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Productivity gaps among groundnut farmers in Kenya and Uganda: A stochastic production frontier analysis

Cresensia Asekenye
International Institute of Tropical Agriculture (IITA), Uganda. E-mail: cresensiaa@gmail.com

Boris E. Bravo-Ureta*
University of Connecticut, USA and Adjunct Professor, University of Talca, Talca, Chile. E-mail: boris.bravoureta@uconn.edu

Mike Deom
University of Georgia, Athens, Georgia. E-mail: deom@uga.edu

Nelson Kidula
Kenya Agricultural Research Institute (KARI), Kisii, Kenya. E-mail: lubafu@yahoo.com

David Kalule Okello
National Semi-Arid Resources Research Institute (NaSARRI), Soroti, Uganda. E-mail: kod123@yahoo.com

Nasambu Okoko
Kenya Agricultural Research Institute (KARI), Kisii, Kenya. E-mail: nasambu_okoko@yahoo.co.uk

Naveen Puppala
New Mexico State University, Las Cruces, New Mexico. E-mail: npuppala@nmsu.edu

* Corresponding author

Abstract

Productivity gaps for 321 groundnut farmers from Uganda and Kenya were analysed using data from the 2009 growing seasons. Farmers who planted improved varieties enjoyed output advantages of 143% in Uganda and 58.6% in Kenya over those who planted only local varieties. Farmers had a mean technical efficiency of 54.6% in Uganda and 54.4% in Kenya. No significant differences were found in the mean technical efficiencies of research and non-research farmers, and between male- and female-managed plots. Productivity therefore could be enhanced if high-efficiency households invest more in improved varieties and if low-efficiency households make better use of their existing technology. Continued development of improved varieties will further shift the production frontier outward. The apparent spill-over effect of the technical support received by research and non-research farmers suggests that farmer education has a multiplier effect. An improvement in extension service delivery could help to enhance the managerial skills of both farmer categories.

Key words: stochastic production frontiers; productivity gaps; groundnuts; Kenya; Uganda

1. Introduction

Africa accounts for 40% of the global area planted to groundnuts, but for only 26% of production, with the highest average yields observed in Southern Africa and the lowest in East Africa (ICRISAT 2012; FAOSTAT 2013; World Bank 2015). In 2006, the average groundnut yield recorded in sub-Saharan Africa was 980 kg/ha, considerably less than the world average of 1 690 kg/ha (Bucheyeki *et al*. 2008). Pests, diseases, lack of appropriate production technologies, inadequate markets and information, and poor post-harvest handling practices are among the factors that influence the low production and profitability of groundnuts in East Africa (Mutegi 2010; Okello *et al*. 2010; Masette & Candia 2011). Using improved varieties developed for better disease resistance, higher yields and good market acceptability could enhance overall productivity. To maximise benefits, the adoption of improved seeds should be coupled with the use of improved crop husbandry techniques, along with enhanced opportunities to sell any marketable surpluses (Kassie *et al*. 2011). Although yield increases resulting from the adoption of improved technologies have been reported in recent studies, sharp gaps remain between yields from farmer-managed farms and those reported by experimental stations and managed trials as part of on-farm research (Okello *et al*. 2010).

The aim of this study was to analyse productivity gaps among groundnut producers in Kenya and Uganda in terms of technological progress (TP) and technical efficiency (TE). TP in this context relates to productivity gains stemming from the adoption of improved seeds, while TE is the ability to achieve maximum output using existing resources and technology (Coelli *et al*. 2005). The specific objectives were: (1) to analyse productivity gaps stemming from the use of improved seeds versus local varieties; and (2) to examine productivity gaps associated with the managerial performance of research farmers versus non-research farmers, and of male- versus female-managed farms. Research farmers (RF) are defined as those who received direct support from researchers on groundnut farming and/or were engaged in on-farm groundnut trials. In contrast, non-research groundnut farmers (NRF) are those farmers who received no direct intervention from researchers and/or extension agents. The analysis uses farm-level data for the two cropping seasons of 2009 in both countries.

2. Review of related literature

Many productivity studies involve the use of production frontiers that describe the technical relationship between inputs and outputs and define the maximum output attainable from a given bundle of inputs and technology (Coelli *et al*. 2005; Bravo-Ureta *et al*. 2007). Production frontiers can be used to decompose productivity growth into TE and TP (Nishimizu & Page 1982). TE can be interpreted as a relative measure of managerial ability for a given technology, i.e. the difference between the maximum or frontier output and the actual output of a farm reflects TE. By contrast, TP captures “jumps” in the production function arising from the application of improved inputs and better farming practices. Research and development are the forces behind TP, while education and experience are essential for improving TE (Ahmad & Bravo-Ureta 1995; Anderson & Feder 2007). It therefore is important to decompose productivity growth into the TP and TE components when designing policies aimed at improving performance (Nishimizu & Page 1982; Antle & Capalbo 1988).

Table 1 presents TE estimates for African agriculture reported in studies published between 2005 and 2015 that used farm-level data. The studies are categorised according to the methodology employed in the analysis and are displayed by including first author, year of publication, country, enterprise(s) analysed, number of observations, and the mean TE (MTE) reported. For studies that reported more than one TE estimate, the number of observations and TE estimates are reported separately.

The 22 studies reviewed yielded a total of 29 TE estimates, with 28 being from stochastic and one from a non-parametric model. We included two studies published before 2005 because these were the only ones found focusing on groundnuts. The lowest mean TE reported was 36% for maize, vegetable and fruit intercrop in South Africa, while the highest was 95% for cocoyam in Nigeria. The overall average TE for the 29 cases is 69.5%, which is lower than the 73.7% overall average reported by Bravo-Ureta *et al*. (2007) for the 28 cases they analysed for Africa.

As indicated, only two studies were found that focused on TE for groundnut farms. One of these studies (Thiam & Bravo-Ureta 2003) reported an average TE of 70.3% for a sample of Senegalese groundnut producers. The other, by Binam *et al*. (2004), reported a MTE of 77% for groundnut monocrop and 75% for maize-groundnut farming systems in Cameroon.

In sum, the studies included in Table 1 show that there is considerable room to raise agricultural output from African farms, given the prevailing technology and without additional conventional inputs.

Table 1: Technical efficiency estimates from African studies published between 2005-2015

First author	Year published	Country	Enterprise(s)	Sample size	MTE %
a) Parametric stochastic frontiers					
Binam	2004	Cameroon	*Groundnut*	150	77
Binam	2004	Cameroon	Maize-*groundnut*	150	75
Thiam	2003	Senegal	*Groundnut*	501	70
Asante	2014	Ghana–Ashanti	Yam	103	85
Asante	2014	Ghana–Brong Ahafo	Yam	272	89
Mugonola	2013	Uganda	Banana	246	51
Bonabana-Wabbi	2013	Uganda	Potatoes	108	69
Dhehibi	2012	Tunisia	Wheat	51	77
Mignouna	2012	Kenya	Maize	600	70
Ofori-Bah	2011	Ghana	Cocoa mixed crop	161	86
Ofori-Bah	2011	Ghana	Cocoa	161	47
Maganga	2011	Malawi	Potatoes	200	83
Lovo	2010	South Africa	Maize/vegetables/fruits	547	36
Rao	2010	Kenya	Traditional market vegetables	269	54
Rao	2010	Kenya	Supermarket vegetables	133	80
Uaiene	2009	Mozambique	Crops	4 104	65
Tchale	2009	Malawi	Maize/burley tobacco	9 788	53
Ogundari	2009	Nigeria	Food crops	846	81
Iheke	2008	Nigeria	Cassava	160	77
Binam	2008	Cameroon	Cocoa	824	65
Binam	2008	Ghana	Cocoa	861	44
Binam	2008	Nigeria	Cocoa	1 041	74
Binam	2008	Côte d'Ivoire	Cocoa	1 020	58
Okoye	2008	Nigeria	Cocoyam	120	95
Idiong	2007	Nigeria	Rice	112	77
Chirwa	2007	Malawi	Maize	156	46
Obwona	2006	Uganda	Tobacco	65	78
Amaza	2006	Nigeria	Food crops	1 086	68
ATE stochastic frontiers					**68.9**
b) Non-parametric frontiers					
Chavas	2005	Gambia	Food crops	120	85
Overall ATE					**69.5**

3. Data

The Kenya Agricultural Research Institute (KARI) and the National Semi-Arid Resources Research Institute (NaSARRI) in Uganda conducted a household survey between April and August 2010. Farm-level data for the 2009 cropping seasons was collected from smallholder farmers in the districts of Kumi, Amuria, Soroti, Pallisa, Budaka, Jinja, Kamuli, Pader, and Lira in the Teso, Busoga and Northern regions of Uganda, and from the Ndhiwa, Nyarongi and Kobama divisions of Ndhiwa district in Kenya. A stratified random sampling technique was used to select households within these locations.

Total annual production was obtained by aggregating output from the first and second seasons. Then, plots with pure groundnut stands and intercrops were identified, the area devoted to groundnuts was computed in each case and total acreage was calculated. Total seed sown, in kilograms, was computed by adding the quantity of seeds purchased to that received as gifts. The expenditure on family labour was calculated by multiplying the number of labour days by the daily wage. The total value of labour used was then computed by summing the values of hired and family labour. All input and output quantities are aggregates of the two cropping seasons.

Outlier observations were identified using Cook's distance, or D. This is a normalised measure of the influence of point i on all predicted mean values, and it is used to assess the influence of outliers in a regression model. An observation is considered an outlier if it exceeds the Cook's D critical value given by $4/n$-(k+1), where n is the sample size and k is the number of parameters estimated (Chatterjee *et al*. 2000). A simple regression model was run in which total output was regressed on the amount of land, seed, labour and two dummies, one capturing regional differences and the other seed type. Critical values of 0.028 for Uganda and 0.021 for Kenya were computed. Eight and 13 households from Uganda and Kenya respectively had values greater than the computed critical values for a total of 21 outliers. These 21 outliers, and households with missing data for one or more variables, were discarded, yielding a final sample with 321 households – 141 from Uganda and 180 from Kenya.

Tables 2 and 3 present descriptive statistics, including means and standard deviations, of the key variables used in the analysis. The overall average age was 49 years in Uganda and 44 in Kenya. The average farm size was 2.8 hectares (ha) in both countries. Farmers planted groundnuts on an average area of 1.15 ha in Uganda and 0.64 ha in Kenya. Higher quantities of seeds were sown per ha in Uganda than in Kenya; nevertheless, average yields were lower in Uganda than in Kenya (685 kg/ha versus 907 kg/ha respectively). Farmers who planted improved seeds obtained higher yields. In both countries, male-managed plots had lower average yields compared to female-managed plots.

Table 2: Socio-economic characteristics of groundnut farmers in Uganda and Kenya

	Uganda			Kenya		
	Age of household head (years)	**Education household head (years completed)**	**Distance to nearest research station (km)**	**Age of household head (years)**	**Education household head (years completed)**	**Distance to nearest research station (km)**
Total sample						
Sample size	141	141	141	180	180	180
Mean	49.8	7.4	39.2	44.8	7.2	80.1
Std. dev.	*12.6*	*4.1*	*25.2*	*14.2*	*3.4*	*14.5*
Female-headed households						
Sample size	76	76	76	70	70	70
Mean	49.5	7.4	38.4	42.4	6.3	81.2
Std. dev.	*12.7*	*4.5*	*26.5*	*12.7*	*3.5*	*12.2*
Male-headed households						
Sample size	65	65	65	110	110	110
Mean	50.2	7.6	40.1	46.3	46.3	46.3
Std. dev.	*12.5*	*3.7*	*23.8*	*15.0*	*15.0*	*15.0*
Research farmers						
Sample size	79	79	79	84	84	84
Mean	48.7	7.6	32.9	44.7	7.4	83.1
Std. dev.	*11.5*	*4.0*	*27.6*	*14.1*	*3.3*	*16.3*
Non-research farmers						
Sample size	62	62	62	96	96	96
Mean	51.3	7.3	47.2	44.8	6.9	77.5
Std. dev.	*13.7*	*4.2*	*19.2*	*14.4*	*3.5*	*12.3*

Table 3: Descriptive statistics of production variables used in the models

	Uganda				Kenya		
Variable	**Sample size**	**Mean**	***Std. dev.***		**Sample size**	**Mean**	***Std. dev.***
Groundnut land (ha)	141	1.2	*0.9*		180	0.6	*0.7*
Labour (US$[a])	141	194.2	*165.5*		180	113.5	*105.9*
Seed (kg)	141	45.4	*43.7*		180	31.0	*33.0*
Farm size (ha)	141	2.8	*1.8*		180	2.8	*1.3*
Yield (kg/ha) by variety							
D =1 if improved variety	120	749.5	*771.4*		174	918.5	*542.5*
D = 0 if local variety only	21	319.7	*231.7*		6	588.3	*166.9*
Yield (kg/ha) by farmer type							
D = 1 if RF	79	776.8	*778.3*		84	925.9	*561.2*
D = 0 if NRF	62	569.1	*658.3*		96	891.3	*518.1*
Yield (kg/ha) by gender							
D = 1 if female	76	623.6	*664.3*		70	867.2	*521.1*
D = 0 otherwise	65	757.8	*804.8*		110	933.1	*548.3*
Productivity							
Total yield (kg/ha)	141	685.5	*732.8*		180	907.5	*537.4*
Seed/ha	141	48.4	*47.2*		180	58.0	*77.7*
Labour/ha	141	250.9	*281.6*		180	284.0	*713.0*

[a] Expressed in US dollars computed using the IMF 2009 average exchange rates of 2 030.5 Ugandan shilling and 77.4 Kenyan shilling per US dollar.
Source: World Development Indicators (WDI) and Global Development Finance (GDI) 2010

4. Methodology

The stochastic production frontier (SPF) model of Battese and Coelli (1995) was used to estimate separate frontiers for each country. This model can be expressed as:

$$Y_i = f(X; \beta) + v_i - u_i \qquad i = 1, 2 \ldots n \tag{1}$$

where Y_i is the output of the i^{th} firm; X is a vector of inputs; β is a vector of parameters to be estimated; $f(.)$ represents the functional form; v_i is a two-sided random error term that is assumed to be identically and independently distributed with a normal distribution [N (0, σv^2)]; and u_i is a one-sided non-negative random error that captures technical inefficiency in production. The terms v and u are assumed to be independent of each other.

Following Battese and Coelli (1995), the technical inefficiency effects equation was specified as a linear function of explanatory variables reflecting farmer specific characteristics, as:

$$u_i = Z\delta + w_i \tag{2}$$

where w_i is a random variable defined by the truncation of the normal distribution, with a mean of zero and variance σ^2, such that the point of truncation is equal to $-Z\delta$, i.e. $w_i \geq -Z\delta$. The assumptions are consistent with u_i being a non-negative truncation of the N ($Z\delta$, σ^2) distribution. The TE of the i^{th} firm, defined relative to the estimated frontier output of an efficient firm using the same set of inputs, is calculated as (Battese & Coelli 1995):

$$TE_i = exp(-u_i) = exp(-Z_i\delta - w_i) \tag{3}$$

Both the Cobb–Douglas (CD) and the translog (TL) functional forms are used to fit the SPF. The output and input variables in the TL are expressed as deviations from their sample geometric means; thus, the first-order coefficients can be interpreted as partial elasticities of output at the geometric mean of the data (Coelli *et al*. 2003). The CD and TL production frontiers estimated are expressed below as equation (4) and (5) respectively:

$$lnY_i = \beta_0 + \beta_1 lnX_{1i} + \beta_2 lnX_{2i} + \beta_3 lnX_{3i} + \beta_4 T_D + \beta_5 D_i + v_i - u_i \tag{4}$$

$$lnY_i = \beta_0 + \beta_1 lnX_{1i} + \beta_2 lnX_{2i} + \beta_3 lnX_{3i} + \beta_4 T_D + \beta_5 D_i + 0.5\,\beta_6 ln\,(X_1)^2 + \beta_7\, lnX_{1i}X_{2i} + \beta_8\, lnX_{1i}X_{3i} + 0.5\,\beta_9\, ln(X_{2i})^2 + \beta_{10}\, lnX_{2i}X_{3i} + 0.5\,\beta_{11}\, ln(X_{3i})^2 + v_i - u_i \tag{5}$$

where ln is the natural logarithm and i refers to the i^{th} farmer in the sample. The variables are defined as follows:

Y = total farm output of groundnuts measured, in kilograms;
X_1 = land under groundnut cultivation, in hectares;
X_2 = quantity of groundnut seeds sowed, in kilograms (kg);
X_3 = the value of family and hired labour, in US dollars;
T_D = dummy equal to 0 if only local seed varieties are used and 1 otherwise;
D_i = dummy that captures regional differences. In the Uganda model it is equal to 1 if the farm is located in the northern region and 0 otherwise. In the Kenya model it is equal to 1 if the farmer is located in the Ndihwa division and 0 otherwise.

The variables used in the inefficiency effects component for both the CD and the TL functions are defined as in equation 6:

$$U_i = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \delta_5 Z_{5i} + w_i \qquad (6)$$

Z_1 = dummy for gender of the plot manager, equal to 1 if female and 0 otherwise;
Z_2 = farmer type, equal to 1 if RF and 0 if NRF;
Z_3 = age of the household head, in years;
Z_4 = education of the household head, in years of schooling completed;
Z_5 = distance to the nearest research institute, in kilometres (km).

The variables in equation (6) are farm-specific factors, management factors and regional differences. Farmer age has been included as a proxy for farming experience. Female-managed plots are also expected to perform better than male-managed plots, since groundnuts are regarded as a women's crop in the area of study; hence, women are expected to have more experience. The variable years of schooling of the farm manager is used as a proxy for education. Education may affect agricultural productivity directly through its cognitive and non-cognitive effects, or through indirect effects such as improved access to credit (Appleton & Balihuta 1996). Education can also increase productivity among neighbouring farmers through spill-over effects (Weir & Knight 2006).

The two key objectives of this study, as discussed above, gave rise to three null hypotheses (H_0):

H_o1: The parameter of β_4, for seed type (T_D) = 0

H_o2: Mean TE_{RF} = Mean TE_{NR}

H_o3: Mean TE_{MALE} = Mean TE_{FEMALE}

Farmers using improved seed varieties are expected to operate on a higher production frontier than those using local varieties. In addition, the MTE for the RF (captured by variable Z_2) is expected to be higher than that of NRF, because the former received technical support from researchers and/or extensionists. It is important to highlight that a well-functioning extension service is key for investments in research and technology to have an impact on agricultural productivity. On the one hand, extension promotes the adoption and diffusion of new practices and technologies, such as improved seeds, by translating research-based knowledge into information that is relevant to farmers. On the other hand, research focusing on solving problems and relaxing constraints actually faced by farmers is also facilitated by a well-functioning extension service that provides feedback from the field to researchers (Anderson & Feder 2007).

The first hypotheses (H_o1) is depicted graphically in Figure 1. The distance between Y_2 and Y_4 represents the jump in the production frontier due to technological improvements resulting from the cultivation of improved varieties, holding all else constant. The distances Y_1 to Y_2 and Y_3 to Y_4 correspond to TE gaps for users of traditional varieties (TV) and improved varieties (IV) respectively, again holding other variables constant.

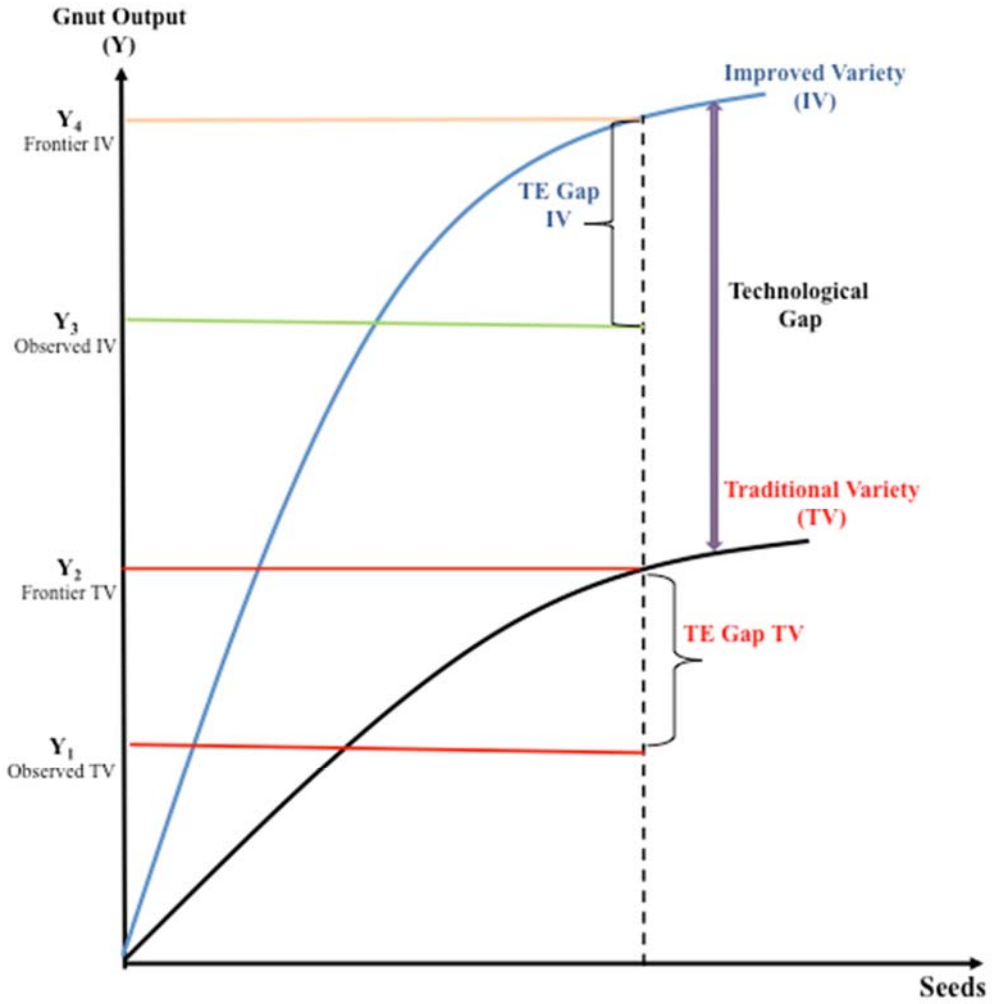

Figure 1: Illustration of the technological and management (TE) gaps: Improved (IV) versus traditional (TV) varieties

5. Results

Separate, individual country stochastic frontier models were specified. A base model, referred to as Model I, incorporated the inefficiency effects component following Battese and Coelli (1995). Two additional models, II and III, were estimated, and these were of the Aigner, Lovell and Schmidt (1977) type. Models I, II and III can be specified in general terms as in equations (7), (8) and (9) below respectively:

$Y_i = f(X; \beta) + v_i - g(Z;\delta)$ Model I (Base model) (7)

$Y_i = f(X, Z; \beta, \delta) + v_i - u_i$ Model II (8)

$Y_i = f(X; \beta) + v_i - u_i$ Model III (9)

Model I includes five variables (X) in the deterministic component and another five variables (Z) in the inefficiency effects component, while Models II and III include 10 (X, Z) and five (X) variables respectively. The explanatory variables are as defined above, and Tables 2 and 3 provide details.

A likelihood ratio (LR) test was performed to investigate the adequacy of the CD functional form relative to the less restrictive TL.[1] In this test, if the second-order and interaction parameters of the TL are zero, then the CD is considered as an adequate representation of the data. The LR test did not reject H_o for both countries, therefore the CD was chosen over the TL production specification. The maximum-likelihood (ML) estimates for the parameters in the CD for the three models are presented in Table 4 for Uganda and in Table 5 for Kenya.[2]

Table 4: Estimated production frontier models for Uganda (Uga)

		Model I-Uga	**Model II-Uga**		**Model III-Uga**
		Coefficients (std. errors)			**Coefficients (std. errors)**
Constant	β_0	5.83*** (0.80)	5.17*** (0.72)	β_0	4.89*** (0.58)
LnLand (ha)	β_1	0.42*** (0.12)	0.44*** (0.12)	β_1	0.44*** (0.12)
LnSeed (kg)	β_2	0.30*** (0.10)	0.28*** (0.09)	β_2	0.25*** (0.09)
LnLabor (US$)	β_3	0.05 (0.09)	0.03 0.08)	β_3	0.02 (0.08)
Seed variety (local = 0; 1 otherwise)	β_4	0.93*** (0.25)	0.97*** (0.25)	β_4	0.89*** (0.25)
Location (North = 1; 0 otherwise)	β_5	0.48** (0.25)	0.55*** (0.21)	β_5	0.53*** (0.2)
Constant	δ_0	1.67* (0.97)	NA		NA
Plot manager (female = 1; 0 otherwise)	δ_1	0.02 (0.21)	-0.03 (0.17)		NA
Farmer type (RF = 1; 0 otherwise)	δ_2	-0.12 (0.23)	0.06 (0.18)		NA
Age	δ_3	-0.002 (0.01)	0.003 (0.01)		NA
Education	δ_4	0.03 (0.03)	-0.03 (0.02)		NA
Distance to research station (km)	δ_5	0.01 (0.004)	-0.006* (0.004)		NA
Sigma-squared	σ^2	1.12*** (0.24)	1.81*** (0.53)	σ^2	1.55*** (0.51)
Gamma	γ	0.91*** (0.17)	0.72*** (0.20)	γ	0.55* (0.3)
Log-likelihood function		-197.87	-197.75		-200.13

Note: *** Significant at the 1% level; ** significant at the 5% level; *significant at the 10% level
NA: Not available

[1] The LR test requires estimation of the model under the null (restricted) and alternative (unrestricted) hypotheses. The test statistic is calculated as $LR = -2[\ln L(H_0) - \ln L(H_A)]$, where $\ln L(H_0)$ and $\ln L(H_A)$ are values of the log likelihood functions(LLF) under the null and alternative hypotheses respectively. The degrees of freedom for the chi-square statistic are given by the difference between the number of parameters estimated under H_A and H_0 (Coelli *et al*. 2005; Battese *et al*. 2004).
[2] The ML estimates for the translog models are available from the authors.

Table 5: Estimated production frontier models for Kenya (Ken)

		Model I-Ken	**Model II-Ken**		**Model III-Ken**
		Coefficients (std. errors)		**Coefficients (std. errors)**	
Constant	β_0	5.35*** (0.35)	5.31*** (0.47)	β_0	5.32*** (0.33)
LnLand (ha)	β_1	0.60*** (0.06)	0.62*** (0.06)	β_1	0.60*** (0.06)
LnSeed (kg)	β_2	0.29*** (0.06)	0.28*** (0.06)	β_2	0.29*** (0.05)
LnLabor (US$)	β_3	0.11** (0.05)	0.12** (0.05)	β_3	0.11** (0.05)
Seed variety (local = 0; 1 otherwise)	β_4	0.48** (0.20)	0.54*** (0.20)	β_4	0.46** (0.20)
Location (Ndihwa = 1; 0 otherwise)	β_5	-0.05 (0.08)	-0.09 (0.08)	β_5	-0.06 (0.07)
Constant	δ_0	0.10 (0.73)	NA		NA
Plot manager (female = 1; 0 otherwise)	δ_1	0.04 (0.24)	-0.06 (0.08)		NA
Farmer type (RF = 1; 0 otherwise)	δ_2	0.03 (0.20)	-0.03 (0.08)		NA
Age	δ_3	0.002 (0.01)	0.001 (0.003)		NA
Education	δ_4	-0.05 (0.04)	0.02 (0.013)		NA
Distance to research station (km)	δ_5	-0.01 (0.01)	-0.002 (0.003)		NA
Sigma-squared	σ^2	0.68*** (0.04)	0.86*** (0.12)	σ^2	0.89*** (0.12)
Gamma	γ	0.94*** (0.03)	0.95*** (0.03)	γ	0.95*** (0.03)
Log-likelihood function	-147.24	-148.26		-149.97	

Note: *** Significant at the 1% level; ** significant at the 5% level; *significant at the 10% level
NA: Not available

The stochastic frontier models were estimated using the half-normal and the truncated-normal distributions for the one-sided error, and these two alternative distributions were contrasted against each other using a LR test. The LR test (χ^2 critical value = 0.523) failed to reject the null hypothesis in Kenya, and the truncated-normal distribution did not converge for the Ugandan data. Thus, the half-normal distribution was adopted for both datasets. The robustness of Models I, II and III was also tested using the LR test, and the results indicated that Model III was the most robust for both Kenya and Uganda. Hence, Model III was used in the analysis that follows for both countries.

5.1 Coefficients of the production frontier

As shown in Tables 4 and 5, all coefficients for the inputs in Model III have the expected positive signs and are statistically significant, with the exception of labour in Uganda. In Uganda, land exhibits the highest partial elasticity (0.44), followed by seed (0.25), and labour has the lowest partial elasticity (0.02), with a function coefficient of 0.71, indicating decreasing returns to scale. Similarly, in Kenya, land has the highest partial elasticity, (0.60), followed by seeds (0.29), while labour has the lowest partial elasticity (0.11), with a function coefficient of 1.00, denoting constant returns to scale.

More formally, the null hypothesis of constant returns to scale was evaluated using LR ratio tests. The LR test rejected H_0 (χ^2 critical value = 0.039) in Uganda and failed to reject it (χ^2 critical value =

0.89) in Kenya. This confirms the returns-to-scale measures reported above, indicating that groundnut farmers had decreasing returns to scale in Uganda and constant returns to scale in Kenya.

The dummy that captures regional differences among farmers in Uganda has a value of 0.533 and is significant at the 1% level. This indicates that farmers in northern Uganda have a higher output than those in Teso and Busoga, holding all else constant. The value of this coefficient implies that, *ceteris paribus*, farmers in northern Uganda can produce 70.4% ([$(e^{0.533})$ - 1]*100) more than those in other regions, and this could be a reflection of more suitable agro-ecological conditions.[3] This result is consistent with the fact that land in the northern region had remained fallow for several years, because the population had been displaced to refugee camps due to a rebel insurgence during this period (Oxfam 2008). A similar geographical variable was introduced in the models for Kenya, and in this case no location effect was present.

Several other hypotheses were evaluated for Model III. The first of these hypotheses involved a t-test and a LR test to determine the significance of γ (gamma), which is equal to the ratio of the variance of the one-sided term divided by the variance of the composed error. Gamma is bounded between 0 and 1 and, the closer to 1, the more significant is the output shortfall associated with inefficiency (Battese & Corra 1977; Coelli *et al*. 2005). In both countries, γ is significant, implying that inefficiency is indeed present. Therefore, the frontier specification is preferable over the average function, which would be estimated using OLS (Coelli *et al*. 2005).

The γ parameter value of 0.95 in Kenya indicates that 95% of the variation in groundnut output was due to technical inefficiency. This result is consistent with that of the one-sided generalised LR test, in which H_0 was rejected (LR = 16.68 > critical value of 2.71). However, this was not the case in Uganda, where the significance of γ contradicted the results obtained with the LR ratio test. According to Coelli (1995), the one-sided LR test is a better option in such cases, because it has more power than the t-test. However, the Uganda results need to be interpreted with caution, given the inconsistency between the two tests.

5.2 Technical efficiency (TE)

The predicted average TE of groundnut farmers was 54.6% in Uganda, with a range that went from 11.7% to 77.9%. In the case of Kenya, average TE was 54.4%, ranging from 9.8% to 92.0%. Thus, these results indicate that, utilising existing resources and technology, farmers in the samples from both countries could increase production by 46%.

Another way of looking at this TE gap is that, if an average farmer in the sample were to achieve the TE of its most efficient counterpart, then that farmer could increase production by 29.9% [1-(54.6/77.9)*100] in Uganda and 40.9% [1-(54.4/92)*100] in Kenya.

The average TE values for both countries fall within the MTE for the group of African studies included in Table 1. The range for the MTE values in that table goes from 36% to 95%. However, the TE averages for Uganda and Kenya are lower than the stochastic frontier average of 68.9% and the overall mean TE of 69.5 %, also shown in Table 1.

5.3 Productivity gaps – formal tests of our three hypotheses

Now we turn to the core objectives of this paper, which, as discussed earlier, are succinctly expressed in three hypotheses. The first of these hypotheses (H_o1) indicates that seed type should have no effect

[3] To calculate this effect in percentage terms for the CD, it is necessary to take the antilog of the estimated parameter for the dummy variable, subtract 1 from it and multiply the difference by 100 (Halvorsen & Palmquist 1980).

on productivity, while the alternative suggests that the use of improved seed varieties should lead to a higher production frontier relative to local varieties, *ceteris paribus*. We referred to this difference earlier as a technological gap. The parameter β_4 in Model III in Tables 4 and 5 captures this gap for Uganda and Kenya respectively.

The null hypothesis of no technological gap was rejected at the 1% and 5% significance levels in Uganda and Kenya respectively. In other words, holding other things constant, the output is indeed higher for farmers who planted improved varieties compared to those who used local varieties. The β_4 coefficient is equal to 0.89 in Uganda and 0.46 in Kenya, which implies that farmers who planted improved groundnut varieties enjoyed a 143% (Uganda) and 58.6% (Kenya) output advantage over those who planted only local varieties.

The second hypothesis (H_o2) concerns the effect that the technical support provided to research farmers would have on their productivity relative to farmers that do not receive such support. This hypothesis was evaluated by testing if the mean TE for the NRF farmers (i.e. those who did not receive support from researchers and/or extensionists) was equal to that of the RF farmers (i.e. those that did receive such support). According to the data shown in Table 6, the mean TE for the NRF group in Uganda was 53% and that for the RF group was 56%, and these numbers are not statistically different from each other. The respective numbers for the Kenya sample were 54% and 55%, and again there was no statistical difference.

The presence of spill-over effects, whereby NRF learn management techniques from their neighbours who have access to information from researchers, could explain why there was no difference in MTE for farmer types.

The third hypothesis (H_o3) concerns average TE and gender. The null is that there would be no difference, while the alternative sketched above is that women managers of groundnut plots might exhibit a higher level of TE than their male counterpart because of the importance of this commodity for female farmers. Table 6 reveals that the mean TE for farmers according to gender is very close in both countries for both genders, ranging between 53% (males in Kenya) and 55% (females in both countries), and these figures are statistically equal.

Based on the results from the respective coefficients in the inefficiency effects, the testing of the hypotheses regarding type of farmer and gender were not done, because Model III, the one deemed most robust and selected for our analysis, does not incorporate an inefficiency effects component. Nevertheless, if one looks at the coefficients for gender and type of farmer obtained from Models I and II, we arrive at the same conclusions for both countries as derived from the test of mean stemming from Model III, as discussed above.

Table 6: Mean sample tests by type of farmer and gender for Ugandan and Kenyan groundnut farmers

	Uganda				Kenya			
	N	**Mean TE**	**Diff[b]**	**t-value**	**N**	**Mean TE**	**Diff**	**t-value**
Type of farmer								
NRF	62	0.53	-0.02	-0.92	96	0.54	-0.01	-0.20
RF	79	0.56			84	0.55		
Gender of plot manager								
Female	65	0.55	0.01	0.24	110	0.55	0.23	0.66
Male	76	0.54			70	0.53		

[b] Difference in the mean TE level between the groups

6. Concluding remarks

A clear and important finding that emerges from this study is that farmers who planted improved groundnut varieties enjoyed, on average, a 143% and a 58.6% output advantage over those who planted only local varieties in Uganda and Kenya respectively. Increased output is important, because this leads to enhanced food security and better nutritional levels (Kassie *et al*. 2011). This suggests that research devoted to the generation of improved varieties, coupled with extension work to promote the adoption and diffusion of such varieties, can enhance household welfare because higher productivity leads to higher income and thus reduced poverty (Asfaw *et al*. 2012). A related implication is that varieties need to be developed bearing in mind the unique characteristics across different agro-ecological zones. This is especially relevant now, as climate change is expected to play an increasing role in agricultural productivity across the globe.

Another salient result is that average technical efficiency is lower compared to that found in recent studies that have examined this issue (Bravo-Ureta *et al*. 2007; 2015). In fact, average TE hovers around 55% for both female and male managers of groundnut plots, and for farmers who have had support from extension and/or research (RF) and those who have not (NRF). Moreover, this finding is consistent for both Uganda and Kenya. Thus, this evidence indicates that there is considerable room for increasing groundnut production by making better use of the existing resources and technology.

Fifteen percent of the farms in Uganda and 32% of the farms in Kenya had MTE values greater than 70%. Since these farmers are operating close to their respective production frontiers, productivity could be enhanced by a more intensive use of improved varieties that shift the frontier outward. In contrast, the productivity of low-efficiency households could be improved by addressing the management issues that prevent them from making better use of their current technology. The most efficient farmers in both countries are, on average, those situated closest to research institutes. This suggests that access to information coming from these institutions plays a positive role in farm productivity. The apparent spill-over effect of the technical support received by research farmers (RF) in comparison to non-research farmers (NRF) suggests that an improvement in the delivery of extension services targeting the former group could also help the latter.

Improving the efficiency of women in groundnut production will help to reduce malnutrition, increase income, and empower women. Understanding the determinants of the TE gaps and the factors that can narrow this gap is crucial. Surprisingly, the parameters of most of the variables included in the inefficiency components of the estimated models were not statistically significant. Therefore, more research is needed to better understand the factors that influence the TE of groundnut farmers in both Uganda and Kenya.

It is interesting to note that, in northern Uganda, the use of improved varieties had a sharp effect on yields, but this was not the case in the Teso and Busoga regions. The August 2006 cessation of hostilities between the government of Uganda and the Lord Resistance Army brought peace to northern Uganda. Consequently, the population returned to their homeland after years in camps for internally displaced people (Oxfam 2008). The output advantage of farmers in northern Uganda therefore could be a result of the input support received from government and development partners, and the relative fertility of the land that had lain fallow for years.

The available evidence from several studies confirms the importance of well-functioning agricultural research and extension systems to generate relevant information and then educate farmers on the attributes of the new technologies (Anderson & Feder 2007). In the case of seeds, if research and extension are well articulated, then extensionists can provide researchers with feedback on the attributes that breeding programmes should target. Therefore, policy makers at different levels should work with the relevant institutions to ensure that research is facilitated so that appropriate seed varieties are generated and that extension is prepared to disseminate the advantages of the new material to the final users. This also requires economic analysis to ensure that the new seeds can be expected to generate significant additional benefits compared to those currently in use. Finally, in the case of groundnut seeds in Africa, the evidence suggests that there is a need for public-private partnerships so that appropriate seed delivery models can be developed and implemented (Mofya-Mukuka & Shipekesa 2013; Siambi *et al*. 2013).

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