Technical efficiency of olive oil manufacturing and efficacy of modernization programme in Tunisia

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Contributed Paper presented at the Joint 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19-23, 2010.

Technical efficiency of olive oil manufacturing and efficacy of modernization programme in Tunisia

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Abstract

This study investigates firm level technical efficiency of production and its determinants in a sample of 137 olive oil manufacturing firms in Tunisia using a stochastic frontier production model applied to cross-section data. Results indicate that technical efficiency of production in the sample of olive oil manufacturing firms investigated ranges from a minimum of 47.1% to a maximum 99.5% with an average technical efficiency estimate of 86.5%. This implies olive oil manufacturing firms in Tunisia can increase their production on average by 13.5% through more efficient use of technology and production inputs. The fact that 93 firms represented more than 64.4% of the sample hit more than 80% of technical efficiency score implies the efficacy of modernization programme implemented in Tunisia. The estimated coefficients in the technical inefficiency effects model indicate that level of technology, frequent use of computer and internet, the owner's age, the share of skilled labour, the employment of management staff, and the input sourcing by the own production have a significant and positive effect on technical efficiency. On the other hand, negative relationships are found between technical efficiency and entrepreneur dummy variable, continuous relationship with the suppliers in the same district, and with the private sector and trader as customers. These results imply that the adoption of new technology, accumulation of skill and knowledge as well as stable input sourcing contribute to improve the technical efficiency of olive oil manufacturing.

Keywords: olive oil manufacturing; stochastic frontier production function; technical efficiency; modernization programme; Tunisia

1. Introduction

The olive oil sector constitutes an important part of the Tunisian agricultural economy. Investigation on level of productivity and degree of efficiency not only on olive growing

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farms but also olive oil manufacturing firms may provide valuable insights into potential improvement of productivity. This is particularly important due to the implementation of free trade agreement with EU that lead to elimination of tariffs and other trade barriers on agricultural commodities traded with EU. The modernization of the olive oil manufacturing has began in the 1990s with the national industrial upgrading program (know as programme de mise à niveau). This program has been launched in 1996 aiming to improve the competitiveness of the manufacturing sector to meet the new challenges of the accession of Tunisia to WTO and the European partnership. Substantial financial support had been granted through a dedicated fund for "improvement of industrial competitiveness". The upgrading process had two components: physical investment in modernization and laboratory equipment; and intangible investment in the form of training and capacity building mainly for quality control and adoption of ISO or European quality schemes. The program is run in conjunction with the Industrial Modernization Progamme (IMP) and the support of the European Union (Zaibet, 2007).

The olive oil manufacturing, being the first agro-food exporting sector was among the first served by these programmes. An assessment of an improvement in technical efficiency as a result of the above programmes would reveal useful insights about the efficacy of these programmes but also on future steps and programmes. It would have also useful to have baseline (at the beginning) estimated of these efficiency scores but our search show no references and the paper, to our best knowledge is the first to assess technical efficiency in the olive oil sector in Tunisia.

In the olive oil sector fewer studies are found in the literature. In Tunisia, there are two studies on (at the farm level) technical efficiency: Zaibet and Omezzine (1998) and Lachaal et al. (2005). These studies point to the relatively low level of technical efficiency scores and their determinants namely the small size, the high number of plots by farm as well as scarce skilled labor and training. Olive oil being Mediterranean-site specific product, we could also encounter more studies in the region, such as the work done by Tzouvelekas et al. (1999) on olive oil production in Greece. The authors used a decomposition of output growth into its three components and investigated the relative contribution of technical efficiency, technological change and increased input use to the output growth of the Greek olive-oil sector. Findings show that the overall efficiency of olive-growing farms in Greece remained stable during the study period and that the contribution of conventional inputs was the main source of that growth. Although most studies have been devoted to investigating technical efficiency on olive growing farms, studies focus on the stage of olive oil manufacturing are merely absent.

This paper investigates firm level technical efficiency on manufacturing of olive oil in Tunisia, using a stochastic frontier production model with technical inefficiency effects applied to a sample of 137 olive oil manufacturing factories. The objective is to identify the sources of technical efficiency in the stage of manufacturing of olive oil by explaining differences in efficiency levels. First, we measure technical efficiency of a sample of olive oil manufacturing firms in Tunisia. Second, we analyze the determinants of technical efficiency variation among these firms.

This paper assumes that adoption of new technology, accumulation of skill and knowledge as well as stable input sourcing contributes to improve technical efficiency of manufacturing as internal factors. As those of external, resource of management with respect to marketing would have positive effect on enhancing technical efficiency. The rest of the paper is organized as follows. In the next section, a quick review of the Tunisian olive oil sector and its manufacturing firms is described. In section 3 methodological framework of the stochastic frontier model is described. Data collection and model specification are presented in Section 4. In Section 5 we present the empirical results and discussions. Conclusion is highlighted in the Section 6.

2. Olive oil sector in Tunisia

Olive orchards in Tunisia occupy 1.7 million ha, the equivalent of 30% of the total arable land, and represent about 19% of the world olive orchards (second largest olive land after Spain which counts 3 million ha). Sixty-six million olive trees are widespread all-over the country: North, Centre and South. The olive oil sector contributes to the Tunisian socioeconomic development providing 40 millions working days per year (20% of agricultural employment) and decreasing exodus by fixing rural population. The olive oil sector employs directly or indirectly over 1 million persons and 269,000 farmers are dedicated to this growing.

Olive oil production in Tunisia is highly dependent on precipitations. During the last decade, the lowest production registered for the 2001-02 campaign was about 35,000 tons due to water shortage. The highest production was obtained in 2003-04 season with 280,000 tons. For the last three years olive oil production was stabilized around 170,000 tons/year. Tunisian government is encouraging the use of irrigation (intensive or hyper-intensive growing) to increase the proportion of irrigated olive orchards (2% actually) in order to decrease production fluctuation mainly due to climatic change.

Olive oil consumption in Tunisia ranges between 35,000 to 50,000 tons per year (25% to 30% of total production). Trend consumption is showing a decreasing pattern during the last decade essentially due to price increment, but also to culinary and habit changes in the Tunisian population. Compared to other producing countries, olive oil per capita consumption in Tunisia is very low. Greece, Spain and Italy present annual per capita consumption of 24, 14 and 13 kg respectively, whereas Tunisian average consumption is about 4 kg/capita/year. Olive oil consumption is mainly in bulk. Tunisian consumers are used to purchase olive oil directly from the manufacture. Bottled olive oil purchase still very limited (3% of total consumption) and concentrated in large cities like Tunis Capital.

Olive oil exports account for 120,000 tons per year representing 70% of total production. These exports are mainly directed to the European Union (Italy and Spain) and to the USA. Tunisia occupies the fourth position as olive oil exporter preceded by Spain, Italy and Greece. Tunisian olive oil exports are mainly in bulk (99%) and a large proportion of it forms part of the olive oil contingent free-trade agreement signed between Tunisia and the E.U. Tunisian government is seeking to increment bottled olive oil exports to reach 10% of total exports by 2010, but this goal was not achieved. Only 2% to 3% are actually exported in bottle. The aim of increasing bottled olive oil exports is to generate higher added value and to be present in overseas markets with Tunisian country of origin label. Actually olive oil exports represent 10% of total exports in values and about 45% of agro-food exports.

Improving product quality is an important factor to increase Tunisian olive oil competitiveness in local and especially in foreign markets. Extra-virgin olive oil (higher quality) export proportion is increasing compared to ordinary virgin olive oil. It represented 56% of total Tunisian olive oil exports in 2008. To improve product quality, Tunisian government supported olive oil manufactures (through the fund for improvement of industrial competitiveness) to improve triturating processes and capacities by renewing machinery and adopting new technologies. The number of modern olive oil mills (called continuous chains) has substantially increased during the last fifteen years leading to a national triturating capacity of 38,000 tons per day three times greater than the triturating capacity during the eighties.

The Tunisian olive oil manufacturing system is composed by three triturating systems that coexist actually: the traditional one called “classic”, the Super-Press, and the modern one. The red accounts for 1702 olive oil mills (APIA, 2008) decomposed as follows: 719 classic units, 450 Super-Press, 515 continuous chains and 18 mixed units. Mixed units are composed of more than one type of processing. In addition to this processing structure, the sector counts with 40 industrial units for olive oil packaging, or for pomace olive oil extraction. Actually the overall trend is to increase the number of modern olive oil mills.

3. Methodological framework

Following the seminal paper by Farrell (1957), frontier production functions were introduced. The stochastic frontier production function (SPF) was then introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van don Broeck (1977). Jondrow et al. (1982), who extended the SPF to allow for the estimation of individual farm efficiency levels with cross-sectional data, introduced a major development in the SPF. Whereas the original model by Jondrow was defined for the analysis of cross-sectional data, extensive literature show the use of these models to account for panel data (see Cornwell, Schmidt and Sickles, 1990; Kumbhakar, Ghosh and Mcgukin,1991; Battese, Malik and Broca,1993 and Battese, Malik and Gill, 1996). Since then, the SPF has been widely used in empirical work. Applications include the estimation of farm efficiency in US dairy farms (Kumbhaker et al., 1989), and technical efficiency in commercial fisheries (Kirkley et al., 1995), and technical efficiency in banking (Caudill et al., 1995).

Efficiency indicators are management oriented measures. Lovell (1993) considers productive efficiency as success indicators, performance measures of production units. Shu and Lee (2003) assert that efficiency measurement gives more management implications; technical efficiency tells how much deviation the real production is to the maximum level of production. Lovell further emphasized the need to explore the sources of these inefficiencies: “the identification of sources is essential to the institution of public and private policies designed to improve performance.” Efficiency of production has then become an important indicator of firm performance and considerable efforts have been devoted to introduce policies aiming at increasing efficiency to improve economic growth.

Lovell provides a framework to the measurement of productive efficiency and a distinction is made between technical efficiency and allocative efficiency. Technical efficiency with respect to an input-output vector $(\boldsymbol{x}, \boldsymbol{u})$ corresponds to a firm producing to its maximum production level. Allocative efficiency is defined with respect to an input-output vector of prices (***w***, ***p***) for a firm that is technically efficient and producing to its minimum cost (use of inputs at optimal proportions). A firm that is both technically efficient and allocatively efficient is called profit efficient or also economic and cost efficient (the ratio of minimum cost to observed cost).

Techniques to estimate efficiency scores ranges from programming approach (non parametric) to statistical frontier or parametric approaches. The programming approach initially proposed by Farrell (1957) has gained from the developments made by Charnes, Cooper and Rhodes (CCR) among others, who called the technique "Data Envelopment Analysis (DEA)" approach (Charnes, Cooper and Rhodes, 1978). DEA is a mathematical programming methodology that provides non-parametric measures of optimal relative efficiency. The most common measures of the CCR Ratio (Multiplier) model are: Input-oriented CCR Ratio Model and Input-oriented BCC Convex Model (Archimedean form)[2].

More recently, Bardhan, Cooper and Kumbhakar (1998) suggested a two-stage ordinary least squares (OLS) method which uses DEA efficiency measures as dummies to estimate the frontier of production. The method uses an aggregate output as the response variable and predictors that include Technical efficiency dummy variables and other inputs. The OLS regression estimates help to identify influential sources of efficiency as well as returns to scale.

The deterministic statistical frontier approach on the other hand uses statistical techniques to estimate the production frontier and the associated efficiency scores. The technique with the first developments of Richmond (1974) and Greene (1980) has gained from more recent improvements made by Kumbhakar in the 1990s. While Richmond and Greene proposed the estimation of the efficiency parameters by the Corrected OLS method or by Maximum likelihood and then estimate their determinants separately, Kumbhakar et al (1991) used system approaches and proposed a one stage procedure to estimate efficiency measures along with their determinants. This approach has since then been widely used and made popular due to the development of computer applications, namely Frontier (Coelli, 1996).

Given the above, we adopt the Battese and Coelli (1995) model of stochastic frontier production function, but in the context of a cross-section data.

$$y_i = f(x_i;\beta) + v_i - u_i, \tag{1}$$

where y_i denotes gross output value for the ith firm; β is a vector of unknown parameters to be estimated; x_i is a vector of inputs of production and other explanatory variables associated with the ith firm; v_i refers to statistical random disturbance terms, assumed to be an independently and identically distributed $N(0, \sigma_v^2)$. u_i represents non-negative random variables, assumed to be independently and identically distributed $N(0, \sigma_u^2)$ with truncations at zero.

In this specification, $(-u_i)$ measures distance between the realized output and the frontier output. The Exp $(-u_i)$, varies between 0 and 1, is a measure of the technical efficiency of the ith firm. Following Battese and Coelli (1995), the technical inefficiency

[2] See Zaibet and Dharmapala (1999).

effect, u_i, in the stochastic frontier model (1) could be specified in equation (2),

$$u_i = \delta z_i + w_i \,, \tag{2}$$

where δ is a vector of unknown parameters to be estimated; z_i is a vector of explanatory variables associated with technical inefficiency in production; w_i is a random variable with zero mean and variance σ^2 defined by the truncation of the normal distribution such that the point of truncation is $-z_i\,\delta$, i.e. $w_i \geq -z_i\,\delta$. The technical efficiency of production of the *i*th firm is defined by the ration of the observed output to the corresponding frontier output:

$$TE_i = \exp(-u_i) = \exp(-z_i\delta - w_i). \tag{3}$$

The prediction of technical efficiencies of the *i*th firm relies on the conditional expectation of u_i, given the model assumption. Given the assumptions of the statistical distribution of u_i and v_i and the maximum likelihood (ML) estimates of production frontier, the best predictor of u_i, given $v_i - u_i$ is obtained as (Battese and Coelli, 1993):

$$E[\exp(-u_i) \mid (v_i - u_i)] = \left[\exp\left\{\frac{1}{2}\sigma_*^2 - u_i^*\right\}\right]\left[\frac{\Phi[(u_i^*/\sigma_*) - \sigma_*]}{\Phi(u_i^*/\sigma_*)}\right], \tag{4}$$

where $u_i^* = \dfrac{\sigma_v^2(\delta z_i) - \sigma_u^2(w_i)}{\sigma_v^2 + \sigma_u^2}$ and $\sigma_*^2 = \dfrac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$

The function $\Phi(\cdot)$ denote the cumulative distribution function (cdf) of the standard normal random variable evaluated at (μ_i^*/σ_*).

4. Data collection and model specification

4.1. Data collection

The data used in this study was drawn from a survey conducted in February and March 2009 in Tunisia. It was directed to the owner or the director of the olive oil manufacture. The studied olive oil mills are located in the north, centre and south of the country. In total 137 questionnaires were completed. The olive oil manufactures were randomly selected and the number of questionnaires completed in each region was 45, 43 and 49 respectively for the north, centre and south of Tunisia. In Table 1, sample stratification by location and type of olive oil mills is summarized.

Table1: Olive oil mills geographical distribution

	North		Centre		South	
Type	Freq.	%	Freq.	%	Freq.	%
Classical	11	24.4	0	0.0	14	28.6
Super-Press	9	20.0	1	2.3	4	8.2
Continuous	25	55.6	40	93.0	23	46.9
Mixed*	0	0.0	2	4.7	8	16.3
Total	45	100	43	100	49	100

Note: * It has more than one type of olive oil mill.

4.2. Model specification

In this study, the following translog functional form was used for the estimation of the stochastic frontier production function:

$$\ln y_i = \beta_0 + \sum_{j=M}^{L} \beta_j \ln x_{ji} + \frac{1}{2} \sum_{j=M}^{L} \sum_{k=M}^{L} \beta_{jk} \ln x_{ji} \ln x_{ki} + \beta_N DN + \beta_S DS + v_i - u_i, \qquad (5)$$

where the subscript i refer to the ith firm; j and k represents inputs applied to olive oil production (j, k = M, F, E, W, K, L); y_i denotes gross output value for the ith firm measured in Tunisian Dinar; x_{Mi} is volume of intermediate inputs utilized in production in Tunisian Dinar; x_{Fi} , x_{Ei} , x_{Wi} denote cost expenses of fuel, electricity, water, respectively; x_{Ki} is the capital stock of the ith firm in Tunisian Dinar; x_{Li} is total cost of labour devoted to olive oil production by the ith firm; DN, DS are dummy variables represent north, south region, respectively; v_i is iid random disturbance term, and u_i refers to iid non-negative truncations of the normal distribution. Summary statistics of the variables are presented in Table 2.

Table 2: Summary statistics of the variables

Variables	Gross Output Values	Intermediate Inputs	Cost of Fuel	Cost of Electricity	Cost of Water	Capital Stock	Cost of Labor
Mean Values	1612.6	1301.0	1.5	9.6	1.7	319.3	15.3
Standard Deviation	1512.2	1253.1	3.2	6.8	1.7	244.8	12.2
Maximum	10000.0	8000.0	20.0	35.0	9.0	1380.5	100.0
Minimum	52.5	38.4	0.0	0.6	0.0	12.1	0.9

Note: All variables are in thousand Tunisian Dinar (1TND ≈ 0.540 €).

The technical inefficiency effects to be estimated is defined as follows:

$$\begin{aligned} u_i &= \delta_0 + \delta_1(TEC) + \delta_2(INT) + \delta_3(AGE) + \delta_4(ENT) + \delta_5(OTH) + \delta_6(SKL) + \delta_7(MAS) \\ &+ \delta_8(SOW) + \delta_9(SMA) + \delta_{10}(SFA) + \delta_{11}(SDT) + \delta_{12}(CHH) + \delta_{13}(CPR) + \delta_{14}(CTR) + w_i, \end{aligned} \qquad (6)$$

where TEC is discrete variables that represent level of technology on a scale of 1 to3 (1: traditional, 2: modern, 3: up-dated); INT shows frequency of use of computer and internet on a scale from 1: no use at all to 5: frequent use; AGE denotes the firm owner's age (years); OTH is the dummy variable that equals to 1 if the owner engaged in other activities, zero otherwise; ENT denotes the entrepreneur dummy variable that equals 1 if the current owner established the firm, zero otherwise; SKL is the share of skilled labour to total employee; ASM is the management dummy variable that equals to 1 if the firm employed management staff for accounting, supplying, or marketing, zero otherwise; SOW is the supplier dummy variable that equals to 1 if the main supplier is own production, zero otherwise; MAS is the supplier dummy variable that equals to 1 if the main supplier is olive seeds market, zero otherwise; SFA is the supplier dummy variable that equals to 1 if the main supplier is olive farmers, zero otherwise; SDT is the supplier dummy variable that equals to 1 if the relation with supplier in same district is continuous, zero otherwise; CHH is the customer dummy variable that equals to 1 if the relation with households as customer is continuous, zero otherwise; CPR is the customer dummy variable that equals to 1 if the relation with private sector as customer is continuous, zero otherwise; *CTR* is the customer dummy variable that equals to 1 if the relation with trader as customer is continuous, zero otherwise; w_i refers to random term. The parameters of the stochastic frontier production function in (5) and the model for technical inefficiency effects in (6) may simultaneously be estimated by the maximum likelihood model (Reinfschneider and Stevenson, 1991; Huang and Liu, 1994).

5. Empirical results and discussions

Maximum likelihood estimates of the parameters of the models of translog stochastic frontier production and the technical inefficiency effects are obtained using the computer program FRONTIER 4.1 (Coelli, 1996). Parameters estimates and *t*-values of the ML estimators are given in Table 3. The sings of the estimated parameters of the translog stochastic frontier production model are as expected, except for intermediate inputs, and costs of fuel and water. As expected, estimated coefficients of cost of electricity, capital stock and cost labour are positive and statistically significant. These results indicate positive relationship between input of capital, labor and electricity and production of olive oil. The negative coefficients of the intermediate input and expense of water are insignificant. The coefficient sign of cost of fuel is negative and statistically significant. The reason for this unexpected sign may be due to the world cost of fuel increase during the survey year. The regional dummy variables are both positive and statistically significant. The estimated parameter of north region is higher than that of south. These results show the north region of Tunisia enjoyed higher level of production compared with south and central region.

The estimated coefficients in the technical inefficient model are also as expected. The estimated coefficients of the level of technology (*TEC*) and frequency of use of computer and internet (*INT*) are negative and statistically significant, which confirms their positive effect on technical efficiency. The owner's age variable (*AGE*) also has a significant and positive effect on technical efficiency. On the contrary, the estimated coefficient of the entrepreneur dummy variable (*ENT*) is positive and statistically significant at 5% level. These results suggest that having more experience have positive effect on increase in technical efficiency. The variable of the share of skilled labour (*SKL*) is negative and statistically significant at 1% level. This indicates that an increase in the share of skilled labour contributes to higher technical efficiency levels for olive oil manufacturing. Also, the negative sign of estimated coefficient of the employment of management staff for accounting, supplying, or marketing (*MAS*) indicates that knowledge of management also contributes to increase the level of technical efficiency. Regarding supplier of olive oil production, the estimated coefficients of own production (SOW) is negative and statistically significant at 1% level. The positive sign of the (*SDT*) indicates technical efficiency declines with the continuous relationship with the suppliers in the same district. As for customers, the variable of private sector (*CPR*) and that of trader (*CTR*) are found to be positive and statistically significant. These results suggest the continuous relationship with private sector and trader as customers does not contribute to improve technical efficiency.

Table 3: Parameter estimates and *t*-values of the inefficiency frontier model of a sample of olive oil manufacturing firms in Tunisia

Variables	Estimates	*t*-values	
Stochastic frontier model			
Intercept	-4.682	-3.995	***
$\ln x_M$	-0.443	-1.182	
$\ln x_F$	-0.147	-1.704	**
$\ln x_E$	1.011	2.149	**
$\ln x_W$	-0.030	-0.304	
$\ln x_K$	1.271	2.874	***
$\ln x_L$	0.738	1.873	**
$\ln x_M^2$	0.040	1.908	**
$\ln x_F^2$	-0.008	-1.627	*
$\ln x_E^2$	0.053	1.601	*
$\ln x_W^2$	0.002	0.624	
$\ln x_K^2$	-0.043	-1.412	*
$\ln x_L^2$	-0.021	-1.066	
$\ln x_M \ln x_F$	-0.005	-0.823	
$\ln x_M \ln x_F$	-0.024	-0.634	
$\ln x_M \ln x_W$	0.005	0.470	
$\ln x_M \ln x_K$	0.003	0.077	
$\ln x_M \ln x_L$	0.041	1.092	
$\ln x_F \ln x_E$	0.002	0.221	
$\ln x_F \ln x_W$	0.001	0.453	
$\ln x_F \ln x_K$	0.022	2.875	***
$\ln x_F \ln x_L$	-0.001	-0.074	
$\ln x_E \ln x_W$	-0.022	-2.039	**
$\ln x_M \ln x_F$	-0.033	-0.710	
$\ln x_E \ln x_L$	-0.113	-2.531	***
$\ln x_W \ln x_K$	-0.005	-0.590	
$\ln x_W \ln x_L$	0.022	1.569	*
$\ln x_K \ln x_L$	0.000	-0.005	
DN	0.341	3.987	***
DS	0.115	1.798	**
Inefficiency effects model			
Intercept	0.529	4.869	***
TEC	-0.156	-5.137	***
INT	-0.932	-2.225	**
AGE	-0.003	-2.427	***
ENT	0.077	2.146	**
OTH	0.044	1.078	
SKL	-0.007	-3.581	***
MAS	-0.056	-1.337	*
SOW	-0.057	-1.630	*
SMA	0.051	3.790	***
SFA	0.048	0.957	
SDT	0.092	1.904	**
CHH	0.026	0.705	
CPR	0.098	2.053	**
CTR	0.071	1.874	**
Variance parameters			
σ^2	0.013	7.448	***
γ	0.168	3.442	***
Log-likelihood	113.031		

Note: *, **, *** indicate significant at the 10% level, 5% level, 1% level, respectively.

The estimate of variance parameters γ is positive and statistically significant at 1% level, implying inefficiency effects are significant in determining the level and the variability of the olive oil manufacturing firms (Table 3). Thus, the stochastic frontier inefficiency model is empirically justified. Further, several hypotheses for the parameters of the model are examined in Table 4 using likelihood test[3]. First, the empirical validity of the translog specification over the Cobb-Douglas form, the null hypothesis that $\beta_{jk} = 0$ (j, $k = M, F, E, W, K, L$) = 0, is rejected. It is suggested translog specification is a better representation of the production of olive oil manufacturing firms in Tunisia than the Cobb-Douglas one. Second, null hypothesis of no inefficiency effects is also rejected. Third, we rejected the null hypothesis that no firm specific factor makes significant contribution to the explanation of the inefficiency effects.

Table 4: Tests of hypotheses for the parameters of the stochastic frontier inefficiency model of a sample of olive oil manufacturing firms in Tunisia

Null Hypotheses	Log-likelihood ratio	d.f.	Critical Value at 5%	Decision
Cobb-Douglas	55.948	21	32.671	Reject H_0
$\beta_{jk} = 0$ ($j, k = M, F, E, W, K, L$)				
No inefficiency effects	58.547	16	26.296	Reject H_0
$\gamma = \delta_i = 0$ (i = 0, 1, 2, ...14)				
No firm specific effects	65.991	14	23.685	Reject H_0
$\delta_i = 0$ (i = 1, 2 , 3, ...14)				

Note: The value of the log-likelihood function under the specification of alternative hypothesis (i.e. unrestricted model) is 113.031.

The estimations of frequency distribution of technical efficiency are given in Table 5. Estimated efficiency scores indicate that there exists technical inefficiency firms while more than half shows relatively technical efficient. The average level of technical efficiency is 86.5% ranging from a minimum of 47.1% to a maximum 99.5%. It is suggested that firms in this sample are producing on average at 86.5% of their potential with the given present state of technology and input levels. 80 firms represented 58.39% in a sample are relatively more efficient than of which an efficient score greater than 90%; however 28.2% of the sample shows relatively inefficient with their score ranging from 60% to 80%. These results imply the possibility of these firms that can increase their production by 13.5% given the present state of technology and inputs level. Compared with regions, firms locate in central region of Tunisia hits relatively high efficiency score at 96.1% while those in north remain 69.4%. 93 firms represented more than 64.4% of the sample shows relatively technical efficient, which hit more than 80% of technical efficiency score. This result provides an empirical justification of the efficacy of modernization programme for up grading competitive of manufacturing sector.

[3] The null hypothesis can be tested using the generalized likelihood-ratio statistic, λ, given by $\lambda = -2\{L(H_0) - L(H_1)\}$. $L(H_0)$, $L(H_1)$ denote the values of likelihood function under the null (H_0), the alternative hypothesis (H_1), respectively. If the given null hypothesis is true, λ has approximately Chi-square distribution or mixed Chi-square distribution.

Table 5: Frequency distribution of technical efficiency for a sample of olive oil manufacturing firms in Tunisia

Technical efficiency (%)	Olive Oil Manufacturing firms	Percentage
40 < TE ≤ 50	1	0.73
50 < TE ≤ 60	5	3.65
60 < TE ≤ 70	18	12.14
70 < TE ≤ 80	22	16.06
80 < TE ≤ 90	11	8.03
90 < TE ≤ 100	80	58.39
North	69.4	
Centre	96.1	
South	93.6	
Mean efficiency	86.5	
Min. efficiency	47.1	
Max. efficiency	99.5	

6. Conclusion

In this paper, we have investigated firm level technical efficiency of production and its determinants of olive oil manufacturing firms in Tunisia using a stochastic frontier production model. The data used in this study was a sample of 137 olive oil manufacturing firms locate in north, centre and south region of Tunisia, which was collected through the survey implemented during February and March 2009.

This study revealed that the translog specification is a better representation of the technology used in olive oil manufacturing in Tunisia. The estimated coefficient of electricity, capital and labour are positive and statistically significant. Results of estimation of the technical inefficiency effects model indicate that level of technology (*TEC*), frequency of use of computer and internet (*INT*), the owner's age (*AGE*), the share of skilled labour (*SKL*), the employment of management staff (*MAS*) have a significant and positive effect on technical efficiency. The positive and significant effect was also found in input sourcing by the own production (*SOW*). A negative relationship with technical efficiency with entrepreneur dummy variable (*ENT*), continuous relationship with the suppliers in the same district (*SDT*), continuous relationship with private sector (*CPR*) and trader (*CTR*) as customers are found.

Empirical findings in the estimated efficiency of olive oil manufacturing firms indicate that there exists technical inefficient firms while more than half shows relatively technical efficient. Estimated efficiency scores vary ranging from a minimum of 47.1% to a maximum 99.5% with a mean value of 86.5%. This result implies olive oil manufacturing firms in Tunisia that can increase their production by 13.5% through more efficient use of technology and production inputs. The fact that 93 firms represented more than 64.4% of the sample hit more than 80% of technical efficiency score implies the efficacy of modernization programme implemented in Tunisia.

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