

FARM SIZE AND EFFICIENCY NEXUS: EVIDENCE FROM A META-REGRESSION

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ABSTRACT

Research background: Many studies have reported the relationship between farm size and productivity. Whilst some meta-regressions on efficiency have been published, none has addressed the issue of farm size efficiency relative to the dimensions of productive efficiency and its variants.

Purpose of the article: We investigated the effect of farm size on productivity in Ghanaian agriculture within a meta-regression framework.

Methods: Using data on 93 primary studies with 177 observations on efficiency in agriculture in Ghana, the Ordinary Least Squares estimator was applied in estimating the meta-regression model, a form of meta-analysis that specially formulated to assess empirical economics research. The farm size–efficiency effects were computed based on the Wald.

Findings, value added & novelty: The results were mixed. Whilst no farm size–efficiency nexus was established for allocative and scale efficiencies, the inverse effect was confirmed in the case of the cost-economic, profit, technical and metafrontier technical efficiencies. Improved technology would be compatible with reduced farm size, reduction of the technology gap that would move farmers closer to the metafrontier. We contribute to the farm size–efficiency debate as we performed a quantitative review of the farm size–efficiency relationship. We addressed the farm size–efficiency relationship within the meta-regression framework and accounted for the full range of efficiency measures. Unlike other meta-regressions that used the standard error of the estimates, we obtained additional effect size, that for farm size–efficiency, our key result, from the specified model. We then dissociated the effect size into the range of efficiency measures reported in the primary studies. The paper covers data on farming in Ghana.

Keywords: meta-regression; metafrontier technical efficiency; scale efficiency

JEL Codes: D13; Q12; O55

INTRODUCTION

Land is important to agricultural production. As the soil, it is a store of nutrients and provides mechanical support to crops and pasture. As a ground surface, it serves as space for farm structures, grazing animals, ponds, and water bodies for holding irrigation water and a home for aquatic life, among others. Total agricultural land globally for 2017 is estimated at 4,827 mega hectares (m ha), with Africa contributing 1,139.5 m ha (and Ghana 15.7 m ha) (FAOSTAT, 2020). Together with other resources like labour and capital, the area of land, measured in System International (SI) units as hectares, is essential in determining the population of plants, the number of products to be obtained and total biomass (Englund, 2020; Gopal *et al.*, 2020; Perpiña *et al.*, 2013; Prokop, 2018).

How effectively land and other resources contribute to output is referred to as productivity. Narrowly, input productivity is the ratio of the agricultural output to a unit of the input, thus, the productivity of land (also designated as yield), labour productivity and productivity of capital (Boyes & Melvin, 2012; Cowell, 2018). As there are

varied capital resources including fertiliser, other agrochemicals and farm machinery, the productivity is expressed in terms of the specific capital input. A broader measure of productivity is productive efficiency. Technical efficiency is the extent to which the potential output is obtained (Farrell, 1957). Other counterparts of technical efficiency include allocative, cost, economic, profit, and scale efficiencies (Fried *et al.*, 2008; Lovell & Schmidt, 1988; Simar & Wilson, 2020). As profit is revenue less cost, revenue efficiency is also known in the literature (Hansen *et al.*, 2019; Soleimani-Chamkhorami *et al.*, 2019; Mostafae & Hladik, 2019).

Sen (1962, 1966) pioneered research into farm size and land productivity relationships. Following the finding of an opposite relationship, many studies have investigated the issue further (Bardhan, 1973; Byiringiro & Reardon, 1996; Carletto, Savastano & Zezza, 2013; Fan & Chan-Kang, 2005; Feder, 1985; Julien, Bravo-Ureta & Rada, 2021; Li *et al.*, 2013; Mazumdar, 1965; Van Asdul, 2020). Notwithstanding the inverse relationship, Alvarez & Arias (2004), Freitas *et al.* (2019) and Singh *et al.* (2017) concluded that the relationship between the two is positive. Adachi *et al.*

(2010), Bojnec & Latruffe (2007), Li et al. (2013), Rahman et al. (2012) and Sarpong (2002) however found no significant relationship between farm size and land productivity. Considering the conflicting findings, what is the relationship between farm size and productivity based on combined evidence? We conducted a meta-regression of farm size and efficiency, broadly defined, to respond to the question.

Studies on farm size-productivity relationship abound. However, review papers on the subject are rare. Saini (1980) reviewed the association between farm size and income per acre for India. Shi and Lang (2013) addressed the subject in a review of studies on China with a focus on other measures of productivity. Several meta-regressions on technical efficiency and productivity in agriculture have also been published (Djokoto, 2015; Djokoto et al. 2016; Djokoto & Gidiglo, 2016; Geffersa et al., 2019; Hina & Bushra, 2016; Mareth et al., 2016; Solomon & Mamo, 2016). However, none of these addressed the farm size-productivity nexus. Whilst review studies on farm size-productivity relationship are few, quantitative reviews are non-existent. Our paper makes the following contributions to the literature. First, we perform a quantitative review of the farm size-efficiency relationship. Second, unlike other meta-regressions that used the standard error of the estimates or its equivalent and their transformations, so that the estimated coefficients become the effect size, we obtained additional effect size, that for farm size-efficiency, our key result, from the specified model. Thirdly, we dissociated the effect size into the range of efficiency measures reported in the primary studies.

On a debated issue such as the farm size-productivity relationship, for which the literature is full of many and conflicting findings, analysing these jointly offers one of the most reliable approaches for a definitive contribution to the issue. Thus, we applied a meta-regression analysis.

Many primary publications that studied the effect of farm area on agricultural output focused on partial (narrow) measures of productivity; output per unit area (Carter, 1984; Barrett, 1996; Ansoms, Verdoodt & Van Raust, 2008; Dieninger et al., 2018; Cheng, Zheng & Henneberry, 2019; IPBES, 2018; Van Ausdal, 2020). However, since the partial productivity measures may favour small producers, a broader measure of productivity measures would be preferable (Anang et al., 2016; Kumbhakar & Lovell, 2000; Li et al., 2013). Not only do we use primary studies that measure productivity broadly, but we also estimate the farm size-efficiency relationship for a range of the broad efficiency measures reported in the primary studies. These contributions are based on data on Ghanaian agriculture.

The next section presents a review of the literature on farm size efficiency relationships. The data and methods section follows. Before the conclusions and conclusions section, the results are presented and discussed.

LITERATURE REVIEW

The literature context regarding the subject consists of the foundations of the farm size – efficiency relationship, the

empirical review, and the methodological context of meta-regression.

Some foundations of the opposite farm size and productivity association

The inverse relationship has been explained variously. Sen (1962) acknowledging the general inverse relationship between farm size and productivity provided two reasons, the indivisibility of inputs e.g., bullocks and that family labour is large in total labour, so that as farm sizes get smaller, total labour per acre increases.

Chayanov (1966) put forward the theory of self-exploitation. The thesis states: “the degree of self-exploitation is determined by a peculiar equilibrium between family demand satisfaction and the drudgery of labour itself” (p. 4). Stated differently, the productivity of labour is mainly explained by the constitution of the family and its size, the number of work-capable members, the productivity of the labour unit, and the extent of labour deployment (Nepomuceno, 2019). This is termed the degree of self-exploitation. Thus, a working family rich in labour without hiring opportunities, but constrained in the land, has no option but to apply this labour to the land. Whilst this would increase the output per unit of land, labour productivity may decrease.

Others have adduced imperfect input factor markets which results in the land, labour force and credit market differences between the large-scale farmers and small-scale farmers (Sen, 1966; Carter, 1984; Lamb, 2003; Li et al., 2013; Newell et al., 1997; Reardon et al., 1996). According to Sen (1966, p. 443) “The peasant family is guided properly by its calculation of the real labour cost, reflecting the rate at which the members are ready to substitute labour for output, but the capitalist farmer is misguided by an inefficient market mechanism. His allocation is, therefore, correspondingly distorted”.

Differences in quality of land, measured by soil type, irrigation, and the value of farmland and utilisation degree also account for the opposite relationship between farm size and productivity (Byiringiro & Reardon, 1996; Lamb, 2003). Assuncao & Ghatak (2003) explained that heterogeneities in farmers’ farming skills and occupational choice and resources account for the inverse relation. In the view of Eswaran & Kotwal (1985) and Li et al. (2013), transaction costs, supervision costs differences and principal-agent problems in the farm organisation could accentuate the opposite relationship.

Empirical review

Reviewing several studies on farm size and efficiency in India, Saini (1980) acknowledged the opposite association of farm size-revenue productivity in the 1950s. The non-uniformity of income arising from non-uniform distribution of land was to some extent reduced by productivity differences between small and large farms (Ali & Deininger, 2014). Since the Green Revolution, however, this relationship has undergone a significant change. As farm size increased, the income increased more than proportionately. Saini (1980) suggested that changes might have taken place during the seventies which might have negated the conclusions of the evidence from earlier years.

Placing the farm size-agricultural productivity association debate within the Chinese environment, the review of **Shi & Lang (2013)** acknowledged the importance and policy implications for the formulation of agricultural development strategies related to the scale of operation. In a comprehensive review of studies on the subject covering China, it was found that selecting different productivity indicators would lead to inconsistent conclusions about the relationship between farm size and productivity. Previous studies mostly interpreted the traditional inverse relationship from the perspectives of incomplete factor markets and omitted variables, among others. Few explanations had been adduced to explain other types of relationships. Consequently, **Shi & Lang (2013)** suggested that in carrying out the scale operation, local governments in China should consider the regional conditions.

Three data structures are common in econometrics: time series, cross-section, and panel data. The relative strengths and weaknesses of these data structures have implications for the outcome of relationships between variables in efficiency meta-regressions. **Greene (1993)** and **Djokoto et al. (2020)** noted that other data structures are likely to yield less accurate efficiency estimates than panel data models given that there are repeated observations on each unit in the case of panel data. Mean technical efficiency (MTE) from cross-sectional data sets produced lower estimates than those from panel data analysis (**Aiello and Bonanno, 2016; Djokoto et al., 2020; Nguyen & Coelli, 2009; Thiam et al., 2001**). **Hina & Bushra (2016)** and **Djokoto et al. (2020)** have found technical efficiency (TE) values to be lower for cross-sectional data sets than for time series data sets. However, the data structure was unresponsive to technical efficiency (**Djokoto & Gidiglo, 2016; Djokoto et al., 2020**).

The diverse strands of estimating frontier efficiency have crystallised into two main ways: stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Since some of the errors in frontier efficiency models are accounted for as inefficiency, deterministic models do bias TE estimates upwards (**Kumbhakar & Lovell, 2000**). However, recent improvements in DEA efficiency measurements are expected to reduce the upward bias (**Djokoto et al., 2020; Emrouznejad, Parker & Tavares, 2008; Cook & Seiford, 2009; Kao, 2014; Koronakos, 2019; Mariz Almeida & Aloise, 2018**). Nevertheless, some studies have shown that TE estimates from DEA models are higher than those from SFA models (**Bravo-Ureta et al., 2007; Iiyasu et al., 2014**), whilst the findings of **Djokoto (2015)** and **Ogundari (2014)** were inconsistent. Other studies could not differentiate TE (**Djokoto et al., 2020; Fall et al., 2018**).

Spatial disparities in efficiency are not uncommon in the literature. Publications that focused on southern Nigeria produced higher mean technical efficiency than others (**Ogundari & Brümmer, 2011**). The better development in the coastal regions than others culminated in better efficiency in economic endeavours for agriculture and agribusiness in Ghana (**Djokoto et al., 2016; Djokoto & Gidiglo, 2016**). Recently and in a multi-sectoral study, however, **Djokoto et al. (2020)** found the contrary, that,

MTEs for middle and northern sections were higher than those covering Ghana (and COASTL).

Time is often used to capture technological improvement because of the positive correlation between technology and time. Consequently, it is expected that efficiency would improve overtime as well. Whilst **Ogundari & Brümmer (2011)** and **Djokoto & Gidiglo (2016)** agreed with this, **Odeck & Brathen (2012)** and **Ogundari (2014)** reported the opposite. Mean technical efficiency was not found to be responsive to time in some studies (**Djokoto et al., 2020; Solomon & Mamo, 2016**).

Studies on efficiency and productivity have also been seen to follow the usual order of diffusion of research results; theses-working papers-conference papers-journals. Across these outlets, variations in MTE have been found (**Djokoto et al., 2020**). Specifically, **Djokoto et al. (2016)**, **Geffersa et al. (2019)** and **Ogundari (2014)** found higher TE from journals as opposed to other dissemination media (**Djokoto et al., 2020**). Whilst **Aiello & Bonanno (2015)**, **Djokoto & Gidiglo (2016)** found the opposite, **Djokoto et al. (2020)** and **Solomon & Mamo (2016)** however, concluded on significant differentiation in efficiency based on dissemination outlet.

Meta-regression

Meta-regression as a form of meta-analysis is specially formulated to assess empirical economics research (**Campbell & Fogarty, 2006; Stanley & Jarrell, 1989; Jarrell & Stanley, 1990**). Identified as “analysis of analysis” (**Glass, 1976, pg. 3**), MRA can also be viewed as a secondary analysis. **Binder (2016)**, **Campbell & Fogarty (2006)**, **Stanley (2001)** and **Sterne (2009)** outlined four goals for MRA; 1. Identify the extent to which the choice of methods, design and data affect reported results. 2. Useful in explaining the wide variation found among research outcomes and proffer reasons, that emanates from studies, why the evidence on a certain issue appears conflicting or so different. 3. Propose useful approaches for future study. 4. Propose a prediction of the outcomes such a new study would arrive at. The abundance of studies on a phenomenon does necessitate MRA (**Djokoto et al., 2020; Hunter & Schmidt, 1990**).

As a methodology, MRA enables the analysis of results from many individual studies to integrate the findings (**Stanley, 2001; Djokoto et al., 2020**). This involves searching for individual studies, identifying the appropriate measures of interest informed by the objective of the study (**Djokoto & Gidiglo, 2016; Djokoto et al., 2020**). Further, MRA helps to explore the variability in the concept under investigation and its drivers (**Djokoto et al., 2020; Hess & von Cramon-Taubadel, 2008; Nelson & Kennedy, 2009**). The concept under study is usually a summary statistic, often a regression parameter (**Stanley, 2001**).

The summary statistic in the case of efficiency MRA, the mean efficiencies (MEs) are identified and isolated from the studies assessed and the related properties noted (**Djokoto et al., 2020; Stanley, 2005, 2008; Stanley & Jarrell, 1989**). The data so collected is modelled using regression analysis to explore the heterogeneity and the factors responsible for variation in the summary ME. As each study may constitute an observation or data point,

more than one MEs from a primary publication are included as individual data points in the regression (Djokoto, 2015; Djokoto et al., 2020; Espey, Espey & Shaw, 1997). Evidence from the literature point to diverse estimation procedures for efficiency MRAs; fractional regression modelling, OLS, logistic, truncated regression, transformed truncated regression and Tobit (Djokoto & Gidiglo, 2016; Djokoto et al., 2020; Nandy, Singh & Singh, 2018; Ogundari & Brümmer, 2011).

Following some initial MRAs in economics, Stanley (2001) presented an influential review. Since then, there has been an increase in MRA applications in economics. For example, meta-regression analysis was applied by 626 papers in economics between 1980 and 2010, with a huge jump in the 2000s (Poot, 2012). The first MRA on efficiency within the agricultural economics literature was published by Thiam et al. (2001). Other MRAs on efficiency in agriculture have been published subsequently (Bravo-Ureta et al., 2007; Djokoto & Gidiglo, 2016; Djokoto et al., 2016; Hina & Bushra, 2016; Iliyasu et al., 2014; Nandy et al., 2018; Ogundari, 2014; Ogundari & Brümmer, 2011; Solomon & Mamo, 2016).

MRA synthesises very different studies (Glass, 1976; Glass et al., 1981). Notwithstanding the benefit of pooling results of previous studies, there is a shortcoming. That is, assembling different studies into a common data set, described as the ‘apples and oranges’ problem. According to Aiello & Bonanno (2016), this shortcoming can be ameliorated by re-specifying the issue under investigation. Secondly, appropriate identification of the ‘apples’ and ‘oranges’ and their isolation in the regression model, is another curing opportunity.

DATA AND METHODS

The data, modelling and estimation procedure constitutes the materials and methods section.

Data

The starting point for the data collection was the data from Djokoto et al. (2020). This was updated to include additional studies in 2019, 2020 and 2021. Data collection followed the recommendations of Stanley et al. (2013). The search which yielded 3,512 publications, ended at 17:00GMT on 31st August 2021.

To be included in the metadata, the study must relate to agriculture. Additionally, SFA or DEA and its associated procedures should be the approach to the measurement of efficiency. Further, the characteristics of the study should include the agricultural sector and the geographical coverage as well as the mean of frontier efficiency or efficiencies. Furthermore, the study should report mean farm size. The use of these criteria and removal of repeated observations culminated in 93 publications with 177 observations (data points). Other authors reviewed the data extracted by one author.

Modelling

As publication bias is an issue in meta-regression, we started our modelling by specifying the equation of the funnel plot (Djokoto et al., 2020; Egger et al., 1997; Rose

& Stanley, 2005; Stanley, 2005; Stanley & Doucouliagos, 2012) (Eq. 1).

$$MEFF_i = \beta_1 + \beta_0 SE_i + e_i \quad (1)$$

Where:

β_1 is the overarching effect-size and β_0 is the quantitative representation of the asymmetry of the funnel plot; extent of publication bias and e_i is the error term (Djokoto et al., 2020). *MEFF* is mean efficiency. Equation 1 is heteroscedastic. As a solution, both sides of the equation were divided by SE to yield Eq. 2.

$$\frac{MEFF_i}{SE_i} = \beta_1 \left(\frac{1}{SE_i} \right) + \beta_0 + \varepsilon_i \quad (2)$$

Where:

β_1 is still the overarching effect size whilst β_0 denotes the asymmetry of the funnel plot. In the absence of standard errors (SE), a proxy, inverse of the square root of the sample size, was used (Djokoto et al., 2020; Ogundari, Amos & Okoruwa, 2012) (Eq.3).

$$\frac{MEFF_i}{TR_i} = \beta_1 \left(\frac{1}{TR_i} \right) + \beta_0 + \delta_i \quad (3)$$

Where:

TR is the transformation variable.

The assumption for Eq. 3 is $\beta_0 \neq 0$ implies publication bias, also, $\beta_1 \neq 0$ captures a quantitative effect of the *MEFF* estimates. Where there is no publication bias, the reported *MEFF* should spread indeterminately encircling the true *MEFF* estimate, while the presence of a true quantitative effect supposes that the estimated β_1 has been adjusted for bias over the studies compiled. Our key variable is farm size, and this must be captured in Eq 3. Further, our dependent variable is made up of different frontier efficiency estimates (allocative, cost, profit, scale and technical). To isolate the effect of the farm size-efficiency nexus for each dimension of the frontier efficiency, we interact farm size with each of the efficiency dimensions as in Eq. 4.

$$MEFF_TR_i = \beta_0 + \beta_1 INV_TR_i + \beta_2 FS_i + \beta_3 FSAE_i + \beta_4 FSCEE_i + \beta_5 FSPE_i + \beta_6 FSSE_i + \beta_7 FSMFTE_i + \beta_8 XSECTION_i + \beta_9 SFA_i + \beta_{10} DEA_i + \beta_{11} NORTH_i + \beta_{12} MID_i + \beta_{13} COSTL_i + \beta_{14} TIME_i + \beta_{15} JOURNAL_i + \beta_{16} CONF_i + \beta_{17} WP_i + \epsilon_i \quad (4)$$

Whilst the inclusion helps to identify the extent to which the choice of methods, design and data affect reported results (Campbell & Fogarty, 2006; Djokoto et al., 2020; Stanley 2001), these controls also ensure minimisation and possible elimination of publication bias (Appiah-Adu & Djokoto, 2015; Djokoto et al., 2020). The variables in Eq. 4 and their descriptions are contained in Table 1. It must be noted that the primary studies used cost efficiency (CE) and economic efficiency (EE) interchangeably, hence the construction of CEE from CE and EE.

Farm size-efficiency nexus

We use interaction terms to isolate the effect of the different frontier efficiency measures. The use of interaction terms has found use in primary efficiency studies in recent times (Alter & Elekdag, 2020; Duval, Hong & Timmer, 2020; Hanousek, Shamshur & Tesl, 2019; Neves, Gouveia & Proenca, 2020). These are useful in isolating economic effects (Rajan & Zingales, 1998). From Eq. 4 and recalling that the dimensions of frontier efficiency on the RHS of the equation are dummy variables, β_i where $i = 3, \dots, 7$ are partial effects whilst β_2 is the main effect. The farm size-efficiency effect for allocative efficiency then is $\beta_2 + \beta_3 * \overline{AE}$. That for cost-economic efficiency is $\beta_2 + \beta_4 * \overline{CEE}$ whilst $\beta_2 + \beta_5 * \overline{PE}$ captures effect for profit efficiency. For scale efficiency: $\beta_2 + \beta_6 * \overline{SE}$ and metafrontier technical efficiency is $\beta_2 + \beta_7 * \overline{MFTE}$. The outstanding effect is technical efficiency, which is β_2 . β_1 is the joint effect of all the efficiency dimensions. Although the efficiencies measure different aspects of the production activity, their common measure ranging between 0 and 1 make the joint-effect meaningful.

Estimation procedure

Different approaches have been used in meta-regression; fractional regression (Djokoto & Gidiglo, 2016; Djokoto et al., 2020; Ogundari & Brümmer, 2011), Ordinary Least Squares (OLS) (Nguyen & Coelli, 2009; Papadimitriou, 2013) and Tobit (Bravo-Ureta et al., 2007; Thiam et al., 2001). However, the transformation moved the MEFF_TR outside the unit interval. Hence, amenable to estimation with OLS.

RESULTS AND DISCUSSION

For ease of appreciation, the section is sub-sectioned into four. The background to the data, the results, discussion of the results of the control variables and finally the discussion of the farm size efficiency nexus.

Background of data

The mean efficiency ranged from 0.0740 to 0.9810 (Table 2). However, after transformation, this changed to 0.7020 to 46.2894 with a mean of 10.0187. That for the INV_TR ranged from 2.6458 to 88.1703. Allocative efficiency, cost-economic efficiency, and profit efficiency each contributed about 4% to the sample. This is because whilst some studies reported these jointly, others reported separate efficiencies. Consequently, these have a common contribution of observations to the metadata. Technical efficiency was most popular with efficiency investigators, hence the 76% contribution to the metadata. The mean farm size is 2.92ha. This is less than the standard deviation of 7.78 such that the variance would still exceed the mean. Hence, farm size is over-dispersed around the mean. Despite the interaction with farm size, the mean of all the efficiencies was less than 1 except FSTE.

More than 90% of the metadata was generated from cross-sectional studies with 78% of the 177 observations arising from SFA studies. Studies that focused on the NORTH constituted 54% of the metadata. Peer-reviewed journals were popular with authors of studies found, 81% of the dataset.

Table 1: Definition of variables

Variable	Definition
MEFF_TR	Mean efficiency weighted by the inverse square root of sample size (Dependent variable)
INV_TR	1 divided by the inverse of the square root of sample size
FS	Farm size in hectares
FSAE	FS interacted with allocative efficiency defined as 1 and 0 otherwise.
FSCEE	FS interacted with cost and economic efficiency defined as 1 and 0 otherwise
FSPE	FS interacted with profit efficiency defined as 1 and 0 otherwise
FSSE	FS interacted with scale efficiency defined as 1 and 0 otherwise
FSTE	FS interacted with technical efficiency defined as 1 and 0 otherwise
XSECTION	Cross-section data is 1, and 0 otherwise. Reference is panel data
SFA	Stochastic frontier analysis is 1, and 0 otherwise. Reference is distance function
DEA	Data envelopment analysis is 1, and 0 otherwise. Reference is distance function
NORTH	Studies covering Northern, Upper East and Upper West Regions. Reference: country coverage studies.
MID	Studies covering Ashanti, Brong-Ahafo and Eastern Regions. Reference: country coverage studies.
COSTL	Studies covering Central, Greater Accra, Volta, and Western Regions. Reference: country coverage studies.
TIME	Four-digit year
JOURNAL	Study published in journal as 1 and 0 otherwise. Reference is Thesis
CONF	Study published as conference paper is 1 and 0 otherwise. Reference is Thesis
WP	Study published as working paper is 1 and 0 otherwise. Reference is Thesis

Table 2: Summary statistics

Variable	Mean	Standard deviation	Minimum	Maximum
<i>MEFF</i>	0.6584	0.1795	0.0740	0.9810
<i>MEFF_TR</i>	10.0187	5.6210	0.7020	46.2894
<i>INV_TR</i>	15.3937	9.2371	2.6458	88.1703
<i>FS</i>	2.9215	7.7774	0.1500	101.5000
<i>FSAE</i>	0.1054	0.6578	0	5.4300
<i>FSCEE</i>	0.1071	0.6567	0	5.4100
<i>FSPE</i>	0.1624	0.9618	0	8.8000
<i>FSSE</i>	0.1134	0.5165	0	3.4000
<i>FSTE</i>	2.0873	7.6649	0	101.5000
<i>FSMFTE</i>	0.3450	1.9240	0	15.6000
<i>XSECTION</i>	0.9266	0.2616	0	1
<i>PANEL</i>	0.0734	0.2616	0	1
<i>SFA</i>	0.7797	0.4157	0	1
<i>DEA</i>	0.2034	0.4037	0	1
<i>NORTH</i>	0.5424	0.4996	0	1
<i>MID</i>	0.1695	0.3762	0	1
<i>COSTL</i>	0.0960	0.2955	0	1
<i>TIME</i>	2016.277	3.3434	2000	2021
<i>JOURNAL</i>	0.8136	0.3906	0	1
<i>CONF</i>	0.0508	0.2203	0	1
<i>WP</i>	0.0452	0.2083	0	1

Results

Although the transformation of Eq. (2) – Eq. (4) was partly to account for heteroscedasticity, this applied to the β_1 (Table 2). Model 1 (Table 3) arose from the OLS estimation of Eq. (3). The farm size efficiency interaction terms were then introduced to generate model 2. Estimation of Eq. (4) is model 3. The Breusch-Pagan test however showed that the estimation of Eq. (2) was heteroscedastic, hence the correction with robust standard errors. Likewise, models 2 and 3 were also treated similarly. Testing of each estimation showed the presence of misspecification. The inclusion of the square of the prediction of the dependent variable as additional explanatory variables are reported in Table 3 (model 1 - model 3).

The statistical significance suggests the misspecification has indeed been accounted for. The variance inflation factor for the key variables is within limits. In the case of model 3, the VIF for the SFA exceeds 10. Whilst this is below the liberal threshold of 20 (Greene, 2019; O'brien, 2007), the closeness to 10, alleys fear of substantial influence on the estimates of β_9 . In all cases, the adjusted R squared is greater than 79%. Whilst these suggest that a substantial portion of the variability in the dependent variable is explained by the explanatory variables, the statistically significant F statistics imply that the explanatory variables jointly explain the dependent variable. The similarity of the estimates of *INV_TR* suggests the robustness of the estimates. Additionally, the estimate of the coefficient of *INV_TR* is statistically significant, and magnitude is within the unit interval. Also, the statistical insignificance of the constant across all the models implies that publication bias is absent in the meta-regression. These two observations show the necessary conditions of an appropriate meta-regression in efficiency have been met. It is commonplace to find publication bias in model 1 that

would require the inclusion of control variables to eliminate it (Aiello & Bonanno, 2016; Appiah- Adu & Djokoto, 2015; Djokoto et al., 2020). The absence of publication bias in model 1 is rather rare. This may be attributable to the correction for misspecification. Since model 3 is the full model, we focus our attention on it for discussion.

Discussion: control variables

The coefficient of the *XSECTION* is positive and statistically significant implying that efficiency values of cross-sectional data are higher than those from panel data (Table 3). The result is contrary to some empirical findings that reported the reverse (Aiello & Bonanno, 2016; Djokoto et al., 2020; Nguyen & Coelli, 2009; Thiam et al., 2001). Djokoto & Gidiglo (2016) and Djokoto et al. (2020) found no effect of data structure on mean technical efficiency.

The negative and statistically significant coefficient of SFA suggests SFA efficiency estimates are lower than those from distance functions. Similarly, DEA estimates of efficiency are also lower than those from distance functions. Djokoto & Gidiglo (2016) however, provided contrary evidence for agribusiness in Ghana. The pertinent literature had noted DEA efficiency estimates are biased upwards (Kumbhakar & Lovell, 2000), although recent improvements in DEA estimation procedures have reduced the gap (Djokoto et al., 2020; Emrouznejad, Parker & Tavares, 2008; Cook & Seiford, 2009; Kao, 2014; Koronakos, 2019; Mariz Almeida & Aloise, 2018). Our result is different from others that could not differentiate efficiency estimation procedures (Djokoto et al., 2020; Fall et al., 2018).

The coefficients for all the spatial variables are statistically significant. Specifically, studies in the south posted higher efficiency estimates than those in the middle regions as well as those in the northern regions.

Specifically, studies covering southern regions show higher efficiency than others. The better development in the coastal regions than others culminated in better efficiency in economic endeavours for agriculture and agribusiness in Ghana (Djokoto et al., 2016; Djokoto & Gidiglo, 2016). Also, soil and agroecological conditions have accounted for this. Our finding agrees with the literature (Ogundari & Brümmer, 2011) for Nigeria and (Djokoto et al., 2016; Djokoto & Gidiglo, 2016; Djokoto et al., 2020) for Ghana. Our findings are contrary to the recent conclusion of Djokoto et al. (2020) for multiple sectors of Ghana. That is, MTEs for middle and northern sections were higher than those covering Ghana (and COASTL).

The coefficient of TIME of 0.0839 is statistically insignificant signifying that collectively, the efficiencies did not change over time. Although the sign of the coefficient seems to agree with the existing literature on efficiency progression (Aiello & Bonanno, 2016; Ogundari & Brümmer, 2011), the finding certainly disagrees with efficiency regression (Iliyasu et al., 2014; Ogundari, 2014). Other agricultural efficiency meta-regressions certainly agree with our finding (Brons et al., 2005; Nandy et al., 2018; Solomon & Mamo, 2016; Thiam et al., 2001).

The coefficients of the study dissemination media are statistically insignificant. This result is like the findings of Djokoto (2015), Djokoto et al. (2020) and Solomon & Mamo (2016) but departs from others. The result implies the mean efficiencies did not vary across these media.

Discussion: Farm size-efficiency nexus

Although the frontier efficiencies measure different aspects of efficiency, values close to 1.00 imply better efficiency compared to values close to 0.00. Therefore, the overall efficiency effect size of 0.69 shows the agriculture decision-making units in the primary studies attained about 70% of their potential, equal to the 0.70 found by Djokoto et al. (2020) for all industries in Ghana (Table 3). The inefficiency (gap) of about 30% can be closed without the use of additional resources.

The Wald of the farm size – efficiency effect is reported in Table 4. The sign for all six is negative. Thus, the farm size-efficiency nexus may be negative. This fits into the early works of Saini (1980) in India. The congruence may be attributable to the similarities of farm structures. Also, the non-uniformity of income arising from non-uniform distribution of land was to some extent reduced by productivity differences between small and large farms (Ali & Deininger, 2014). Julien et al. (2021) also recently showed the inverse nexus suggesting that the distribution of farm size and TE is quadratic.

The chi-square test of the magnitudes of the Wald shows statistically insignificant Wald for allocative and scale efficiencies effects. These mean notwithstanding the negative sign, the effect of farm size on allocative and scale efficiency is neutral. Indeed, there is no discernible effect. The Wald of the other four (cost-economic, profit, technical and metafrontier technical efficiency) are statistically significant. Thus, a negative farm size – efficiency nexus for cost-economic, profit, technical and metafrontier technical efficiencies exists.

The reference frontier for efficiency measurements in the model is the metafrontier, an overarching frontier that envelopes the group frontiers. Thus, by construction, MFTE is lower than TE. Nonetheless, the MFTE essentially measures technical efficiency, the extent to which the observed output is close to the potential or frontier output. The farm size-metafrontier effect size of -0.0493 implies that an increase in farm size by 1 hectare would induce a 0.05 reduction in MFTE. This is an inverse relation, which is not surprising. Also, the effect for technical efficiency is -0.0194. This is lower than that of TE. The reason is that since the metafrontier is farther from the observed output than the TE frontier, larger adjustments would be required for the MFTE than for the TE in response to farm size.

It must be recalled that within the production function framework, the observed output result from the physical relationship or combination of the classical factors of production, land, labour, and capital. Capital such as pesticides and machinery (e.g. tractors) can easily be substituted for labour. However, this is more beneficial and cost-effective with large farm size. Farm holdings of 90% of farmers do not exceed 2 hectares (MOFA, 2007). Fertiliser usage is 7.4 – 13.4 kg/ha (MOFA, 2009; Benin et al., 2013). This is behind the average for other developing regions of the world such as South Asia (104 kg/ha), Southeast Asia (142 kg/ha) and Latin America (86 kg/ha) (Benin et al. 2013; Crawford et al. 2006). The usage of other agrochemicals such as pesticides and herbicides in Ghana for 2008-2017 averaged 376 tonnes/year compared to 1894 tonnes/year for Africa (FAOSTAT, 2020). Tractor per 100sq. km of arable land has declined from 8.183 in 1985 to 4.518 in 2005 (World Bank, 2020). These levels of input use are associated with small farm sizes. However, the nature of the technology (the combination of inputs) is such as to produce an appreciable level of efficiency. The arguments of indivisibility of inputs e.g., bullocks; than family, labour looms large in total labour so that as farm sizes get smaller, total labour per acre increases; imperfect input factor markets which result in differences of land, labour force and credit market between the large- and small-scale farmers (Carter, 1984; Li et al., 2013; Newell et al., 1997; Reardon et al., 1996; Sen, 1962, 1966) can explain our results.

The gaps in the input use noted earlier, suggest a technology that is incompatible with large farm size. On the other hand, a technology change would be necessary for reduced farm size (Li et al., 2013). The adoption of modern agricultural technology including breeding of input-intensive seeds and chemical fertiliser usage would improve land productivity (Li et al., 2013), without the need for an increase in land size, thus being scale-neutral (Hayami & Rutan, 1985; Li et al., 2013). However, the use and spread of agricultural technology have a positive association with land size (Feder, 1980; Just & Zilberman, 1983; Hu et al., 2019; Li et al., 2013; Rodewald Jr & Folwell, 1977). Thus, technology change would increase observed output, reduce the technology gap, and move farmers closer to the metafrontier.

To be cost and economically efficient, farm size must decline. This is because the reduction in farm size would

help the producer minimise costs given the input prices. As cost influences profits given the revenue, it is unsurprising that the Wald are similar. As the dimensions of efficiency are largely managerial, the managerial reasons in the literature are apt. There are heterogeneities in efficiency in Ghanaian agriculture (Djokoto & Gidiglo, 2016; Djokoto et al., 2016). These arose from

heterogeneities in farmers' farming skills and occupational choice as well as resources (Assuncao & Ghatak, 2003). Also, differences in transaction costs, supervision costs as well as principal-agent problems in the farm organisation exist (Eswaran & Kotwal, 1985; Li et al., 2013). These reasons account for the inverse farm size-efficiency nexus.

Table 3: Estimation results

VARIABLES	1	2	3
	<i>MEFF_TR</i>	<i>MEFF_TR</i>	<i>MEFF_TR</i>
<i>INV_TR</i>	0.7164*** (0.0685)	0.6797*** (0.0676)	0.6895*** (0.0559)
<i>FS</i>		-0.0138*** (0.0052)	-0.0194** (0.0079)
<i>FSAE</i>		0.2723 (0.2360)	0.3064 (0.1918)
<i>FSCEE</i>		-0.0675 (0.1847)	-0.0408 (0.1383)
<i>FSPE</i>		-0.1150 (0.1657)	-0.2500** (0.1148)
<i>FSSE</i>		0.6643*** (0.2093)	0.1852 (0.3013)
<i>FSMFTE</i>		-0.4119*** (0.0506)	-0.4819*** (0.0702)
<i>XSECTION</i>			1.1361** (0.5033)
<i>SFA</i>			-3.6392*** (1.2034)
<i>DEA</i>			-5.4403*** (1.2548)
<i>NORTH</i>			1.5010*** (0.4792)
<i>MID</i>			3.0711*** (0.5248)
<i>COSTL</i>			2.5372*** (0.6016)
<i>TIME</i>			0.0839 (0.0914)
<i>JOURNAL</i>			0.6677 (0.6363)
<i>CONF</i>			-0.1111 (1.1910)
<i>WP</i>			-1.2490 (1.2180)
<i>PMEFF_1_SQ</i>	-0.0075*** (0.0024)		
<i>PMEFF_2_SQ</i>		-0.0064*** (0.0024)	
<i>PMEFF_3_SQ</i>			-0.0058*** (0.0019)
<i>CONSTANT</i>	-0.0709 (0.7095)	0.4664 (0.6834)	-167.9933 (184.0563)
Model diagnostics			
Observations	177	177	177
VIF	8.58 (<i>INV_TR</i>)	8.99 (<i>INV_TR</i>)	11.09 (<i>SFA</i>)
Adjusted R sq.	0.7934	0.8034	0.8101
F statistic	637***	265***	244***

Note: Robust standard errors in parenthesis. Significance levels: * p<0.10, ** p<0.05, ***p<0.01

Table 4: Farm size – efficiency effect

Efficiency dimension	Wald	Chi square statistic	Effect
Allocative	-0.0073	0.43	Neutral
Cost/economic	-0.0210	4.85**	Negative
Profit	-0.0293	12.20***	Negative
Scale	-0.0089	0.24	Neutral
Technical	-0.0194	6.11**	Negative
Metafrontier technical	-0.0493	26.08***	Negative

Note: Significance levels: ** p<0.05, ***p<0.01

CONCLUSIONS AND RECOMMENDATIONS

We contribute to the farm size-efficiency debate by performing a quantitative review of the farm size-efficiency relationship. Unlike other farm size-efficiency studies that used factor productivity, we employed all dimensions of the comprehensive efficiency in production theory, reported in the primary studies to investigate the farm size - efficiency relationship. We used data on 177 primary studies on efficiency in agriculture of Ghana and estimated a model with interaction terms using OLS.

We found no farm size-efficiency nexus for allocative and scale efficiency. However, we found a negative effect for cost-economic, profit, technical and metafrontier technical efficiency nexus with farm size. As the negative sign implies a reduction in farm size to induce higher *CEE*, *PE*, *TE* and *MFTE* concurrently, this presents an opportunity to change technology. Thus, we recommend technology change in Ghanaian agriculture. Specifically, increased use of fertiliser and other agrochemicals, tractors, and improved management skills. As the cost of these is one of the limiting factors, financing arrangements supported by government and non-governmental organisations would be necessary.

As the existing evidence on the inverse farm size efficiency relationship has largely been based on farm size and land productivity, our conclusion of a negative farm size nexus for four dimensions of efficiency is instructive.

We used the mean efficiencies and mean farm size as key variables for Ghana. As attempts to explore the quadratic effect of the farm size productivity resulted in serious multicollinearity issues with the key variables, this could be explored for other countries and on the global stage. These could provide insight into the possible quadratic effect of farm size and a cross country perspective to the combined evidence. The meta-regression approach could also be adopted to examine the farm size efficiency nexus for large farm size studies.

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