International Journal of Applied Operational Research
Vol. 3, No. 2, pp. 43-51, Spring 2013

Journal homepage: www.ijorlu.ir

# Application of DEA and SFA on the Measurement of Agricultural Technical Efficiency in MENA[1] Countries

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**Received:** 16 August 2012 ; **Accepted:** 6 December 2012

**Abstract** The purpose of this paper is to investigate the levels of technical efficiency in agricultural sector of MENA countries by using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) approaches in 2007-2008. The results show that the total average of technical efficiency is as follows: $DEA_{BCC}(0.770)>DEA_{CCR}(0.744)>SFA(0.479)$, and among all MENA countries, the best performance in both models is related to Qatar. Furthermore, the empirical results indicate that both the parametric and non-parametric methods provide the same rank of countries; However, in all cases SFA results are lower than those found by using DEA, which expresses high levels of random error in the data.

**Keywords** Technical Efficiency, MENA Countries, Agriculture, Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA).

## 1 Introduction

Increasing agricultural productivity and technical efficiency is a very important policy objective in most developing countries, because it is one of the main sources of overall growth. Recently, Measuring agricultural productivity and technical efficiency has become an important and appealing research area due to the changes in agricultural economic and regulatory environment. Considering Farell [1], technical efficiency is the ability of a firm to obtain maximal output for a given set of inputs. Also aggregate productivity can be defined as the amount of output that can be obtained from given levels of inputs in a sector or an economy. Two main methodologies have been developed for measuring efficiency and productivity, the parametric (econometric) and non-parametric (mathematical programming) approach. These approaches have different strengths and weakness. The essential differences largely reflect the different maintained assumption used in estimating the frontier. The main

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[1] Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Qatar, Saudi Arabia, Sudan,Syria, Tunisia, Turkey, United Arab Emirates and Yemen.

strength of the parametric approach stems from the fact that frontier is stochastic, and this allows the effects of noise to be separated from the effects of inefficiency. However, the statistical approach is parametric- it requires the specification of functional form. This implies that structural restrictions are imposed, and the effects of misspecification of functional form might be confounded with inefficiency. The reverse is true for the non-parametric approach. The non-parametric approach is free from the misspecification of functional form and other restrictions, but it does not account for statistical noise and is therefore vulnerable to outliers. (Ferrier and Lovell [2]; Sharma et al. [3]; Fulginiti and Perrin, [4]; Kwon and Lee [5]).

The purpose of this paper is to estimate agricultural technical efficiency across MENA countries by applying two different frontier methods, DEA and SFA. Internationally, the comparison of the results of the stochastic frontier model to the DEA efficiency scores will contribute to the growing literature on the comparison of DEA and SFA methodologies. There are numerous researches that try to compare technical efficiency estimates using DEA and SFA methods. In some of them, results are different such as, Banker et al. [6], Coeilli and Peralman [7], Bauer et al. [8], Resti [9], Charnes et al. [10], Mortimer [11], Berger and Mester [12], Hassan and Hunter [13], Allen and Rai [14], Casu and Girardone [15], Fiorentino et al.[16]. Also in some of articles, SFA technical efficiency estimates are lower than those found using DEA. (Webster et al. [17], Ganon [18], Ferrier and Lovell [2], Sheldom [19], Kasman and Turgutlu [20], Nunamaker [21]). This paper proceeds as follow: first, we give a brief introduction in to DEA and SFA methodologies, also SFA model is specified here followed by data description. In Section 4, we estimate the stochastic frontier function and provide a discussion of results from DEA and SFA. And section 5 concludes the paper.

## 2 Mathematical framework

### 2.1 Data envelopment analysis

The DEA method is introduced by Charnes, Cooper and Rhodes [10] at the first and based on Farrell [1] theory of using a non- parametric piece-wise-linear technology and combined with mathematical programming for efficiency rating. DEA compares a set of homogeneous Decision Making Units (DMUs) relatively and assigns an efficiency score to each DMU by finding the distance of each unit with that of its peers on the best practice (frontier). Those units that lie on the frontier are recognized as efficient, and those that do not, as efficient. The definition of frontier is very dependent to the selection of input output variables and the efficiency score is very dependent to the DEA model used. Two basic DEA models are CCR (constant returns to scale) which introduced by Charnes et al. [10] and BCC (variable return to scale) which introduced by Banker, et al. [22]. The CCR model used constant return to scale (CRS) concept to assess relative productive efficiencies of decision making units (DMUs) with multiple inputs and outputs. With the CCR model and assumes m inputs, s outputs and n DMUs respectively, the linear programming problem for DMUk is declare as:

$$Max \quad h_x = \frac{\sum_{r=1}^{s} U_r X_{rk}}{\sum_{i=1}^{m} V_i X_{ik}} \tag{1}$$

$s.t.$

$$\frac{\sum_{r=1}^{s} U_r X_{rk}}{\sum_{i=1}^{m} V_i X_{ik}} \leq 1$$

$$U_r, V_i > 0, r = 1,2,...,s, i = 1,2,...,m.$$

where: $h_k$ is relative efficiency of the kth DMU, $Y_{rj}$ is rth outputs of the jth DMU, $X_{ij}$ is ith inputs of the jth DMU, $U_r$ is a weight of rth output and$V_i$ is a weight of ith output.

According to above formulation, the maximum of a ratio of weighted outputs to weighted inputs are the relative efficiency scores of CCR model [10].

The dual problem of CCR model can be written as:

$$Min \quad h_x = \theta - \varepsilon[\sum_{r=1}^{s} S_x^+ + \sum_{i=1}^{m} S_i^-] \tag{2}$$

$s.t.$

$$\sum \lambda_j Y_{rj} - S_r^+ \geq Y_{rj}$$

$$\lambda_j \geq 0, S_r^+, S_i^- \geq \varepsilon \geq 0, \quad \forall i, r, j$$

$$r = 1,2,...,s, i = 1,2,...,m, j = 1,2,...,n.$$

where $\varepsilon$ is a small positive number, $\lambda_j$ is a weight of Jth DMU, $S_r^+$ is a slack variable of rth output and $S_i^-$ is a slack variable of ith input.

Considering the convexity restriction$\left(\sum_{j=1}^{n} \lambda_j = 1\right)$, Banker, Charnes and Cooper introduced BCC model and evaluated technical efficiency and scale efficiency of DMUs. The linear programming dual of BCC model is represented by:

$$Min \quad \theta - \varepsilon[\sum_{r=1}^{s} S_x^+ + \sum_{i=1}^{m} S_i^-] \tag{3}$$

$s.t.$

$$\sum_{j=1}^{n} \lambda_j X_{ij} + S_i^- \leq \theta X_{ij},$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj} - S_r^+ \geq Y_{ij},$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0, S_r^+, S_i^- \geq \varepsilon \geq 0, \forall i, r, j, r = 1,2,...,s, i = 1,2,...,m, j = 1,2,...,n.$$

## 2.2 Stochastic frontier analysis (SFA)

Stochastic Frontier Models were introduced by Aigner, Lovell and Schmidt [23] and Meeusen and van den Broeck [24]. the nature of the stochastic frontier problem reviewed here:

Suppose the production function $q_i = f(z_i, \beta)$ for the ith firm (in this paper, country), stochastic frontier analysis assumes that each firm potentially produces less than it might due to a degree of inefficiency. Specifically,

$$q_i = f(z_i, \beta)\xi_i \tag{4}$$

$\xi_i$ is the level of efficiency for firm i and must be in the interval $(0,1]$. Because the output is assumed to be strictly positive $(q_i \succ 0)$ the degree of technical efficiency is assumed to be strictly positive $(\xi_i \succ 0)$. Output is also assumed to be subject to random shocks, implying that

$$q_i = f(z_i, \beta)\xi_i \exp(v_i) \tag{5}$$

Taking the natural log of both sides yields

$$\ln(q_i) = \ln\{f(z_i, \beta)\} + \ln(\xi_i) + v_i \tag{6}$$

With k inputs and assuming that the production function is linear in logs, defining $u_i = -\ln(\xi_i)$ yields

$$\ln(q_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(z_{ji}) + v_i - u_i \tag{7}$$

Considering $u_i$ is subtracted from $\ln(q_i)$, restricting $(u_i \succ 0)$ implies $(0 \prec \xi_i \le 1)$, as specified above. From equations (7), the two components $v_i$ and $u_i$ are assumed to be Independent of each other, where $v_i$ is the two-sided, normally distributed random error $(V_i \sim N(0, \sigma_v^{\ 2})$, and $u_i$ is the one-sided efficiency component with a half normal distribution $(U_i \sim / N(0, \sigma_u^{\ 2})$. $q_i$ Is output and $z_{ji}$ is vector of inputs. Theβ's are unknown parameters to be estimated together with the variance parameters. The variances of the parameters, symmetric $v_i$ and one-sided $u_i$, are $\sigma_v^{\ 2}$ and $\sigma_u^{\ 2}$ respectively and the overall model variance given as $\sigma^2$ are related thus $\sigma^2 = \sigma_v^{\ 2} + \sigma_u^{\ 2}$ .

On the assumption that $v_i$ and $u_i$ are independent and normally distributed, the parametersβ, $\sigma^2$ , $\sigma_u, \sigma_v$ and $\lambda$ can be estimated by method of Maximum Likelihood Estimates.

When the distribution of inefficiency term assumed to be half-normal, the log-likelihood function is as follow:

$$Lnl = \sum_{i=1}^{N} \{\frac{1}{2}\ln(\frac{2}{\pi}) - \ln\sigma_s + \ln\Phi(-\frac{\lambda \in_i}{\sigma_s}) - \frac{1}{2}(\frac{\in_i}{\sigma_s})^2\} \tag{8}$$

where $\sigma_s = (\sigma_u{}^2 + \sigma_v{}^2)^{\frac{1}{2}}, \lambda = \frac{\sigma_u}{\sigma_v}, \in_i = \ln(q_j) - \beta_0 + \sum_{j=1}^{k} \beta_j \ln(Z_{ji})$ and $\Phi()$ is the cumulative distribution function of the standard normal distribution (Kumbhakar & Lovell, 25). The estimation of $u_i$ can be obtain by mean or mode of the conditional distribution $f(\frac{u}{\in})$.

$$E(u_i|\in_i) = \mu_{*i} + \sigma_* \left\{ \frac{\varnothing(-\mu_{*i}/\sigma_*)}{\Phi(\mu_{*i}/\sigma_*)} \right\}) \tag{9}$$

Then the technical efficiency will be estimated by:

$$E_i = E\{\exp(-u_i)|\in_i\} = \{\frac{1-\Phi(\sigma_* - \mu_{*i}/\sigma_*)}{1-\Phi(-\mu_{*i}/\sigma_*)}\} \exp \mu_{*i} + \frac{1}{2}\sigma_*{}^2) \tag{10}$$

where $\mu_{*i}$ and $\sigma_*$ are defined for the half-normal model as

$$\mu_{*i} = \frac{-\in_i \sigma_u^2}{\sigma_s^2} \tag{11}$$

$$\sigma_* = \sigma_u \sigma_v / \sigma_s \tag{12}$$

Kumbhakar & Lovell, [25]

### 2.3 Data analysis

The study is based on data exclusively drawn from the AGROSTAT system of the Statistics Division of the Food and Agricultural Organization of the United Nations. This includes 21 Middle East and North Africa countries.

**Output Series**

Due to the problems of estimating multiple outputs primal production functions, we use the FAO concept that is the output from the agriculture sector net of quantities of various commodities used as feed and seed, which is why feed and seed, are not included in the input series.

**Input Series**

In this research, it is chosen only five input variables. This variable covers arable land, tractor, labor, livestock, and fertilizer. Land refers to the sum of area under arable land (land under temporary crops, temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow); permanent crops (land cultivated with crops that occupy the land for long periods and need not be replanted after each harvest, such as cocoa, coffee and rubber); and permanent pastures (land used permanently for herbaceous forage crops, either cultivated or growing wild). Tractor refers to total wheel and crawler tractors (excluding garden tractors) used for agricultural production. Labor is the economically active population in agriculture for each year, in each country, the economically active population in agriculture is defined as all persons engaged or seeking employment in agriculture, forestry, hunting or fishing sector, whether as employers, own-account workers, salaried employee or unpaid workers. Following other studies on inter-country comparisons, of agricultural productivity (Nkamleu, GB [26], Shahabinejad & Akbari [27]) we use the sum of nitrogen, potash and phosphate content of various fertilizer consumed, measured in thousands of metric tons in nutrient units. The livestock input variable used in the study is the sheep-equivalent of five categories of animals. The categories considered are: buffaloes, cattle, pigs, sheep, and goats. Numbers of these animals are converted into sheep equivalents using convention factors of 8.0 for buffalo and cattle and 1.00 for sheep's, goats and pigs. Chicken numbers are not included in the livestock figures.

## 3 Results

### 3.1 estimated stochastic frontier function

Table 1 presents the results of a maximum likelihood estimate of frontier for SFA with Cobb-Douglas, and STATA 11 is adopted for calculation. The coefficient for all inputs (except labor) is positive and statistically significant. For instance, a one percent increase in land and tractor results in a 0.064 and 0.061percent increase in output respectively. In addition, a one percent increase in fertilizer and livestock leads respectively to a 0.059 and 0.12 percent increase in input. On the contrariwise, a one percent decrease in labor increases 0.081 percent in output. Also the output includes estimate of standard deviations of the two error components, $\sigma_u$ and $\sigma_v$, which are reported as sigma_u and sigma_v, respectively. The estimates of the total error variance, $(\sigma_s^2 = \sigma_u^2 + \sigma_v^2)$ and the estimate of the ratio of the standard deviation of the inefficiency component to standard deviation of the idiosyncratic component, $(\lambda = {}^{\sigma_u}/_{\sigma_v})$ are reported sigma2 and lambda, respectively. At the bottom of the output, there is the result of a test that is no technical inefficiency component in the model. This is a test of the null hypothesis $H_0:\ \sigma_u^2 = 0$ against the alternative hypothesis $H_1: \sigma_u^2 \succ 0$ . If the null hypothesis is true, the stochastic frontier model reduces to an OLS model with normal errors. As shown in table1 for half-normal, LR equals 24.7 with a p-value of 0.000; therefore the null hypothesis is rejected.

**Table1** Stochastic frontier estimation results

| Stoc. Frontier model | | | number of obs =21 | | | |
|---|---|---|---|---|---|---|
| | | | Wald chi2(5) = 1.03e+10 | | | |
| log likelihood=7.1119802 | | | pro> chi2 =0.000 | | | |
| Ln output | Coef. | Std. Err | Z | $P \succ \lvert Z \rvert$ | [95% Conf. interval] | |
| Ln land | .0637053 | 5.67e-06 | 1.1e+04 | 0.000 | .0636942 | .0637164 |
| Ln labor | -.0811451 | 6.18e-06 | -1.3e+04 | 0.000 | -.0811572 | -.081133 |
| Ln Tractor | .0613225 | 3.29e-06 | 1.9e+04 | 0.000 | .061316 | .0613289 |
| Ln fertilizer | .0593164 | .0000148 | 3994.74 | 0.000 | .0592873 | .0593455 |
| Ln livestock | .1217045 | 8.66e-06 | 1.4e+04 | 0.000 | .1216875 | .1217215 |
| Cons. | 3.401589 | .0001317 | 2.6e+04 | 0.000 | 3.401331 | 3.401847 |
| Lnsigma2v | -39.77103 | 772.1445 | -0.05 | 0.959 | -1553.147 | 1473.604 |
| Lnsigma2u | -2.547075 | .3922323 | -6.49 | 0.000 | -3.315837 | -1.778314 |
| Sigma_v | 2.31e-9 | 8.92e-07 | | | 0 | 0 |
| Sigma_u | .2798399 | .0548811 | | | .1905352 | .411002 |
| Sigma2 | .0783104 | .0307158 | | | .0181084 | .1385123 |
| Lambda | 1.21e+8 | .0548811 | | | 1.21e+08 | 1.21e+08 |
| Likelihood-ratio test of sigma_u=0: chibar2(01)=24.7 prob $\geq$ chibar2=0.000 | | | | | | |

### 3.2 Analysis of efficiency scores

We selected five inputs of MENA countries, including labor, land, tractor, livestock and fertilizer and single output.The stochastic frontier estimates of technical efficiency are reported in table 2. Among all countries, Qatar has the most technical efficieny equal 0.937. It is interesting to observe the high correlations between the SFA technical efficiency estimates and the DEA technical efficiency scores. The analysis has been carried out using both CRS and VRS assumptions with output orientation. The results are shown in table 2. The investigation under CRS assumptions shows that out of 21 MENA countries only Jordan, Lebanon and Qatar are technically efficient. All the remaining countries are relatively less technically efficient as they have the CRS scores less than one. The average efficiency score under CRS assumption is 0.744. Countries Iran, Iraq, Kuwait, Mauritania, Oman, Saudi, Sudan, Syria, Turkey, United Arab Emirate and Yemen have scored lower than the average efficiency score. The lowest efficiency score (0.491) is investigated for Bahrain. Therefore, the overall performance of Bahrain is very poor.

The results of efficiency score under VRS assumption are shown in table 2. It shows that countries are relatively less technical efficiency as they have scores less than one, except Jordan, Lebanon, Libya, Qatar and Tunisia. It is interesting to point out that in several countries, VRS scores is more than CRS scores. For example, Libya have relatively low CRS score (0.962), but obtains unit VRS scores. This undoubtedly shows that these countries are able to convert their inputs into output efficiently, but the lowering of their technical efficiency is due to their disadvantageous size.

The analysis also shows that total average of efficiency score of $DEA_{BCC}$(0.770)>$DEA_{CCR}$(0.744)>SFA(0.479). The importance of SFA results is that they are lower than those found using DEA in all cases, indicating that inefficiency (deviation from the best practice frontier) is lower than inefficiency measured by SFA. This suggests that the SFA results have removed any random noise that had been included in the DEA efficiency scores. Among the 21 MENA countries, efficiency scores of Qatar is No.1 and demonstrate the best performance in each of the three models. Also remaining countries show less variation of performance in different models. As shown in table 2 $DEA_{CCR}$ has three efficient countries including Jordan, Lebanon and Qatar and $DEA_{BCC}$ has five efficient countries.

**Table 2** DEA and SFA technical efficiency scores in selected countries (2008)

| Countries | DEA(CCR) | ranking | DEA(BCC) | ranking | SFA | ranking |
|---|---|---|---|---|---|---|
| Algeria | 0.841 | 6 | 0.855 | 6 | 0.576 | 7 |
| Bahrain | 0.491 | 21 | 0.522 | 21 | 0.222 | 21 |
| Egypt | 0.750 | 9 | 0.777 | 9 | 0.540 | 9 |
| Iran | 0.550 | 20 | 0.564 | 20 | 0.280 | 18 |
| Iraq | 0.631 | 16 | 0.654 | 16 | 0.336 | 16 |
| Israel | 0.769 | 8 | 0.800 | 8 | 0.548 | 8 |
| Jordan | 1.000 | 2 | 1.000 | 2 | 0.888 | 2 |
| Kuwait | 0.613 | 17 | 0.639 | 18 | 0.224 | 20 |
| Lebanon | 1.000 | 3 | 1.000 | 3 | 0.585 | 5 |
| Libya | 0.962 | 4 | 1.000 | 4 | 0.608 | 4 |
| Mauritania | 0.590 | 19 | 0.641 | 17 | 0.335 | 17 |
| Morocco | 0.782 | 7 | 0.817 | 7 | 0.584 | 6 |
| Oman | 0.602 | 18 | 0.620 | 19 | 0.240 | 19 |

| Countries | DEA(CCR) | ranking | DEA(BCC) | ranking | SFA | ranking |
|---|---|---|---|---|---|---|
| Qatar | 1.000 | 1 | 1.000 | 1 | 0.937 | 1 |
| Saudi Arabia | 0.654 | 15 | 0.692 | 15 | 0.368 | 15 |
| Sudan | 0.713 | 10 | 0.732 | 10 | 0.438 | 11 |
| Syria | 0.700 | 12 | 0.726 | 12 | 0.390 | 14 |
| Tunisia | 0.930 | 5 | 1.000 | 5 | 0.630 | 3 |
| Turkey | 0.682 | 13 | 0.718 | 13 | 0.410 | 13 |
| United Arab Emirate | 0.664 | 14 | 0.696 | 14 | 0.436 | 12 |
| Yemen | 0.702 | 11 | 0.730 | 11 | 0.490 | 10 |
| Average | 0.744 | | 0.770 | | 0.479 | |
| Min | 0.490 | | 0.522 | | 0.222 | |
| Max | 1.000 | | 1.000 | | 0.937 | |

## 4 Conclusions

The analysis of agricultural efficiency and productivity can make a major contribution to overall growth in developing countries. Two main methodologies have been developed to measure efficiency and productivity, the parametric and non-parametric approach. Although non-parametric doesn't make accommodation for statistical noise, parametric makes accommodation for statistical noise such as random variables of weather, machine breakdown and other events beyond the control of firms, and measures error. However both DEA and SFA provide a suitable way of treating the measurement of agricultural efficiency. Using agricultural sector data for 21 MENA countries in year 2007-2008, this paper estimates the technical efficiency with two current models, data envelopment analysis and stochastic frontier analysis. The analysis shows that the total average of technical efficiency scores of $DEA_{BCC}$ model is the highest (0.770), followed by $DEA_{CCR}$ model (0.744), SFA (0.479) is the smallest. Among 21 countries, Qatar demonstrates the best performance in the three models, while some of other countries show variation of performance in different models. Also the empirical results nearly, show that the parametric and non-parametric methods provide similar rankings of countries but in all cases SFA results are lower than those found using DEA that Indicates the SFA results have removed any random noise that had been included in the DEA efficiency scores. In future research, by analyzing total factor productivity in these countries, researchers will be able to measure changes in efficiency over time, and decompose this change in to technological change and pure efficiency change.

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