A META-ANALYSIS OF TECHNICAL EFFICIENCY IN FARMING: A MULTI-COUNTRY PERSPECTIVE

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ABSTRACT

A META-ANALYSIS OF TECHNICAL EFFICIENCY IN FARMING: A MULTI-COUNTRY PERSPECTIVE

The objective of this study is to undertake a meta-analysis seeking to explain the variation in average technical efficiency focusing on the agricultural sector. For this purpose, a meta-analysis of 126 technical efficiency studies on the agricultural sector of developing and developed countries was undertaken. In addition, the study contributes to cross-country productivity literature because the existing body of work in this area typically uses aggregate (i.e., national) level data to estimate total factor productivity and has ignored the technical efficiency component of productivity.

The econometric results suggest that stochastic frontier models generate higher mean technical efficiency estimates than deterministic models, while parametric frontier models yield lower estimates than non-parametric. The difference between parametric and non-parametric frontiers is reduced when the translog specification is used. Also, frontier models using cross-sectional data produce lower estimates than those based on panel data. The econometric results also suggest that low-income countries (LICs) present a lower mean technical efficiency than high-income countries (HICs). A more detailed analysis reveals that Western European countries and Australia present, on average, the highest levels of mean technical efficiency among all regions after accounting for some methodological features of the studies. Eastern European countries exhibit the lowest estimate followed by Asian and African countries, while studies from Latin America and Caribbean countries, and from North American countries are in an intermediate position.

A META-ANALYSIS OF TECHNICAL EFFICIENCY IN FARMING: A MULTI-COUNTRY PERSPECTIVE

The objective of this paper is to conduct a multi country analysis of technical efficiency using the results of 126 published papers that have relied on farm level data from 14 high-income countries and from 23 low-income countries. This paper constitutes a significant extension of the work by Thiam, Bravo-Ureta and Rivas (2001) who provided an analysis that focused on 34 studies covering 13 low-income countries. In addition, this study contributes to the cross-country agricultural productivity literature because the existing body of work in this area typically uses aggregate (i.e., national) level data to estimate total factor productivity. Major shortcomings of this literature include data comparability problems (Capalbo, Ball and Denny, 1990) and the fact that it has ignored the technical efficiency component of productivity.

To accomplish the objective set forth, a meta-analysis seeking to explain the variation in average technical efficiency focusing on the agricultural sector is undertaken. Meta-analysis is an approach that uses published empirical estimates of some indicator, technical efficiency in the present case, and attempts to explain the variation of these estimates based on differences across studies as explanatory variables in a regression model (Phillips, 1994; Espey, Espey and Shaw, 1994).

The paper first presents the concept of technical efficiency followed by a brief review of its measurement. We then present the data sources and the empirical models employed. Next, we present a summary of technical efficiency (TE) measures reported in the literature for a wide range of countries and, on the basis of the econometric results, we compare TE for groups of countries characterized by different levels of development. Finally, a summary is presented along with some suggestions for further research.

OVERVIEW OF THE FRONTIER FUNCTION METHODOLOGY

Over three decades ago, Farrell (1957) introduced a methodology to decompose economic efficiency into technical and allocative efficiency, which gave rise to the prolific frontier function literature. In Farrell's model, TE is defined as the firm's ability to produce maximum output given a set of inputs and technology. Allocative (or price) efficiency (AE) measures the firm's success in choosing the optimal input proportions, i.e., where the ratio of marginal products for each pair of inputs is equal to the ratio of their market prices. In Farrell's framework, economic efficiency is a measure of overall performance and is equal to the product between TE and AE.

The frontier function methodology has become a widely used tool in applied production as evidenced by the proliferation of methodological and empirical frontier studies over the last two decades (Battese, 1992; Bravo-Ureta and Pinheiro, 1993). Frontier models can be classified into two basic types: parametric and non-parametric. Parametric frontiers required the specification of a functional form while the non-parametric do not.

Parametric models can be separated into deterministic and stochastic. The deterministic model assumes that any deviation from the frontier is due to inefficiency, while the stochastic approach allows for statistical noise. Therefore, a fundamental problem with deterministic frontiers is that any measurement error, and any other source of stochastic variation in the dependent variable, is embedded in the one-sided component making the resulting TE estimates sensitive to outliers (Greene, 1993). The stochastic frontier production model addresses this sensitivity problem by incorporating a composed error structure with a two-sided symmetric term and a one-sided component. The one-sided component reflects inefficiency, while the two-sided error captures the random effects outside the control of the production unit.

Econometric models for the estimation of efficiency can also be separated into primal and dual approaches, depending on the underlying behavioral assumptions that are made. The primal approach has been more common in frontier estimation although dual cost and particularly profit function models have gained increasing attention in recent years (Kumbhakar, 2001). The estimation of frontier functions can also be categorized, according to the type of data, as cross-section or panel data studies. The estimation of stochastic frontiers with panel data is very appealing because it can avoid several limitations present in cross-sectional studies (Schmidt and Sickles, 1984).

Non-parametric technical efficiency models, also referred to as data envelopment analysis (DEA), are based on mathematical programming techniques. The main feature of DEA methods is that they do not require the specification of a functional form. Nevertheless, a major drawback of these methods is that they are deterministic and thus affected by extreme observations. Another characteristic of DEA methods is the potential sensitivity of efficiency scores to the number of observations as well as to the number of outputs and inputs (Nunamaker, 1985).

Despite the significant advances in the frontier function literature, many methodological questions remain. Examples of these questions include the effect of functional form on parametric models, the lack of *a priori* justification for the selection of a particular distributional form for the one-sided inefficiency term in stochastic frontiers, potential simultaneous equation bias in primal models, and the validity of dual models, particularly when profit maximization is the maintained hypothesis in the context of developing country agriculture. To what extent efficiency estimates are sensitive to model specification is a matter of on going discussion. Authors like Coelli (1995) and Hjalmarsson et al. (1996) have discussed the advantages and limitations of the different methodological approaches for the measurement of efficiency.

DATA AND METHODOLOGY

An important consideration in studies using the meta-analysis framework is to do as complete a search of the relevant literature as possible. To this end, in the present paper a thorough online review was made of the following data bases: Agricola; Agris International; Ingenta; Social Science Citation Index; Science Direct; Uncover; and the World Agricultural Economics and Rural Sociology Abstracts. In addition, a complementary search was performed in the following Journals (J): American J. of Agricultural (Ag.) Economics (Econ.); European Review of Ag. Econ.; Canadian J. of Ag. Econ.; Australian J. of Ag. Econ.; J. of Ag. and Applied Econ; J. of Ag. Econ.; Ag. and Resource Econ. Review; J. of Comparative Econ.; J. of Productivity Analysis; European J. of Operational Research; and J. of Econometrics.

The literature search yielded a total of 126 published papers, which include the type of information required for the analysis presented in this study.

Given that many of the papers report several technical efficiency estimates, the data set under analysis comprises a total of 484 observations or cases.

The basic hypothesis of this paper is that the variation in the mean TE indices reported in the literature can be explained by the attributes of the studies, including functional form, sample size, product analyzed, number of variables in the model, estimation technique and country/region where the farm data for the study was collected. To investigate this issue formally, the following three models are estimated:

Model 1:

$$TE = f(STO, CD, OF, TL, CS, RIGR, SIZE, VAR, PRI)$$

Model 2:

$$TE = f(STO, CD, OF, TL, CS, RIGR, SIZE, VAR, PRI, LIC)$$

Model 3:

$$TE = f(STO, CD, OF, TL, CS, RIGR, SIZE, VAR, PRI, ASIA, NAMR, AFRI, LTCR, EAST)$$

where *TE* is the mean technical efficiency reported in a study; *STO* is a dummy variable equal to one if the model is a stochastic frontier and zero otherwise; *CD* is a dummy variable equal to one if the Cobb-Douglas functional form is used and zero otherwise, *TL* is a dummy variable equal to one if the functional form is translog, *OF* is a dummy variable equal to one if a functional form other than Cobb Douglas or Translog is used and the omitted category is the non-parametric studies; *CS* is a dummy variable equal to one if the data is cross-sectional and zero otherwise; *PRI* is a dummy variable equal to one if a primal model is estimated and zero otherwise; *SIZE* is the number of observations used in a study; *VAR* is the number of explanatory variables used in a study; *RIGR* is a dummy variable equal to one if the model is for rice or grains and zero otherwise; *LIC* is a dummy variable equal to one for lower and lower-middle income countries and zero otherwise; *ASIA* is a dummy variable equal to one if the study used data from Asia and zero otherwise, *NAMR* is a dummy variable equal to one if the study used data from North

America and zero otherwise, *AFRI* is a dummy variable equal to one if the study used data from Africa and zero otherwise, *LTCR* is a dummy variable equal to one if the study used data from Latin America or Caribbean and zero otherwise, *EAST* is a dummy variable equal to one if the study used data from Eastern Europe and zero otherwise, and the excluded region is Western Europe and Australia.

The three models are estimated using the two-limit Tobit procedure of SHAZAM given that the efficiency scores are bounded between zero and one.

RESULTS

Before examining the statistical results it is useful to take a look at descriptive statistics of the studies. Table 1 presents descriptive statistics focusing on methodological features of the studies under examination. As indicated earlier, a total of 126 studies are included in the analysis. Of this total, 51 are based on deterministic models and 87 on stochastic models, which gives a number higher than 126 because some studies employ both types of models. The majority of the cases use parametric models, panel data, the Cobb Douglas functional form and a primal representation of the technology.

The data presented in Table shows that the average mean TE (AMTE) for all deterministic models is 75.2% compared to 77.3% for all stochastic models. A comparison between the parametric and non-parametric estimates shows that the former are lower (71.9%) than the latter (80.2%) as would be expected on a theoretical basis.

An interesting pattern is observed when one looks at the effect of functional form. For the deterministic models, the Cobb Douglas form yields a higher AMTE (74.4%) than the translog (67.6%) while the opposite pattern is observed for the stochastic models.

Table 1. Descriptive Statistics by Methodological Characteristics

Category	Deterministic			Stochastic			Overall			
	Mean TE			Mean TE			Mean TE			Number of Cases
	Avg .	Max.	Min.	Avg .	Max.	Min.	Avg .	Max.	Min.	
Approach										
Parametric	71.9	95.9	44.6	77.3	89.1	55.2	76.3	90.1	53.3	429

Non Parametric	80.2	98.3	48.7				80.2	98.3	48.7	55
Data										
Panel	77.8	94.6	46.4	78.6	88.8	59.7	78.5	89.2	58.0	278
Cross Sectional	74.1	97.3	45.7	74.4	89.9	44.7	74.3	93.0	45.1	206
Functional Form										
Cobb-Douglas	74.4	95.7	44.3	75.8	88.2	56.8	75.5	89.4	54.1	294
Translog	67.6	100.0	51.5	80.2	93.0	49.1	79.5	93.3	49.2	118
Others	64.6	N.D.	N.D.	85.0	85.0	85.0	65.8	N.D.	N.D.	17
Technology Representation										
Primal	75.4	96.8	46.1	77.0	89.3	54.0	76.5	91.1	51.8	402
Dual	69.6	97.5	37.5	78.4	88.2	61.2	78.1	88.6	60.2	78
Total										
Average	**75.2**	**96.7**	**45.9**	**77.3**	**89.1**	**55.2**	**76.7**	**90.8**	**53.1**	
Number of Cases		**135**			**349**					**484**
Number of Studies		**51**			**87**					**126**

A final point from Table 1 is that the panel data and the dual models yield higher AMTE than the cross sectional and the primal estimates, respectively.

Table 2 contains descriptive statistics focusing on two non-methodological features of the studies: the product analyzed in the studies; and the institutional affiliation of the first author. With regard to type of product, dairy farming is the dominant category with 168 cases, followed by other crops (119), rice (85), other grains (48), whole farm (37), and other animal products (27). The highest AMTE is reported for the other animal studies (84.4%), followed by dairy (81.3), while the lowest is for other grains (71.4%).

The dominant category for affiliation of the senior author is university with 416 cases, followed by private sector (57) and government (11). A fair amount of variability is exhibited in the AMTE across senior author affiliation going from a high of 78.7% for private sector researchers to a low of 68.8% for studies conducted by government researchers.

Table 3 summarizes the TE measures according to six geographical locations were the studies were conducted. The largest number of cases is for Asia (180), followed by Western Europe and Australia (137), North America (91), Latin America and the Caribbean (44), Eastern Europe (17) and Africa (15). The highest AMTE when stochastic and deterministic studies are combined is for Western Europe and Australia at 83.2% while the lowest is for Asia and Eastern Europe at 72.5% for both groups. When the deterministic and stochastic AMTEs are calculated separately, Western Europe and Australia still exhibits the highest level but there is some change in the rankings for the other regions.

Also displayed in Table 3 is the AMTE for all Low Income Countries (LICs) combined and for all High Income Counties combined (HICs). The LICs include Africa, Latin America and the Caribbean, Asia (excluding Malaysia) and the Ukraine. The HICs include Western Europe and Australia, North America, Malaysia and Slovenia. The AMTE for the LICs when the deterministic and stochastic measures are combined is 73.8% while that for the HICs is 79.7%. By comparison, when one looks only at the deterministic cases, the AMTE for

Table 2. Descriptive Statistics of Non Methodological Characteristics

Category	Number of Cases	Mean TE		
		Average	Min.	Max.
Products				
Rice	85	71.5	56.2	85.0
Other Grains	48	71.4	49.7	94.1
Other Crops	119	74.6	47.4	90.7
Whole Farm	37	77.0	59.3	84.6
Dairy	168	81.3	56.0	96.8
Other Animals	27	84.4	51.0	99.1
Senior Author Affiliation				
University	416	76.8	53.4	90.2
Government	11	68.8	48.2	100.0
Private	57	78.7	50.9	96.0

Table 3. Average of the Mean Technical Efficiency by Region

Region	No. Cases	Deterministic Mean TE			Stochastic Mean TE			Overall Mean TE		
		Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.
Asia	180	64.3	94.6	42.1	73.5	86.2	53.0	72.5	86.9	52.0
W. Europe & Australia	137	82.0	100.0	53.9	83.8	98.1	58.4	83.2	98.6	56.5
N. America	91	74.3	96.1	42.4	78.0	95.4	59.7	75.7	95.8	49.2
L. America & Caribbean	44	76.4	100.0	43.3	78.3	87.9	62.3	78.0	89.7	59.5
E. Europe	17	75.0	95.3	48.5	71.5	ND	ND	72.5	95.3	48.5
Africa	15	53.5	93.5	13.8	78.6	95.9	42.8	75.3	95.5	37.5
LICs*	248	67.7	97.4	41.1	74.6	86.9	54.4	73.8	88.0	53.0
HICs*	236	77.1	96.5	47.7	82.0	97.0	58.2	79.7	96.7	52.8

***LICs: Africa, Latin America &Caribbean, Asia (w/o Malaysia), Ukraine**
***HICs: Western Europe and Australia, North America, Malaysia, Slovenia**

the LICs is 67.8% and 77.1% for the HICs, and for the stochastic cases the AMTE is 74.6% for the LICs and 82.0% for the HICs. In sum, the HICs consistently exhibit a higher level of average mean TE than the LICs.

Table 4 presents the econometric results for Models I, II and III based on two-limit Tobit estimations. Model I ignores the possible presence of a country effect, Model II introduces a dummy variable that takes the value of one for the studies performed in the LICs and zero otherwise, and Model III incorporates five dummies capturing the regional effect on the mean technical efficiency levels (MTEs). The regional dummies included in the model are *ASIA*, *AFRI*, *LTCR*, *EAST* and *NAMR* representing Asian, African, Latin American and Caribbean, Eastern European, and North American countries, respectively. The excluded category is Western Europe and Australia.

According to Table 4, Model I has seven out of 10 regression coefficients that are statistically significant at the 10% level or better. To start out, the parameter for the *STO* variable has a negative and statistically significant coefficient indicating that stochastic frontier models generate higher mean technical efficiency estimates than deterministic models. This is consistent with what would be expected on a theoretical basis given that deterministic models assume all the deviation from the frontier represents inefficiency.

The negative signs on the parameters for the variables, *CD*, *OF* and *TL*, and keeping in mind that the excluded category for this group of variables is non-parametric, indicate that parametric frontier models consistently yield lower MTEs. This finding is consistent with *a priori* expectations and corroborates the averages shown in Table 1. Specifically, imposing a functional form other than Cobb-Douglas and Translog to the data (*OF*), results in the lowest estimate of MTE relative to non-parametric models. The fact that the translog specification (*TL*) is the closest to the non-parametric is likely due to the greater flexibility of this functional form.

Another variable with a negative and significant effect on the MTE is *CS*. Therefore, this suggests that frontier models using cross-sectional data produce lower mean technical efficiency estimates than models based on panel

Table 4. Maximum Likelihood Estimates of the Two-Limit Tobit Models for Mean Technical Efficiency

Variable	Model I	Model II	Model III
CONSTANT	82.872*** (4.001)	83.667*** (4.003)	85.997*** (4.248)
STO	3.531* (1.830)	5.892*** (1.902)	5.984*** (1.854)
CD	-8.279*** (2.369)	-6.984*** (2.350)	-7.794*** (2.336)
OF	-9.752*** (3.663)	-10.560*** (3.612)	-10.206*** (3.584)
TL	-6.668** (2.771)	-7.305*** (2.733)	-8.693*** (2.821)
CS	-3.352** (1.395)	-2.890** (1.377)	-1.993 (1.442)
RIGR	-6.238*** (1.493)	-4.310*** (1.539)	-3.294** (1.585)
SIZE	0.0003 (0.4E-03)	0.0002 (0.4E-3)	0.0005 (0.6E-3)
VAR	0.072 (0.058)	0.056 (0.058)	0.025 (0.058)
PRI	0.029 (1.812)	-0.541 (1.718)	-0.094 (1.843)
LIC		-5.758*** (1.453)	
ASIA			-9.023*** (1.777)
NAMR			-5.137*** (1.982)
AFRI			-6.111* (3.590)
LTCR			-4.700* (2.592)
EAST			-11.080*** (3.745)
Log-Likelihood	-1913.26	-1905.41	-1897.51
SQCORR[1]	0.11	0.14	0.17

*Significance at the 10% level ** Significance at the 5% level ***Significance at the 1% level

[1]**SQCORR**: Squared Correlation between observed and expected values

data. The parameter for the variable *RIGR* also presents a negative coefficient, suggesting that frontier models for rice and grains present, on average, lower levels of MTE than those models focused on other products such as dairy, other crops or the whole-farm.

The variables with non significant coefficients are the number of observations in the data set that was used to estimate the underlying model (*SIZE*), the number of explanatory variables used in that model (*VAR*), and whether the model used a primal representation of the technology (*PRI*).

An important objective of this paper is to examine if there is a country or regional effect on the estimated MTE. To this end, we first separate the data in two groups of counties, the HICs and the LICs and a dummy variable is introduced to capture this effect, as explained earlier. The results are shown in Table 4 under the column for Model II. The coefficient for the dummy for the LICs is negative and statistically significant. Therefore, these results suggest that, on average, the studies from the LICs present a lower MTE estimate than studies from the HICs.

The next step in the analysis was to disaggregate the HICs and the LICs in order to get a more detailed view of the possible association between income category and MTE. To accomplish this, the LIC variable in Model II is replaced by the dummy variables *ASIA*, *NAMR*, *AFRI*, *LTCR* and *EAST* and the excluded category is Western Europe and Australia. These results can be seen in the column for Model III in Table 4.

The coefficients for all the regional dummies included in Model III are significant and negative, meaning that Western European countries and Australia present, on average, the highest levels of MTE among all regions after controlling for some methodological features of the studies. Looking at individual coefficients, we observe that studies utilizing data from Eastern European countries produce, on average, the lowest estimate of MTE followed by Asian and African countries. Studies using data from Latin America and Caribbean countries, and from North American countries are in an intermediate position.

It is interesting to note that the results associated with the methodological aspects of the studies are consistent across the three models shown in Table 4. Finally, all models have a relatively week explanatory power as evidenced by the low squared correlation between observed and expected values obtained in all the models. The highest level of explanatory power, however, is for model III, which presents a squared correlation of 0.17.

SUMMARY AND CONCLUSIONS

The objective of this study was to undertake a meta-analysis seeking to explain the variation in average technical efficiency focusing on the agricultural sector. The mean technical efficiency estimates reported in 126 published papers, 14 from high-income countries and 23 from low-income countries, were explained by some of the major methodological characteristics of the studies. Alternative models incorporated dummy variables to capture the income level of the countries and their location. The study contributes to cross-country productivity literature because the existing body of work in this area typically uses aggregate (i.e., national) level data to estimate total factor productivity and has ignored the technical efficiency component of productivity.

The econometric results suggest that stochastic frontier models generate higher mean technical efficiency estimates than deterministic models, while parametric frontier models yield lower estimates. The difference between parametric and non-parametric frontiers is reduced when the translog specification is used. In addition, frontier models using cross-sectional data produce lower estimates than those based on panel data.

The econometric results also suggest that low-income countries (LICs) present a lower mean technical efficiency than high-income countries (HICs). A more detailed analysis reveals that Western European countries and Australia present, on average, the highest levels of mean technical efficiency among all regions after accounting for some methodological features of the studies. Eastern European countries exhibit the lowest estimate followed by Asian and African countries, while studies from Latin America and Caribbean countries, and from North American countries are in an intermediate position.

In conclusion, the body of published articles focusing on technical efficiency suggests that, given the state of technology prevailing in the various regions/countries at the time the studies were conducted, the shortfall in technical efficiency and thus in managerial ability, is most significant in Eastern European countries followed by Asia and Africa. By contrast, managerial improvements as a means to increase productivity are least promising in Western Europe and Australia, followed by North America, and Latin American and Caribbean countries. Hence, in very broad terms, the evidence presented in this paper suggests a positive relationship between average technical efficiency and the level of economic development of a country. More conclusive statements on this matter will need refinements on the data used and further analysis.

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Note : The studies used for the estimation can be obtained directly from the authors.

About the Authors :

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