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Justice G. DJOKOTO*

Technical efficiency of organic agriculture: a quantitative review

This article examines the variations in mean technical efficiency estimates in organic agriculture and the factors that explain the observed variations. A three-stage process was employed in data collection. Firstly, journals on organic agriculture and related disciplines were identified and searched. Secondly, several publishers' websites and databases, namely Cambridge Journals, Elsevier, Emerald, Oxford University Press, Sage, Taylor and Francis, and Wiley, among others, were covered. Databases included AgEcon Search, CAB Abstracts, DOAJ, EBSCOhost, Google Scholar and ScienceDirect. Thirdly, the reference lists of studies found in the first and second stages were searched to identify additional literature. In all, 42 studies constituting 109 observations published in the period 2002-2014 were found. Unlike existing literature on technical efficiency quantitative reviews in agriculture, this article employs a battery of tests to select the appropriate solution for multiple observations from the same primary study, as well as the appropriate functional form for the selected fractional regression model. The mean technical efficiency of organic agriculture for the period of study and the effects of other study characteristics are thoroughly discussed.

Keywords: fractional regression, meta-regression, organic agriculture, quantitative review, technical efficiency

* Central University College, P.O. Box DS 2310, Dansoman, Accra, Ghana. jdjokoto@central.edu.gh; http://orcid.org/0000-0002-2159-2944

Introduction

Organic agriculture (OA) seeks to combine tradition, innovation and science to benefit the environment and promote fair relationships and a good quality of life for all involved. This production system is intended to sustain the health of soils, ecosystems and people. It relies on ecological processes, biodiversity and cycles adapted to local conditions rather than the use of chemical inputs that can have adverse effects (IFOAM, 2015).

Ramesh *et al.* (2005) noted that the benefits of OA to the developed nations include environmental protection, biodiversity enhancement, reduced energy use and CO_2 emissions. These have been enhanced by providing aid payments to organic farmers and premiums for organic products. For developing countries which are largely exporters of organic products, the benefits of OA lie in sustainable resource use, increased crop yields without over-reliance on costly external inputs, and environment and biodiversity protection. For these countries in particular, depletion and degradation of land and water resources pose serious challenges to the production of sufficient food and other agricultural products to sustain livelihoods and meet the needs of urban populations. Studies that focus on OA are therefore relevant because agriculture has a substantial impact on natural resources that must be better managed to supply sustainable ecosystem services, particularly in the light of climate change (Lakner *et al.*, 2012).

Although OA is a common practice in many areas of the developing world, certification of OA is relatively recent (Bouagnimbeck, 2013; Paull, 2013a, b). Certified OA is underpinned by the principles of health, ecology, fairness and care (IFOAM, no date). Certification bodies evaluate operations according to different organic standards and can be formally recognised by more than one authoritative body. The label of a given certification body, therefore, informs the consumer of the type of recognition granted to the certification body. There are other categories of standards such as international voluntary standards, national mandatory standards and local voluntary standards (FAO, 2015).

Organics certification generally predates the 1972 founding of IFOAM, the International Foundation for Organic Agriculture (Paull, 2010). In Australia, for example, there has been active and structured advocacy of OA since 1944 but organics certification only started in 1987 (Paull, 2008; 2013a). Certification is based on a pledge by certified farmers (operators) to comply with standards which are produced and enforced by both private institutions and governments and which originate mostly in developed countries (Latruffe and Nauges, 2014). The UK Soil Association has its own standards although Council Regulation 2092/91 of the European Union (EU) is in force in the EU. Countries such as Australia, Canada, Japan and the USA have their national standards (Mayen *et al*. 2009). Given the many standards, there are certainly some differences; nevertheless, these standards recognise the organic principles. For the purpose of this study, organic practices are recognised so long as they are certified by a national or international organic certifying body.

The OA applicant usually completes a questionnaire at the start of the certification process. Where the land has been cultivated, applicants are granted in-conversion status. When this period (usually between two and five years, depending on the crop or livestock) elapses, full organic status may be granted. After the first inspection, there is an annual inspection to ensure compliance. Farmers are expected to ensure that farm facilities and production methods conform to the standards, and maintain extensive records detailing the farm history and current set-up. Keeping written day-to-day farming and marketing records covering all activities (which must be available for inspection at any time) forms an integral part of OA. A written annual production plan would usually be submitted.

The difference between the observed output and what is attainable is technical efficiency (TE) (Farrell, 1957). TE and productivity of agriculture are fundamental for food security and poverty reduction (POST, 2006). The increase in TE provides an opportunity for farmers to increase output using the same level of resources (Beltrán-Esteve and Reig-Martínez, 2014). This has led to a plethora of studies in agricultural efficiency. Studies focusing on conventional agriculture (CA) have demonstrated variations in mean technical efficiency (MTE) (the sample's average) over time (Thiam *et al.,* 2001; Bravo-Ureta *et al.,* 2007; Ogundari and Brummer, 2011; Ogundari, 2014). Additionally, study attributes such as methodology, product and location have explained the observed differences. Therefore, some questions come to the fore in respect of OA. Firstly, how has MTE in OA varied over time? Secondly, what factors explain the variations in reported MTE in OA? Thirdly, do these factors influence MTE of OA similarly as CA?

Since a single study will not resolve a major issue in science, meta-analysis provides an effective alternative for assessing the generalisability of research in science (Hunter and Schmidt, 1990). Thiam *et al.* (2001), Bravo-Ureta *et al*. (2007), Moreira Lopez and Bravo-Ureta (2009), Ogundari and Brümmer (2011), Iliyasu *et al*. (2014) and Ogundari (2014) conducted meta-regression on TE in agriculture which focused on CA. However, this article assesses the variations in reported MTE in OA. It also investigates the roles of other factors in explaining the variations in reported MTE and identifies the similarities and differences in the effect of these factors on MTE of OA.

Only Ogundari (2014) used a fractional regression model (FRM) and selected the logit functional form without any statistical test as Papke and Wooldrige (1996) did. In this article, batteries of tests were employed to select the appropriate functional form for the selected FRM. The contribution of multiple observations from the same primary study to the metadata set in meta-regression is a common occurrence with its associated biases to the metadata set. Ogundari (2014) used sample weighted regression (WR) *a priori*. In this article, a solution was chosen based upon a set of statistical tests such as the goodness-of-functional form tests (Ramalho *et al*., 2010; 2011).

Methodology

Meta-analysis

Pooling together these studies for further investigation constitutes meta-analysis. Quantitative review allows researchers to combine results of several homogenous studies into a unified analysis that provides an overall estimate of interest for further discussion (Sterne, 2009). A general model for carrying out meta-analysis is to relate a key (dependent) variable to some characteristics that are believed to explain that variable (Alston *et al*., 2000). With reference to the present study, MTE from the primary study is considered as the dependent variable, while study attributes; methodological characteristics, product and regional groups, and publishing outlet and quality are taken as explanatory variables. In accomplishing TE meta-analysis, various MTEs are extracted from the studies reviewed. The corresponding study characteristics are identified and the resulting metadata set is fitted to a model. Multiple observations on MTE reported in a study constitute observations; otherwise, each primary study constitutes one observation.

Data

To gather data, firstly, journals on organic and related disciplines were identified and searched. Secondly, various publishers' websites and databases, namely Cambridge Journals, Elsevier, Emerald, Oxford University Press, Sage, Taylor and Francis, and Wiley, among others, were covered. Databases included AgEcon Search, CAB Abstracts, DOAJ, EBSCOhost, Google Scholar and ScienceDirect. Thirdly, the reference list of studies found in the first and second stages was searched to identify additional literature. In all, 42 studies constituting 109 observations covering the period 2002-2014 were found (Table 1).

Table 1: Literature from which metadata were extracted.

Author(s) and year	MTE	Product	Year	Country
Alkahtani and Elhendy (2012)	0.650	Date palm	2010	SAU
Alkahtani and Elhendy (2012)	0.470	Date palm	2010	SAU
Arandia and Aldanondo-Ochoa (2008)	0.140	Vineyard	2001	ESP
Arandia and Aldanondo-Ochoa (2008)	0.138	Vineyard	2001	ESP
Arandia and Aldanondo-Ochoa (2008)	0.140	Vineyard	2001	ESP
Arandia and Aldanondo-Ochoa (2008)	0.136	Vineyard	2001	ESP
Artukoglu *et al.* (2010)	0.677	Olive	2008	TUR
Artukoglu *et al.* (2010)	0.748	Olive	2008	TUR
Bayramoglu and Gundogmus (2008)	0.852	Raisin	2004	TUR
Beltrán-Esteve and Reig-Martínez (2014)	0.656	Citrus	2009	ESP
Beltrán-Esteve and Reig-Martínez (2014)	0.607	Citrus	2009	ESP
Breustedt *et al.* (2009)	0.965	Dairy	2005	GER
Breustedt *et al.* (2009)	0.833	Dairy	2005	GER
Charyulu and Biswas (2010)	0.737	Multiple crops	2010	IND
Charyulu and Biswas (2010)	0.667	Multiple crops	2010	IND
Chen *et al.* (2012)	0.982	Rice	2006	CHN
Chen *et al.* (2012)	0.999	Rice	2006	CHN
Chen *et al.* (2012)	0.892	Rice	2006	CHN
Chen *et al.* (2012)	0.983	Rice	2006	CHN
Cisilino and Madau (2007)	0.422	Crops and livestock	2003	ITA
Cisilino and Madau (2007)	0.543	Crops and livestock	2003	ITA
Elhendy and Alkahtani (2013)	0.135	Date palm	2010	SAU
Elhendy and Alkahtani (2013)	0.543	Date palm	2010	SAU
González (2011)	0.327	Crops and livestock	2005	NIC
González (2011)	0.433	Crops and livestock	2005	NIC
Guesmi *et al.* (2012)	0.796	Grapes	2008	ESP
Guesmi *et al.* (2014)	0.975	Cereals and horticulture	2010	EGY
Jayasinghe and Toyoda (2004)	0.450	Tea	2002	LKA
Karagiannias *et al.* (2006)	0.809	Dairy	2002	AUT
Karagiannias *et al.* (2012)	0.783	Dairy	1997	AUT
Karagiannias *et al.* (2012)	0.808	Dairy	1998	AUT
Karagiannias *et al.* (2012)	0.788	Dairy	1999	AUT
Karagiannias *et al.* (2012)	0.794	Dairy	2000	AUT

Author(s) and year	MTE	Product	Year	Country
Karagiannias *et al.* (2012)	0.770	Dairy	2001	AUT
Karagiannias *et al.* (2012)	0.756	Dairy	2002	AUT
Kramol *et al.* (2015)	0.416	Vegetables	2008	THA
Kramol *et al.* (2015)	0.220	Vegetables	2008	THA
Kumbhakar *et al.* (2009)	0.796	Dairy	1998	FIN
Kumbhakar *et al.* (2009)	0.798	Dairy	1998	FIN
Kumbhakar *et al.* (2009)	0.759	Dairy	1998	FIN
Lakner (2009)	0.640	Dairy	2005	GER
Lakner *et al.* (2012)	0.740	Grass	2005	GER
Lakner *et al.* (2014)	0.825	Crops and livestock	2006	CHE
Lakner *et al.* (2014)	0.772	Crops and livestock	2006	AUT
Lakner *et al.* (2014)	0.847	Crops and livestock	2006	GER
Lakner *et al.* (2014)	0.579	Crops and livestock	2006	CHE
Lakner *et al.* (2014)	0.532	Crops and livestock	2006	AUT
Lakner *et al.* (2014)	0.564	Crops and livestock	2006	GER
Larsen and Foster (2005)	0.440	Multiple crops	2002	SWE
Latruffe and Nauges (2014)	0.850	Cereals and oil seeds	2006	FRA
Latruffe and Nauges (2014)	0.790	Other field crops	2006	FRA
Latruffe and Nauges (2014)	0.800	Fruits and vegetables	2006	FRA
Latruffe and Nauges (2014)	0.850	Horticulture	2006	FRA
Latruffe and Nauges (2014)	0.720	Wine with origin	2006	FRA
Latruffe and Nauges (2014)	0.630	Fruits and vegetables	2006	FRA
Latruffe and Nauges (2014)	0.750	Permanent crops	2006	FRA
Latruffe and Nauges (2014)	0.900	Multiple crops	2006	FRA
Lohr and Park (2006)	0.713	Multiple crops	1997	USA
Lohr and Park (2006)	0.722	Multiple crops	1997	USA
Lohr and Park (2006)	0.789	Multiple crops	1997	USA
Lohr and Park (2006)	0.847	Multiple crops	1997	USA
Lohr and Park (2006)	0.660	Multiple crops	1997	USA
Lohr and Park (2007)	0.787	Multiple crops	1997	USA
Lohr and Park (2007)	0.856	Multiple crops	1997	USA
Lohr and Park (2007)	0.805	Multiple crops	1997	USA
Lohr and Park (2007)	0.812	Multiple crops	1997	USA
Lohr and Park (2007)	0.801	Multiple crops	1997	USA
Lohr and Park (2007)	0.764	Multiple crops	1997	USA
Lohr and Park (2010)	0.581	Multiple crops	1997	USA
Lohr and Park (2010)	0.588	Multiple crops	1997	USA
Lohr and Park (2010)	0.592	Multiple crops	1997	USA
Lohr and Park (2010)	0.560	Multiple crops	1997	USA
Madau (2007)	0.831	Multiple crops	2002	ITA
Mayen *et al.* (2010)	0.817	Dairy	2005	USA
Mayen *et al.* (2010)	0.770	Dairy	2005	USA
Nastis *et al.* (2012)	0.420	Alfalfa	2008	GRC
Nastis *et al.* (2012)	0.540	Alfalfa	2008	GRC
Onumah *et al.* (2013)	0.800	Cocoa	2011	GHA
Onumah *et al.* (2013)	0.590	Cocoa	2011	GHA
Oude Lansink *et al.* (2002)	0.910	Multiple crops	1997	FIN
Oude Lansink *et al.* (2002)	0.860	Multiple crops	1997	FIN
Oude Lansink *et al.* (2002)	0.880	Livestock	1997	FIN
Oude Lansink *et al.* (2002)	0.930	Livestock	1997	FIN
Park and Lohr (2010)	0.716	Multiple crops	2008	USA
Park and Lohr (2010)	0.727	Multiple crops	2008	USA
Park and Lohr (2010)	0.725	Multiple crops	2008	USA
Park and Lohr (2010)	0.735	Multiple crops	2008	USA
Pechrová and Vlašicová (2013)	0.790	Cereals and oil seeds	2008	CZE
Poudel *et al.* (2011)	0.890	Coffee	2010	NPL
Serra and Goodwin (2009)	0.940	Cereals and oil seeds	2002	ESP
Sipiläinen *et al.* (2008)	0.658	Multiple crops	1996	FIN
Sipiläinen *et al.* (2008)	0.664	Multiple crops	1997	FIN
Sipiläinen *et al.* (2008)	0.697	Multiple crops	1998	FIN
Sipiläinen *et al.* (2008)	0.598	Multiple crops	1994	FIN
Sipiläinen *et al.* (2008)	0.646	Multiple crops	1999	FIN
Sipiläinen *et al.* (2008)	0.651	Multiple crops	2000	FIN
Sipiläinen *et al.* (2008)	0.690	Multiple crops	2001	FIN
Sipiläinen *et al.* (2008)	0.631	Multiple crops	2002	FIN
Sipiläinen *et al.* (2008)	0.654	Multiple crops	1995	FIN
Songsrirote and Singhapreecha (2007)	0.866	Multiple crops	2006	THA
Tiedemann and Latacz-Lohmann (2013)	0.928	Multiple crops	2007	GER
Toro-Mujica *et al.* (2011)	0.660	Sheep	2008	ESP
Tzouvelekas *et al.* (2001a)	0.716	Olive	1996	GRC
Tzouvelekas *et al.* (2001b)	0.691	Olive	1996	GRC
Tzouvelekas *et al.* (2002a)	0.683	Olive	1996	GRC
Tzouvelekas *et al.* (2002a)	0.746	Cotton	1996	GRC
Tzouvelekas *et al.* (2002a)	0.760	Raisin	1996	GRC
Tzouvelekas *et al.* (2002a)	0.680	Grapes	1996	GRC
Tzouvelekas *et al.* (2002b)	0.845	Wheat	1999	GRC

Model

Consider

$$y=f(x) \tag{1}$$

where y is MTE and x is vector of covariates;

ORGONLY, ORGMEAT, DATAYEAR, DATASIZE, SFA, DEA, CS, CD, TL, TERMS, CRS, VRS, CAOS, OFC, FAV, NEH, PC, MC, DAIRY, LIVESTOCK, NAMERICA, CAMERICA, ASIA, EUROPEM, SCAND, JOURNAL, IF

Models for TE meta-analysis have quite a number of dummy variables constituting the total number of variables: Thiam *et al*. (2001), 10 out of 13; Bravo-Ureta *et al*. (2007), 12 out of 13; Ogundari and Brummer (2011), 10 out of 14; Ogundari (2014), 14 out of 17. These references are evidence of the importance of dummy variables in TE meta-analysis models. Dummy variables are useful in capturing factors that determine the study-to-study variation in the MTE (Nelson and Kennedy, 2009). Therefore, the multiplicity of dummy variables in the TE meta-analysis model specified above and described below is relevant. Fears of not obtaining robust estimates may be attenuated by the battery of tests employed in the model selection to be described shortly. The statistical insignificance of dummies may have research and policy implications. Thus, the high number of predictors, 27, used in the estimation model is important and represents one of the highest in agricultural TE meta-analysis.

The output-oriented MTE which is the dependent variable is defined as the simple average of the computed technical efficiencies of primary studies. *ORGONLY* represents studies that considered only organic data as opposed those that used organic and conventional sub-samples. *ORGONLY* took 1 and 0 otherwise. The coefficient of this variable may be positive or negative. *ORGMETA* represents studies that used metafrontier production function. *ORGMETA* is 1 and 0 otherwise. Since metafrontiers are farther from the group or primary frontier, the coefficient of *ORGMETA* is hypothesised to be negatively signed.

Year of data (*DATAYEAR*) refers to the year in which the data were collected in the case of cross-sectional data. For panel and time series data, the terminal year was used to represent year of data. However, where the MTE reported pertains to a specific year, that was taken as the *DATAYEAR*. It is anticipated that with time technology will improve, therefore the coefficient of *DATAYEAR* should be positively signed. *DATASIZE* is the number of observations in the primary study. Increased sample size generally produces more efficient estimates. This efficient estimate may not necessarily be high or low. Thus, the sign of the coefficient for *DATASIZE* may be positive or negative. *SFA* represents stochastic frontier estimation: *SFA* = 1 and 0 otherwise (*DEA*, distance functions). DEA stands for the non-parametric approach Data Envelopment Analysis. This dummy takes the value 1 for DEA and 0 otherwise (SFA and distance functions). Owing to the nature of the error term, the coefficient of the variable SFA should be positively signed. Data type (CS) represents cross-sectional data. *CS* = 1 and 0 otherwise (panel data). Moreira Lopez and Bravo-Ureta (2009) and Ogundari (2014) reported conflicting results on the sign of the coefficient of this variable. Thus, the sign of the coefficient may be negative or positive.

Functional forms employed in the estimations of TE in the primary study were observed to be Cobb-Douglas (CD), translog (TL) and non-functional forms. *CD* = 1 and 0 otherwise (translog; *TL* and non-functional forms). Also, *TL* = 1 and 0 otherwise (non-functional forms and *CD*). Bravo-Ureta *et al*. (2007) and Moreira Lopez and Bravo-Ureta (2009) have shown that MTE computed from *CD* functions are higher than those from *TL*. Thus the coefficient of *CD* is hypothesised to be positive. The number of explanatory variables in the TE estimation model of the primary study is *TERMS*. Since TE is estimated as part of the residual from production functions (not in the case of DEA), an increased number of *TERMS* should improve the fit of the model thereby reducing the residual. This would likely result in lower TE, hence MTE. Therefore, the coefficient of *TERMS* is hypothesised to be negative. Returns-to-scale may be constant (*CRS*) or variable (*VRS*): *CRS* = 1 for CRS, and 0 otherwise; *VRS* = 1 for VRS and 0 otherwise. The reference is studies that reported MTE of *CRS* and *VRS* plus distance functions or unspecified RTS. *CRS* and *VRS* were captured for only DEA, and hence the dummies are equal to 0 in the case of other methods to calculate efficiency. Nevertheless, how these variables are expected to influence *MTE* is unclear; thus, no *a priori* expectations have been formulated for them.

The studies found during the literature search contained several products and product groups. These have been classified into groups such as cereals, oil seeds and protein seeds *(CAOS)*; other field crops (*OFC*); fruits and vegetables (*FAV*); horticultural crops (*NEH*); permanent crops (*PC*); multiple crops (*MC*); dairy (*DAIRY*); livestock (non-dairy) (*LIVESTOCK*). One dummy for each of these products was specified. The reference category was mixed products (livestock and crops). Owing to the categorisations, the influence of these on *MTE* is unclear and therefore no *a priori* signs were formulated.

Studies included in the metadata covered diverse geographical areas. *NAMERICA* represented North America, *CAMERICA* represented Central America, *EUROPEM* represented mainland Europe and *SCAND* was used to capture Scandinavian countries. The control group was Africa. Owing to different geographical influences, the sign of the coefficients could not be stated *a priori.*

The method of dissemination of studies was considered. The dummy *JOURNALS* is set to 1 for academic journals, and 0 otherwise (conference papers, working papers among others). Finally, the quality of outlet, measured by the ISI impact factor (*IF*) was considered. The 2013 IF was used as proxy for journal quality. Where the dissemination outlet did not have an impact factor, that study was given *IF* of zero and those with impact factors had *IF* with a numerical index. Since journal quality relates more to the reliability of results than size of statistic, the sign of the coefficient *IF* may be positive or negative.

Estimation procedure

Ordinary least squares (OLS) and Tobit procedures are commonly used in TE meta-regression. With OLS, many predicted values would fall outside the unit interval. Although the Tobit procedure ensures that the predicted values lie within the unit interval, a censored data generation process (DGP) is assumed contrary to the fractional DGP for technical efficiency. Appropriately, fractional regression model (FRM) is employed in this article and specified as:

$$E(y|x) = G(x\theta) \tag{2}$$

where y is the dependent variable (MTE) and x are variables of the nature descried above. The conditional expected mean of y given x is $E(y|x)$. $G(\cdot)$ is some nonlinear function satisfying $0 \le G(\cdot) \le 1$ and θ is a vector of parameters to be estimated.

Papke and Wooldridge (1996) proposed logit and probit, respectively specified as:

logit:

$$G(x\theta) = \frac{e^{x\theta}}{1 + e^{x\theta}} \tag{3.1}$$

with partial effect;

$$\frac{\partial E(y|x)}{\partial x_i} = \theta_i \phi(x\theta)[1 - G(x\theta)] \tag{3.2}$$

and probit:

$$G(x\theta) = \Phi(x\theta) \tag{4.1}$$

with partial effect;

$$\frac{\partial E(y|x)}{\partial x_i} = \theta_i \phi(x\theta) \tag{4.2}$$

However, Ramalho *et al*. (2010, 2011) noted that, the logit and probit are most sensitive to covariates when the

mean of TEs (of DEA in particular) are around 0.5. What if that was not the case? They then showed that the other two models behaved differently:
loglog:

$$G(x\theta) = e^{-e^{-x\theta}} \tag{5.1}$$

with partial effect:

$$\frac{\partial E(y \mid x)}{\partial x_i} = \theta_j g(x\theta)\alpha G(x\theta)^{\alpha - i} \tag{5.2}$$

and cloglog:

$$G(x\theta) = 1 - e^{e^{x\theta}} \tag{6.1}$$

with partial effect:

$$\frac{\partial E(y \mid x)}{\partial x_i} = \theta_j g(x\theta)\alpha[1 - G(x\theta)^{\alpha - i}] \tag{6.2}$$

Indeed, failure to test the latter two could result in mis-specification. Following from these, all four functional forms were estimated.

Tests and model selection

In the absence of *a priori* theoretical formulation of the appropriate functional form for the FRM, statistical methods of selection offer a viable alternative. Also, the second objective of meta-analysis is to identify the determinants of variability in MTE and this study seeks to achieve this. Furthermore, Papke and Wooldridge (1996) and Ogundari (2014) used logit functional form without justification *save* that this is commonly used. Since MTE meta-regression models could well follow functional forms other than logit, selection from a number of model specifications is an appropriate econometric exercise.

This selection was accomplished by three tests: Ramsey RESET test, goodness-of-functional form tests (GOFF-1 and GOFF-2) and non-nested *P* test (Davidson and MacKinnon, 1981). The RESET test examines the presence of mis-specification in the model. Unlike the usual hypothesis test, the RESET, GOFF1 and GOFF2 tests note that the model is free of mis-specification if the null hypothesis cannot be rejected. The goodness-of-functional form tests, test for how well the data fit the functional form specified[1]. It is possible that more than one model would be selected by the RESET and goodness-of-functional form tests. Therefore, the *P* test provides an opportunity for one-on-one tests using the selected models from the first two stages as alternative hypotheses.

Some studies contributed more than one observation to the metadata set. Espey *et al*. (1997) noted this could bias standard errors and hence invalidate hypothesis tests. Their solution to the problem requires limiting multiple observations from the same study to five. Stanley (2008) proposed averaging these multiple observations to one. These recommendations would further limit the organic TE metadata set. An approach that keeps all multiple observations from a study in the metadata set is weighted regression (WR). Ogundari (2014) weighted the MTE by the sample size of the primary study. Perhaps a better weighting approach is to weight the MTE by the number of observations contributed by each primary study to the metadata. Jarrell and Stanley (1990) employed dummy variables to control for the number of data points contributed by primary studies to the metadata. This and the WR approaches were implemented to address the bias identified by Espey *et al*. (1997). The models from these two approaches were subjected to the tests described above. Further, robust standard errors were computed. Despite the barrage of estimations and tests, these were necessary to arrive at a reliable model to be discussed.

Results and discussion

Summary statistics

The studies composing the metadata are almost equally split between *SFA* models on one the hand and *DEA* and distance function models on the other hand (Table 2). The metadata are composed of 74 MTEs obtained from organic-only studies, five of which were computed with respect to a metafrontier. The use of cross-sectional data (CS) was popular among researchers of OA technical efficiency. This may have arisen from the ease and lower cost of collection, unlike

Table 2: Summary statistics of dummy measured variables.

		Number	Percentage
Nature of study	*ORGONLY*	35	32.1
	Comparative	74	67.9
Method of comparison	*ORGMETA*	5	4.6
	Non-frontier approach	104	95.4
Model	*SFA*	59	54.1
	DEA	40	36.7
	DF	10	9.2
Data structure	*CS*	79	72.5
	PL	30	27.5
Functional form	*CD*	23	21.1
	TL	45	41.3
	Non-functional	41	37.6
Returns-to-scale	*CRS*	10	9.2
	VRS	19	17.4
	SFA and DDF, unspecified	80	73.4
Products	*CAOS*	11	10.1
	OFC	3	2.8
	FAV	13	11.9
	NEH	3	2.8
	PC	11	10.1
	MC	37	33.9
	DAIRY	15	13.8
	LIVESTOCK	3	2.6
	CROPS and *LIVESTOCK*	13	11.9
Country	*NAMERICA*	21	19.3
	CAMERICA	2	1.8
	ASIA	18	16.5
	EUROPEM	48	44.0
	SCAND	17	15.6
	AFRICA	3	2.8
Publication outlet	*JOURNAL*	68	62.4
	Others	41	37.6

Source: own composition

[1] See Ramalho *et al*. (2010) for details on type 1 and type 2 GOFF tests; formulation, testing and distributional assumptions.

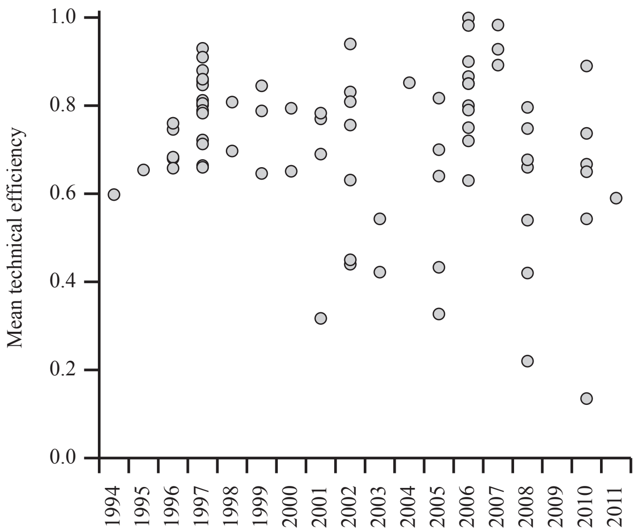

Figure 1: Global organic mean technical efficiency time path (1994-2011).

Source: metadata

panel data. The largest share of observations corresponded to MC farming type. About 60 per cent of the metadata was contributed from studies in Europe (EUROPEM and SCAND).

The time path of the MTE shows that MTE rose from 1994 (0.598) to 1997 (0.859) (Figure 1). MTE witnessed wide fluctuations with a gentle declining trend.

The average MTE (AMTE) of 0.696 (Table 3) implies organic producers could on average increase output by about 30 per cent without any increase in input use. Both the simple AMTE and the weighted AMTE (0.685) are within the range of 0.680 and 0.784 found for previous studies. The earliest data employed in the studies were collected in 1994, close to the latest data year of 1997 for Thiam *et al*. (2001). This is a reflection of the relatively recent nature of certified OA (Paull, 2008, 2013). For the 34 observations extracted from journals with an ISI 2013 impact factor, the lowest impact factor was 0.33 with a peak of 3.19 (Table 3). It must be noted however that the impact factors are related to different disciplines and not all studies had an ISI impact factor.

Choice of multiple observation amelioration approach

The RESET test was statistically significant for all functional forms for the sample size-weighted and multiple observation controlled models, implying mis-specification and therefore unsuitable for further use in this article (data not shown). At least one functional form could not be rejected by the RESET test (Table 4). Thus, the number of observations-weighted approach is preferred to the other two.

Model selection

From Table 4, all functional forms are mis-specified except the logit functional form. Similarly, at least one of the GOFF tests, GOFF2 showed that the logit functional form is well fitted to the data. Since only the logit passes both RESET and GOFF2 tests, there is no need for comparison with any other functional form.

Table 3: Summary statistics of scale measured variables.

	MTE	*DATASIZE*	*TERMS*	*DATAYEAR*	*IF*
N	109	109	109	109	109
Minimum	0.135	18	2	1994	0.33
Maximum	0.999	1717	40	2011	3.19
Simple mean	0.696	176	10	2003	1.60
Weighted mean	0.685	-	-	-	-
Standard deviation	0.190	227	9.00	4.90	0.90

Source: own composition

Table 4: Specification tests of number of observations-weighted regression estimation.

	Logit	Probit	Loglog	Cloglog
RESET†	2.579	3.458*	6.510**	4.164**
GOFF1†	3.212*	3.263*	-	4.401**
GOFF2	2.558	3.651*	6.919***	-
P-test				
H_{1Logit}	-	4.041**	10.479***	0.399
$H_{1Probit}$	3.166*	-	9.314***	0.508
$H_{1Loglog}$	0.012	2.078	-	0.045
$H_{1Cloglog}$	5.340**	6.662***	13.564***	-

***,**,* represent levels of significance of 1%, 5% and 10% respectively;

† H_1: model is mis-specified

Source: own composition

Discussion of selected estimated model

The selected logit model produced an R^2 type measure of 0.670 implying the explanatory variables accounted for about 67 per cent of the variability in the MTE (Table 5). The residual degree of freedom of 82 arose from the 27 explanatory variables. In the literature, Ogundari (2014) employed the highest number of explanatory variables in TE meta-regression in agriculture, 17. The 27 explanatory variables therefore constitute a departure from previous studies. The statistical insignificance of the constant term may have arisen from the high number of explanatory variables employed, suggesting the adequacy of the explanatory variables employed in the model. The explanatory variables can be categorised into four groups: methodological, products, region and dissemination. Except the dissemination, at least two coefficients and marginal effects are statistically significant. Despite the numerous variables, no correlation coefficient above 0.6 was found.

Despite the declining trend of MTE over time (Figure 1), the parameters of *DATAYEAR* are positive and statistically insignificant. The recognition of other factors that influence MTE may have caused a change of sign from a negative to positive. The statistically insignificant parameters imply MTE for OA have not increased significantly over the period. The finding of a non-increasing MTE over time for organic agriculture is not different from the earlier conclusions of Thiam *et al*. (2001) and Iliyasu *et al*. (2014) for CA. Indeed, in the literature, multi-country meta-analysis of TE has shown either stagnation or decline in MTE over time. Since an individual country study (Ogundari and Brummer, 2011) has shown a positive change in MTE over time, the effect of good performers in TE may have been masked by those of poor performers.

While studies using organic data only constituted 32 per cent of the metadata set, the positive and statistically signifi-

Table 5: Selected logit estimation results.

	Coefficients	Robust SE	Marginal effects	
			dy/dx	Delta method SE
DATAYEAR	0.096	0.075	0.016	0.012
ORGONLY	0.997***	0.438	0.163***	0.069
ORGMETA	-0.286	0.334	-0.047	0.055
DATASIZE	0.001	0.001	0.000	0.000
SFA	1.908***	0.693	0.312***	0.114
DEA	-2.814**	1.122	-0.460**	0.181
CS	1.263***	0.462	0.207***	0.072
CD	-3.577***	0.542	-0.585***	0.088
TL	-4.059***	0.871	-0.663***	0.138
TERMS	-0.006	0.018	-0.001	0.003
CRS	-0.848***	0.283	-0.139***	0.046
VRS	-1.033**	0.411	-0.169**	0.068
CAOS	-0.578	0.526	-0.094	0.086
OFC	-0.244	0.739	-0.040	0.121
FAV	1.507***	-0.535	-0.246***	0.087
NEH	1.840**	-0.709	0.301**	-0.114
PC	-1.079**	0.505	-0.176**	0.081
MC	-0.567*	0.324	-0.093*	0.053
DAIRY	-0.085	0.494	-0.014	0.081
LIVESTOCK	-0.394	0.787	-0.064	0.128
NAMERICA	-1.435*	0.850	-0.235*	0.139
CAMERICA	-3.085***	0.696	-0.504***	0.108
ASIA	0.568	0.484	0.093	0.079
EUROPEM	0.119	0.692	0.019	0.113
SCAND	0.250	1.135	0.041	0.185
JOURNAL	0.569	0.375	0.093	0.061
IF	-0.006	0.107	-0.001	0.018
CONSTANT	-190.9	150.7	-	-
Model properties				
R2-type measure		0.669		
No. of observations		109		
Residual d.f.		82		
Deviance		12.1		

***,**,* represent levels of significance of 1%, 5% and 10% respectively
Source: own composition

cant coefficient and marginal effect show that these studies produced higher MTE than those that used both organic and conventional data (Tables 2 and 5). It must be noted that the latter contains MTEs that are measured with respect to the meta-frontier, which is farther from the group frontier thus, producing lower values of MTE. Although the magnitude of the coefficient and marginal effect of *ORGMETA* are not statistically different from zero, the negative sign of the parameter confirms this explanation. The statistical insignificance also implies that differences between the two sets of MTEs are statistically immaterial.

The infinitesimal value of the parameters of *DATASIZE* suggests little influence of this variable on MTE. Moreover, the parameters are statistically insignificant. Thus, controlling for the other 26 explanatory variables, the observed differences in size of study sample did not influence MTE. Since certified OA is recent and the certification process constitutes a barrier that prevents farmers from signing-on, fewer farmers participate, unlike conventional production. Therefore smaller numbers of farmers and consequently small samples for studies would result. The resulting sample sizes, although seemingly adequate, did not influence the size of the MTE. For conventional studies, the conclusions of Thiam *et al*. (2001) and Bravo-Ureta *et al*. (2007) are consistent with the finding of this study while those of Moreira Lopez and Bravo-Ueta (2009) and Ogundari and Brummer (2011) are not.

The estimated parameters of *SFA* imply MTE estimated from stochastic frontier models are higher than those estimated from DEA and distance functions. Also, for *DEA*, MTE estimated from *DEA* are lower than those from distance functions. The result found for DEA vs. SFA is intuitive. Theoretically, the error term in *SFA* is composed such that not all the error in the *SFA* model is attributable to TE, and hence TE calculated with SFA does not capture noise and thus is always higher than TE calculated with DEA. Iliyasu *et al*. (2014), however, found a negative sign for the *SFA* variable while Thiam *et al*. (2001) showed a statistically insignificant parameter. Following from the results of the *SFA* and *DEA*, MTEs from distance functions are higher than those of *DEA* but lower than those of *SFA*. This result is enlightening as none of the previous studies considered distance functions as variables except Ogundari (2014), who combined distance functions and non-functional forms with translog and Cobb-Douglas functions but found no statistical difference between these.

The statistically significant parameters of *CS* imply that MTE estimated from cross-sectional data are higher than those estimated from panel data. Cross-sectional data captures TE at a point in time. On the other hand, panel data represent both point-in-time and point-over-time situations. Thus, at points in time, TEs estimated may be increasing. However, other factors in the model and related to panel data studies may have created a negative pressure over time within the panel environment thereby resulting in a lower MTE for panel data MTEs. While this finding is consistent with the theoretical assertion of Greene (1993), Thiam *et al*. (2001), Bravo-Ureta *et al*. (2007) and Moreira Lopez and Bravo-Ureta (2009) found the opposite. No reasons were however assigned for the departure from the theoretical position. Ogundari (2014), however, reported a parameter statistically not different from zero. The multi-dimensional representation of panel data requires disentangling the effect of the two dimensions in arriving at appropriate conclusions. Also, the cost of gathering this is higher than for cross-sectional data. These points notwithstanding, the choice of data structure should be informed by the objectives of the study.

The negatively signed coefficients of *CD* and *TL* imply that the reference, *DEA* and distance functions produce higher MTEs. It must be recalled that together *DEA* and distance functions constitute the reference category. Since *DEA* MTEs were earlier found to be lower than SFA, the MTEs of distance functions certainly have overshadowed the effect of MTEs from *DEA* to produce this finding. While previous studies showed MTE from translog are higher than those from Cobb-Douglas functions (Bravo-Ureta, 2007; Moreira Lopez and Bravo-Ureta, 2009), recent studies provide contrary evidence, that is, translog functional forms generate lower MTEs than MTEs estimated from Cobb-Douglas functions (Iliyasu *et al*., 2014; Ogundari, 2014). Since Ogundari (2014) used a logit fractional regression model, his conclusions corroborate that of this study. This shows another similarity in the results from conventional and organic data estimations.

By construction, the *TL* has more than twice the number of terms of *CD*. Thus, the negative sign of *TERMS* is consistent with the negative sign of *TL*. Therefore, for organic studies there is a tendency for estimation models with a high number of terms to yield lower estimates of TE. Researchers should therefore be mindful of decisions on inclusion of explanatory variables in the production function. This finding for OA differs from those of CA.

The coefficients of *CRS* and *VRS* are negative and statistically significant. These results are expected as the sign of *DEA* was earlier found to be negative. In line with the explanation for *DEA*, MTE estimated with both reported *CRS* and *VRS* are lower than those of unreported *CRS*, *VRS*, *SFA* and distance functions. Since the reference group includes *DEA* MTEs for which the returns-to-scale have not been reported, the concordance of the signs of *DEA* and *VRS* cum *CRS* parameters implies that the MTEs from unreported returns-to-scale similarly follow the behaviour of *DEA* MTEs with reported returns-to-scale. Since the sizes of the marginal effects are similar, it is most likely that their effects via magnitudes will be similar. Thus, for the organic metadata used in this study, in as much as the choice of returns-to-scale in estimating technical efficiency in *DEA* environment influences MTE, these effects of *CRS* and *VRS* on MTE are similar. These results bring up some important points. Firstly, to a limited extent, the behaviour of *VRS* and *CRS DEA* towards MTE may be generalised even if returns-to-scale is unknown. Secondly, there is no apparent difference in the effect of *CRS* and *VRS* on MTE. These results on returns-to-scale are rare since none of the previous studies reported the effect of returns-to-scale on MTE. Although the results follow the direction of *DEA*, it provides empirical evidence, at least for this organic metadata, that *CRS* and *VRS* models influence MTE in a similar fashion.

The coefficients of all product groups are negatively signed implying that, generally, there is the tendency that MTE of these organic product groups are lower than those of the reference group, crops and livestock. The statistical significance of *MC*, although weak, shows the general high risk associated with crop farming. The statistical significance of the parameters of these variables suggests the relatively risky nature of these products.

The parameters of *DAIRY* and *LIVESTOCK* are statistically insignificant from zero, signifying statistical parity in the MTEs of these product groups with those of the control. Since some of the crop products groups have statistically significant negative parameters, there is a tacit pointer to the seemingly strong positive influence of livestock and related products on MTE. The greater MTE of crops and livestock combination is particularly instructive. The finding of Ponisio *et al*. (2015) that agricultural diversification within the organic system significantly reduced yield gaps between organic and conventional production suggests that organic producers should consider agricultural diversification. These findings are inconsistent with some previous studies on conventional agriculture. However, Bravo-Ureta *et al.* (2007) showed that for both developed and developing countries, animal production enterprises posted higher MTE, while Thiam *et al.* (2001) found a neutral effect of products on MTE.

The results for *CAMERICA* and *NAMERICA* imply MTE of organic production in these regions are lower than those in Africa. Thus differences in climatic conditions may explain the differences in MTE. However, production practices for specific products captured for countries (regions) in the metadata may be important. Certified organic production is certainly more developed in the US than in Africa. However, as noted by Paull (2008; 2013a, b), uncertified organic production predates recent certifications. In Ghana for example, many cocoa farmers have relied on no-chemical production for so long and are essentially *de facto* organic producers (Afari-Sefa *et al*., 2010). Thus, application of certified organic practices should not be that difficult to implement. The literature on CA has shown that largely Africa has produced lower MTEs compared to other regions, especially North America and Europe.

The statistical insignificance of the parameters of *JOURNAL* implies indifference between MTEs from studies published in journals and those in sources other than journals. These points to statistical parity in estimated MTE of organic agricultural operations. The finding of this study is however inconsistent with that of Ogundari (2014) who showed that studies published as journal articles showed higher MTE than those presented in working papers, conference proceedings and theses. Organic agriculture MTEs are indistinguishable based on the quality of journals in which it is published. Unlike publishing outlet, the findings of organic agriculture are consistent with those of conventional agriculture (Ogundari, 2014).

Conclusions

The study examined the variations in MTE estimates in organic agriculture and the factors that explain the observed variations using fractional regression modelling. The metadata consisting of 42 studies and 109 observations revealed TE, on average, which did not increase over time. The non-increasing MTE over time implies efforts to develop OA have not reflected positively on global MTE on average. Generally, there is a need to re-invigorate efforts to increase productivity of organic inputs. Specifically, further improvements in more responsive breeding stock and planting materials, increased availability and use of more diverse fertilising materials and crop protection products would be needed. While stakeholders' support is important in this direction for crops in particular, special attention should be given to fruits and vegetables, other horticultural crops and permanent crops.

The numbers of factors that account for variability in the MTEs vary for OA compared to CA while in some cases they influence MTEs in similar fashion. To further elucidate the findings of this article, more individual country TE meta-analyses in agriculture and specifically for OA and those that assess the role of distance functions and returns-to-scale on MTE would be useful. While policy makers may discriminate between journal and other sources on the one hand and between 'quality' journals and 'non-quality' journals on the other, the results for technical efficiency are unlikely to be different since MTEs from studies published in journals and those in sources other than journals do not differ statistically.

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