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Technical efficiency in farming: a meta-regression analysis

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Abstract A meta-regression analysis including 167 farm level technical efficiency (TE) studies of developing and developed countries was undertaken. The econometric results suggest that stochastic frontier models generate lower mean TE (MTE) estimates than non-parametric deterministic models, while parametric deterministic frontier models yield lower estimates than the stochastic approach. The primal approach is the most common technological representation. In addition, frontier models based on cross-sectional data produce lower estimates than those based on panel data whereas the relationship between functional form and MTE is inconclusive. On average, studies for animal production show a higher MTE than crop farming. The results also suggest that the studies for countries in Western Europe and Oceania present, on average, the highest levels of MTE among all regions after accounting for various methodological features. In contrast, studies for Eastern European countries exhibit the lowest estimate followed by those from Asian, African, Latin American, and North American countries. Additional analysis reveals that MTEs are positively and significantly related to the average income of the countries in the data set but this pattern is broken by the upper middle income group which displays the lowest MTE.

Keywords Meta-Regression · Frontier Models · Technical Efficiency · International Agriculture

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1 Introduction

As is well established in the literature, productivity growth can be decomposed into technological change (TC) and technical efficiency (TE). This decomposition makes it possible to study the sources of productivity growth from different points of view (Nishimizu and Page 1982). Specifically, TE can be interpreted as a relative measure of managerial ability for a given technology, while TC evaluates the effect in productivity from the adoption of new production practices. In other words, gains in TE are derived from improvements in decision-making, which in turn are related to a host of variables including knowledge, experience and education. By contrast, TC relates to investments in research and technology (Nishimizu and Page 1982; Ahmad and Bravo-Ureta 1996).

In measuring TE, different methodologies and strategies have been proposed and considerable controversy has surrounded the choice and merits of a specific methodology and the impact of such choice on the ensuing analysis (Olesen et al. 1996; Coelli and Perelman 2000). Wadud and White (2000) indicate that in most empirical studies the selection of the methodology used to measure TE is arbitrary and mainly based on the objective of the study, the data available and the personal preference of the researcher. Using a simulation analysis comparing the outcomes from parametric and non-parametric techniques, Resti (2000) concludes that there is no clear advantage of one method over the other. However, empirical studies using agricultural data have shown that the selection of a specific methodology can seriously affect the estimated TE scores (e.g., Kalaitzandonakes and Dunn 1995; Sharma et al. 1999; Wadud and White 2000; Solís 2005).

The main goal of this paper is to examine the impact of various attributes of a study (e.g., estimation technique, functional form, sample size) on TE estimates. To accomplish the objective set forth, a meta-regression analysis of 167 frontier studies of TE focusing on the agricultural sector is undertaken. Meta-regression analysis is a quantitative method used to evaluate the effect of methodological and other study-specific characteristics on published empirical estimates of some indicator, TE in our case, using differences across these studies as explanatory variables in a regression model (Alston et al. 2000).

The rest of this paper is divided into four additional sections. Section 2 discusses the concept of TE followed by a brief review of its measurement. Section 3 describes the data sources and empirical model employed in the study followed by the results and analysis. The last section presents a summary along with some suggestions for further research.

2 An overview of the frontier function methodology

The original frontier function model introduced by Farrell (1957) uses the efficient unit isoquant to measure economic efficiency (EE), and to decompose this measure into TE and allocative efficiency (AE). In this model, TE can be defined as the firm's ability to produce maximum output given a set of inputs and technology. It is important to distinguish TE from TC, where the latter reflects an upward shift of the production function or a downward shift of the unit isoquant. AE (or price efficiency) 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, EE is a measure of overall performance and is equal to TE times AE (i.e., EE = TE $\times$ AE).

The frontier function methodology has become a widely used tool in applied production analysis due mainly to its consistency with the textbook definition of a production, profit or cost function (i.e., with the notion of maximization or minimization). This popularity is evidenced by the proliferation of methodological and empirical frontier studies over the last two decades as shown in the reviews by Battese (1992), Bravo-Ureta and Pinheiro (1993), Thiam et al. (2001), and Gorton and Davidova (2004).

Frontier models can be classified into two basic types: parametric and non-parametric. Furthermore, 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 overcome 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 for the technology as is the case for parametric models. Nevertheless, a major drawback of these methods is that they are deterministic and thus are 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 dimensionality of the frontier (Ramanathan 2003).

Recent work has focused on extending the stochastic frontier approach in order to deal with multi-output technologies within a primal framework. To this end, the stochastic distance function approach has been proposed and is now becoming widely used in the efficiency literature. The main advantage of using a distance function is that price information is not needed and the production frontier can be estimated without assuming separability of inputs and outputs (Kumbhakar et al. 2003).

Despite 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. Several authors have discussed the advantages and limitations of the different methodological approaches available to measure efficiency (e.g., Coelli 1995; Hjalmarsson et al. 1996; and Alvarez and Orea 2002); however, the extent to which efficiency estimates are sensitive to model specification is a matter of on going debate.

This paper contributes to the existing literature by conducting a systematic analysis of the effects that different methodologies and study-specific characteristics have on mean TE estimates using a data set created from 167 published papers that have relied on farm level data from around the world. Specific issues examined include: (1) whether parametric deterministic or parametric stochastic frontiers produce different TE estimates than non-parametric studies; (2) whether functional form has a discernable effect on TE; (3) whether panel data frontier models produce the same mean TE than cross-sectional data frontier models; (4) whether TE from studies using a primal approach differ from those using a dual approach; (5) whether model dimensionality (sample size and the number of variables) has a significant impact on TE; (6) whether TE varies with the type of product under analysis; (7) whether geographical location generates a significant variation on mean TE; and (8) whether the income level of the country under study has an impact on TE estimates. The work reported here constitutes a significant extension of the study by Thiam et al. (2001) that provided an analysis focusing on 34 articles covering only developing countries.

3 Data and methodology

An important consideration in studies using the meta-regression analysis framework is to define a clear approach to be followed when searching the relevant literature. To this end, in the present paper a thorough review was made in the following databases: Agricola; Agris International; Ingenta; Science Direct; Social Science Citation Index; and the World Agricultural Economics and Rural Sociology Abstracts. In addition, a complementary search was performed in the following Journals (J): Agricultural (Ag.) and Resource Economics (Econ.) Review; American J. of Ag. Econ.; Australian J. of Ag. Econ.; Canadian J. of Ag. Econ.; European J. of Operational Research; Eur Rev Ag. Econ.; J. of Ag. and Applied Econ; J. of Ag. Econ.; J. of Comparative Econ.; J. of Econometrics; and J. of Productivity Analysis.

The literature search yielded a total of 167 published papers, which include the type of information required for the present study.[1] This search was done for studies published between January 1979 and June 2005. Given that many of the papers report multiple TE estimates, the dataset under analysis comprises a total of 569 observations. An overview of all the papers used in this evaluation, including the first author, year of publication, country and product analyzed, average number of observations and mean TE, is presented in Table 1. In addition, all these papers are sorted by the methodology implemented in the studies. To save space on the table, for those studies that reported more than one estimate using the same methodology, both the average number of observations and mean TE are presented. However, for studies reporting multiple estimators using different methodologies, both the average number of observations and mean TE by methodology are

[1] Several other papers were found in the databases and journals included in the search but they did not contain all the variables needed; thus, they had to be excluded from the analysis.

Table 1 Overview of empirical studies of technical efficiency in farming[a]

First Author	Year	Country	Product(s)	No. obser.	Mean TE
I. Non-parametric					
Abay	2004	Turkey	Other crops	300	45.6
Asmild	2003	Netherlands	Dairy	1,808	80.5
Brümmer	2001	Slovenia	Whole farm	185	44.0
Byrnes	1987	USA	Grains	107	99.4
Chandra	1979	Costa Rica	Whole farm	30	79.3
Chavas	1993	USA	Whole farm	545	96.4
Cloutier	1993	Canada	Dairy	187	89.8
Dawson	1985	UK	Whole farm	224	96.0
de Koeijer	2002	Netherlands	Other crops	467	63.0
de Koeijer	2003	Netherlands	Whole farm	57	55.0
Dhungana	2004	Nepal	Rice	76	68.0
Featherstone	1997	USA	Cattle	195	78.0
Fernandez-Cornejo	1994	USA	Vegetables	87	60.8
Fletschner	2002	Paraguay	Whole farm	283	84.0
Fraser	1999	Australia	Dairy	50	88.5
Gillespie	1997	USA	Ratite	57	67.0
Jaforullah	1999	New Zealand	Dairy	264	89.0
Kalaitzandonakes	1992	USA	Grains	250	94.0
Kalaitzandonakes	1995	Guatemala	Maize	82	93.0
Kwon	2004	Rep. of Korea	Rice	5,130	72.0
Lansink	2002	Finland	Whole farm	2,014	92.0
Lansink	2004	Netherlands	Pork	96	90.0
Latruffe	2004	Netherlands	Dairy, other crops	222	64.0
Latruffe	2005	Netherlands	Dairy, other crops	199	69.8
Lissitsa	2005	Ukraine	Whole farm	920	83.5
Mehdian	1988	USA	Grains	116	59.7
Piesse	1996	Slovenia	Dairy	272	93.0
Radam	1995	Malaysia	Rice	317	49.8
Reinhard	2000	Netherlands	Dairy and Cattle	1,535	79.7
Rowland	1998	USA	Swine	129	89.0
Sarker	2004	India	Other crops	80	99.0
Shafiq	2000	Pakistan	Cotton	117	77.0
Sharma	1997	USA	Other Animals	60	64.4
Sharma	1999	USA	Swine	53	70.1
Sherlund	2002	Cote d'Ivoire	Rice	464	35.0
Tauer	1993	USA	Dairy	395	78.3
Tauer	1998	USA	Dairy and Cattle	630	91.8
Thiele	1999	Germany	Whole farm	601	92.0
Thomas	1994	USA	Dairy	125	89.2
Wadud	2000	Germany	Rice	150	85.6
Weersink	1990	Canada	Dairy	105	91.8
Wu	2003	USA	Other crops	147	88.0
Mean					78.3
II. Parametric					
Deterministic frontier					
Ahmad	1996	USA	Dairy	1,072	76.5
Alvarez	1999	Spain	Dairy	410	72.0
Alvarez	2004	Spain	Dairy	196	70.0
Aly	1987	USA	Grains	88	58.0
Amara	1999	Canada	Potato	82	80.3
Bakhshoodeh	2001	Iran	Wheat	164	92.0
Bravo-Ureta	1986	USA	Dairy	222	82.2
Bravo-Ureta	1990	USA	Dairy	404	63.3
Chandra	1981	Costa Rica	Whole farm	62	77.3
Croppenstedt	1997	Ethiopia	Crops	344	41.0
Dawson	1985	UK	Whole farm	224	63.0
Dawson	1991	Philippines	Rice	96	54.1
Dawson	1991	Philippines	Rice	22	59.0
Ekanayake	1987	Sri Lanka	Rice	62	51.5
Hallam	1996	Portugal	Dairy	340	62.5
Heshmati	1995	Sweden	Pork	1,506	91.0

Table 1 continued

First Author	Year	Country	Product(s)	No. obser.	Mean TE
Kalaitzandonakes	1992	USA	Grains	250	57.0
Kalaitzandonakes	1995	Guatemala	Maize	82	52.0
Karagiannis	2002	UK	Dairy	2,147	77.6
Kontos	1983	Greece	Whole farm	83	57.0
Maietta	2000	Italy	Dairy	533	55.0
Neff	1991	USA	Grains	170	64.5
Orea	2004	Spain	Dairy	445	65.9
Piesse	1996	Slovenia	Dairy	272	57.5
Poe	1992	USA	Dairy	675	74.8
Rebelo	2000	Portugal	Whole farm	281	84.1
Russell	1983	UK	Whole farm	56	72.5
Shah	1994	Pakistan	Maize	380	66.6
Shapiro	1983	Tanzania	Cotton	37	66.0
Tauer	1987	USA	Dairy	432	69.3
Turk	1995	Slovenia	Dairy	272	77.1
Wicks	1984	Sri Lanka	Rice	96	58.0
Mean					70.2
Stochastic frontier					
Abdulai	2000	Ghana	Rice	120	73.0
Abdulai	2001	Nicaragua	Maize	120	72.0
Admassie	1999	Ethiopia	Other crops	64	90.8
Aguilar	1993	Kenya	Crops	347	93.9
Ahmad	1996	USA	Dairy	1,072	81.0
Ajibefun	1999	Nigeria	Other crops	98	67.0
Ajibefun	2002	Nigeria	Other crops	67	82.0
Ali	1989	Pakistan	Rice	120	72.0
Ali	1994	Pakistan	Crops	436	24.0
Amaza	2002	Nigeria	Other crops	123	69.0
Araujo	1999	Brazil	Crops	100	86.7
Audibert	1997	Mali	Rice	836	69.5
Bagi	1982	USA	Whole farm	48	80.5
Bagi	1983	USA	Livestock	97	77.0
Bailey	1989	Ecuador	Dairy	68	78.1
Bakhshoodeh	2001	Iran	Other grains	164	33.0
Bashir	1995	Pakistan	Wheat	150	33.0
Battese	1988	Australia	Dairy	336	70.7
Battese	1989	India	Other crops	289	83.7
Battese	1992	India	Rice	129	89.1
Battese	1993	India	Other grains	279	84.0
Battese	1993a	India	Other grains	279	84.0
Battese	1993a	Pakistan	Other grains	273	74.6
Battese	1996	Pakistan	Wheat	499	68.0
Battese	1997	Pakistan	Other grains	330	90.0
Bhattacharyya	1996	India	Crops	105	85.6
Binam	2004	Cameroon	Other crops	150	75.0
Bravo-Ureta	1990	USA	Dairy	404	83.9
Bravo-Ureta	1991	USA	Dairy	511	83.0
Bravo-Ureta	1994	Paraguay	Cotton & Cassava	94	58.5
Bravo-Ureta	1997	Dominican Rep.	Crops	60	70.0
Brümmer	2000	Germany	Whole farm	5,093	96.0
Brümmer	2001	Slovenia	Whole farm	185	74.4
Brümmer	2002	Germany, Poland and Netherlands	Dairy	300	86.9
Coelli	1996	India	Crops	277	73.4
Coelli	2004	Papua New Guinea	Other crops	72	78.0
Cuesta	2000	Spain	Dairy	410	82.7
Dawson	1987	UK	Dairy	434	85.3
Dawson	1988	UK	Dairy	406	81.0
Dawson	1990	UK	Dairy	306	86.9
Dawson	1990	UK	Dairy	306	85.7
Dawson	1991	Philippines	Rice	101	69.7
Dawson	1991	UK	Dairy	306	86.0

Table 1 continued

First Author	Year	Country	Product(s)	No. obser.	Mean TE
Dawson	1991	UK	Dairy	22	89.0
Demir	1998	Turkey	Crops	67	55.0
Ekanayake	1987	Sri Lanka	Rice	62	75.0
Fan	1991	China	Whole farm	406	77.9
Ghosh	1994	USA	Dairy	145	91.9
Giannakas	2000	Greece	Other crops	875	69.7
Giannakas	2001	Canada	Wheat	900	76.9
Hadri	2003	England	Other grains	606	86.4
Hadri	2003	England	Other grains	612	86.0
Hallam	1996	Portugal	Dairy	340	81.0
Hasnah	2004	Sumatra	Oil Palm	80	66.0
Heshmati	1994	Sweden	Dairy	600	82.2
Heshmati	1996	Uganda	Plantain	144	65.3
Heshmati	1997	Sweden	Other crops	929	75.8
Heshmati	1998	Sweden	Dairy	3,979	94.5
Huang	1984	India	Whole farm	151	89.0
Huang	1997	China	Rice	358	72.0
Iráizoz	2003	Spain	Vegetables	46	80.0
Iráizoz	2005	Spain	Dairy	2,594	84.3
Ivaldi	1994	France	Grains	405	61.2
Johnson	1994	Ukraine	Potato	6,136	71.5
Kalaitzandonakes	1992	USA	Grains	250	85.0
Kalaitzandonakes	1995	Guatemala	Maize	82	74.0
Kalirajan	1983	Philippines	Rice	79	50.0
Kalirajan	1984	Philippines	Rice	81	63.0
Kalirajan	1986	Philippines	Maize	73	64.7
Kalirajan	1986	Malaysia	Rice	191	65.0
Kalirajan	1989	India	Rice	102	70.0
Kalirajan	1990	Philippines	Rice	103	79.0
Kalirajan	1991	India	Rice	120	69.0
Kalirajan	2001	India	Rice	500	67.5
Karagiannis	2001	Greece	Olive	770	78.6
Kumbhakar	1989	USA	Dairy	89	78.9
Kumbhakar	1991	USA	Dairy	519	70.4
Kumbhakar	1994	India	Rice	227	75.5
Kumbhakar	1995	Sweden	Dairy	1,425	84.7
Kurkalova	2003	Ukraine	Other grains	164	94.2
Kwon	2004	Rep. of Korea	Rice	5,130	75.0
Lansink	2000	Netherlands	Other crops	985	66.9
Latruffe	2004	Netherlands	Dairy, other crops	250	80.5
Liu	2000	China	Crops	3,964	86.8
Mochebelele	2000	Lesotho	Whole farm	150	70.0
Parikh	1995	Pakistan	Other crops	436	88.5
Paul	2004	USA	Maize	16,590	93.5
Phillips	1986	Guatemala	Maize	1,384	76.0
Pierani	2003	Italy	Dairy	533	66.2
Rawlins	1985	Jamaica	Crops	101	71.7
Reinhard	1999	Netherlands	Dairy	1,545	89.4
Reinhard	2000	Netherlands	Dairy and Cattle	1,535	89.5
Reinhard	2000	Netherlands	Dairy and Cattle	2,589	83.8
Rezitis	2002	Greece	Whole farm	21,856	70.5
Rezitis	2003	Greece	Whole farm	5,544	70.2
Seyoum	1998	Ethiopia	Maize	20	86.6
Shah	1994	Pakistan	Sugarcane	380	79.2
Sharma	1997	USA	Other Animals	60	74.9
Sharma	1999	USA	Swine	53	75.2
Sherlund	2002	Cote d'Ivoire	Rice	464	43.0
Squires	1991	Indonesia	Beans	305	63.0
Tadesse	1997	India	Rice	129	83.0
Taylor	1986	Brazil	Crops	217	70.5
Taylor	1986	Brazil	Crops	217	17.5
Tian	2000	China	Crops	298	89.2

Table 1 continued

First Author	Year	Country	Product(s)	No. obser.	Mean TE
Tran	1993	Vietnam	Other crops	165	59.0
Trewin	1995	Indonesia	Rice	1,026	86.5
Tzouvelekas	2001	Greece	Other crops	29	76.0
Tzouvelekas	2001	Greece	Other crops	86	63.9
Wadud	2000	Bangladesh	Rice	150	79.1
Wang	1996	China	Crops	1,786	62.1
Wang	1996	China	Whole farm	1,889	61.0
Wilson	1998	UK	Potato	140	89.5
Wilson	2001	UK	Wheat	362	87.0
Wu	1995	China	Whole farm	28	54.1
Xu	1998	China	Rice	30	84.8
Yao	1998	China	Crops	30	64.1
Mean					77.3
Overall mean					76.6

[a] It is important to notice that several studies computed TE using more than one methodology. Therefore, in this table a study is presented each time a different methodology is applied

displayed. Nevertheless, the data used in the analysis incorporates all observations found in the sources cited that contain the variables necessary to undertake the meta-regression analysis reported below.

Table 2 presents the methodological features of these studies. As indicated, a total of 167 studies are included in the analysis out of which 68 apply deterministic models and 117 stochastic models. As can be noticed, the sum of deterministic and stochastic studies (185) is larger that the reported number of papers (167) because in some studies both techniques are implemented. In general, most of the studies rely on parametric models, panel data, the Cobb–Douglas functional form, and a primal representation of the technology.

Table 2 also shows that the average mean TE (AMTE) for all deterministic models is 74.6% compared to 77.3% for all stochastic models. A comparison of AMTEs between the parametric and non-parametric estimates shows that the former are lower (76.3%) than the latter (78.3%) but these differences are not statistically significant, which is contrary to what would be expected on conceptual grounds (Kumbhakar and Lovell 2000). A possible explanation for this result is that non-parametric studies usually present several TE indexes equal to 100%.[2]

An interesting pattern is observed regarding the effect of functional form. For the deterministic models, the Cobb–Douglas form yields a higher AMTE (72.6%) than the translog (68.1%) while the opposite pattern is observed for the stochastic models, but these differences are not statistically significant. Only within stochastic frontier models, studies specifying a translog functional form (79.7%) produce a significantly higher AMTE than studies using a Cobb–Douglas function (76.3%). Another interesting difference for deterministic studies is that primal models produce a higher AMTE than dual models. Although a similar pattern was reported by Thiam et al. (2001), there is no clear explanation for this result (Greene 1993).

Finally, Table 2 suggests that studies using panel data display a significantly higher AMTE (77.5%) than studies with cross sectional data (72.8%) among deterministic models. This result is consistent with the findings by Thiam et al. (2001). Even though Greene (1993) argues that models relying on panel data are likely to yield more accurate efficiency estimates, there are no a priori expectations regarding the impact of data type (i.e. cross-sectional versus panel) on the magnitude of efficiency scores.

Table 3 summarizes the AMTE measures according to the geographical region where the studies were conducted. The largest number of cases is for Asia (189), followed by Western Europe and Oceania (157), North America (United States and Canada, 103), Latin America and the Caribbean (47), Eastern Europe (45) and Africa (28). The highest AMTE when stochastic and deterministic studies are combined is for Western Europe and Oceania at 82.0%, while the lowest is for Eastern Europe at 70.0%. The differences across geographic regions are significant at the 10% level or better. When the deterministic and stochastic AMTEs are calculated separately, Western Europe and Oceania still exhibit the highest level but some change is found in the rankings for the rest of the regions.

Also displayed in Table 3 is the AMTE for all Lower Income Countries (LICs), Lower Middle

[2] Independent *t*-tests and One-Way ANOVA are used to compare AMTEs. The former is used to compare means between two groups whereas the latter is applied when comparing more than two groups (Field 2005).

Table 2 Average mean technical efficiency (AMTE) by methodological characteristics

Category	No. of cases	Deterministic			Stochastic			AMTE
		Avg.	Max.	Min.	Avg.	Max.	Min.	
Approach								
Parametric	482	70.2	95.5	26.0	77.3	100.0	17.0	76.3
Non-parametric	87	78.3	100.0	35.0	–	–	–	78.3
Data								
Panel	340	77.5	96.0	35.0	78.4	96.0	43.0	78.2
Cross sectional	229	72.8	100.0	26.0	75.2	100.0	17.0	74.2
Functional form[a]								
Cobb–Douglas	308	72.6	95.5	41.0	76.3	100.0	17.0	75.7
Translog	146	68.1	77.6	49.0	79.7	99.8	24.0	78.9
Others	28	64.6	79.7	26.0	73.2	86.4	66.2	68.3
Technology representation								
Primal	478	75.5	100.0	26.0	77.0	100.0	33.0	76.5
Dual	91	67.7	86.7	49.0	79.0	96.0	17.0	76.9
AMTE			74.6			77.3		76.6
Number of cases			159			410		569
Number of studies[b]			68			117		167

[a] Valid for parametric approach studies

[b] Several studies report various measures of TE stemming from the application of different methods

Table 3 Average mean technical efficiency (AMTE) by geographical region

Geographical region	No. of cases	Deterministic			Stochastic			AMTE
		Avg.	Max.	Min.	Avg.	Max.	Min.	
Africa	28	47.3	66.0	35.0	76.8	98.8	43.0	73.7
Asia	189	67.3	99.0	26.0	74.9	100.0	24.0	74.0
L. America	47	77.4	93.0	52.0	78.0	96.0	17.0	77.9
N. America[a]	103	74.3	100.0	45.9	78.7	93.5	60.8	76.2
E. Europe	45	65.9	93.0	44.0	71.9	94.2	55.0	70.0
W. Europe and Oceania	157	81.2	96.0	49.0	82.4	99.8	53.8	82.0
LICs	158	68.7	99.0	35.0	74.7	98.8	24.0	74.1
LMICs	112	64.8	93.0	26.0	76.8	100.0	17.0	75.7
UMICs	17	68.0	85.0	45.6	69.2	88.0	55.0	68.3
HICs	282	76.9	100.0	44.0	80.3	99.8	53.8	78.8

LICs: lower income countries, LMICs: lower middle income countries, UMICs: upper middle income countries, and HICs: higher income countries (World Bank 2005)

[a] North America includes the United States and Canada

Income Countries (LMICs), Upper Middle Income Countries (UMICs) and Higher Income Countries (HICs).[3] The AMTEs, when the deterministic and stochastic measures are combined, is 74.1%, 75.7%, 68.3%, and 78.8% for the LICs, LMICs, UMICs and HICs, respectively. By comparison, the AMTE, using a deterministic approach, is 68.7%, 64.8%, 68.0% and 76.9% for LICs, LMICs, UMICs and HICs, respectively. The AMTEs for the stochastic approach follow a slightly different pattern equal to 74.7%, 76.8%, 69.2% and 80.3% for LICs, LMICs, UMICs and HICs, respectively. The only statistically significant difference is within the stochastic group where HICs exhibit a higher AMTE than LICs.

Table 4 displays the AMTEs by product type. As shown in this table, Other Crops is the dominant category with 51 studies, followed by Dairy and Cattle (46), Rice (28), Whole Farm (23), Other Grains (20), Maize (10), and Other Animals (6). The highest AMTE is reported for Other Animals (84.5%) followed closely by Dairy and Cattle (80.6%), while the lowest result is found for Rice (72.4%). The

[3] Based on the World Bank (2005), the LICs that are included in this study are Bangladesh, Cameroon, Cote d'Ivoire, Ethiopia, Ghana, India, Kenya, Lesotho, Mali, Nepal, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Tanzania, Uganda and Vietnam. The LMICs include Brazil, China, Dominican Republic, Ecuador, Guatemala, Indonesia, Iran, Jamaica, Paraguay, Philippines, Sri Lanka and the Ukraine. The UMICs include Costa Rica, Malaysia and Turkey. The HICs comprise Australia, Canada, Finland, France, Germany, Greece, Italy, Netherlands, New Zealand, Poland, Portugal, Republic of Korea, Slovenia, Spain, Sweden, United Kingdom and the United States.

Table 4 Average mean technical efficiency (AMTE) by product

Product	No. of cases	No. of studies	Technical efficiency		
			AMTE	Max.	Min.
Rice	86	28	72.4	100.0	26.0
Maize	18	10	74.5	93.7	52.0
Other grains	37	20	73.2	99.4	33.0
Other crops	172	51	74.4	99.0	17.0
Dairy and Cattle	178	46	80.6	100.0	45.9
Other animals	22	6	84.5	95.5	64.3
Whole farm	56	23	76.8	97.2	44.0

statistical test of comparisons of means shows that studies analyzing Other Animal and Dairy Cattle exhibit a significantly higher AMTE than studies for Rice. Studies of Other Grains and of Other Crops produce a lower AMTE than those of Other Animals, while Dairy and Cattle studies generate a significantly higher AMTE that those for Other Crops.

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

Model 1:

$$\text{MTE} = f(\text{PSTO,PDET,TL,CD,CS,PRI,VARSIZE,GRAIN}) \quad (1)$$

Model 2:

$$\text{MTE} = f(\text{PSTO,PDET,TL,CD,CS,PRI,VARSIZE,GRAIN,ASIA,NAMR,AFRI,LTCR,EAST}) \quad (2)$$

Model 3:

$$\text{MTE} = f(\text{PSTO,PDET,TL,CD,CS,PRI,VARSIZE,GRAIN,LIC,LMIC,UMIC}) \quad (3)$$

where the dependent variable MTE is mean technical efficiency as reported in the studies. PSTO is a dummy variable equal to one if the model is a parametric stochastic frontier, PDET is a dummy variable equal to one for parametric deterministic frontiers and the omitted category is the non-parametric studies. TL is a dummy variable equal to one if the translog functional form is used, CD is a dummy variable for the Cobb–Douglas functional form and the excluded category is Other Functional forms along with 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; VARSIZE is the ratio between the number of explanatory variables and the number of observations included in the study; and GRAIN is a dummy variable equal to one if the model is for grains (rice, maize and other grains) and zero otherwise.[4]

The regional variables are ASIA which is a dummy equal to one if the study used data for that part of the world; NAMR is a dummy variable equal to one if the data comes from North America (United States and Canada); AFRI is a dummy variable equal to one if the study used data from Africa; LTCR is a dummy variable equal to one if the study used data from Latin America or the Caribbean; and EAST is a dummy variable equal to one if the study used data from Eastern Europe. The omitted region is Western Europe and Oceania. Finally, the income level dummies are LIC, which is equal to one for low income countries; LMIC which is equal to one for lower-middle income countries; and UMIC, a dummy that takes the value of one for upper-middle income countries. The excluded category in this case is the high income country studies or HICs.

Given that the efficiency scores are bounded between zero and one, Models I, II and III are estimated using the two-limit (i.e., doubly censored) Tobit procedure (Greene 2002). However, for comparison, these models are also estimated using the Ordinary Least Square (OLS). However, Judge et al. (1988) show that when an econometric model contains a ratio form as the dependent variable OLS could suffer heteroskedasticity problems. Therefore, we use a robust covariance matrix to correct for heteroskedasticity.

[4] As suggested by one of the referees, it would be interesting to include the orientation of the efficiency measures (i.e., input- versus output-oriented) and, for panel data studies, whether TE is time variant or not, and if time variant then the specification used. The former factor is not included, however, because very few studies are input oriented and almost all of them are non-parametric so not much would be gained by including a separate variable for orientation. In terms of the second comment, the models already have a control for panel data but the inclusion of further related effects would be more appropriate if the analysis was restricted to panel data studies with sufficient variability in the behavior of TE overtime.

Table 5 Meta-regressions of mean technical efficiency (MTE) in farming[a]

Variable	Model I		Model II		Model III	
	OLS	Tobit	OLS	Tobit	OLS	Tobit
CONSTANT	81.764***	81.742***	83.523***	83.508***	82.696***	82.668***
	2.582	*2.312*	*2.602*	*2.401*	*2.564*	*2.293*
PSTO	–6.277**	–6.275**	–2.950	–2.942	–7.114**	–7.115**
	3.025	*3.027*	*3.012*	*2.982*	*2.972*	*2.988*
PDET	–11.212***	–11.225***	–10.523***	–10.531***	–13.660***	–13.678***
	3.045	*2.944*	*3.057*	*2.881*	*3.081*	*2.932*
TL	5.696**	5.703**	1.920	1.918	6.495***	6.509**
	2.590	*2.782*	*2.700*	*2.828*	*2.522*	*2.738*
CD	3.543	3.561	3.268	3.283	6.249**	6.270**
	2.495	*2.636*	*2.488*	*2.639*	*2.595*	*2.670*
CS	–4.005***	–3.982***	–3.133**	–3.103**	–3.584***	–3.557***
	1.234	*1.126*	*1.411*	*1.215*	*1.241*	*1.114*
PRI	–0.818	–0.812	0.296	0.301	–0.621	–0.607
	1.845	*1.576*	*1.750*	*1.602*	*1.828*	*1.566*
VARSIZE	11.394	11.339	16.877	16.838**	14.801	14.707*
	8.959	*7.915*	*10.759*	*8.131*	*9.567*	*7.960*
GRAIN	–3.991***	–3.964***	–1.951	–1.927	–2.024	–1.995
	1.309	*1.241*	*1.573*	*1.343*	*1.440*	*1.326*
LIC	–	–	–	–	–5.392***	–5.412***
					1.640	*1.484*
LMIC	–	–	–	–	–4.591**	–4.564***
					1.889	*1.647*
UMIC	–	–	–	–	–10.445***	–10.455***
					3.527	*3.085*
ASIA	–	–	–8.112***	–8.118***	–	–
			1.817	*1.640*		
NAMR	–	–	–3.357**	–3.579**	–	–
			1.691	*1.800*		
AFRI	–	–	–7.930**	–7.967***	–	–
			3.876	*2.797*		
LTCR	–	–	–6.526**	–6.542***	–	–
			2.866	*2.471*		
EAST	–	–	–12.323***	–12.336***	–	–
			2.150	*2.163*		
Log likelihood	–2,235.4	–2,233.9	–2,214.6	–2,213.1	–2,224.2	–2,222.7
F	7.90***		9.66***		7.72***	
χ^2	56.10***	55.59***	97.76***	97.18***	78.57***	78.05***

*Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level

[a] Figures in italics are the robust standard errors

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4 Results and analysis

Table 5 contains the econometric results for Models I, II and III using the OLS and the two-limit Tobit approach. Generally speaking, both procedures display similar patterns. However, given the characteristics of the data used in this analysis the Tobit technique is the most appropriate one from a methodological point of view. Consequently, the discussion below is based on the results obtained using the latter procedure. With respect to the empirical specifications, Model I ignores the possible presence of a regional effect, Model II introduces a set of five dummy variables to capture potential regional effects, while Model III includes three dummies to account for the effect of income level on MTE. As shown in Table 5, most of the parameters of Models I through III are significant at the 5% level or better.

The variables PSTO and PDET capture the effect of the methodology used to estimate the frontier on MTE estimates (the excluded category for this group of dummies is the non-parametric frontier approach). The negative sign and statistical significance of the parameter for PSTO indicates that parametric stochastic models consistently yield lower MTEs than non-parametric deterministic ones. This result can be explained by the fact that non-parametric determin-istic studies typically yield numerous TE indexes equal to 100% and such high measures increase the reported MTEs. The estimated parameter for PDET is also negative, significant and higher in absolute value than the parameter for PSTO which is consistent with a priori expectations based on the fact that parametric deterministic models consider all variations from the frontier as inefficiency, while stochastic models make it possible to disentangle random shocks from inefficiency (Kumbhakar and Lovell 2000).

The effect of functional form on TE displays mixed results across the three estimated models (the excluded category for this group of dummies is Other Functional forms). The translog (TL) specification is statistically significant in Models I and III, and the Cobb–Douglas (CD) is only significant in Model III. The TL yields higher MTEs than both the CD and Other Functional forms in Models I and III, while the CD does so in Model II (but the parameter is not significant). These results suggest that a more flexible functional form (TL) tends to yield a higher MTE. These findings are similar to those reported by Ahmad and Bravo-Ureta (1996), Resti (2000) and Thiam (2003), among others.

The parameter for CS (Cross Sectional data) displays a negative and highly significant effect on MTE. This result suggests that frontier models using cross-sectional data produce lower MTE estimates than models based on panel data; this is consistent across the three model specifications. In addition, the parameter for GRAIN is also consistently negative suggesting that frontier models for grain crops present, on average, lower levels of MTE than those for Dairy and Cattle, Other Crops or Whole Farm. However, whether the model relies on a primal (PRI) or dual representation of the technology does not have a significant effect on MTE.

The econometric results indicate that the ratio used to analyze the effect of model dimensionality (VARSIZE) does have a significant effect on the MTE measures in the Tobit equations for Models II and III, which is consistent with Thomas and Tauer (1994) and Chavas, Petrie and Roth (2005).

Models II and III introduce additional variables where the former incorporates the geographical region where the studied country is located, while Model III includes the country's average income level on the estimated MTE. It is important to indicate that based on generalized likelihood ratio tests, the Tobit estimates of Models II and III are preferred over Model I, indicating that regional/country effects are indeed important in analyzing the estimated MTEs.

The coefficients for all the regional dummies included in Model II are negative and statistically significant. Given that the excluded category for this group of dummies is for countries located in Western Europe and Oceania, these results imply that countries in these regions present, on average, the highest levels of MTE among all regions after controlling for methodological features of the studies. By contrast, the results show that Eastern European countries exhibit, on average, the lowest estimate of MTE followed by Asian, African, Latin American and North American countries. The joint statistical significance of the parameters associated with the regional dummies was also confirmed by using a generalized likelihood ratio test.

Lastly, to examine whether the country's income level is associated with the estimated MTEs, the data is separated in four groups of countries, HICs, UMICs, LMICs and LICs, and three dummy variables are introduced to capture this effect, as explained earlier (HICs is the excluded category). The results, shown in Table 5 under Model III, indicate that the coefficients for the dummies for the LICs, LMICs and UMICs are all negative and highly significant. These results suggest that, on average and controlling for all other effects included in the model, studies from HICs present the highest MTE estimates followed by LMICs and LICs, while studies from UMICs display the lowest.

5 Summary and conclusions

The objective of this study was to undertake a meta-regression analysis seeking to explain the variation in Mean Technical Efficiency (MTE) for studies focusing on the agricultural sector. The MTE estimates reported in 167 published papers were explained by major methodological characteristics of the studies. In addition, alternative models incorporated regional and income dummy variables to capture the country effect on MTE. This study contributes to the 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 TE component of productivity.

The econometric results suggest that non-parametric deterministic models generate higher MTE estimates than stochastic frontier models, while parametric deterministic frontier models yield lower estimates. The effect of functional form on TE is inconclusive. In addition, frontier models based on cross-sectional data produce lower estimates than those based on panel data. In addition, the studies focusing on countries in Western Europe and Oceania present, on average, the highest levels of MTE while studies for Eastern European countries exhibit the lowest, after accounting for key methodological features. Additional analysis reveals that MTE tends to be positively and significantly related to the average income of the countries in the data set. However, this pattern is broken by the UMICs group which displays the lowest MTE.

The large body of published articles included in this study focusing on TE suggests that, given the state of technology prevailing in the various regions/countries at the time that the studies were conducted, the shortfall in TE and thus in managerial ability, is most significant in Eastern European countries followed by Asia, Africa and Latin America. By contrast, managerial improvements as a means to increase productivity are least promising in Western Europe and Oceania, followed by North American countries. More conclusive statements on this matter will need refinements on the data used and further analysis.

In conclusion, in this study we have attempted to organize the ‘flood of numbers’ (Heckman 2001) stemming from a substantial body of literature that has emerged over the past few decades on technical efficiency measurement in agriculture. The empirical studies and the conceptual literature reveal mixed results and conflicting views concerning the merits of the various methodologies that have been developed. Thus, the meta-regression analysis presented here seeks to integrate a wide range of empirical findings to shed light in a systematic fashion on the effects of alternative methodological assumptions on farm level TE measures. The authors hope that this work will make this vast literature more accessible to researchers while also providing a broad frame of reference for those that seek to evaluate the sensitivity of their results to the choice of method.

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