



AgEcon SEARCH

RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.



Agrekon

Agricultural Economics Research, Policy and Practice in Southern Africa

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ragr20

Productive efficiency and farm size in East Africa

Jacques C. Julien, Boris E. Bravo-Ureta & Nicholas E. Rada

To cite this article: Jacques C. Julien, Boris E. Bravo-Ureta & Nicholas E. Rada (2021) Productive efficiency and farm size in East Africa, *Agrekon*, 60:3, 209-226, DOI: [10.1080/03031853.2021.1960176](https://doi.org/10.1080/03031853.2021.1960176)

To link to this article: <https://doi.org/10.1080/03031853.2021.1960176>



Published online: 04 Aug 2021.



Submit your article to this journal [↗](#)



Article views: 276



View related articles [↗](#)



View Crossmark data [↗](#)



Citing articles: 5 View citing articles [↗](#)



Productive efficiency and farm size in East Africa

Jacques C. Julien ^a, Boris E. Bravo-Ureta ^{b,c} and Nicholas E. Rada^d

^aCentro de Investigación de la, Universidad del Pacífico, Lima, Peru; ^bUniversity of Connecticut, Storrs, CT, USA; ^cUniversity of Talca, Talca, Chile; ^dU.S. Patent and Trademark Office, Alexandria, VA, USA

ABSTRACT

In this study, we undertake a comparative analysis to re-examine the inverse relationship hypothesis between farm size and land productivity, paying special attention to possible errors in land measurement and the role of technical efficiency (TE). Our primary focus is on the distribution of TE over farm size, so that we may assess the productivity and efficiency relationship with land that has been discussed extensively in the literature. We hypothesize that the distribution of TE over farm sizes is non-linear. To test our hypothesis, we use the Living Standards Measurement Study–Integrated Surveys on Agriculture and a stochastic production frontier with Greene’s (2005) true random effects framework. Specifically, we ask if smaller farms – within the range of farm sizes prevalent in Malawi, Tanzania, and Uganda – are more technically efficient than larger ones after accounting for a number of attributes often ignored such as measures of the production environment, including transportation infrastructure, public extension visits, among other characteristics. The results confirm a robust overall inverse relationship between farm size and land productivity in all three countries. However, the relationship between farm size and TE is positive across some size segments, resulting in a U-shape distribution.

ARTICLE HISTORY

Received 4 February 2021
Accepted 20 July 2021

KEYWORDS

Farm size; inverse relationship hypothesis; stochastic production frontier; true random effects; sub-Saharan Africa; technical efficiency; single-factor productivity

JEL CODES

O12; O13; Q10; Q12; Q13;
Q15

1. Introduction

An inverse relationship between farm size and productivity in developing countries has been documented by many studies over a long period of time, but it remains a puzzle for development economists. The theory of economies of scale predicts a reduction in per-unit production costs as farm size increases, thus making large farms more productive than small ones (Duffy 2009). Empirical analysis in developing countries have tended to support the Inverse Relationship Hypothesis (IR-H), which predicts the opposite result. In light of these conflicting views, it is necessary to first identify the IRH, then analyze its main sources. We focus particularly on whether the distribution of technical efficiency over farm sizes is linear. Large gaps in relative productivity, as identified by our model, indicate where policy initiatives might elevate farmer productivity, and thus increase farm output and income.

To analyze the inverse productivity-size relationship, studies have focused on the effects of price uncertainty, land distribution, and soil quality (Kimhi 2006; Ali and Deininger 2015). A few studies, including those of Lamb (2003), Carletto, Savastano, and Zezza (2013), Holden and Fisher (2013), and Cohen (2015), examine the link between the IR-H and possible land measurement errors. Imprecise land area measurements may generate biased estimates, leading to ambiguous results and

erroneous policy prescriptions. Indeed, a critical factor in the IR-H research is the quality of the data available for empirical studies. As the agricultural sector in many developing countries is characterised by limited and poor-quality data (Ainembabazi 2007; Christiaensen 2017), imprecise measures of farm size is of particular concern when examining the IR-H. Carletto, Savastano, and Zezza (2013), Holden and Fisher (2013), and Cohen (2015) found that the IR-H effect is even more substantial when Global Positioning System (GPS) devices are used to obtain more refined measures of cultivated land than when the farmer reported estimates are employed.

Evidence of the IR-H has been documented in some African countries, particularly in sub-Saharan Africa (SSA), where small farms are dominant (Carletto, Savastano, and Zezza 2013; Holden and O'Donnell 2015; Wassie, Abate, and Bernard 2019; Julien, Bravo-Ureta, and Rada 2019). In the SSA region, smallholders are central to agricultural and rural development. These small units account for approximately 80% of all farms in the region and contribute up to 90% of the agricultural output in some countries (Wiggins 2009; AGRA 2014; Julien, Bravo-Ureta, and Rada 2019). Thus, they are crucial for food security and poverty alleviation (Livingston, Schönberger, and Delaney 2014; FAO 2015). Given the predominant role of agriculture in the economic development of the SSA region, decision-makers need to promote farm productivity and efficiency; and to do so, they need robust empirical evidence.

This study focuses on farm technical efficiency (TE) in Malawi, Tanzania, and Uganda. These countries are located in eastern SSA and share several economic, geographic, climatic, and agricultural features. Farming remains the pillar of societies in these countries where economic and social policies are needed to boost productivity and ensure sustainable growth and poverty reduction (FAO 2001; World Bank 2008; Brooks 2010). We hypothesize that – after controlling for possible errors in land measurement, as well as a number of environmental attributes, including public investments in extension services and transportation infrastructure – there are substantial gaps in relative farm productivity. Identifying the least efficient farm sizes informs policymakers where targeted interventions could lift farm productivity, output, and income.

In testing our hypothesis, we address several shortcomings in the broad IR-H literature. First, we use comprehensive and consistent datasets that include climatic, environmental, and agroecological variables – factors that go beyond the conventional inputs and household attributes commonly considered in the literature. Incorporating these control variables in our empirical production models avoids, or at least mitigates, specification bias (Griliches 1957). Second, we use two alternative land area measurements – self-reported by the farmer and a GPS-based – to test the influence this might have on conclusions with respect to the IR-H. Third, we adopt Greene's (2005) true random effects (TRE) stochastic production frontier (SPF) model, incorporating the Battese and Coelli (1995) approach – hereinafter referred to as the TRE-BC95 model – to examine the association between technical inefficiency and aggregate yield across farm size groups.

We use a large set of control variables and a stochastic production frontier (SPF) methodology to identify how TE varies with farm size. The results provide evidence of the IR-H hypothesis for both self-reported and GPS land measures for all three SSA countries; that is, smaller farms have higher aggregate yields (total output per hectare) than larger ones. However, we also find that the relationship between TE frequently departs from the productivity distributions, exhibiting at times a U-shape pattern.

The remainder of this article is organised as follows: Section 2 provides an overview of the evidence regarding the IR-H. Section 3 contains the methodological framework and discusses the TRE-BC95 stochastic production frontier model. Section 4 presents the empirical framework and the data. The empirical results are presented in section 5, and our summary and conclusions in section 6.

2. Literature review

The IR-hypothesis argument can be traced back to Chayanov who, in 1926, examined the relationship between farm size and productivity in Russia. At that time, Russian agriculture was mainly based

on unpaid family labor (Thorner, Kerblay, and Smith 1966; Hammel 2005; Barrett, Bellemare, and Hou 2010). Chayanov analyzed the nature of the peasant agricultural economy and suggested that a family-farm is a subsistence unit whose workers expend only the effort or labor necessary to satisfy the needs of the household members. Thus, peasant survival strategies are systematically different from the profit-making expectations of farming businesses (Netting 1993).

2.1 Mounting evidence in support of the inverse productivity-size relationship

Many years after Chayanov's initial work, Sen (1962) noted that six regions he studied in India uniformly revealed that productivity per acre decreased as the size of holdings increased. The same type of relationship has been documented in several subsequent studies in India, including those of Saini (1969), Bardhan (1973), and Netting (1993). Decades after, the puzzle remains unsolved and evidence from Lamb (2003), Assunção and Braido (2007), Gaurav and Mishra (2015), and Wang et al. (2015) have confirmed the IR-H in India. The puzzle also remains in China (Rada, Wang, and Qin 2015) as well as in several African countries (Byiringiro and Reardon 1996; Barrett 1996; Kirsten and van Zyl 1998; Kimhi 2006; Barrett, Bellemare, and Hou 2010; Carletto, Savastano, and Zezza 2013; Holden and Fisher 2013; Ali and Deininger 2015; Cohen 2015; Conradie et al. 2019; Julien, Bravo-Ureta, and Rada 2019).

In the last two decades, researchers have focused predominantly on finding factors that explain the IR-H. Several explanations for it are discussed in the literature, including imperfections in factor and credit markets, heterogeneity of land and soil quality, and imprecise methods of land measurement. A recent explanation of the IR-H, dubbed the "edge effect", describes a situation in which productivity is higher around the periphery of plots because greater labor intensity and improved management practices tend to be applied to those areas (Bevis and Barrett 2020). Recent literature introduces efficiency as a factor that should be considered when examining the farm size-productivity puzzle (Li et al. 2013; Henderson 2015; Kagin, Taylor, and Yúnez-Naude 2016; Julien, Bravo-Ureta, and Rada 2019).

Li et al. (2013), Barrett, Bellemare, and Hou (2010), and Helfand and Levine (2004) have analyzed market imperfections as a possible economic explanation of the IR-H in developing countries where factor markets are neither well established nor efficient. However, even controlling for market imperfections, the IR-H has been confirmed by these last authors, though with nuances. Barrett, Bellemare, and Hou (2010) found that only a modest share of the inverse productivity-size relationship is explained by market imperfections. In contrast, Ali and Deininger (2015) identified labor market imperfections as one of the IR-H key drivers in Rwanda.

Lamb (2003), using panel data from India, also examined the role of imperfect labor markets, along with land quality differentials, and found that these factors explained most of the variability in the farm size-productivity relationship. However, Assunção and Braido (2007), who considered multiple plots cultivated by a single household during each season in India, ruled out labor market imperfections and cross-household heterogeneity as contributors to the observed inverse relationship between plot size and productivity. Using data from Madagascar, Barrett (1996) found support for the IR hypothesis coming from price uncertainty and uneven land distribution, and suggested incomplete insurance markets and risk as possible explanations.

Assunção and Ghatak (2003) showed that the IR-H could result from heterogeneity in farmer skills. Thus, they suggested that the size-productivity analysis should control for farmer's ability; otherwise, selection bias will generate misleading results. Lamb (2003) examined the role of omitted variables and found that excluding soil quality and market failures in the models accounts for much of the IR-H, while errors in land area measurement also play a role, especially when using fixed effects for unmeasured household-specific differences. However, Barrett, Bellemare, and Hou (2010) showed that omitted soil quality measurements are not a statistically significant factor contributing to the IR-H.

Recently, Rada, Helfand, and Magalhães (2019) use data from 1985 to 2006 for Brazil to analyze the variation of agricultural total factor productivity (TFP) within and between farms of different size. The authors found that productivity measures and TFP growth are sensitive to key factors such as improvements in technical assistance, credit, and education. The authors find a positive linear relationship between TFP and size for 1985 but, by 2006, a U-shaped distribution had emerged. The smallest farm size class (0-5 hectares) achieved the fastest 1985–2006 TFP growth. The largest size class, which includes farms of 500 hectares and more, achieved the highest TFP levels in 1985 and 2006. The performance of medium-sized classes lagged while those ranging between 100 and 500 hectares contained the most farms with negative productivity growth. Notably, these farms had less government and private support relative to smaller and larger-sized farms.

Other recent studies point to land mismeasurement as a primary concern in farm productivity findings in SSA (Abay, Bevis, and Barrett 2019; Gollin and Udry 2021; Lobell et al., 2020; Fuglie et al. 2019). Carletto, Savastano, and Zezza (2013), Holden and Fisher (2013), and Cohen (2015) used GPS devices to provide careful measurements of the land area controlled by farmers in Uganda, Malawi, and Tanzania. While these studies rely on three distinct methodologies – Carletto, Savastano, and Zezza (2013) used OLS and cross-sectional data, Holden and Fisher (2013) used panel data and village fixed effects, and Cohen (2015) used instrumental variables (IV) – their results align. The empirical evidence in these three studies leads to the rejection of the IR hypothesis as a statistical issue resulting from land measurement errors. On the contrary, in all three, the results indicate that the evidence for IR-H strengthens when using data obtained by GPS devices. GPS data provide more accurate land area measurements than self-reported data from farmers.

Fuglie et al. (2019) tackle the issue of mismeasurement that can stem from multiple sources, such as the presumption of homogeneity in the physical production environment and inaccurate accounting or poor data reporting. Abay, Bevis, and Barrett (2019) analyze mechanisms generating measurement error in agricultural surveys and identify two major sources – misperceptions and misreporting. On the one hand, farmers can misconstrue conditions or information about behaviours, prices, social norms and the probability of stochastic events, which could generate measurement error in plot size or other agricultural data. On the other hand, misreporting might be the source of measurement error for self-reported land measures. The authors suggest that farmers' misperceptions of plot size may contribute to factor misallocation if their beliefs affect expenditures on inputs.

Gollin and Udry (2021) found that output measurement error along with heterogeneity may account for a large fraction of the dispersion in measured productivity. Gourlay, Kilic, and Lobell (2019) used a two-round household panel survey in eastern Uganda to analyze farmers' reports about maize production, soil fertility assessment, and maize variety identification. The authors suggest that the observed inverse relationship between farm size and productivity might be due to inaccurate data on land area reported in the survey and these errors tended to be greater for smaller than larger plots.

Muyanga and Jayne (2019) tested the IR relationship in Kenya, combining a five-wave panel survey of 1,300 farms from 1997 to 2010 with a 2012 survey of 200 medium-scale farms. The authors find a U-shaped relationship between farm size and productivity regardless of whether productivity is measured as single- or multi-factor productivity. The IR-H holds for farms cultivating 3 hectares or less. For farms between 3 and 5 hectares, the relationship between farm size and productivity is relatively flat. However, for farms in the rather broad 5–70 hectare range, the relationship is positive. Productivity appears highest among farms in the 20–70-hectare range.

Although the IR hypothesis has received considerable empirical support, the factors adduced to explain this phenomenon are not well identified. In most cases, they do not provide a robust explanation. The literature shows considerable variability in the factors that contribute to the IR puzzle (Lamb 2003; Assunção and Braido 2007; Henderson 2015; Carletto, Savastano, and Zezza 2013; Rada, Wang, and Qin 2015). Indeed, Rada, Helfand, and Magalhães (2019) suggest that there is no economically optimal agrarian structure in the farm size and productivity debate. The size-

productivity relationship depends on the country's economic development, demographic pressure, and agrarian policy where some farms may face productivity disadvantages. For instance, in low-income countries, because of population pressure and the need for many people to engage in subsistence activities, policies tend to favour land fragmentation to guarantee agricultural activities and economic livelihoods to rural families. In such a situation, land constraints benefit the intensive use of family labor, resulting in smaller units producing more per hectare than larger ones. In contrast, large farms in developed countries are replacing labor with machines and apply an array of technologies to increase productivity.

2.2 Focusing on the productive efficiency-size distribution

Only a few IR-H studies have incorporated the TE dimension. One study that does is by Helfand and Levine (2004), who used linear programming techniques and found an inverted U-shape relationship between TE and farm size in the central-west region of Brazil. Henderson (2015) examined labor market imperfections as the probable driving force behind the IR-H in Nicaragua. He used a four-stage empirical framework that is based on a stochastic production frontier model. Henderson showed the IR-H does not hold for most farmers and suggested a non-linear size-efficiency relationship. More recently, Kagin, Taylor, and Yúnez-Naude (2016), also using a stochastic production frontier, found strong evidence for the IR-H in their examination of the relationship between land area and TE in Mexico. These authors assumed a linear relationship between farm size and efficiency and ignored the possible differential influence of public policies on the performance of farms of various sizes, especially as it relates to improving farmer managerial performance and facilitating a transition to commercialisation.

Li et al. (2013) found that the relationship between farm size and efficiency is mixed – the relationship may be positive, negative, or uncorrelated, depending on how efficiency is defined. However, they found a strong inverse relationship between farm size and land productivity. Conradie, Cookson, and Thirtle (2006) use a Battese and Coelli (1995) stochastic frontier model to test the efficiency of Western Cape grape growers in South Africa. The authors examine the correlation between inefficiency and farm size assuming a linear relationship and found a positive association.

In this study, we build on the received literature on the IR-H relationship and apply up-to-date methods to measure output-oriented TE, defined as the distance between a farm's observed and maximum (frontier) output achieved given inputs, the environment and the technology. It is important to highlight that TE is a measure of managerial performance (Martin and Page 1983; Triebs and Kumbhakar 2013). We therefore explicitly test for the relationship between managerial performance (i.e., TE) and farm size for Malawi, Tanzania, and Uganda.

3. Methodology

To assess how managerial performance differs over farm size, we adopt a stochastic production frontier (SPF) approach, in which the underlying assumption is that farmers seek to get the maximum output given their inputs, technology, and environment (Kumbhakar and Lovell 2000; Coelli et al. 2005). Specifically, a producer or decision-making unit (DMU) – a farmer in this study – uses multiple inputs represented by the vector X to produce output Y (Fried, Lovell, and Schmidt 2008). We adopt a Cobb–Douglas functional form because it is well behaved and globally consistent with key economic theoretical properties (O'Donnell 2012, 2014, 2016). Importantly, evidence suggests that TE scores are not significantly affected by functional form (Bravo-Ureta et al. 2007).

The cross-sectional stochastic production frontier (SPF) model proposed by Aigner, Lovell, and Schmidt (1977) has been generalised for panel data, and several alternative models have been proposed over the past three decades. Schmidt and Sickles (1984), who introduced the first such model in which TE is time-invariant, argued that panel data provide advantages over cross-sectional data. Later models treat firm-specific TE as being time-variant, while more recent specifications separate

time-invariant cross-firm heterogeneity from time-variant TE (Battese and Coelli 1995; Coelli et al. 2005; Greene 2005). We adopt a variant of the latter.

The general form of a panel data SPF can be written as:

$$y_{it} = \alpha + \beta'x_{it} + \gamma'z_{it} + v_{it} - u_{it} \quad (1)$$

where y_{it} denotes the output of farm i in period t ; x_{it} is a vector of conventional inputs; z_{it} is a vector of environmental or other variables; α is the intercept; and α , β and γ are parameters to be estimated. The v_{it} term is the idiosyncratic error and u_{it} captures inefficiency.

A significant contribution to the stochastic production frontier menu when panel data are available, owed to Greene (2005), are the true fixed effects (TFE) and true random effects (TRE) models. These models allow for distinguishing time-invariant unobserved heterogeneity from time-varying inefficiency. However, when the time period (T) covered by the panel is short compared to the number of units, the TFE model suffers from the incidental parameters problem (Greene 2005; Belotti and Ilardi, 2012; Belotti et al. 2013). To address this shortcoming, we apply the TRE model, since the datasets employed here contain thousands of farmers but only two years of data for Malawi and Uganda, and three for Tanzania. The TRE stochastic frontier is specified as follows:

$$y_{it} = (\alpha + \tau_i) + \beta'x_{it} + \gamma'z_{it} + v_{it} - u_{it} \quad (2)$$

where the error term has two components: v_{it} is a typical zero-mean independently distributed error term; and u_{it} , a one-sided error term representing technical inefficiency (TI) relative to the best-practice, stochastically estimated frontier. The term τ_i is a random time-invariant farm-specific effect that captures unobserved heterogeneity.

Another lasting contribution, made by Battese and Coelli (1995), is an SPF model where the inefficiency term can be expressed as a function of covariates and estimated simultaneously with the frontier specified in Equation (2). In this study, we seek to test the association between TI and farm size. Our study considers a TRE model, represented in Equation 2, along with the following inefficiency term:

$$u_{it} = L_{it}\theta_m + \omega_{it} \quad (3)$$

where L_{it} is a vector of covariates associated with the TI of farm i in period t , and θ_m is a vector of m associated coefficients. The TE of the i th farmer is given by:

$$TE_{it} = \exp(-u_{it}) = \exp(-L_{it}\theta_m - \omega_{it}) \quad (4)$$

The calculated TE is then used to examine the connection between managerial performance and farm size. For convenience, we partition the sample into farm size deciles.

4. Data, empirical model, and descriptive statistics

The data used in our analysis, for Malawi, Tanzania and Uganda, come from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). The data set contains detailed plot-level information related to land area, labor, use of fertilisers, pesticides, and other purchased inputs, and equipment. Also, the LSMS-ISA data contain farm, village, and district-level information. The panel data used to represent two years of records for Malawi (2010 and 2013) and Uganda (2010 and 2011), and three years for Tanzania (2008, 2010, and 2012).

As indicated above, we use the TRE SPF methodology incorporating the Battese and Coelli (1995) TI component. The dependent variable in the empirical specification is farm-level average value of production (AVP) expressed in real US dollars/ha using constant prices across farms. We index the first round of the panel for each country at 1.00, such that 2010 represents the index base for Malawi and Uganda, and 2008 is the base for Tanzania.

The model includes four traditional inputs – land, labor, input expense, and capital. We consider two alternative land measures, one reported by farmers and the other collected using GPS devices. In

addition, the models incorporate several covariates to control for agroecological, climate, and socio-economic conditions associated with the farm, such as cropping system, temperature, precipitation, slope, elevation, soil quality, number of plots, access to extension, proximity to roads, experience, education, and gender. A more detailed description is provided in [Table 1](#).

The farm-level AVP frontier is specified as Cobb–Douglas and can be written as:

$$\ln(Y_{it}/A_{it}) = (\alpha_0 + \tau_i) + \alpha_1 \ln A_{it} + \sum_{k=1}^K \beta_k \ln \frac{X_{itk}}{A_{it}} + \sum_{m=1}^M \gamma_m \ln Z_{itm} + \sum_{l=2}^T \delta_l t_l + v_{it} - u_{it} \quad (5)$$

where i and t denote farm and year respectively; Y_{it} is farm output; A_{it} is farm size in hectares; X_{itk} is the vector of traditional non-land inputs; and Z_{itm} represents a vector of soil quality and environmental variables. The variables T_t are time dummies denoting the second year of the panel for Malawi and Uganda, and the second and third year for Tanzania, where the first year is the excluded category.

We hypothesize that the relationship between TE and land area is not linear, so we include both a linear (A_{it}) and a quadratic term (A_{it}^2) in the inefficiency part of the model. Thus, TI for farmer i in period t is specified as follows:

$$u_{it} = \theta_1 A_{it} + \theta_2 A_{it}^2 + \omega_{it} \quad (6)$$

The TE of the i th farmer is given by $TE_i = \exp(-u_{it})$ and is calculated following Jondrow et al. (1982). The coefficients θ_1 and θ_2 are the parameters of interest to be estimated.

[Figure 1](#) shows that average farm and plot size are small for both SR and GPS measurements. After cleaning the data and removing extreme values that differ significantly from the other observations, the maximum farm size considered was 8 ha in Malawi, 50 ha in Tanzania, and 15 ha in Uganda. In Malawi, there is virtually no difference in size between the two measures and average size is 0.8 ha. In contrast, for Tanzania, the average SR farm size is 3.0 ha whereas the average for GPS is 2.7 ha, suggesting that farmers tend to overestimate their hectarage. The average size of farms in Uganda is 2.4 ha according to SR and 1.8 ha according to GPS, a difference of 0.6 ha, again showing significant overestimation. Thus, farms and plots are smaller in Malawi than in the two other countries and average plot size is 0.4 ha for SR and 0.3 ha for GPS. In Tanzania, average plot size is 1.1 ha for SR and 1.0 ha for GSP while in Uganda it is between 1.1 and 0.9 ha for SR and GPS, respectively.

Table 1. Definition of variables included in the econometric models.

Variables	Definition
AVP	Average value of farm production (real US dollars)
Land	Farm size in ha reported by the farmer or from a GPS measure
Labor	Family and hired worker equivalent days used for all farming tasks (Men = 1; Women = 0.8; Children < 14 years of age = 0.5)
Input expense	Total expenses on purchased inputs (real US dollars)
Capital	Total value capital (real US dollars)
Cropping system	Cropping system: Dummy variable equal to 1 if intercropping, 0 otherwise
Temp	Degrees Celsius (°C)
Precip	Precipitation in millimeters (mm)
Slope	Percent
Elev	Meters above sea level (m.a.s.l.)
SoilQ	Dummy for soil quality equal to one if reported moisture is adequate
Plots	Number of plots on the farm
Exten	Number of training programs received by the household head (HHH)
Road	Distance of the farm to the nearest paved road in kilometers
Exper	Experience of the HHH, proxied by age
Educ	Years of education of the HHH
Gender	Dummy variable equal to 1 if HHH is male and 0 otherwise

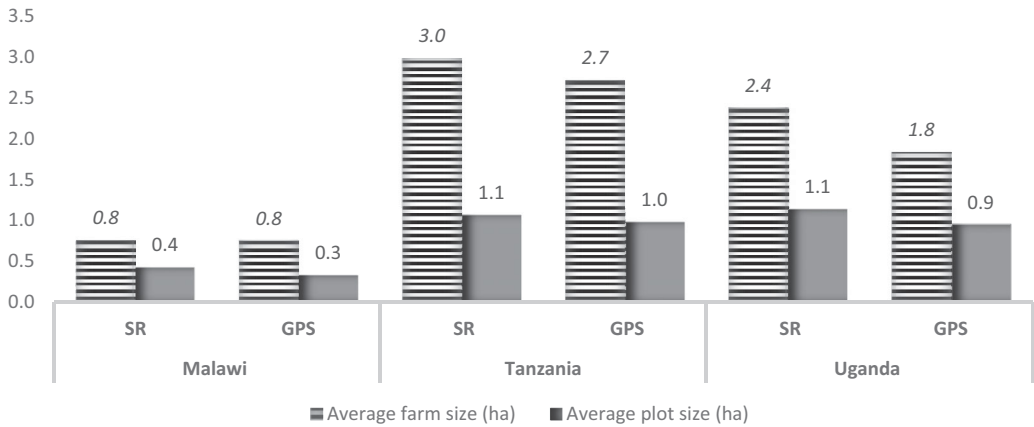


Figure 1. Average farm and plot size (ha): first year in the data for each country.

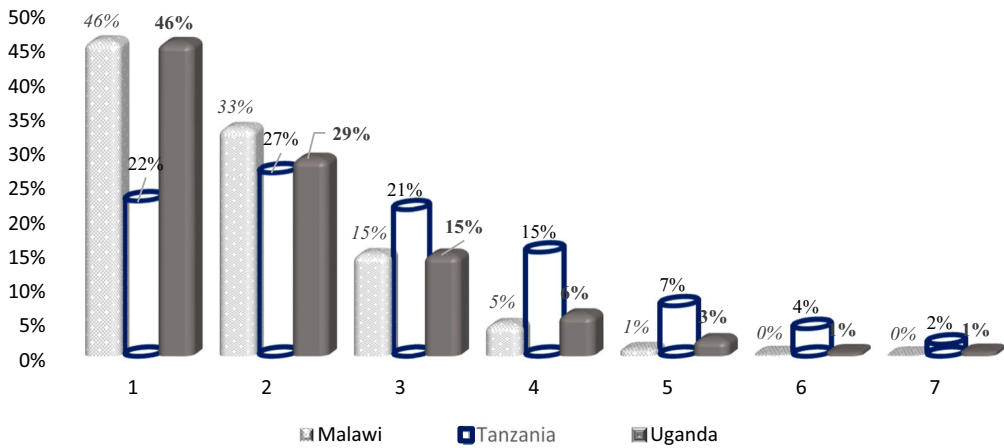


Figure 2. Number of plots owned.

Figure 2 shows the percentage of farmers who own one or more plots. About 46% of farmers own only one plot in Malawi, 33% own two, and 21% own more than two plots. The respective figures for Tanzania (Uganda) are 22% (46%), 27% (29%) and 51% (25%). To a certain extent, Tanzania presents a slightly different structure than Malawi and Uganda in terms of farm and plot size which could be reflected in the model and TE distribution.

5. Results

In what follows we present and discuss the estimates of the TRE-BC95 production frontier models presented above for each country – Malawi, Tanzania, and Uganda – to test the IR-H and the size-efficiency relationship.

5.1 Testing the IR-H

Table 2 presents the empirical results for the three countries. The self-reported (SR) and GPS models provide clear evidence supporting the inverse relationship in all three countries. For Malawi, the

coefficient of the variable “Land” in the SR model is -0.392 , which is close to -0.358 , the coefficient from the GPS model. Both coefficients are significant at the 1% level. Although the descriptive statistics in Figure 1 show that farm size averages are equal for both self-reported and GPS data, the results indicate that an increase in land size would decrease productivity more rapidly for the SR model.

Table 2. Stochastic production frontier models for Malawi, Tanzania and Uganda using two alternative measures of land area.

Output/ha	Malawi		Tanzania		Uganda	
	SR	GPS	SR	GPS	SR	GPS
Land	-0.392^{***} (0.0608)	-0.358^{***} (0.0518)	-0.342^{***} (0.0589)	-0.346^{***} (0.0556)	-0.286^{***} (0.0734)	-0.315^{***} (0.0486)
Labor/ha	0.076^{***} (0.0224)	0.059^{***} (0.0223)	0.017^{**} (0.00784)	0.019^{**} (0.00785)	0.298^{***} (0.0251)	0.293^{***} (0.0248)
Input expense/ha	0.019^{***} (0.00765)	0.017^{**} (0.00757)	0.017^{***} (0.00374)	0.017^{***} (0.00376)	0.032^{***} (0.00661)	0.034^{***} (0.00663)
Capital/ha	0.128^{***} (0.0156)	0.119^{***} (0.0155)	0.154^{***} (0.0149)	0.183^{***} (0.0148)	0.092^{***} (0.0194)	0.115^{***} (0.0191)
Cropping system	0.0548 (0.0459)	0.0284 (0.0453)	-0.182^{***} (0.0548)	-0.192^{***} (0.0552)	n/i	n/i
Temp	0.747 (0.527)	0.488 (0.520)	-0.190^* (0.105)	-0.0664 (0.105)	n/i	n/i
Precip	-0.366^{***} (0.132)	-0.192 (0.132)	0.099 (0.1000)	0.003 (0.100)	0.601^{***} (0.152)	0.574^{***} (0.152)
Slope	-0.0428 (0.0325)	-0.0356 (0.0318)	0.00545 (0.0381)	0.0253 (0.0386)	0.030 (0.0451)	0.029 (0.0453)
Elevation	0.462^{***} (0.0859)	0.418^{***} (0.0856)	0.036 (0.0282)	0.024 (0.0288)	0.900^{***} (0.189)	0.858^{***} (0.189)
SoilQ	-0.0492 (0.0542)	-0.0380 (0.0534)	-0.007 (0.247)	0.127 (0.249)	n/i	n/i
Plots	0.555^{***} (0.0515)	0.577^{***} (0.0500)	0.128^{**} (0.0500)	0.166^{***} (0.0506)	0.133^{***} (0.0495)	0.196^{***} (0.0465)
Extension	0.009 (0.00535)	0.007 (0.00529)	0.0092 (0.00911)	0.013 (0.00918)	0.023^{***} (0.00670)	0.026^{***} (0.00672)
Road	-0.0174^* (0.00973)	-0.0211^{**} (0.00963)	0.033^{***} (0.0154)	0.029^* (0.0156)	0.060^{***} (0.0175)	0.053^{***} (0.0175)
Experience	0.063 (0.0657)	0.012 (0.0650)	-0.140 (0.0852)	-0.088 (0.0865)	-0.203^{**} (0.0844)	-0.175^{**} (0.0845)
Educ	0.0105^* (0.00538)	0.0105^{**} (0.00532)	0.043^{***} (0.00972)	0.049^{***} (0.00979)	0.005 (0.00546)	0.003 (0.00548)
Gender	0.089 (0.0547)	0.077 (0.0538)	0.027 (0.0616)	0.060 (0.0621)	-0.249^{***} (0.0696)	-0.273^{***} (0.0698)
T2	-1.206^{***} (0.0478)	-1.171^{***} (0.0456)	-0.136^* (0.0695)	-0.167^{**} (0.0701)	0.325^{***} (0.0519)	0.337^{***} (0.0520)
T3			-0.870^{***} (0.0708)	-0.884^{***} (0.0709)	n/a	n/a
Constant	2.669 (2.267)	2.924 (2.238)	6.118^{***} (0.517)	6.359^{***} (0.525)	-5.504^{***} (1.770)	-5.008^{***} (1.770)
<i>Inefficiency estimates</i>						
Land	-0.223^* (0.079)	-0.147^* (0.074)	0.358^{**} (0.172)	0.665^{***} (0.164)	0.333 (0.212)	0.449^{***} (0.150)
Land square	-0.153^* (0.0787)	-0.168^{**} (0.0685)	-0.0239 (0.0317)	-0.0617^{**} (0.0301)	-0.110 (0.0729)	-0.0653 (0.0478)
σ_u	1.199^{***} (0.068)	1.232^{***} (0.065)	5871^{***} (0.496)	3.106^* (1.600)	0.709^{**} (0.247)	0.867^{***} (0.151)
σ_v	0.722^{***} (0.024)	0.713^{***} (0.037)	1.139^{***} (0.030)	1.144^{***} (0.038)	1.069^{***} (0.062)	1.043^{***} (0.0445)
$\lambda = \sigma_u/\sigma_v$	1.659^{***} (0.096)	1.728^{***} (0.091)	5.155^{***} (0.509)	2.714^* (1.583)	0.663^{**} (0.306)	0.831^{***} (0.019)
N	2598	2598	2901	2901	3284	3284

Notes: ***, **, * are 1%, 5% and 10% level of significance respectively.

S.E: (): Standard error. Variables are measured in natural log.

n/i: Not included; n/a: Not-available.

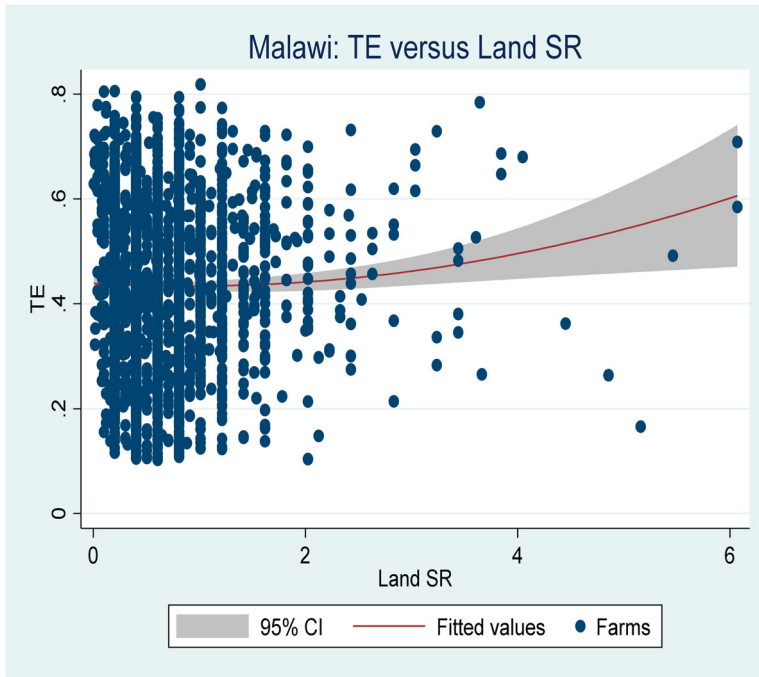


Figure 3. TE versus land (SR) in Malawi.

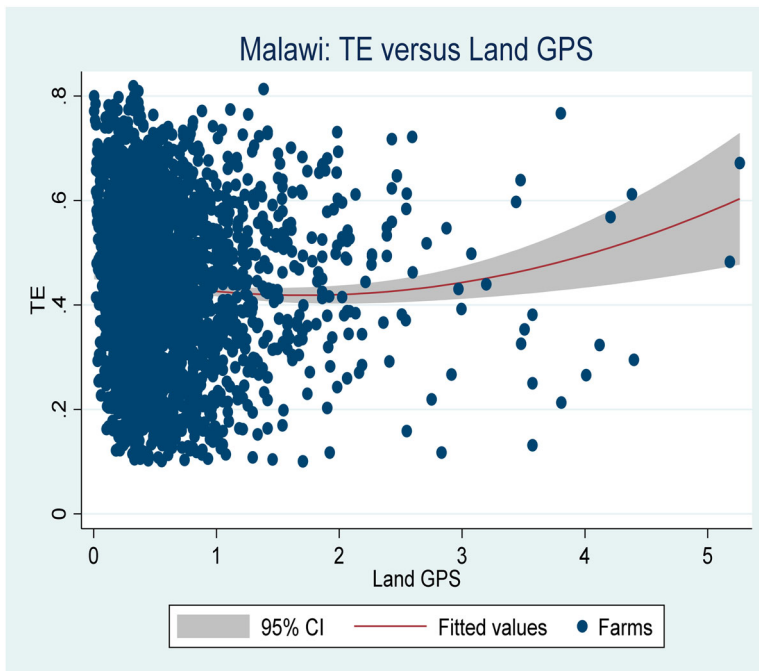


Figure 4. TE versus land (GPS) in Malawi.

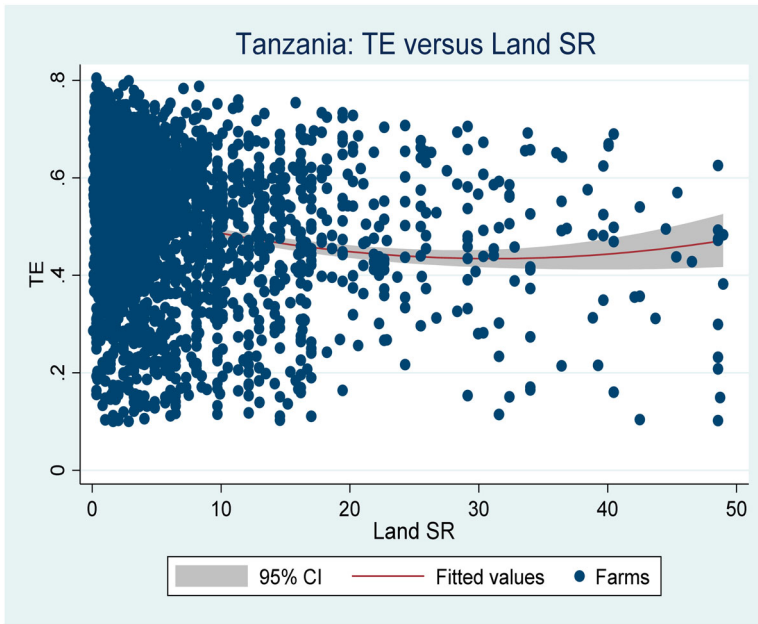


Figure 5. TE versus land (SR) in Tanzania.

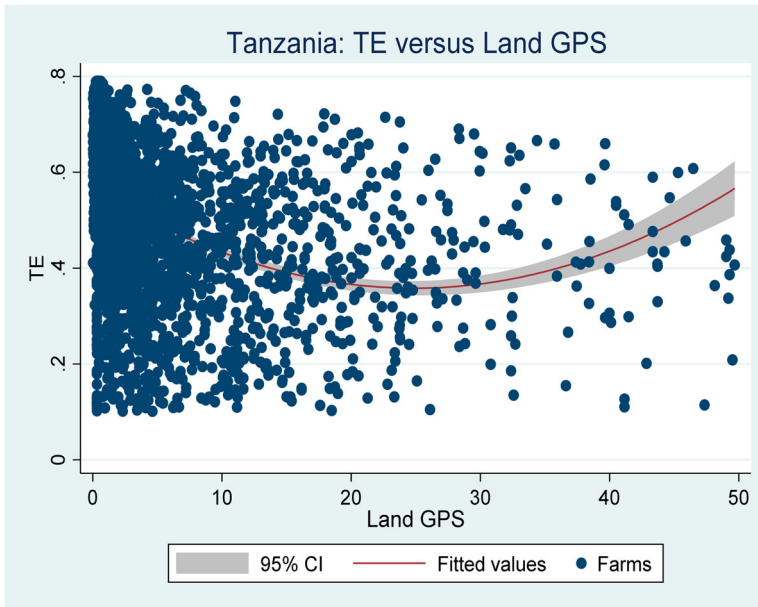


Figure 6. TE versus land (GPS) in Tanzania.

or less in Uganda for the GPS model (Figure 7). The fitted values in Figure 8 suggest higher TE for farms greater than 10 ha than those between 5 and 10 ha, though more research and data is needed given the relative thinness of observations at the higher end of the farm size distribution in Uganda.

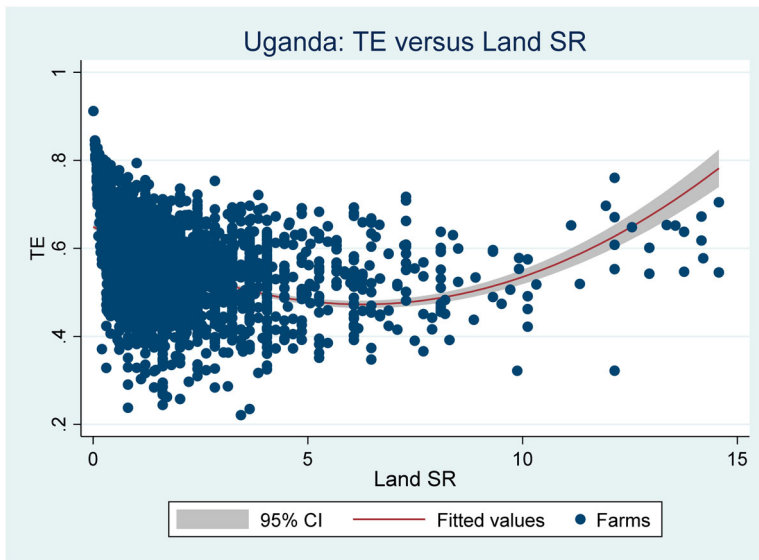


Figure 7. TE versus land (SR) in Uganda.

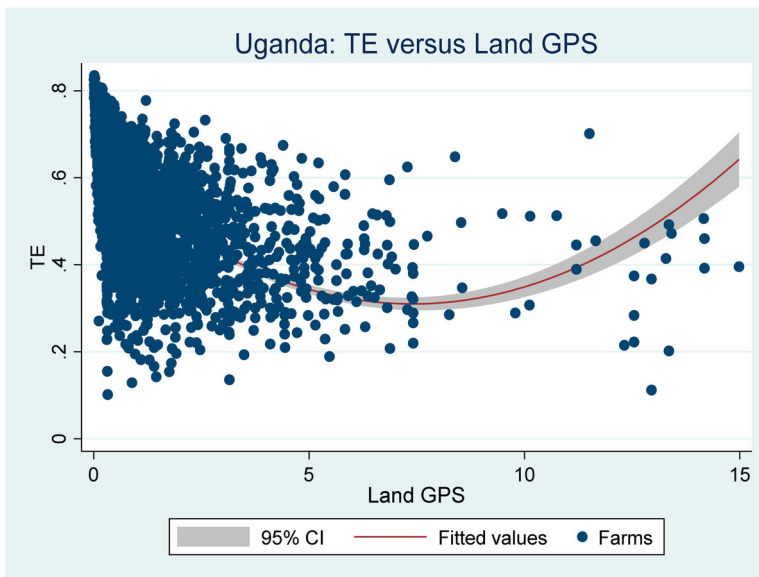


Figure 8. TE versus land (GPS) in Uganda.

Table 4 depicts the distribution of TE by farm size class, generally indicating that smaller farms have higher TE than larger ones. In Malawi, the overall average TE is 43% in both the SR and GPS models. This is consistent with the findings of Edriss, Tchale, and Wobst (2004) and Tchale (2009) who characterise smallholder agriculture in Malawi as inefficient. Moreover, the results show that for the SR model, farm size classes 1 and 10 have the same TE level (46%), while class 8 has the lowest TE at 40%. The pattern is somewhat different for the GPS model, where class 1 has the highest levels of managerial performance (49%) and classes 6, 7, and 9 have the lowest level of agricultural performance at about 41%. Despite these differences, the results in Table 4 support Malawi’s U-shape relationship presented above.

Table 4. Average TE by class and model (SR, GPS) for Malawi, Tanzania and Uganda.

Farm size class	Malawi		Tanzania		Uganda	
	SR	GPS	SR	GPS	SR	GPS
1	0.46	0.49	0.60	0.69	0.71	0.71
2	0.42	0.43	0.57	0.62	0.64	0.65
3	0.41	0.42	0.53	0.57	0.62	0.61
4	0.44	0.42	0.54	0.52	0.59	0.57
5	0.42	0.44	0.53	0.51	0.57	0.54
6	0.42	0.41	0.51	0.47	0.56	0.51
7	0.41	0.41	0.49	0.45	0.54	0.49
8	0.40	0.42	0.49	0.43	0.53	0.48
9	0.43	0.41	0.47	0.41	0.53	0.46
10	0.46	0.44	0.46	0.39	0.53	0.41
<i>Overall</i>	0.43	0.43	0.52	0.51	0.58	0.54

The analysis of managerial performance by class for Tanzania shows that for the SR model, class 1 has the highest TE (60%), while class 9 has the lowest (about 47%). For the GPS model, class 1 has the highest TE (69%), and these values decrease across classes to the lowest TE level, 39%, in class 10. Of the three countries under study, Uganda has the highest average TE score, 58% in the SR model and 54% in the GPS model, and, class 1 shows the highest TE (71%) for both models. Managerial performance decreases with farm size for the SR model and the lowest levels are for classes 8, 9, and 10 (53%), while in the GPS model, the lowest level is for class 10 (41%). The average TE numbers in [Table 4](#) support an inverse relationship rather than a U-shape land-efficiency relationship as revealed by the models and graphs for Tanzania and Uganda. The inverse relationship depicted when computing the TE averages is consistent with those of Kagin, Taylor, and Yúnez-Naude (2016) and Julien, Bravo-Ureta, and Rada (2019), which report both an inverse productivity and an inverse efficiency relationship with respect to farm size. Moreover, all TE estimates reveal a substantial gap in managerial performance, which is consistent with existing empirical evidence for farmers in Africa (Bravo-Ureta et al. 2007; Tchale 2009; Ogundari 2014).

The size-TE distribution results for Tanzania exhibit a distinct structure compared to Malawi and Uganda. In Tanzania farm size is larger than in the two other countries and, according to Arce and Caballero (2015), farmers are more focused on commercialisation, which can increase their vulnerability to income variability and potential losses of economic benefits. This would encourage Tanzanian farmers to adopt low-risk and low yield crop and production patterns in order to mitigate weather, pest, and disease risks. This high level of uncertainty and the complex management of household consumption and crop commercialisation require farmers to have strong management skills to ensure higher efficiency and productivity levels.

6. Summary and conclusions

We tested the inverse relation hypothesis (IR-H) between farm size and productivity, controlling for possible land measurement errors, soil quality, and environmental characteristics, in three East African countries. To this end, we estimated a true random effects (TRE) production frontier model including farm size on the inefficiency terms to examine managerial performance across farm size classes. The inclusion of household attributes and climatic, environmental, and agroecological measures makes it possible to mitigate biases from omitted variables, a typical shortcoming in this type of work.

We find a consistent inverse relationship between farm size and managerial performance, captured by technical efficiency (TE), that generally holds for all three countries and for models that use self-reported and GPS land measurements. Our results suggest that for Malawi, the IR is stronger in the SR model, while for Tanzania and Uganda it is stronger in the GPS models. These findings are consistent with those of Carletto, Savastano, and Zezza (2013), and Holden and

Fisher (2013). These results cast doubt on the notion that the incorporation of environmental variables, such as soil quality and climatic conditions, can mitigate results regarding the IR-H in these countries.

We also tested the functional form of the relationship between farm size and productivity over the size distributions specific to each country. We found a linear relationship for the SR model in Tanzania and the GPS model in Uganda, but a U-shaped curve for both the SR and GPS models in Malawi and for the GPS model in Tanzania. The size-TE relationship analysis supports the use of a non-linear functional form on the inefficiency component of the model. In Malawi, the results reveal that the average level of farm efficiency is over 43% for both SR and GPS models, while in Tanzania average TE levels are 52% (SR model) and 51% (GPS model). In Uganda, the average TE goes from 58% (SR model) to 54% (GPS model).

The evidence suggests that it is important to scale up extension programs to improve farm efficiency and ensure greater productivity, especially for intermediate-sized farms, where managerial performance tends to be at its lowest in this region. Thus, a critical mission of extension programs could be to ensure that farmers are provided knowledge and taught skills specific to their farm size. These programs should also include a period of coaching to encourage farmers to make good use of the skills and lessons learned from the training sessions.

The IR-H found in these three East African countries is consistent with evidence found by most agricultural economists who study the topic. Since access to land constitutes a critical economic, environmental, and sociopolitical issue in SSA countries, our findings have significant policy implications for land distribution, managerial performance, and other strategies to increase productivity and efficiency while contributing to poverty alleviation. The farms in the three countries analyzed are predominantly family operations that tend to be subdivided from one generation to the next, which leads to increasing land fragmentation over time. This social aspect should be considered along with factors affecting efficiency when designing policies. Decision-makers need to consider the costs of implementing productivity-enhancing and agricultural extension programs in cases where farm subdivision would lead to a significant increase in the number of farms. Smaller farms have higher transaction and marketing costs, which will trap the smallest producers in subsistence agriculture preventing them from achieving economic sustainability. Hence, it is critical to consider how small-scale farms can be made commercially viable and integrated into the agricultural system of the country.

Finally, smallholders like those analyzed in this study, rely heavily on land and other natural resources and climatic and agroecological characteristics to increase productivity; therefore, climate change is particularly threatening to the development and food security of these farmers (FAO 2013). Thus, designing agricultural policies focusing on extension projects that aim to enhance efficient use of natural resources and sustainable development with environmentally safe practices is of high priority. Integrating farmers along with the size distribution and accommodating techniques and approaches that allow for adaptation and resilience to climate change are important steps to enhancing future productivity and efficiency.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The authors gratefully acknowledge financial support provided by the U.S. Department of Agriculture, Economic Research Service through Grant 58-6000-50060. Any views expressed are the authors' and do not necessarily reflect those of the U.S. Department of Agriculture or the Economic Research Service. The views expressed also do not necessarily reflect the official positions of the Office of the Chief Economist or the U.S. Patent and Trademark Office.

ORCID

Jacques C. Julien  <http://orcid.org/0000-0003-1611-1904>

Boris E. Bravo-Ureta  <http://orcid.org/0000-0001-9575-3053>

References

- Abay, K.A., L. Bevis, and C.B. Barrett. 2019. *Measurement error mechanisms matter: Agricultural intensification with farmer misperceptions and misreporting*. NBER Working Paper No. 26066. Cambridge, MA: National Bureau of Economic Research.
- AGRA. 2014. *Africa agriculture status report 2014: climate change and smallholder agriculture in Sub-Saharan Africa*. Nairobi: Alliance for a Green Revolution in Africa (AGRA).
- Aigner, D.J., C.K. Lovell, and P.J. Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6: 21–37.
- Ainembabazi, J.H. 2007. *Landlessness within the vicious cycle of poverty in Ugandan rural farm household: Why and how it is born?* Kampala: Economic Policy Research Centre (EPRC).
- Ali, D.A., and K. Deininger. 2015. Is there a farm size–productivity relationship in African agriculture? Evidence from Rwanda. *Land Economics* 91, no. 2: 317–343.
- Arce, C.E., and J. Caballero. 2015. *Tanzania: Agricultural sector risk assessment*. Washington, DC: World Bank.
- Assunção, J.J., and L.H. Braidó. 2007. Testing household-specific explanations for the inverse productivity relationship. *American Journal of Agricultural Economics* 89, no. 4: 980–990.
- Assunção, J., and M. Ghatak. 2003. Can unobserved heterogeneity in farmer ability explain the inverse relationship between farm size and productivity. *Economics Letters* 80: 189–194.
- Bardhan, P.K. 1973. Size, productivity, and returns to scale: an analysis of farm-level data in Indian agriculture. *Journal of Political Economy* 81, no. 61: 1370–1386.
- Barrett, C. 1996. On price risk and the inverse farm size–productivity relationship. *Journal of Development Economics* 51: 193–215.
- Barrett, C., M. Bellemare, and J. Hou. 2010. Reconsidering conventional explanations of the inverse productivity–size relationship. *World Development* 38, no. 1: 88–97.
- Battese, G.E., and T.J. Coelli. 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20: 325–332.
- Belotti, F., and G. Ilardi. 2012. *Consistent estimation of the “true” fixed-effects stochastic frontier model*. CEIS Research Papers (231).
- Belotti, F., S. Daidone, G. Ilardi, and V. Atella. 2013. Stochastic frontier analysis using Stata. *Stata Journal* 13, no. 4: 719–758.
- Bevis, L.E.M., and C.B. Barrett. 2020. Close to the edge: high productivity at plot peripheries and the inverse size–productivity relationship. *Journal of Development Economics* 143: 102377. doi:10.1016/j.jdeveco.2019.102377.
- Bravo-Ureta, B.E., D. Solís, V. Moreira, J. Maripani, A. Thiam, and T. Rivas. 2007. Technical efficiency in farming: a meta-regression analysis. *Journal of Productivity Analysis* 27, no. 1: 57–72.
- Brooks, J. 2010. *Agricultural policy choices in developing countries: a synthesis*. Paris: Organisation for Economic Co-operation and Development (OECD).
- Byiringiro, F., and T. Reardon. 1996. Farm productivity in Rwanda: effects of farm size, erosion, and soil conservation investments. *Agricultural Economics* 2: 127–136.
- Carletto, C., S. Savastano, and A. Zezza. 2013. Fact or artifact: the impact of measurement errors on the farm size–productivity relationship. *Journal of Development Economics* 103: 254–261.
- Christiaensen, L. 2017. Agriculture in Africa – telling myths from facts: a synthesis. *Food Policy* 67: 1–11.
- Coelli, T., D. Rao, C. O’Donnell, and G. Battese. 2005. *An introduction to efficiency and productivity analysis*. New York: Springer.
- Cohen, A. 2015. *Measurement error and the farm size–productivity relationship: An instrumental variables approach using self-reported land area and GPS estimates*. Working Paper.
- Conradie, B., G. Cookson, and C. Thirtle. 2006. Efficiency and farm size in Western Cape grape production: pooling small datasets. *The South African Journal of Economics* 74, no. 2: 334–343.
- Conradie, B., J. Piessse, C. Thirtle, and N. Vink. 2019. South African wine grape production, 2005–2015: regional comparisons of scale and technical efficiencies and total factor productivity. *Agrekon* 58, no. 1: 53–67. doi:10.1080/03031853.2018.1537190.
- Duffy, M. 2009. Economies of size in production agriculture. *Journal of Hunger and Environmental Nutrition* 4: 375–392.
- Edriss, A.H., H. Tchale, and P. Wobst. 2004. *The impact of labour market liberalization on maize productivity and rural poverty in Malawi*. Working paper, policy analysis for sustainable Agricultural Development (PASAD). Center for Development Research, University of Bonn.
- FAO. 2001. *The state of food and agriculture*. Rome: FAO.

- FAO. 2013. *Climate-smart agriculture sourcebook*. Rome: FAO.
- FAO. 2015. *The economic lives of smallholder farmers: An analysis based on household data from nine countries*. Rome: FAO.
- Fried, H., C. Lovell, and S. Schmidt. 2008. *The measurement of productive efficiency and productivity growth*. New York: Oxford University Press.
- Fuglie, K., M. Gautam, A. Goyal, and W.F. Maloney. 2019. *Harvesting prosperity: technology and productivity growth in agriculture*. Washington, DC: World Bank Group.
- Gaurav, S., and S. Mishra. 2015. Farm size and returns to cultivation in India: revisiting an old debate. *Oxford Development Studies* 43, no. 2: 165–193.
- Gollin, D., and C. Udry. 2021. Heterogeneity, measurement error, and misallocation: Evidence from African agriculture. *Journal of Political Economy* 129, no. 1: 1–80.
- Gourlay, Sydney, Talip Kilic, and David B Lobell. 2019. A new spin on an old debate: errors in farmer-reported production and their implications for inverse scale – productivity relationship in Uganda. *Journal of Development Economics* 141: 102376.
- Greene, W. 2005. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics* 126: 269–303.
- Griliches, Z. 1957. Specification bias in estimates of production functions. *Journal of Farm Economics* 39, no. 1: 8–20.
- Hammel, E.A. 2005. *Chayanov revisited: a model for the economics of complex kin units*. Berkeley, CA: Departments of Demography and Anthropology, University of California.
- Hazell, P., and A. Rahman. 2014. *New directions for Smallholder agriculture*. Oxford: Oxford University Press.
- Helfand, S.M., and E.S. Levine. 2004. Farm size and the determinants of productive efficiency in the Brazilian center-west. *Agricultural Economics* 31: 241–249.
- Henderson, H. 2015. Considering technical and allocative efficiency in the inverse farm size–productivity relationship. *Journal of Agricultural Economics* 6, no. 2: 442–469.
- Hillel, D. 1991. In so many words: language in relation to the soil. *Soil Science* 152, no. 6: 403–404.
- Holden, S., and M. Fisher. 2013. *Can area measurement error explain the inverse farm size productivity relationship?* IDEAS Working Paper Series from RePEc, IDEAS Working Paper Series from RePEc, 2013.
- Holden, S.T., and C.J. O'Donnell. 2015. *Maize Productivity and Input Subsidies in Malawi: A State-Contingent Stochastic Production Frontier Approach*. School of Economics and Business Working Paper No. 2/2015. Norway: Norwegian University of Life Sciences, Aas.
- Jondrow, J., C.A.K. Lovell, I.S. Materov, and P. Schmidt. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* 19, no. 2–3: 233–238.
- Julien, J.C., B.E. Bravo-Ureta, and N.E. Rada. 2019. Assessing farm performance by size in Malawi, Tanzania, and Uganda. *Food Policy* 84: 153–164.
- Kagin, J., E. Taylor, and A. Yúnez-Naude. 2016. Inverse productivity or inverse efficiency? Evidence from Mexico. *The Journal of Development Studies* 52, no. 3: 396–411.
- Kimhi, A. 2006. Plot size and maize productivity in Zambia: is there an inverse relationship? *Agricultural Economics* 35: 1–9.
- Kirsten, J.F., and J. van Zyl. 1998. Defining small-scale farmers in the South African context. *Agrekon* 37, no. 4: 551–562.
- Kislev, Y., and W. Peterson. 1986. *Economies of scale in agriculture: a survey of the evidence*. Washington, DC: World Bank.
- Kumbhakar, S., and C.A.K. Lovell. 2000. *Stochastic frontier analysis*. Cambridge: Cambridge University Press.
- Lamb, R.L. 2003. Inverse productivity: land quality, labor markets and measurement error. *Journal of Development Economics* 71: 71–95.
- Li, G., Z. Feng, L. You, and L. Fan. 2013. Re-examining the inverse relationship between farm size and efficiency: the empirical evidence in China. *China Agricultural Economic Review* 5, no. 4: 473–488.
- Livingston, G., S. Schönberger, and S. Delaney. 2014. Right place, right time: the state of smallholders in agriculture. In *New directions for smallholder agriculture*, eds. P. Hazell, and A. Rahman, 36–37. Oxford: Oxford University.
- Lobell, D. B., G. Azzari, M. Burke, S. Gourlay, Z. Jin, T. Kilic, and S. Murray. 2020. Eyes in the Sky, Boots on the Ground: Assessing Satellite- and Ground-Based Approaches to Crop Yield Measurement and Analysis. *American Journal of Agricultural Economics* 102, no. 1: 202–219. <https://doi.org/10.1093/ajae/aaz051>.
- Martin, J., and J. Page. 1983. The impact of subsidies on x-efficiency in LDC industry: theory and an empirical test. *Review of Economics and Statistics* 65, no. 4: 608–617.
- Muyanga, M., and T.S. Jayne. 2019. Revisiting the farm size-productivity relationship based on a relatively wide range of farm sizes: evidence from Kenya. *American Journal of Agricultural Economics* 101, no. 4: 1140–1163.
- Netting, R.M. 1993. *Smallholders, householders: farm families and the ecology of intensive, sustainable agriculture*. Stanford, CA: Stanford University Press.
- Nishimizu, M., and J. Page. 1982. Total factor productivity growth, technological progress and technical efficiency change: dimensions of productivity change in Yugoslavia. *Economic Journal* 92, no. 368: 920–936.
- Njuki, E., and B.E. Bravo-Ureta. 2015. The economic costs of environmental regulation in U.S. dairy farming: a directional distance function approach. *American Journal of Agricultural Economics* 97, no. 4: 1087–1106.

- O'Donnell, C.J. 2012. Nonparametric estimation of the components of productivity and profitability change in U.S. agriculture. *American Journal of Agricultural Economics* 94, no. 4: 873–890.
- O'Donnell, C.J. 2014. An economic approach to identifying the drivers of productivity change in the market sectors of the Australian economy. Paper Prepared for the IARIW-UNSW Conference on Productivity: Measurement, Drivers and Trends Sydney, Australia, November 26–27, 2013.
- O'Donnell, C.J. 2016. Using information about technologies, markets and firm behaviour to decompose a proper productivity index. *Journal of Econometrics* 190: 328–340.
- Ogundari, K. 2014. The paradigm of agricultural efficiency and its implication on food security in Africa: what does meta-analysis reveal? *World Development* 64: 690–702.
- Rada, N., S. Helfand, and M. Magalhães. 2019. Agricultural productivity growth in Brazil: large and small farms excel. *Food Policy* 84: 176–185.
- Rada, N., C. Wang, and L. Qin. 2015. Subsidy or market reform? Rethinking China's farm consolidation strategy. *Food Policy* 57: 93–103.
- Saini, G.R. 1969. Farm size, productivity and returns to scale. *Economic and Political Weekly* 4, no. 26: A119–A122.
- Schmidt, P., and R. Sickles. 1984. Production frontier and panel data. *Journal of Business & Economic Statistics* 2, no. 4: 367–374.
- Sen, A.K. 1962. An aspect of Indian agriculture. *Economic Weekly* 14: 4–6.
- Tchale, H. 2009. The efficiency of smallholder agriculture in Malawi. *African Journal of Agricultural and Resource Economics* 3, no. 2: 101–121.
- Thorner, D., B. Kerblay, and R.F. Smith. 1966. *A. V. Chayanov on the theory of peasant economy*. Madison: University of Wisconsin Press.
- Triebs, T.P., and S.C. Kumbhakar. 2013. Productivity with general indices of management and technical change. *Economics Letters* 120: 18–22.
- Wang, J., K.Z. Chen, S. Das Gupta, and Z. Huang. 2015. Is small still beautiful? A comparative study of rice farm size and productivity in China and India. *China Agricultural Economic Review* 7, no. 3: 484–509.
- Wassie, S.B., G.T. Abate, and T. Bernard. 2019. Revisiting farm size-productivity relationship: New empirical evidence from Ethiopia. *Agrekon* 58, no. 2: 180–199.
- Wiggins, S. 2009. *Can the smallholder model deliver poverty reduction and food security for a rapidly growing population in Africa? Expert meeting on how to feed the world in 2050*. Rome: FAO.
- World Bank. 2008. *Agriculture for development*. Washington, DC: The World Bank.