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

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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.

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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:

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

$s.t.$

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

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

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 andV_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:

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

$s.t.$

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

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

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

where ε is a small positive number, λ_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:

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

$s.t.$

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

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

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

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

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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,

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

ξ_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. The β'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 σ_v^2 and σ_u^2 respectively and the overall model variance given as σ^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 parameters β, σ^2 , σ_u, σ_v and λ 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:

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

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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 μ_{*i} and σ_* 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,

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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, σ_u and σ_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 ≥ chibar2=0.000						

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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

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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.

References

1. Farrel, M. J., (1957). The measurement of productive efficiency. Journal of the royal statistical society, 120, 253-290.
2. Ferrier, G. D., Lovell, C. A. K., (1990). Measuring cost efficiency in banking: econometric and linear programming evidence. Journal of econometric, Vol. 46, 229-245.
3. Sharma, K. R., Leung, P., Zaleski, H. M., (1997). Productive efficiency of the swine industry in Hawaii: stochastic frontier vs. data envelopment analysis. Journal of productivity analysis, vol. 8, 447-459.
4. Fulginiti, L. E., Perrin, R. K., (1998). Agricultural productivity in developing countries. Agricultural economics, vol. 19, 45-51.
5. Kwon, O. S., Lee, H., (2004). Productivity improvement in Korean rice farming: parametric and non-parametric analysis. The Australian journal of agricultural and resource economics, 48(2), 323-346.
6. Banker, R., Charnes, D., Cooper, A. W. W., (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, 30(9), 1078-1092.

[Downloaded from ijaor.com on 2025-07-09]

7. Coeilli, T., Peralman, S., (1996). A Comparison of Parametric and Non- parametric Distance Functions: With Application to European Railways; CREPP Discussion Paper No. 96/11. University of Liege, Liege.
8. Bauer, P. W., Berger, A. N., Ferrier, G. D., Humphrey, D. B., (1998). Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Methods. Journal of Economics and Business, No. 50, 85-114.
9. Resti, A., (1997). Evaluating the Cost Efficiency of the Italian Banking System: What Can Be Learned from the Joint Application of Parametric and Nonparametric Techniques. Journal of Banking & Finance, No. 21, 221- 250.
10. Charnes, A., Cooper, W. W., Rhodes, E., (1978). Measuring the Efficiency of Decision Making Units. European Journal of Operational Research, No. 2, 429-444.
11. Mortimer, D., (2002). A Systematic Review of Direct DEA vs SFA/DFA Comparisons. Working Paper 136. Centre for Health and Evaluation, Australia.
12. Berger, A. N., Mester, L. J., (1997). Inside the Black Box: What Explains Differences in the Efficiency of Financial Institutions. Journal of Banking & Finance, No. 21, 895-947.
13. Hasan, I., Hunter, W. C., (1996). Efficiency of Japanese Multinational Banks in the United States. Research in Finance, No. 14, 157-173.
14. Allen, L., Rai, A., (1996). Operational Efficiency in Banking: An International Comparison. Journal of Banking and Finance, No. 20, 655-672.
15. Casu, B., Girardone, C., (2002). A Comparative Study of the Cost Efficiency of Italian Bank Conglomerates. Managerial Finance, No. 28, 3-23.
16. Fiorentino, Elisabetta et al., (2006). The Cost Efficiency of German Banks: A Comparison of SFA and DEA. Discussion Paper, Series 2, Banking and Financial Studies, No. 10/2006, Deutsche Bundesbank, Germany.
17. Webster, R., Kennedy, S., Johnson, L., (1998). Comparing Techniques for Measuring the Efficiency and Productivity of Australian Private Hospitals. Working Paper No. 98/3. Australian Bureau of Statistics, Australia.
18. Gannon Brenda., (2004). Technical Efficiency of Hospitals in Ireland. Working Paper 18. Economic and Social Research Institute, Ireland.
19. Sheldon, G., (1994). Economies, Inefficiencies and Technical Progress in Swiss Banking. In D. Fair and R. Raymond (Eds.). The Competitiveness of Financial Institutions and Centers in Europe, 115-133. Kluwer.
20. Kasman, A., Turgutlu, E., (2007). A Comparison of Chance- constrained DEA and Stochastic Frontier Analysis: An Application to the Turkish Life Insurance Industry. Türkiye Ekonometri ve İstatistik Kongresi, 24-25 Mayıs 2007 - İnönü Üniversitesi, Malatya.
21. Nunamaker, T., (1985). Using Data Envelopment Analysis to Measure the Efficiency of Non-profit Organisations: A Critical Evaluation. Managerial and Decision Economics, No. 6, 50-58.
22. Banker, R., Gadh, V., Gorr, W., (1993). A Monte Carlo Comparison of Two Production Frontier Estimation Methods: Corrected Ordinary Least Squares and Data Envelopment Analysis. European Journal of Operational Research, No. 67, 332-343.
23. Aigner, D, Lovell, C. A. Knox & Schmidt, P (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. Journal of Econometrics, 6 (1), 21-37.
24. Meeusen, W., van den Broeck, J. (1977). Efficiency estimation from Cobb–Douglas production functions with composed error. International Economic Review, 18, 435–444.
25. Kumbhakar, S. C., Lovell, C. A. K., (2000). Stochastic Frontier Analysis. Cambridge: Cambridge University Press.
26. Nkamleu, G. B., (2004). Productivity Growth, Technical Progress and Efficiency Change in African Agriculture. Afr Dev. Rev. 16, 203-222.
27. Shahabinejad, V., Akbari, A., (2010). Measuring agricultural productivity growth in Developing Eight. Journal of development and agricultural economics, 2(9), 326-332.

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