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Meta-regression Analysis of Technical (In)Efficiency in Agriculture: a Regional Approach[1]

While scientific studies have not reached a consensus on the methodology for examining Technical Efficiency (or Inefficiency), the influence of regions appears to be important for efficiency scores. Therefore, this research aims to investigate the empirical procedures for the achievement of more robust results in the analysis of productive efficiency, as well as to evaluate the effect of the location of farms on such efficiency. The goal was to check whether the most developed regions are the most efficient. Meta-regression analysis provides an adequate method for an accurate assessment of both situations. This technique was applied based on a database of 166 observations on the agricultural sector from countries around the world, published in the period 2010–2017. The criteria used for the database collection and for the conceived model were not previously used and, thereby, enrich the discussion on the topic. The procedure aims to check the variation in the Mean of Technical Inefficiency and conduct an analysis using Quasi-Maximum Likelihood Estimation. The regressions showed that the Mean of Technical Inefficiency could be mainly explained by data, variables, employed empirical models and the region of study. The studies that focus on farms of developed countries present the lowest Mean of Technical Inefficiency, while studies for developing or low-income countries exhibit the opposite. Therefore, for future research on productive analysis, we suggest empirical procedures aimed at achieving robust results that take into account specific regional characteristics of farms.

Keywords: agriculture, technical efficiency, farms inefficiency, meta-regression, parametric and non-parametric methods; regional analysis

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ИССЛЕДОВАТЕЛЬСКАЯ СТАТЬЯ

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Метарегрессионный анализ технической производительности в сельском хозяйстве: региональный подход

Несмотря на то, что исследователи не достигли консенсуса касательно методологии изучения производительности, показатели эффективности в значительной мере зависят от регионов. В данной статье изучены эмпирические методики для достижения надежных результатов в анализе производственной эффективности, а также влияние расположения ферм на производительность. Цель работы — проверить, зависит ли производительность от развитости региона. Для точной оценки данных был применен метарегрессионный анализ на основе опубликованных в 2010–2017 гг. 166 наблюдений в области сельского хозяйства разных стран мира. Новизна исследования состоит в том, что критерии, разработанные для создания базы данных и реализации модели, не использовались ранее. Были проверены вариации среднего значения производительности, а также проведен анализ с использованием оценки квазимаксимального правдоподобия. Регрессии показали, что среднее значение производительности можно объяснить используемыми данными, переменными, эмпирическими моделями и регионом исследования. Проанализированные работы показали, что сельскохозяйственные фермы в развитых странах демонстрируют самый высокий средний показатель производительности, в то время как в развивающихся странах и странах с низким уровнем дохода наблюдается обратная ситуация. В статье представлены методологии, направленные на достижение надежных результатов, а также учитывающие региональные характеристики сельских хозяйств, которые могут быть применены в будущих исследованиях.

Ключевые слова: сельское хозяйство, производительность, неэффективность хозяйств, метарегрессия, параметрические и непараметрические методы, региональный анализ

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1. Introduction

The productive efficiency literature starts with Farrell's work [1] that a frontier model defining a simple measure of firm efficiency that could account for multiple inputs. Farrell [1] stated that efficiency can be described in two main components: Technical Efficiency and Allocative Efficiency. The first indicates that when a certain level of inputs is given, the Decision Making Unit is able to produce the maximum level of outputs or, fixing a certain level of output, the Decision Making Unit is able to minimise the level of input [2]. The Allocative Efficiency reflects the firm's ability to use the inputs in their optimal proportions (given their respective prices) to either minimise the cost or maximise the revenue [3, 4]. Another type of efficiency is the scale efficiency, which shows whether the Allocative Efficiency is operating at an optimal scale [5].

Different methodologies have been proposed to estimate Technical Efficiency or Inefficiency. The selection of the most appropriate one has been a controversial process, with several studies emphasising the advantages and disadvantages of parametric and non-parametric approaches for the measurement of Technical Efficiency [6–8]. Resti [9] concluded that there is no advantage in using one method over the other, and Wadud and White [10] stated that, in most empirical studies, the selection of the method is arbitrary and mainly based on the aim of the study, the available data and the preference of the researcher. Nevertheless, the selection of a specific methodology using agricultural data could seriously affect the estimated Technical Efficiency scores [10–13]. There is no agreement concerning the selection of an appropriate methodology and the choice between parametric and non-parametric methods will continue to be an ongoing debate [4, 14].

Concerns on the topic of empirical conditions for the efficiency analysis have recently been considered as a greater influence on the estimated Technical Efficiency and also in its scores. This paper aims to contribute to this discussion, as it examines aspects that were not studied in previous works. Namely, the Technical Inefficiency perspective instead of the Technical Efficiency allows the integration of a wider range of studies. In addition, we included not only parametric and non-parametric methodologies, but also studies with semi-parametric techniques. The used functional forms according to the Stochastic Frontier Analysis and Data Envelopment Analysis with radial versus directional functions were also useful for formulating the first hypothesis: the Mean of Technical Inefficiency varies according to the chosen methodological or empirical procedure.

Another important aspect revealed by the studies on meta-regression analysis is the divergence of Technical Efficiency results depending on the geographical scope of the application (particularly, examined region and its income level). The studies of Bravo-Ureta et al. [4] and Mareth et al. [14] showed that Western Europe displays higher Technical Efficiency values than other continents and Ogundari [15] proved that East Africa is the most technically efficient region in Africa. Regarding the country income, Bravo-Ureta et al. [4] highlighted that high-income countries have better Technical Efficiency levels. However, Mareth et al. [14] and Djokoto, Srofenyoh and Arthur [16] did not confirm with statistical significance the different Technical Efficiency scores between the countries with distinct income levels and between the diverse regions of Gana, respectively. Taking this into consideration, another hypothesis relevant to our study is whether the Mean Technical Inefficiency in the farms varies according to the region under study (namely, to the continent to which it belongs or according to the income level of the country). The verification of this situation could be used to replicate the most efficient production system of a given country or act as a planning guide for the least efficient farms found in another region or continent.

Thus, the aim of this study is to investigate the empirical procedures conducted to achieve more robust results in the analysis of productive efficiency in the agricultural sector, as well as to assess the impact of regional specification on agricultural Technical (In)Efficiency. To this end, a meta-regression analysis was implemented based on data for the period 2010–2017, which includes several attributes employed by the previous studies that estimate the Technical Efficiency or Inefficiency in the agriculture sector of both developing and developed countries.

2. Theoretical background

The concepts of efficiency are based on the productivity theory of economics that emerged in the work of Farrell [1] on productive efficiency applied to the United States' agricultural sector. The author decomposed efficiency costs into Technical and Allocative Efficiency; these types of efficiency have been detailed in the literature [2, 17]. In addition to this most common decomposition of efficiency, Färe, Grosskopf and Lovell [18–20] also distinguished between purely Technical Efficiency, Congestion and Scale Efficiency.

A variety of efficiency measures has been proposed in a form of frontier functions [7]. Technical Efficiency or Technical Inefficiency components of productivity are based on comparing the actual firm's productivity performance with its optimum, in the same (Technical Efficiency) or in the opposite direction (Technical Inefficiency).

Empirical studies using frontier models based on Farrell's work [1] can be classified in two types: parametric and non-parametric. Parametric models require predetermined functional forms (e. g. Cobb-Douglas, Translog) and error distributions [7, 21, 22]. Additionally, the models can be distinguished as deterministic and stochastic [4, 14, 22]. The deterministic model assumes that any deviation from the frontier is due to inefficiency, while the stochastic approach allows for statistical noise [4, 14, 22].

The most applied non-parametric and parametric methods are Data Envelopment Analysis and Stochastic Frontier Analysis, respectively.

Data Envelopment Analysis is based on mathematical programming techniques and does not require the specification of a functional form. Therefore, it has been used as the main non-parametric and deterministic Technical Efficiency model. Some disadvantages of this technique are linked to the number of observations, variables of outputs and inputs, and the frontier length that may affect the efficiency levels [4, 22, 23]. Additionally, this non-parametric technique does not allow for random noise or measurement error [4, 22].

From the beginning of the first decade of this century, some advances were made in traditional Data Envelopment Analysis. In particular, a bootstrapping technique [24, 25], a semi-nonparametric one-stage estimator [26] and a noise term that follows a truncated distribution [27] were developed.

Stochastic Frontier Analysis was created as an alternative technique to Data Envelopment Analysis [28, 29]. This approach allows the measurement of errors, random shocks and requires a functional form [8]. It was also suggested to combine both techniques, which are mentioned as the semi-parametric or non-parametric Stochastic Frontier Analysis [30–36]. Pioneering studies for these methodologies were published by Fan and Weersink [31] and Kneip and Simar [32] that were applied by Kumbhakar, Parmeter and Zelenyuk [33], while the two-tiered stochastic frontier model was used in the work of Parmeter [37].

The introduction of semi-parametric methodologies represents a substantial breakthrough, since the separation of parametric from non-parametric methodologies is no longer so clear [33, 37].

The estimation of frontier functions can also be categorised according to the type of data used: cross-section or panel data studies. The first measures the Technical Efficiency between different Decision Making Units at one point in time, while the panel data do the same but in different time periods [22], which could produce more accurate estimates of efficiency. The cross-sectional studies have several limitations [7, 38–40]: for example, the peculiarities that can be observed in a particular year under study could not happen in normal years [41]. Moreover, the panel data allows decomposing productivity growth into technological change and Technical Efficiency change [22].

Econometric models are divided into primal and dual approaches, depending on their underlying behavioural assumptions [4, 22]. This duality can be explained by the exploitation of the production function in two different ways: the primal approach (the common approach) and the dual approach (cost function and profit function) [2]. The primal approach is most often used to estimate efficiency, although dual cost and, particularly, profit function models (dual approaches) have gained increasing attention [4, 42].

In productive efficiency, there are the radial and the directional distance functions. The first were developed by Shephard [43–44], so they are often referred to as Shephard distance functions. Later, Chambers, Chung and Färe [45, 46] and Chambers, Fāure and Grosskopf [47] explored the works of Luenberger [48–49] and introduced directional distance functions. Those functions have one main advantage over the radial ones since they do not impose proportional adjustments on the quantities of inputs and outputs [50]. The directional distance function has been very useful in modelling production functions with undesirable outputs [51–53]. However, the theoretical literature on productive efficiency was essentially developed on the basis of radial distance functions of inputs and outputs.

In addition, many authors report that variables used to estimate efficiency play a major role in the Technical Efficiency scores. In particular, various works assessing efficiency in developed and developing countries support this situation. Thiam, Bravo-Ureta and Rivas [22], Bravo-Ureta et al. [4], Djokoto [54], Djokoto, Srofenyoh and Arthur [16] and Mareth et al. [14] have implemented Meta-regression analysis to Technical Efficiency in agriculture. Thiam, Bravo-Ureta and Rivas [22] developed the first study on this subject, but only examined developing countries. This paper analysed 32 studies and had 51 observations between 1983 and 1998. Afterwards, using a large number of studies (167) and observations (185), Bravo-Ureta et al. [4] applied meta-regression analysis in both developing and developed countries on agricultural subjects in the period 1979–2005. Later, Djokoto [54] used meta-regression analysis of Technical Efficiency in organic agriculture with more recent studies (between 2002 and 2014). Outside arable agriculture, Mareth et al. [14] applied the same methodology in dairy farms with a set of 42 studies and 109 observations. Lastly, Djokoto, Srofenyoh and Arthur [16] used meta-regression analysis in agriculture with 34 studies and 49 observations between 2010 and 2015.

The methodology, functional form, number of observations and variables, panel and cross-sectional data, type of agricultural product, year of data or publication, and use of primal or dual approach are the explanatory variables most used in meta-regression analysis of Technical Efficiency [4, 14, 16, 22, 54]. However, the results of the previous meta-regression studies have not reached a consensus neither in the methodology to use in Technical Efficiency studies nor in the influence of regional specification.

The older analyses showed that the parametric and stochastic approaches tend to display lower levels of Technical Efficiency [4, 22], while Mareth et al. [14], Djokoto, Srofenyoh and Arthur [16] and Djokoto [54] obtained higher scores in latter meta-regressions [14, 16, 54]. The influence of functional forms in Technical Efficiency was tested previously in meta-regression studies; some of them revealed that the Translog function has a tendency to display higher Technical Efficiency scores than the Cobb-Douglas function [4, 14]. Others exposed that both Cobb-Douglas and Translog functional forms usually exhibit lower Technical Efficiency scores than other functional forms [14, 54].

The used data, in particular, data derived from the cross-sectional studies, seems to produce lower Technical Efficiency estimates regarding the majority of meta-regression analysis [4, 22, 54]. Mareth et al. [14] and Thiam, Bravo-Ureta and Rivas [22] showed that the number of variables can positively influence Technical Efficiency scores.

3. Data and Methods

3.1. Data

Our database consists of a set of scientific articles examining the Technical Efficiency or Inefficiency measurement on farm level data from countries around the world. To build such a database, the chosen keywords were linked to the measurement of Technical Efficiency (step 1, Figure 1). The combination of both of them promoted three searches that were performed in the two most relevant search engines, Web of Science and Scopus. After the exclusion of the duplicate papers indexed in both search engines, the final database comprised 470 scientific papers from 2010 to 2017 (Figure 1).

The final database from step 1 (470 papers) was used for the next steps (Figure 1). In step 2, we excluded the following materials: (1) papers out of Technical Efficiency or Inefficiency estimation; (2) studies examining non-agricultural industries; (3) works on animal production; and (4) papers that do not contemplate the variables that are intended to study (e. g. functional form; number of observations and variables; panel and cross-sectional data; primary or secondary data; use of primal or dual approach; type of agricultural product; country). According to these criteria, we excluded the works of Rasmussen [55], Sipiläinen, Kumbhakar and Lien [56] and Tsionas, Kumbhakar and Malikov [57]. They provide research on the efficiency applied to the animal production, but use the variables of milk production as output and the feedstuff as input, which are not relevant for this research.

Finally, we selected 100 research papers for meta-regression analysis (Table 1), which correspond to 166 observations from countries around the world. Given that many of the papers report Technical Efficiency estimates and others Technical Inefficiency, we opt to convert all into the Mean of Technical Inefficiency.

Table 1

Overview of empirical studies of TI in agriculture (%)

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Country					
Africa	23	36.65	17.23	7	81
America	7	22.29	8.67	11	39
Asia	47	24.98	13.16	4	57
Europe	23	25.00	10.83	7	47
Product type					
Cereal crops	41	28.95	14.14	4	70
Fruit	14	27.43	13.00	7	52
Protein crops	2	15.50	3.54	13	18
Oilseed	7	27.71	8.58	15	43
Vegetables	3	36.67	18.77	20	57
Whole farm	26	27.21	16.35	6	81
Others	7	25.14	13.89	13	46

Source: Authors' compilation.

The largest number of cases are from Asia (47), followed by Europe (23) and Africa (23) and then America (7). The highest inefficiency mean was observed in Africa (36.65 %), while the lowest was noted in the American Continent (22.29 %), followed by Asia (24.98 %) and Europe (25 %).

Table 1 also displays the Mean of Technical Inefficiency by product type. As shown in this Table, cereal crops is the dominant category with 41 studies, followed by whole farm (26), fruit (14), oilseed (7), vegetables (3), protein crops (2), and others (7). The highest Mean of Technical Inefficiency is reported for vegetables (36.67 %), while the lowest result is found for protein crops (15.5 %). The others have an average value around 25.14–28.95 %.

3.2. Meta-regression analysis

Meta-regression analysis is a quantitative method used to measure the influence of the study-specific characteristics, such as methodological approaches or other useful variable [58]. In this article, the estimated Technical Inefficiency is the dependent variable and the study-specific characteristics of the research papers of our database are used as the explanatory variables.

Regarding the empirical model of meta-regression analysis, McDonald [59] and Ramalho, Ramalho, and Henriques [60] claimed that the Mean of Technical Inefficiency is not a censored

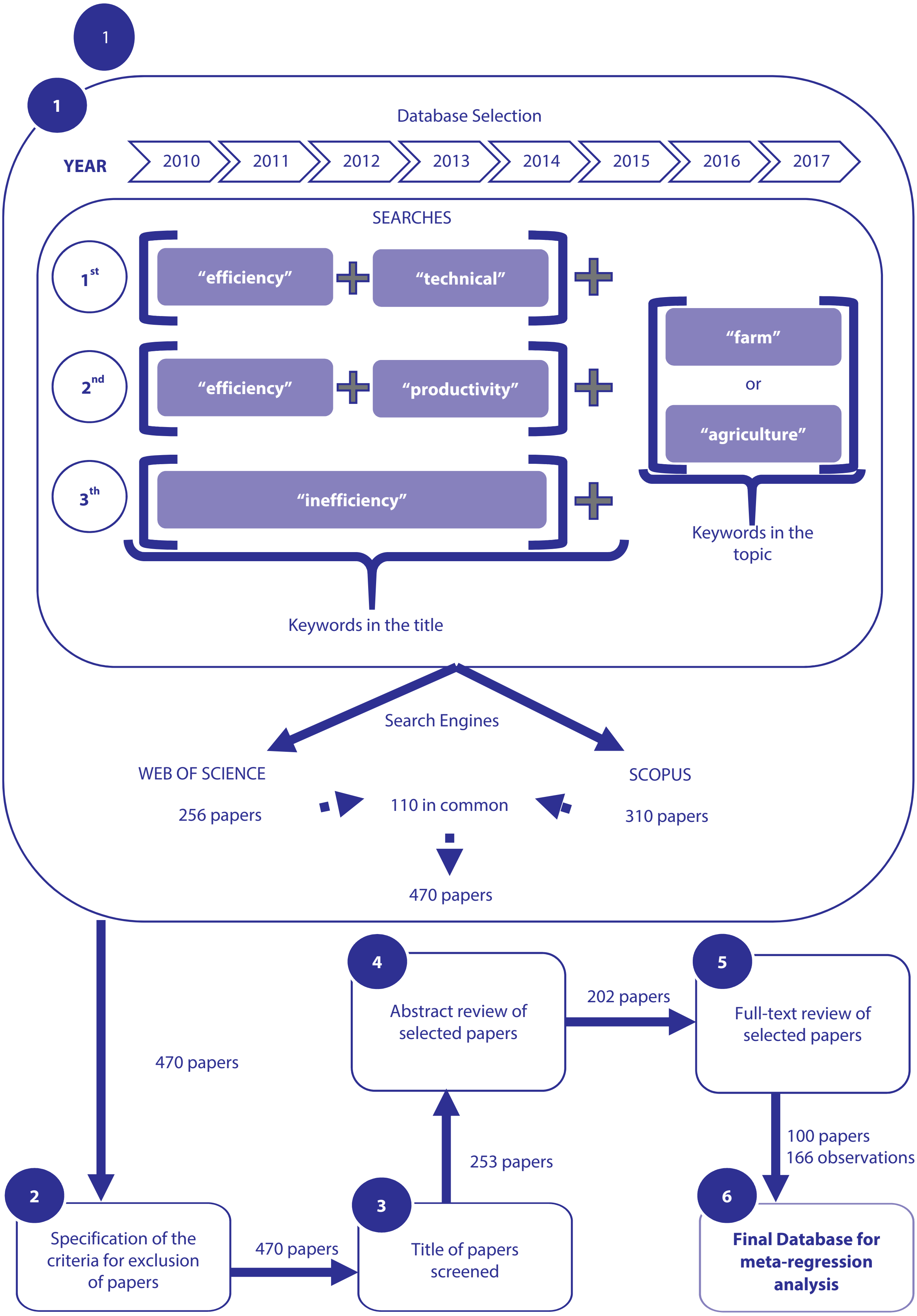

Fig. 1. *Database construction methodology for meta-regression analysis*
Source: Authors' elaboration

Table 2

List of meta-regression explanatory variables

Variable	Description
Radial and Directional	Dummy variables are equal to one if the study used radial distance functions and zero otherwise (directional distance functions)
Cobb, Translog and Quadratic	Dummy variables are equal to one if the study used Cobb-Douglas, Translog or Quadratic functional forms and zero otherwise. Non-parametric approach is the reference variable.
Observations, Nroutputs and Nrinputs	Number of observations, outputs and inputs used in the study
Year	Year of data collection
Panel and cross-sectional	Dummy variables are equal to one if the study used panel data and zero otherwise (cross-sectional data)
Primary and Secondary	Dummy variables are equal to one if the study used primary data and zero otherwise (secondary data)
Dual and Primal	Dummy variables are equal to one if the study used dual approach (cost function) and zero otherwise (primal approach)
Permanent, Temporary and Mixed	Dummy variables are equal to one if the agricultural product is permanent or temporary and zero otherwise (mixed crops)
Asia, America, Europe and Africa	Dummy variables are equal to one if efficiency is estimated in Asian, American or European countries and zero otherwise (African countries)
Lic, Lmic, Umic and Hic	Dummy variables are equal to one if inefficiency is estimated in lower-middle, upper-middle or high income countries (classification of the World Bank) and zero otherwise (lower income countries)
Quartil	Journal's quartile withdrawn from SCImago Journal Rank

Source: Authors' elaboration.

data, but a fractional/proportional data bounded between zero and one. Therefore, Ordinary Least Squares (OLS) and Tobit regressions models may not provide accurate estimations. The fractional response model is estimated using a non-linear model named Quasi-Maximum Likelihood Estimation (QMLE) [61]. In addition, suggested by Nelson and Kennedy [62] we use the weighted regression technique to eliminate the lack of independence in the values of the dependent variable (problem reported by Espey, Espey & Shaw [63]). The weighted regression combines the best of both fixed and random effects [64]. Therefore, the Quasi-Maximum Likelihood Estimation method and the observations were used as weight, following the works of Nelson and Kennedy [62], Ogundari [15] and Stanley [65].

To assess the impact of study-specific characteristics on the Mean of Technical Inefficiency, this study employs the models (1) and (2) and, to capture the country effect, we incorporate regional dummy variables (Table 2):

$$\begin{gathered} E(MTI_i \mid x) = G(\beta_0 + \beta_1 Radial_i + \beta_2 Cobb_i) + \\ + G(\beta_3 Translog_i + \beta_4 Quadratic_i) + \\ + G(\beta_5 Observations_i + \beta_6 Nroutputs_i + \beta_7 Nrinputs_i) + \\ + G(\beta_8 Year_i + \beta_9 Panel_i + \beta_{10} Primary_i + \beta_{11} Dual_i) + \\ + G(\beta_{12} Permanent_i + \beta_{13} Temporary_i + \beta_{14} Lmic_i) + \\ + G(\beta_{15} Umic_i + \beta_{16} Hic_i + \beta_{17} Quartil_i) + \varepsilon_i, \qquad (1) \end{gathered}$$

$$\begin{gathered} E(MTI_i|x) = G(\beta_0 + \beta_1 Radial_i + \beta_2 Cobb_i) + \\ + G(\beta_3 Translog_i + \beta_4 Quadratic_i + \beta_5 Observations_i) + \\ + G(\beta_6 Nroutputs_i + \beta_7 Nrinputs_i + \beta_8 Year_i +) \\ + G(\beta_9 Panel_i + \beta_{10} Primary_i + \beta_{11} Dual_i +) \\ + G(\beta_{12} Permanent_i + \beta_{13} Temporary_i + \beta_{14} Asia_i) + \\ + G(\beta_{15} America_i + \beta_{16} Europe_i + \beta_{17} Quartil_i) + \varepsilon_i, (2) \end{gathered}$$

where *MTI* is the Mean of Technical Inefficiency reported in studies; *i* is the *i*-th primary study; *G*(.) is the logistic function; *x* is a vector of study attributes (displayed in Table 2) which are also used as control variables; β_k are the parameters to be estimated and their sign will generally indicate the direction in which a given variable influences the changes in the Mean of Technical Inefficiency; ε_i is the error term of the regression, which is assumed to be normally distributed with mean 0 and variance σ_ε.

4. Results

Technical Efficiency and Inefficiency in agriculture is a subject that is getting more and more attention in the latter years. Table 3 contains the gathered coefficients of the Quasi-Maximum Likelihood Estimation for the Mean of Technical Inefficiency using Models 1 and 2 (without weights) and Models 3 and 4 (with weights). Columns 1 and 3 are based on Equation (1) and

Table 3

Results of the Quasi-Maximum Likelihood Estimation for the Mean of Technical Inefficiency

VARIABLE	Model 1	Model 2	Model 3	Model 4
Radial	–0.243 (0.383)	–0.279 (0.379)	–1.174** (0.546)	–1.213** (0.601)
Cobb	–0.562*** (0.135)	–0.630*** (0.150)	–1.268*** (0.096)	–1.230*** (0.099)
Translog	–0.347** (0.146)	–0.392*** (0.147)	–0.341*** (0.132)	–0.191 (0.170)
Quadratic	–0.966** (0.492)	–1.076** (0.465)	–1.303*** (0.365)	–1.224*** (0.377)
Observations	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001*** (0.000)
Nroutputs	–0.110* (0.059)	–0.131** (0.058)	–0.141** (0.062)	–0.127* (0.067)
Nrinputs	–0.035 (0.065)	–0.063 (0.068)	0.205** (0.085)	0.099 (0.113)
Year	–0.005** (0.002)	–0.006** (0.002)	–0.009 (0.015)	–0.007 (0.007)
Panel	–0.043 (0.192)	0.075 (0.180)	–0.242 (0.253)	0.246 (0.330)
Primary	–0.008 (0.224)	0.101 (0.258)	–0.860*** (0.296)	–0.465 (0.390)
Dual	0.170 (0.388)	0.199 (0.389)	–0.286 (0.247)	–0.033 (0.277)
Permanent	–0.057 (0.183)	–0.043 (0.182)	0.720*** (0.118)	0.688*** (0.118)
Temporary	–0.164 (0.134)	–0.220 (0.137)	–0.072 (0.123)	–0.126 (0.124)
America	–0.866*** (0.269)		–1.192*** (0.336)	
Europa	–0.529** (0.233)		–0.920*** (0.236)	
Asia	–0.582*** (0.174)		–1.171*** (0.183)	
Lmic		–0.405* (0.210)		–0.300 (0.320)
Umic		–0.879*** (0.226)		–1.245*** (0.322)
Hic		–0.670*** (0.203)		–0.701** (0.295)
Quartil	0.031 (0.074)	0.057 (0.077)	0.177* (0.102)	0.265* (0.140)
Constant	9.403** (4.279)	12.360** (4.826)	18.387 (31.098)	15.033 (13.920)
Log_Pslikelihood	–68.50	–68.61	–66.40	–66.85
Deviance	16.99	17.22	5.61	6.51
Pearson	16.40	16.88	5.78	6.64
(1/DF) Deviance	0.1148	0.1163	0.0379	0.0440
(1/DF) Pearson	0.1107	0.1141	0.0391	.0449
Akaike Information Criterion	1.0421	1.0435	1.0169	1.0223
Bayesian Information Criterion	–739.59	–739.36	–750.96	–750.06
Observations	166	166	166	166

Notes: Models 3 and 4 with weights in the size of observation in the primary study; Robust standard errors in parentheses; The estimated parameter is significantly different from zero at: * 10 %; ** 5 % and *** 1 % significance level.
Source: Authors' data.

columns 2 and 4 are based on Equation (2). All estimations were conducted in Stata version 14.2 by using the generalised linear model (gml) command with family (binomial), link (logit), and robust standard error option.

The analysis of Table 3 shows similar results regarding both positive and negative signs of the estimated coefficients. In addition, the majority of the explanatory variables are statistically significant in at least one of the models with the exception of panel, dual and temporary variables.

The models with weight (3 and 4) have more significant variables. By using the criteria for the model selection from Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), models 3 and 4 have the lowest values, but once again, they are preferred.

The models of Quasi-Maximum Likelihood Estimation with weight reveal that radial functions, which are not used in previous studies, produce a higher Technical Efficiency (significantly at 5 %). Therefore, the directional functions show the opposite.

Studies using a Cobb-Douglas, Translog and quadratic functions yield a significantly lower Mean of Technical Inefficiency (statistically significant in all regressions with exception of the Translog variable in the fourth regression), which means that non-parametric approaches that normally use Data Envelopment Analysis have a higher Mean of Technical Inefficiency.

The empirical studies that compile more observations achieve a higher Mean of Technical Inefficiency that is statistically significant at 5 % or 1 %. They are the benchmarking methodologies. Thus, the higher the number of observations, the higher the benchmark level and the higher the levels of inefficiency of the decision-making units will be. In the opposite way, the number of outputs and the year of data collection have a negative effect on the Mean of Technical Inefficiency.

The papers that analyse the efficiency in permanent crops reveal higher levels of the Mean of Technical Inefficiency in the models with weight (significant at 1 %), otherwise, the year of data has a negative influence on the Mean of Technical Inefficiency in models 1 and 2 (significant at 5 %). Those results could mean that temporary and mixed crops are more efficient than permanent crops (fruits and oilseed) and the Technical Efficiency has been increasing over the years.

To distinguish the efficiency according to the region of study, we use continents (model 1 and 3) and their income level (model 2 and 4) as variables. The obtained results are convergent for both situations, since Africa and low-income countries have lower efficiency levels than other continents or countries.

Finally, in the models with weight, the results show that the larger the journal's quartile, the greater the Mean of Technical Inefficiency is. In the other models, the results were not significant.

5. Discussion and Implications

The literature on productive efficiency in the agricultural sector has focused essentially on the critical aspects of the used methodologies and their empirical procedures, as well as on the main factors that determine and explain efficiency. The effect of the geographical context, evidenced by the country's economy or its level of investment and achieved productivity, was transversal to the various studies on the topic. However, the findings have reached no consensus regarding the methodology used in Technical Efficiency research. Moreover, the works particularly devoted to studying the regional effect on efficiency measures has not led to uniform conclusions.

To explain the variation in the Mean of Technical Inefficiency on studies that are focused on the agriculture sector, we proposed four alternative empirical models using meta-regression analysis. These incorporate the effect of developed and developing countries into 166 observations from 100 papers. The models provided similar results, therefore, they can be considered robust and meaningful. However, the models with weight (3 and 4) that have the lowest values were preferred, which is in line with Ogundari's [15] work.

The econometric results showed that the Mean of Technical Inefficiency reported in academic literature could be explained by two main features: empirical implementation (data, variables and empirical model) and region of study. Despite the controversy of the parametric methods' influence on the Mean of Technical Inefficiency, the results confirmed the ideas of Djokoto [54], Djokoto, Srofenyoh and Arthur [16] and Mareth et al. [14], since the parametric approaches (such as Stochastic Frontier Analysis) allowed measurement error and random shocks while the non-parametric approaches (such as Data Envelopment Analysis) did not.

In light of the research findings, we suggest to apply several alternatives of empirical models that demonstrate the convergence and robustness of the results. Their use will help achieve better and more conclusive results that do not depend on the empirical implementation process.

Relatively to the region of study (by continents and income level), the scientific studies focused on developed countries present the lowest Mean of Technical Inefficiency. Meanwhile, studies for Africa and developing or low-income countries exhibit the highest scores of the Mean of Technical Inefficiency. This situation confirms the conclusions of Bravo-Ureta et al. [4], which were not obtained in recent studies of Mareth et al. [14] and Djokoto, Srofenyoh and Arthur [16].

These findings highlight that the productive systems practiced by developed countries are distinct and should be replicated by developing countries. In this sense, these countries should collaborate to help the planning and adoption of more efficient farms by lower-income countries.

However, we recognise that farms in different locations cannot be always compared using the usual efficiency methods due to the disparity of regions. The development of studies with output and input variables disaggregated as possible and with homogeneous farms can be favourable to collect specific data on each particular production area. In addition, we propose to decompose Technical Efficiency as pure Technical and Scale Efficiency to analyse where the difference between regions comes from. Moreover, the recent decomposition between long-run (persistent) and short-run (transient) inefficiency [66] will make possible to differentiate the evolution of inefficiency in the different regions.

Finally, when panel data is available, productive efficiency evolution and technological change should be analysed to provide a better understanding of the disparities among the farms and their respective regions.

References

1. Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General), 120(3),* 253–290. DOI: 10.2307/2343100.

2. Coelli, T., Rao, D. S. P., O'Donnell, C. J. & Battes, G. E. (2005). *An introduction to efficiency and productivity analysis (2nd Edition).* U.S.: Springer. DOI: 10.1007/b136381.

3. Aparicio, J., Borras, F., Pastor, J. T. & Vidal, F. (2013). Accounting for slacks to measure and decompose revenue efficiency in the Spanish Designation of Origin wines with DEA. *European Journal of Operational Research, 231(2),* 443–451. DOI: 10.1016/j.ejor.2013.05.047.

4. Bravo-Ureta, B. E., Solís, D., Moreira López, V. H., Maripani, J. F. & Thiam, A. (2007). Technical Efficiency in Farming: A Meta-Regression Analysis. *Journal of Productivity Analysis, 27(1),* 57–72. DOI: 10.1007/s11123–006–0025–3.

5. Anang, B. T., Bäckman, S. & Rezitis, A. (2016). Does Farm Size Matter? Investigating Scale Efficiency of Peasant Rice Farmers in Northern Ghana. *Economics Bulletin, 36(4),* 2275–2290.

6. Alvarez, A. & Orea, L. (2001). *Different Approaches to Model Multi-Species Fisheries Using a Primal Approach.* Efficiency Series Paper, 3(200), 17. Retrieved from: https://www.unioviedo.es/oeg/ESP/esp_2001_04.pdf (Date of access: 08.05.2019).

7. Coelli, T. (1995). Recent Developments in Frontier Modelling and Efficiency Measurement. *Australian Journal of Agricultural and Resource Economics, 39(3),* 219–245. DOI: 10.1111/j.1467–8489.1995.tb00552.x

8. Cullinane, K., Wang, T. F., Song, D. W. & Ji, P. (2006). The Technical Efficiency of Container Ports: Comparing Data Envelopment Analysis and Stochastic Frontier Analysis. *Transportation Research Part A: Policy and Practice, 40(4),* 354–374.

9. Resti, A. (2000). Efficiency Measurement for Multi-Product Industries: A Comparison of Classic and Recent Techniques Based on Simulated Data. *European Journal of Operational Research, 121(3),* 559–578. DOI: 10.1016/S0377–2217(99)00054–5.

10. Wadud, A. & White, B. (2000). Farm Household Efficiency in Bangladesh: A Comparison of Stochastic Frontier and DEA Methods. *Applied Economics, 32(13),* 1665–1673. DOI: 10.1080/000368400421011.

11. Kalaitzandonakes, N. G. & Dunn, E. g. (1995). Technical Efficiency, Managerial Ability and Farmer Education in Guatemalan Corn Production: A Latent Variable Analysis. *Agricultural and Resource Economics Review, 24(1),* 36–46. DOI: 10.1017/S1068280500003592.

12. Sharma, K. R., Leung, P. S. & Zaleski, H. M. (1999). Technical, Allocative and Economic Efficiencies in Swine Production in Hawaii: A Comparison of Parametric and Nonparametric Approaches. *Agricultural Economics, 20(1),* 23–35. DOI: 10.1111/j.1574–0862.1999.tb00548.x.

13. Solis, D. A. (2005). *Household Productivity and Investment in Soil Conservation: Evidence from Small-Scale Hillside Farmers in Central America.* Ph.D. Dissertation. Connecticut: University of Connecticut.

14. Mareth, T., Thomé, A. M. T., Cyrino Oliveira, F. L. & Scavarda, L. F. (2016). Systematic Review and Meta-Regression Analysis of Technical Efficiency in Dairy Farms. *International Journal of Productivity and Performance Management, 65(3),* 279–301. DOI: 10.1108/IJPPM-02–2015–0027.

15. Ogundari, K. (2014). The Paradigm of Agricultural Efficiency and Its Implication on Food Security in Africa: What Does Meta-Analysis Reveal? *World Development, 64(1920),* 690–702. DOI: 10.1016/j.worlddev.2014.07.005.

16. Djokoto, J. G., Srofenyoh, F. Y. & Arthur, A. A. A. (2016). Technical Inefficiency Effects in Agriculture — A Meta-Regression. *Journal of Agricultural Science, 8(2),* 109–121. DOI: 10.5539/jas.v8n2p109.

17. Sickles, R. C. & Zelenyuk, V. (2019). *Measurement of productivity and efficiency.* Cambridge, UK: Cambridge University Press, 626. DOI: 10.1017/9781139565981.

18. Färe, R., Grosskopf, S. & Lovell, C. A. K. (1983). The Structure of Technical Efficiency. *The Scandinavian Journal of Economics, 85(2),* 181–190. DOI: 10.2307/3439477.

19. Färe, R., Grosskopf, S. & Lovell, C. A. K. (1985). *The Measurement of Efficiency of Production.* Dordrecht: Springer, 216. DOI: 10.1007/978–94–015–7721–2

20. Färe, R., Grosskopf, S. & Lovell, C. A. K. (1994). *Production Frontiers.* Cambridge, UK: Cambridge University Press, 312. DOI: 10.1016/0954–349X(95)90003-T.

21. Haghiri, M., Nolan, J. F. & Tran, K. C. (2004). Assessing the Impact of Economic Liberalization across Countries: A Comparison of Dairy Industry Efficiency in Canada and the USA. *Applied Economics, 36(11),* 1233–1243.

22. Thiam, A., Bravo-Ureta, B. E. & Rivas, T. E. (2001). Technical Efficiency in Developing Country Agriculture: A Meta-Analysis. *Agricultural Economics, 25(2–3),* 235–243. DOI: 10.1016/S0169–5150(01)00081–0.

23. Ramanathan, R. (2003). *An introduction to data envelopment analysis: a tool for performance measurement.* New Delhi: SAGE Publications, 201. DOI: 10.1177/097206341001300107.

24. Simar, L. & Wilson, P. W. (2000). Statistical Inference in Nonparametric Frontier Models: The State of the Art. *Journal of Productivity Analysis, 13(1),* 49–78. DOI: 10.1023/A:1007864806704.

25. Simar, L. & Wilson, P. W. (2007). Estimation and Inference in Two-Stage, Semi-Parametric Models of Production Processes. *Journal of Econometrics, 136(1),* 31–64. DOI: 10.1016/j.jeconom.2005.07.009.

26. Johnson, A. L. & Kuosmanen, T. (2012). One-Stage and Two-Stage DEA Estimation of the Effects of Contextual Variables. *European Journal of Operational Research, 220(2),* 559–70. DOI: 10.1016/j.ejor.2012.01.023.

27. Banker, R. D. & Natarajan, R. (2008). Evaluating Contextual Variables Affecting Productivity Using Data Envelopment Analysis. *Operations Research, 56(1),* 48–58. DOI: 10.1287/opre.1070.0460.

28. Aigner, D., Lovell, C. A. K. & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6(1),* 21–37. DOI: 10.1016/0304–4076(77)90052–5.

29. Meeusen, W. & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18(2),* 435–444. DOI: 10.2307/2525757.

30. Banker, R. D. & Maindiratta, A. (1992). Maximum Likelihood Estimation of Monotone and Concave Production Frontiers. *Journal of Productivity Analysis, 3(4),* 401–415.

31. Fan, Y., Li, Q. & Weersink, A. (1996). Semiparametric Estimation of Stochastic Production Frontier Models. *Journal of Business & Economic Statistics, 14(4),* 460–468.

32. Kneip, A. & Simar, L. (1996). A General Framework for Frontier Estimation with Panel Data. *Journal of Productivity Analysis, 7(2–3),* 187–212.

33. Kumbhakar, S. C., Parmeter, C.F. & Zelenyuk, V. (2017). *Stochastic Frontier Analysis: Foundations and Advances.* Working Papers, 2017–10. University of Miami, Department of Economics, 103.

34. Kuosmanen, T. & Kortelainen, M. (2012). Stochastic Non-Smooth Envelopment of Data: Semi-Parametric Frontier Estimation Subject to Shape Constraints. *Journal of Productivity Analysis, 38(1),* 11–28. DOI: 10.1007/s11123–010–0201–3.

35. Noh, H. (2014). Frontier Estimation Using Kernel Smoothing Estimators with Data Transformation. *Journal of the Korean Statistical Society, 43(4),* 503–512. DOI: 10.1016/j.jkss.2014.07.005.

36. Parmeter, C. F. & Racine, J. S. (2013). Smooth Constrained Frontier Analysis. In: *Recent Advances and Future Directions in Causality, Prediction, and Specification Analysis: Essays in Honor of Halbert L. White Jr.* (pp. 463–488). New York: Springer. DOI: 10.1007/978–1-4614–1653–1_18.

37. Parmeter, C. F. (2018). Estimation of the Two-Tiered Stochastic Frontier Model with the Scaling Property. *Journal of Productivity Analysis, 49(1),* 37–47. DOI: 10.1007/s11123–017–0520–8.

38. Greene, W. H. (2008). The econometric approach to efficiency analysis. In: *H. O. Fried, C. A. K. Lovell, S. S. Schmidt (Eds.), The measurement of productive efficiency and productivity growth* (pp. 68–119). Oxford, UK: Oxford University Press. DOI: 10.1093/acprof:oso/9780195183528.003.0002.

39. Lovell, C. A. K. (1993). Production Frontiers and Productive Efficiency. In: *H. O. Fried, S. S. Schmidt (Eds.), Measurement of Productive Efficiency: Techniques and Applications* (pp. 3–67). Oxford, UK: Oxford University Press.

40. Schmidt, P. & Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business & Economic Statistics, 2(4),* 367–374. DOI: 10.1080/07350015.1984.10509410.

41. Lovell, C. A. K. (1996). Applying efficiency measurement techniques to the measurement of productivity change. *Journal of Productivity Analysis, 7,* 329–340. DOI: 10.1007/BF00157047.

42. Kumbhakar, S. C. (2001). Estimation of profit functions when profit is not maximum. *American Journal of Agricultural Economics, 83(1),* 1–19. DOI: 10.1111/0002–9092.00133.

43. Shephard, R. W. (1953). *Cost and production functions.* Princeton, N. J.: Princeton University Press, 104. DOI: 10.1017/S1373971900103956.

44. Shephard, R. W. (1970). *Theory of cost and production functions.* Princeton, N. J.: Princeton University Press, 308. DOI: 10.1017/S002205070007457X.

45. Chambers, R. G., Chung, Y. & Färe, R. (1996). Benefit and distance functions. *Journal of Economic Theory, 70(2),* 407–419. DOI: 10.1006/jeth.1996.0096.

46. Chambers, R. G., Chung, Y. & Färe, R. (1998). Profit, directional distance functions, and Nerlovian efficiency. *Journal of optimization theory and applications, 98(2),* 351–364. DOI: 10.1023/A:1022637501082.

47. Chambers, R. G., Fäure, R. & Grosskopf, S. (1996). Productivity growth in APEC countries. *Pacific Economic Review, 1(3),* 181–190. DOI: 10.1111/j.1468–0106.1996.tb00184.x.

48. Luenberger, D. G. (1992). Benefit functions and duality. *Journal of Mathematical Economics, 21(5),* 461–481. DOI: 10.1016/0304–4068(92)90035–6.

49. Luenberger, D. G. (1995). *Microeconomic theory.* New York: Mcgraw-Hill.

50. Costa, L., Lansink, A. O. & Silva, E. (2010). Animals' health control efficiency in Northwest Portugal: A two-stage DEA approach. *Acta Agriculturae Scandinavica, Section C — Food Economics, 7(2–4),* 197–208. DOI: 10.1080/16507541.2010.531941.

51. Ball, V. E., Fare, R., Grosskopf, S. & Nehring, R. (2001). Productivity of the US agricultural sector: the case of undesirable outputs. In: *C. R. Hulten, E. R. Dean, M. J. Harper (Eds.), New developments in productivity analysis* (pp. 541–586). Chicago: University of Chicago Press.

52. Chen, P.-C., Yu, M.-M., Chang, C.-C., Hsu, S.-H. & Managi, S. (2015). The enhanced Russell-based directional distance measure with undesirable outputs: numerical example considering CO2 emissions. *Omega, 53,* 30–40. DOI: 10.1016/j.omega.2014.12.001.

53. Chung, Y. H., Färe, R. & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management, 51(3),* 229–240. DOI: 10.1006/jema.1997.0146.

54. Djokoto, J. G. (2015). Technical Efficiency of Organic Agriculture: A Quantitative Review. *Studies in Agricultural Economics, 117(2),* 61–71. DOI: 10.7896/j.1512.

55. Rasmussen, S. (2010). Scale Efficiency in Danish Agriculture: An Input Distance-Function Approach. *European Review of Agricultural Economics, 37(3),* 335–367. DOI: 10.1093/erae/jbq023.

56. Sipiläinen, T., Kumbhakar, S. C. & Lien, G. (2014). Performance of Dairy Farms in Finland and Norway from 1991 to 2008. *European Review of Agricultural Economics, 41(1),* 63–86. DOI: 10.1093/erae/jbt012.

57. Tsionas, E. g., Kumbhakar, S. C. & Malikov, E (2015). Estimation of Input Distance Functions: A System Approach. *American Journal of Agricultural Economics, 97(5),* 1478–1493. DOI: 10.1093/ajae/aav012.

58. Alston, J. M., Marra, M. C., Pardey, P. G. & Wyatt, T. J. (2000). A Meta-analysis of the Returns to Agricultural R&D. *Australian Journal of Agricultural and Resource Economics, 44(2),* 185–215.

59. McDonald, J. (2009). Using Least Squares and Tobit in Second Stage DEA Efficiency Analyses. *European Journal of Operational Research, 197(2),* 792–98. DOI: 10.1016/j.ejor.2008.07.039.

60. Ramalho, E. A., Ramalho, J. J. S. & Henriques, P. D. (2010). Fractional Regression Models for Second Stage DEA Efficiency Analyses. *Journal of Productivity Analysis, 34(3),* 239–255. DOI: 10.1007/s11123–010–0184–0.

61. Papke, L. E. & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics, 11(6),* 619–632. DOI: 10.1002/(SICI)1099–1255(199611)11:6<619::AID-JAE418>3.0.CO;2–1

62. Nelson, J. P. & Kennedy, P. E. (2009). The Use (and Abuse) of Meta-Analysis in Environmental and Natural Resource Economics: An Assessment. *Environmental and Resource Economics, 42(3),* 345–377. DOI: 10.1007/s10640–008–9253–5.

63. Espey, M., Espey, J. & Shaw, W. D. (1997). Price Elasticity of Residential Demand for Water: A Meta-analysis. *Water Resources Research, 33(6),* 1369–1374. DOI: 10.1029/97WR00571.

64. Stanley, T. D. & Doucouliagos, H. (2015). Neither Fixed nor Random: Weighted Least Squares Meta-analysis. *Statistics in Medicine, 34(13),* 2116–2127. DOI: 10.1002/sim.6481.

65. Stanley, T. D. (2008). Meta-regression Methods for Detecting and Estimating Empirical Effects in the Presence of Publication Selection. *Oxford Bulletin of Economics and Statistics, 70(1),* 103–127. DOI: 10.1111/j.1468–0084.2007.00487.x.

66. Alem, H. (2018). Effects of model specification, short-run, and long-run inefficiency: an empirical analysis of stochastic frontier models. *Agricultural Economics, 648(11),* 508–516. DOI: 10.17221/341/2017-AGRICECON.

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