = \sigma_u^2 / \sigma_u^2 + \sigma_v^2$, is significant. The LR test of asymmetric term compares the null hypothesis estimate of $H_0 : \gamma = 0$ and the alternative hypothesis estimate of $H_1 : \gamma > 0$. For a truncated normal distribution, the critical value is the result of a joint χ^2 distribution. In addition, the γs are significantly inferior to one, which justifies the importance of the stochastic term *v*. In the opposite case, there would be no significant difference with a deterministic frontier estimation.

The gamma value (γ) tells us that the deviation from the frontier is explained by the inefficient sectors at 63%. The evaluation of γ, which is significantly different from zero, indicates the existence of production inefficiencies. This result means that the gap between the real output and potential output of the studied sectors is partly due to their inefficiency. The γ value may seem relatively high compared to the results of the Translog function, in particular, for determining the efficiency of individual sectors.

Indeed, in our study, 37% of the difference between the real and potential sectoral outputs are related to random effects, such as measurement errors arising generally from the nature of the data. Moreover, this value of γ is significantly inferior to one, which justifies the importance of the stochastic term v. In addition, the value of η is significantly different from zero, which indicates that the level of the technical inefficiency has changed a lot over the considered 50 years. Finally, we retained the half-normal distribution for the inefficiency term (u_{it}) where the parameter mu (μ) is restricted to zero for the Translog function. From the above estimates, we shift to the estimation of three types of efficiency: technical, allocative and economic. Table 3 summarizes the results of the technical efficiency estimated by the Cobb-Douglas and the Translog production functions with and without trend. The obtained average scores are very converging. However, the temporal evolution of these efficiency scores (see Figure 1) are cyclical but decreasing along the study period.

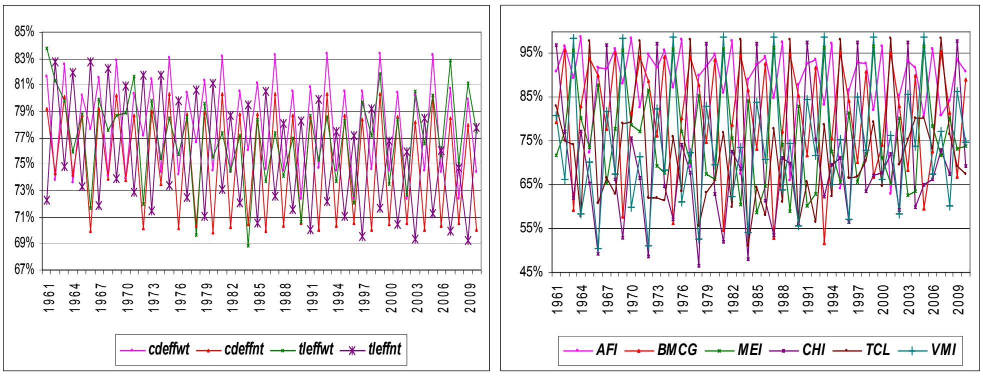
Table 3. Mean Scores of Production Functions Technical Efficiencies in Percentage

	CDEFFWT	CDEFFNT	TLEFFWT	TLEFFNT
Minimum	72.35	69.81	68.29	69.28
Maximum	83.35	80.37	79.63	82.78
Average	77.97	75.10	74.79	75.53
Standard Deviation	3.78	4.32	3.58	4.32
R	-8.9	-11.6	-11.0	7.6
r	-0.2	-0.3	-0.2	0.1

Note: EFF: Efficiency; CD: Cobb-Douglas, TL: Translog, WT: with trend, NT: no trend, R: Overall growth rate, r: Average annual growth rate.

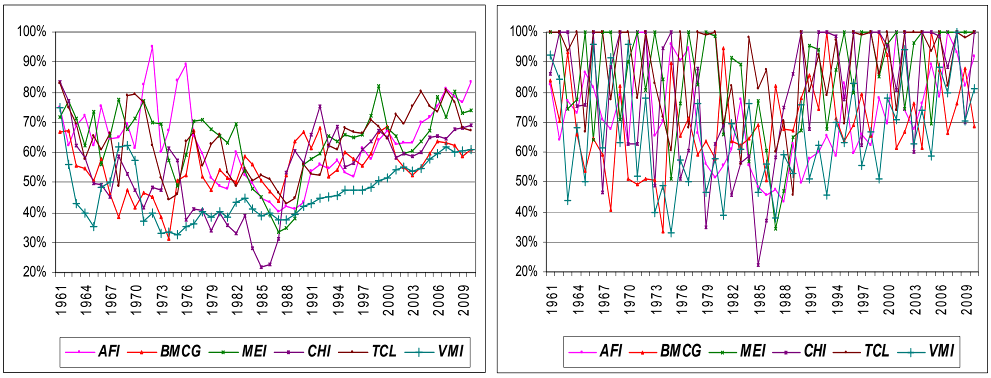
In total, and for the measure of the Translog function efficiency with trend of M2 model (TLEFFWT), the efficiency scores vary between 69% and 80% with a standard deviation of 3.6%. This evolution is characterized by a slight decrease of the average annual growth rate to the order of 0.2%.

At the sectoral level, we presented, in Figures 1 and 2, the evolution of the three components of technical, economic and allocative efficiencies. In addition, we displayed, in Table 4, the descriptive statistics of these efficiency scores. The econometric results show that the arguments of the production function have a particular significant impact on the technical efficiency in the AFI and TCL sectors.



Notes: cd: Cobb-Douglas, tl: Translog, eff: Efficiency; wt: with trend, nt: no trend.
AFI: Agricultural & Food Industries; BMCG: Building Materials, Ceramics & Glass; MEI: Mechanical & Electric Industries; CHI: Chemical Industries; TCL: Textiles, Clothing & Leather and VMI: Various Manufacturing Industries.

Figure 1. Global and Sectoral Evolutions of Different Estimated Technical Efficiencies



Note: AFI: Agricultural & Food Industries; BMCG: Building Materials, Ceramics & Glass; MEI: Mechanical & Electric Industries; CHI: Chemical Industries; TCL: Textiles, Clothing & Leather and VMI: Various Manufacturing Industries.

Figure 2. Sectoral Evolutions of Economic (1st) and Allocative (2nd) Efficiencies

Table 4. Descriptive Analysis of Various Components of Efficiency in Percentage

	AFI	*BMCG*	*MEI*	*CHI*	*TCL*	*VMI*	*Average*
Economic Efficiency (EE)							
Minimum	40.33	31.46	33.32	21.68	43.08	32.54	*38.78*
Maximum	94.87	68.61	82.13	83.40	82.91	74.88	*75.74*
Average	62.91	54.88	63.76	53.81	63.05	46.94	*57.56*
S_D	13.08	8.46	11.48	14.15	11.04	9.68	*8.22*
R	11.3	-8.7	3.0	-17.0	-18.8	-18.9	*-8.6*
r	0.2	-0.2	0.1	-0.4	-0.4	-0.4	*-0.2*
Allocative Efficiency (AE)							
Minimum	43.22	33.36	34.60	22.27	45.72	32.99	*53.45*
Maximum	100.00	100.00	100.00	100.00	100.00	100.00	*94.96*
Average	71.87	70.12	85.03	78.91	88.01	65.33	*76.55*
S_D	15.83	15.38	17.09	21.86	14.87	17.18	*9.56*
R	11.4	-18.6	0.0	16.2	0.0	-12.2	*-0.7*
r	0.2	-0.4	0.0	0.3	0.0	-0.3	*0.0*
Technical Efficiency (TE)							
Minimum	62.88	51.76	58.77	46.54	51.19	50.34	*68.87*
Maximum	98.83	95.62	96.75	97.80	98.45	98.91	*83.79*
Average	88.32	80.37	76.20	70.20	72.85	74.27	*77.04*
S-D	9.37	13.12	11.43	14.94	13.51	14.29	*3.41*
R	-0.1	12.2	3.0	-28.6	-18.8	-7.6	*-7.5*
r	0.0	0.2	0.1	-0.7	-0.4	-0.2	*-0.2*

Notes: S-D: Standard Deviation.

AFI: Agricultural & Food Industries; BMCG: Building Materials, Ceramics & Glass; MEI: Mechanical & Electric Industries; CHI: Chemical Industries; TCL: Textiles, Clothing & Leather and VMI: Various Manufacturing Industries.

The obtained efficiency scores, which are listed in Table 4, enable us to conclude that the AFI sector is technically and economically the most efficient. Therefore, this sector promotes its productive resources better especially the capital. However, the CHI sector is technically and allocatively the least efficient, and that of the BMCG is the least technically, economically and allocatively efficient. In addition, the MEI sector is allocatively the most efficient.

Indeed, the obtained economic efficiency scores show that by avoiding these inefficiencies, we can increase the production of the various sectors. Given the significant scope of the sectoral production growth (at a given level of production by minimizing the cost), we proceeded to identify the determinants of the efficiency levels that will subsequently serve as growth levers for programs of sectoral performance improvement. These results show that there is a significant potential to improve the level of the economic sector efficiency and the overall industry.

It is now interesting to see the statistical significance of the factors that affect the different obtained scores. To this end, we applied the Tobit estimates by defining the technical (TE), economic (EE) and allocative (AE) efficiencies as dependent variables and several macroeconomic factors as independent variables. Productivity: a dummy variable to express the level of the capital average productivity (CAP) of the sector (three groups: low (1), medium (2) and high (3) productivity); Trade [Log(Trade)]: an index measuring the importance of trade in the sector (Trade=[Exports+Imports]/GDP); Labor [Log(L)]: total number of workers; Consumption [Log(Cons)]: the level of intermediate consumption.

From Figures 1 and 2 of the efficiencies evolution, we notice that the six sectors are grouped into three groups of productivity: BMCG and CHI are low, MEI and VMD are medium and AFI and TCL are high. The results deriving from the Tobit model regarding the explanation of technical, allocative and economic efficiencies of the industrial sectors levels are shown in Table 5. These results are related to the explanatory effect of the selected factors of efficiency levels and their significance.

Table 5. Inefficiency Explanation (Tobit Regression)

Variables	Technical efficiency	Economic efficiency	Allocative efficiency
CAP_high	1.025^{***}	0.608^{***}	0.489^{***}
CAP_medium	0.986^{***}	0.535^{***}	0.412^{***}
CAP_low	0.979^{***}	0.528^{***}	0.419^{***}
Log(Trade)	-0.035^{***}	-0.0002	0.052
Log(L)	-0.027^{***}	-0.0003^{***}	0.038^{**}
Log(Cons)	0.010	0.0036	-0.010
Log Likelihood	*182.92*	*201.64*	*-43.15*

Note: *** and **: significant at 1% and 5% .

Table 5 shows the statistical significance of the coefficients related to:

All the productivity levels: the effect of high- productivity sectors is more important compared to others. The more the average productivity of the sector increases, the more inefficiency decreases.

The openness level: the more the business activity increases, the more the technical efficiency decreases and the allocative efficiency increases. The increase of the international transactions improves the allocative efficiency and reduces inefficiency. In contrast, this increase does not affect the economic efficiency.

Labor: the increased number of a sector workers, especially unskilled, causes an increase in the difference of the total cost and reduces efficiency.

Furthermore, the level of intermediate consumption showed no influence on the different efficiencies.

The overall table obtained from the regression analysis shows that large areas, which have a high or medium productivity, significant industrial activities, are profitable. The results show that there is a correlation between the efficiency levels and some of the factors among the selected ones. Therefore, the effect of the rest of the factors on efficiency levels is negligible or even insignificant.

The results also point to the importance of examining not only TE, but also AE and EE when measuring productivity at the firm level. The implication of these findings (TE, EE and AE) point to the fact that, given the production resources at the disposal of the sectors which consist of both medium and small enterprises with limited resources, efficiencies are unfair. It is evident that variation in the economic efficiency largely comes from the difference in the allocative efficiency.

An important conclusion stemming from the analysis is that the overall economic efficiency (EE) of the manufacturing sectors could be improved substantially and that the allocative efficiency constitutes a more serious problem than the technical inefficiency as TE appears to be more significant than AE as a source of gains in EE. Hence, it is from this point of this view that one would like to point out that despite the role a slightly higher efficiency level can have on output, productivity gains resulting from technological innovations remain critical in the manufacturing sectors of Tunisian economy.

4. PRODUCTION BAYESIAN STOCHASTIC FRONTIERS ESTIMATES

The comparison of the results of the classical and Bayesian approaches is one of the objectives of this study. For this reason, we would ideally estimate the dominant models M1 and M2 for the production function using the Bayesian technique. Thus, we could have estimated a Cobb-Douglas and Translog frontiers with a technological change (model M1 and M2) representing the specification of the time dependence of technical efficiency. Furthermore, we use four types of distributions: the exponential, the gamma, the Half-normal and the Truncated Normal (Griffin and Steel, 2005). Moreover, we would describe the steps involved in estimating the models by the MCMC technique using the WinBUGS software. It turns out that WinBUGS is a very powerful and flexible tool for the Bayesian stochastic frontier analysis. Indeed, the MCMC method requires the knowledge of the Bayesian statistics, including the recognition of the potential importance of the prior distributions.

Indeed, the basic model was designated to present the producers' outputs with a maximum production frontier. If a production panel is observed, a simple regression model of the production logarithm y_{it}, associated with the observed sector *i* at time *t*, on a set of explanatory variables x_{it}, will be in the logarithm of input quantities $y_{it} \to \aleph(\alpha + x'_{it}\beta + u_{it}, \sigma^2)$, where $\aleph(\mu, \sigma^2)$ denotes a normal distribution with a mean μ and variance σ^2. The u_{it} inefficiency models the difference between the best practices and the real output, where the formers are supposed to have a unilateral distribution, such as exponential (as it is in Meeusen and Van Den Broeck, 1977).

Let's thus define, $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2 / \sigma_u^2 + \sigma_v^2$ the model parameters. For our Bayesian estimation, we, first, assume that the specific industry term u_{it} has an exponential distribution with the $1/\lambda$ mean. The a priori distribution of λ is $\lambda \to Exp(-\log r^*)$, which implies that the median technical efficiency is r^*, with $r^* = 0.85$. We can then carry out our comparative analysis for M1 and M2 models and for the two production functions. The comparison of the results of both functions is presented in Tables 6 and **7**. It is very easy to change some of the hypotheses of the above models. For example, we can use several inefficiency distributions, such as the half-normal used by Aigner *et al*. (1977) or the truncated normal of Stevenson (1980). For the half-normal distribution, we have $u_i \to \aleph^+(0, \lambda^{-1})$, whereas for the truncated normal distribution, we have $u_i \to \aleph^+(\xi, \lambda^{-1})$.

In this section, we used the M1 and M2 models of the third section, where we have $T = 50$, with the different distributions of inefficiency defined above. The chain was carried out with 1000 iterations of a sample of 10000 observations. The WinBUGS has a number of tools to take the posterior distribution into account.

Table 6. Cobb-Douglas Production Function Estimates of Exponential Distribution

Node	*Average*	*S-D*	*MC σ*	*2.5%*	*Median*	*97.5%*	*Outset*	*Sample*
Constant	-2.0040	0.4793	0.0297	-2.9480	-2.0000	-1.0570	1001	10000
β_L	0.4606	0.0348	0.0005	0.3928	0.4604	0.5281	1001	10000
β_K	-0.0256	0.0503	0.0011	-0.1251	-0.0257	0.0731	1001	10000
β_E	0.3525	0.0713	0.0031	0.2103	0.3542	0.4908	1001	10000
β_t	0.1034	0.0201	0.0004	0.0638	0.1034	0.1433	1001	10000
β_{tY}	-0.0102	0.0032	0.0001	-0.0165	-0.0102	-0.0038	1001	10000
β_{tK}	0.0032	0.0024	0.0001	-0.0014	0.0032	0.0078	1001	10000
β_{tE}	0.0026	0.0025	0.0000	-0.0022	0.0027	0.0075	1001	10000
eff[1]	0.1415	0.0303	0.0028	0.0824	0.1461	0.1924	1001	10000
eff[2]	0.5764	0.1188	0.0107	0.3377	0.6001	0.7615	1001	10000
eff[3]	0.3208	0.0691	0.0063	0.1866	0.3308	0.4375	1001	10000
eff[4]	0.8147	0.1537	0.0138	0.4854	0.8611	0.9947	1001	10000
eff[5]	0.1201	0.0314	0.0027	0.0650	0.1199	0.1855	1001	10000
eff[6]	0.2170	0.0552	0.0048	0.1189	0.2177	0.3273	1001	10000
λ	0.9212	0.3832	0.0144	0.3467	0.8685	1.8220	1001	10000
σ^2	0.0854	0.0071	0.0001	0.0726	0.0850	0.1001	1001	10000

Note: MC σ represents Monte Carlo error and S-D represents Standard Deviation.

A simple summary can be generated showing the posterior mean, the median and the standard deviation at 95% of the posterior credibility interval. The parameter names are related in an obvious way to the initial model. More comprehensive images of the posterior distribution can be provided using the density option in the toolbar which provides an estimate of the density of the core of the posterior distribution of a selected parameter, as it is in the following graphs. Table 6 shows the estimated regression parameters of the Cobb-Douglass production frontier for the Bayesian specification of the exponential distribution. These estimates represent the factor elasticities as well. Comparing these results with those obtained by the SFA method, we notice that they are of different signs and amplitudes. The same results are obtained for the case of the Translog function (Table 7). Nevertheless, there are some similarities for some parameters, namely the trend coefficients.

Table 7. Translog Production Function Estimates of Exponential Distribution

Node	*Average*	*S-D*	*MC* σ	*2.5%*	*Median*	*97.5%*	*Outset*	*Sample*
Constant	1.5090	2.7230	0.0907	-3.7870	1.4570	6.9740	1001	10000
β_K	-1.0130	0.6007	0.0161	-2.2100	-1.0040	0.1522	1001	10000
β_L	1.5370	0.6352	0.0160	0.2836	1.5440	2.7790	1001	10000
β_E	-0.5970	0.6900	0.0275	-1.9680	-0.5849	0.7509	1001	10000
β_t	0.1227	0.0723	0.0024	-0.0166	0.1209	0.2678	1001	10000
β_{KK}	-0.0345	0.0079	0.0002	-0.0503	-0.0344	-0.0191	1001	10000
β_{LL}	0.0044	0.0081	0.0002	-0.0119	0.0045	0.0200	1001	10000
β_{EE}	0.0290	0.0078	0.0003	0.0133	0.0291	0.0442	1001	10000
β_{tt}	0.2488	0.0782	0.0015	0.0954	0.2487	0.4032	1001	10000
β_{KL}	-0.1085	0.1075	0.0026	-0.3193	-0.1074	0.1026	1001	10000
β_{KE}	0.3180	0.1192	0.0047	0.0855	0.3158	0.5563	1001	10000
β_{LE}	0.0008	0.0007	0.0000	-0.0005	0.0008	0.0021	1001	10000
β_{tK}	0.0718	0.0551	0.0011	-0.0334	0.0712	0.1794	1001	10000
β_{tL}	0.0336	0.0625	0.0017	-0.0884	0.0337	0.1572	1001	10000
β_{tE}	-0.3732	0.0914	0.0027	-0.5509	-0.3733	-0.1960	1001	10000
eff[1]	0.0822	0.0185	0.0017	0.0487	0.0827	0.1175	1001	10000
eff[2]	0.3936	0.0806	0.0073	0.2382	0.4005	0.5360	1001	10000
eff[3]	0.1837	0.0421	0.0038	0.1080	0.1845	0.2673	1001	10000
eff[4]	0.8168	0.1439	0.0126	0.4974	0.8527	0.9943	1001	10000
eff[5]	0.1021	0.0317	0.0027	0.0543	0.0981	0.1712	1001	10000
eff[6]	0.1423	0.0350	0.0031	0.0813	0.1417	0.2164	1001	10000
λ	0.7256	0.2932	0.0096	0.2766	0.6858	1.4020	1001	10000
σ^2	0.0652	0.0056	0.0001	0.0554	0.0649	0.0769	1001	10000

Note: MC σ represents Monte Carlo error and S-D represents Standard Deviation.

The comparison of the posterior efficiency distributions of the different sectors shows a clear difference in the descriptive characteristics of the different sectors and even a large difference in the efficiency scores compared to the SFA models. Hence, there is a strong technical inefficiency of the Chemical Industry sector compared to the others. In addition, there is a considerable variation in the mentioned results.

In Figure 3, we show the inefficiency evolutions of the various sectors. As discussed above, the Bayesian estimation shows strong inefficiencies in most of the sectors as previously described in the classical estimate. The most efficient sectors are the AFI and the TCL, while the least are obviously the BMCG and the CHI. Although the Bayesian estimates are different, generally for the SFA estimates, the efficiency results (i.e., inefficiency) are almost the same showing the significant under-utilization of the available resources in the Tunisian manufacturing sector.

A practically interesting function measuring the specific efficiency of each sector is given by the determination of the ranks of efficiencies in each level of confidence. The WinBUGS can automatically calculate, in the sample, a rank of the different efficiencies depending on the used posterior distribution. Table 8 shows a ranking of the six sectors by the production function and the level of confidence. It is always evident that the AFI and the TCL sectors are more efficient compared to others. They hold the first classes. The CHI sector ranks last. Once again, this justifies the previous results. In addition, the posterior distribution clearly shows a large extent of classifications.

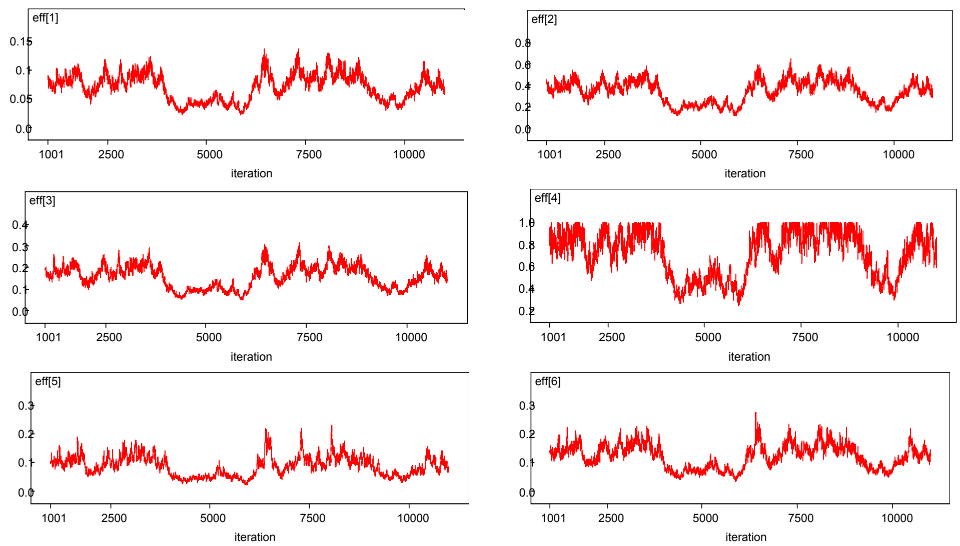


Figure 3. Evolution of Inefficiencies in the Sample: Translog

Table 8. Rank Efficiencies by Quantile of Exponential Distribution

Node	Cobb-Douglas			Translog		
	2.5%	Median	97.5%	2.5%	Median	97.5%
eff[1]	1	2	2	1	1	2
eff[2]	5	5	5	5	5	5
eff[3]	4	4	4	4	4	4
eff[4]	6	6	6	6	6	6
eff[5]	1	1	2	1	2	2
eff[6]	3	3	3	3	3	3

Once this model has been fitted successfully, we can consider some modelling options. As already noted above as there are alternative choices for the inefficiency distribution. We have considered three types of distributions: Gamma, Half-Normal and Truncated Normal.

Table 9. Bayesian Estimates of the Cobb-Douglas Production Function of Other Distributions

Distributions	Gamma			Half-normal			Truncated normal		
	2.5%	*Average*	*97.5%*	*2.5%*	*Average*	*97.5%*	*2.5%*	*Average*	*97.5%*
Constant	-3.5930	-2.2240	-1.1030	-2.8560	-2.0280	-1.1940	-2.7380	-1.8760	-1.0360
β_K	0.3910	0.4600	0.5280	0.3906	0.4596	0.5280	0.3955	0.4619	0.5309
β_L	-0.1223	-0.0261	0.0728	-0.1243	-0.0264	0.0743	-0.1176	-0.0211	0.0758
β_E	0.2094	0.3571	0.4995	0.2208	0.3580	0.4917	0.1981	0.3355	0.4761
β_t	-0.0165	-0.0102	-0.0037	-0.0163	-0.0101	-0.0040	-0.0167	-0.0105	-0.0043
β_{tK}	-0.0015	0.0031	0.0077	-0.0016	0.0031	0.0079	-0.0010	0.0035	0.0081
β_{tL}	-0.0023	0.0026	0.0076	-0.0024	0.0026	0.0075	-0.0020	0.0028	0.0076
β_{tE}	0.0639	0.1035	0.1425	0.0649	0.1040	0.1432	0.0649	0.1034	0.1435
eff[1]	0.0379	0.1226	0.1914	0.0945	0.1397	0.1821	0.1008	0.1492	0.1947
eff[2]	0.1553	0.4994	0.7595	0.3864	0.5696	0.7318	0.4019	0.5988	0.7642
eff[3]	0.0857	0.2776	0.4347	0.2143	0.3162	0.4123	0.2273	0.3369	0.4396
eff[4]	0.2265	0.7077	0.9933	0.5443	0.8136	0.9902	0.5617	0.8374	0.9937
eff[5]	0.0307	0.1037	0.1816	0.0755	0.1170	0.1687	0.0836	0.1301	0.1887
eff[6]	0.0561	0.1873	0.3265	0.1389	0.2120	0.3016	0.1501	0.2329	0.3308
λ	0.2832	1.0990	2.5270	0.1579	0.6383	1.5130	1.3280	3.3010	6.2350
φ	0.6070	1.3500	2.7240	-	-	-	-	-	-
ψ	-	-	-	-	-	-	0.5732	1.7640	2.9850
σ^2	0.0723	0.0853	0.1007	0.0724	0.0853	0.1005	0.0724	0.0854	0.1007

Table 10. Bayesian Estimates of the Translog Production Function of Other Distributions

Distributions	*Gamma*			*Half-normal*			*Truncated normal*		
	2.5%	*Average*	*97.5%*	*2.5%*	*Average*	*97.5%*	*2.5%*	*Average*	*97.5%*
Constant	-4.0220	1.2850	6.8020	-3.9420	1.4710	6.8890	-4.8330	1.1250	6.7690
β_K	-2.1780	-0.9826	0.1919	-2.1620	-1.0050	0.1867	-2.1670	-0.9420	0.2938
β_L	0.3533	1.5880	2.8310	0.3315	1.5630	2.8320	0.3543	1.6100	2.8820
β_E	-1.9260	-0.5255	0.8263	-1.9360	-0.5673	0.8048	-1.9190	-0.4698	0.9990
β_t	-0.0265	0.1153	0.2600	-0.0242	0.1201	0.2625	-0.0385	0.1121	0.2611
β_{KK}	-0.0494	-0.0342	-0.0184	-0.0501	-0.0346	-0.0191	-0.0502	-0.0342	-0.0183
β_{LL}	-0.0111	0.0047	0.0205	-0.0115	0.0046	0.0207	-0.0117	0.0047	0.0213
β_{EE}	0.0144	0.0298	0.0454	0.0138	0.0295	0.0451	0.0144	0.0303	0.0464
β_{tt}	0.0913	0.2463	0.4014	0.1006	0.2490	0.4015	0.0909	0.2435	0.4001
β_{KL}	-0.3149	-0.1110	0.1012	-0.3247	-0.1081	0.1013	-0.3202	-0.1054	0.1131
β_{KE}	0.0732	0.3070	0.5531	0.0771	0.3128	0.5484	0.0451	0.2961	0.5487
β_{LE}	-0.0004	0.0008	0.0021	-0.0004	0.0008	0.0021	-0.0004	0.0009	0.0021
β_{tK}	-0.0366	0.0709	0.1792	-0.0339	0.0711	0.1793	-0.0423	0.0688	0.1802
β_{tL}	-0.0926	0.0306	0.1548	-0.0920	0.0325	0.1563	-0.1033	0.0265	0.1554
β_{tE}	-0.5589	-0.3816	-0.2018	-0.5574	-0.3778	-0.2019	-0.5639	-0.3860	-0.2077
eff[1]	0.0421	0.0851	0.1144	0.0552	0.0860	0.1169	0.0564	0.0884	0.1259
eff[2]	0.2067	0.4072	0.5312	0.2691	0.4115	0.5362	0.2750	0.4147	0.5566
eff[3]	0.0940	0.1902	0.2575	0.1231	0.1925	0.2632	0.1255	0.1973	0.2823
eff[4]	0.4326	0.8378	0.9966	0.5704	0.8516	0.9954	0.5741	0.8417	0.9956
eff[5]	0.0501	0.1067	0.1674	0.0626	0.1076	0.1654	0.0599	0.1147	0.1872
eff[6]	0.0726	0.1456	0.2012	0.0923	0.1488	0.2118	0.0936	0.1535	0.2231
λ	0.2366	0.8832	1.9260	0.1167	0.4402	1.0220	0.9170	2.4700	4.8550
φ	0.5605	1.2140	2.3430	-	-	-	-	-	-
ψ	-	-	-	-	-	-	0.7218	1.9580	3.1410
σ^2	0.0554	0.0653	0.0770	0.0553	0.0652	0.0768	0.0554	0.0654	0.0771

Tables 9 and 10 contrast some results on the parameters for Gamma, Half-Normal and Truncated Normal proposals. The differences on the estimate parameters are quite low. We note that λ does not share the same common interpretations across the models. In addition, the confidence interval for φ is the shape parameter of the gamma distribution, which includes the value 1 corresponding to the exponential model. In addition, a distribution of the error could be considered for the measurement error. Tables 9 and 10 record some results and show that the previous assumption about the degrees of freedom, indicated by v, are rather important since the data provide little information about its value. We can use the DIC criterion to compare the different models.

Table 11 shows the computed values in the format given by WinBUGS. Our suggestion here is to focus only on the DIC value. The method is designed to be easily implemented using a sample from the posterior distribution. In fact, Table 11 compares the DIC scores for the different possible combinations of the error and the inefficiency distributions. The DIC low values suggest better models and thus the *t-Student* errors tend to generate better data than the normal measurement errors. In general, the results prefer the truncated normal distribution for the Cobb-Douglas function and the Gamma distribution for the Translog function. The posterior distribution of the predictive efficiency mean (i.e., Outside the sample) is a useful measure to compare our inference about the distribution of the inefficiency parameters λ and φ.

Table 11. Convergence Diagnostic and Output Analysis of Other Distributions

Distributions	Cobb-Douglas				Translog			
	$\overline{D}$	$\hat{D}$	p_D	*DIC*	$\overline{D}$	$\hat{D}$	p_D	*DIC*
Exponential	111.843	97.751	14.092	125.935	31.092	10.064	21.027	52.119
Gamma	111.688	97.634	14.054	125.742	31.034	10.148	20.887	51.921
Half-normal	111.779	97.752	14.026	125.805	31.319	10.234	21.085	52.403
Truncated normal	112.503	98.366	14.136	126.639	31.863	10.714	21.149	53.012

5. CONCLUSION

This paper used stochastic and bayesian production frontier models to estimate and analyse the technical, economic and allocative efficiencies of six main sectors of manufacturing industry of Tunisia. The analysis reveals an average level of technical, allocative and economic efficiencies equal to 77 percent, 76 percent and 58 percent respectively. Choosing the manufacturing industry is mainly motivated by the fact that this industry has long been protected by the supply policy which forced local producers and importers to raise consumer prices. This policy ensures that industries are relatively heterogeneous and of different sizes.

The mean efficiency level resulting from the two estimates (Stochastic and Bayesian) is about 75 percent indicating that sectors, near the average, can improve their output level by 25 percent with the same set of inputs. The temporal pattern of the technical efficiency shows a decline in the mean efficiency over time. The persistent deviations from the frontier may be an indication of rather low competitive pressures from foreign competitors in the sectors for the 1961-2010 period.

Our evidence above indicates that, during the sample years, the sectors experienced a technical regression and a deterioration in the technical efficiency. These sectors also reported a negative rate of productivity growth attributed particularly to the lack of innovative activities and investment in the improved technology. The decision makers and industry agents must quickly take and introduce several measures aimed at limiting these constraints and improving the technical conditions for the manufacturing industries. An eventual agreement on the trade liberalization can lead to the dismantling of the supply management since the price reductions can force too severe contractions in the local supply. In this case, we might think that the most technically efficient sectors would be preferred to face foreign competition.

REFERENCES

Aigner, D.J., C.A.K. Lovell, and P. Schmidt (1977), "Formulation and Estimation of Stochastic Frontier: Production Models," *Journal of Econometrics*, 6, 21-37.

Battese, G.E., and T.J. Coelli (1992), "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India," *Journal of Productivity Analysis*, 3(1-2), 153-169.

_____ (1995), "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data," *Empirical Economics*, 20, 325-332.

Chavas, J.P., R. Petrie, and M. Roth (2005), "Farm Household Production Efficiency: Evidence from The Gambia," *American Journal of Agricultural Economics*, 87(1), 160-179.

Chukwuji, C.O., O.E. Inoni, O.D. Ogisi, and W.J. Oyaide (2006), "A Quantitative Determination of Allocative Efficiency in Broiler Production in Delta State, Nigeria," *Department of Agricultural Economics and Extension*, Delta State University, Asaba Campus, 71(1), 21-26.

Djokoto, J.G. (2012), "Technical Efficiency of Agriculture in Ghana: A Time Series Stochastic Frontier Estimation Approach," *Journal of Agricultural Science*, 4(1).

Farrell, M.J. (1957), "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society*, Series A, 120(3), 253-290.

Grazhdaninova, M., and Z. Lerman (2005), "Allocative and Technical Efficiency of Corporate Farms," International Congress, August 23-27, European Association of Agricultural Economist.

Greene, W.H. (1990), "A Gamma-Distributed Stochastic Frontier Model," *Journal of Econometrics*, 46, 141-164.

Griffin, J.E., and M.F.J. Steel (2004), "Semiparametric Bayesian Inference for Stochastic Frontier Models," *Journal of Econometrics*, Elsevier, 123(1), 121-152, November.

_____ (2005), "Bayesian Stochastic Frontier Analysis Using WinBUGS," Working Paper, Department of Statistics, University of Warwick, U.K.

Helali, K., and M. Kalai (2015), "Estimate of the Elasticities of Substitution of the CES and Translog Production Functions in Tunisia," *International Journal of Economics and Business Research*, 9(3), 245-253.

Huang, H.C. (2004), "Estimation of Technical Inefficiencies with Heterogeneous Technologies," *Journal of Productivity Analysis*, 21, 277-296.

Iain, M., B. Kelvin, and K. Jae (2006), "Estimating Technical Efficiency of Australian Dairy Farms Using Alternative Frontier Methodologies," *Applied Economics*, 38(19).

Inoni, O.E. (2007), "Allocative Efficiency in Pond Fish Production in Delta State, Nigeria: A Production Function Approach," *Agricultura Tropica et Subtropica*, 40(4), 127-134.

Jondrow, J., C.A.K. Lovell, I.S. Materov, and P. Schmidt (1982), "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model," *Journal of Econometrics*, 19, 233-238, North-Holland Publishing Company.

Kim, Y., and P. Schmidt (2000), "A Review and Empirical Comparison of Bayesian and Classical Approaches to Inference on Efficiency Levels in Stochastic Frontier Models with Panel Data," *Journal of productivity Analysis*, 14, 91-118.

Koop, G., J. Osiewalski, and M.F.J. Steel (1995), "Posterior Analysis of Stochastic Frontier Models using Gibbs Sampling," *Computational Statistics*, 10, 353-373.

Kumbhakar, S. (1990), "Production Frontiers, Panel Data and Time-Varying Technical Efficiency," *Journal of Econometrics*, 46, 201-211.

Kumbhakar, S.C., and C.A.K. Lovell (2000), *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge, UK.

Kumbhakar, S.C., and E.G. Tsionas (2005), "Measuring Technical and Allocative Inefficiency in the Translog Cost System: A Bayesian Approach," *Journal of Econometrics*, 126, 355-384.

Kumbhakar, S.C., S. Gosh, and J.T. McGuckin (1991), "A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms," *Journal of Business and Economic Statistics*, 9, 279-286.

Kurkalova, L.A., and A. Carriquiry (2002), "An Analysis of Grain Production Decline during the Early Transition in Ukraine: A Bayesian Inference," *American Journal of Agricultural Economics*, 84, 1256-1263.

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

Lin, E.T.J., L.W. Lam, and Y.C. Shih (2012), "Using Bayesian Stochastic Frontier Analysis to Examine Province-Based Productive Efficiencies in China," *Journal of Asia Pacific Business Innovation & Technology Management*, 2, 1-16.

Martin, M., and T.G. Taylor (2003), "A Comparison of the Efficiency of Producers under Collective and Individual Modes of Organization," *Colombian Economic Journal*, 1(1), 246-266.

Meeusen, W., and J. Van Den Broeck (1977), "Efficiency Estimation from Cobb-

Douglas Production Function with Composed Errors," *International Economic Review*, 18, 435-444.

Reifschneider, D., and R. Stevenson (1991), "Systematic Departures from the Frontier: A Framework for the Analysis of Firm Inefficiency," *International Economic Review*, 32, 715-723.

Shekhar, K.S. (2009), *Productivity, Efficiency and Pricing in India Post*, Concept Publishing Company.

Spiegelhalter, D.J., N.G. Best, B.P. Carlin, and A. Van Der Linde (2002), "Bayesian Measures of Model Complexity and Fit," *Journal of the Royal Statistical Society B*, 64, 583-640.

Stevenson, R.E. (1980), "Likelihood Functions for Generalized Stochastic Frontier Estimation," *Journal of Econometrics*, 13, 57-66.

Van den Broeck, J., G. Koop, J. Osiewalski, and M.F.J. Steel (1994), "Stochastic Frontier Models: A Bayesian Perspective," *Journal of Econometrics*, 61, 273-303.

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