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Total factor productivity and technical efficiency among smallholder groundnut farmers in Northern Mozambique

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Abstract

This study examines the productivity of smallholder groundnut farmers in North-eastern Mozambique using data for 2016 from two provinces with high total production of said crop. The model used is a Cobb-Douglas True Fixed Effects stochastic production frontier, controlling for geographical heterogeneity, and standard errors clustered at the village level. Our analysis reveals a mean total factor productivity index and technical efficiency score of 0.34 and 0.68 respectively. Seeding rates are found to have major potential for increasing output. This work provides new information to support ongoing efforts to generate greater resilience and robustness in domestic food systems.

Key words: **s**tochastic production frontiers; total factor productivity; technical efficiency; groundnut; Mozambique

1. Background

Many regions and countries throughout the world rely on agriculture as a primary driver of their economies (World Bank 2007; DeJanvry & Sadoulet 2020). In sub-Saharan Africa (SSA), agriculture-based economies are predominant and economic development planning is often tied to agricultural productivity growth. This study focuses on the agricultural sector in Mozambique, which contributes 23.4% to gross domestic product (GDP), employs 80% of the workforce, and is dominated by smallholders who produce 95% of total farm output (USAID 2018). Although agriculture contributes significantly to the Mozambican economy, only 20% of total production exits the farm gate (USDA 2015). Even with 80% of agricultural production dedicated to staple crops for direct household consumption, smallholder production does not meet domestic needs, and food insecurity and undernourishment have remained prevalent (USAID 2019). To address these challenges, the Mozambican Ministry of Agricultural and Food Security [*Ministério da Agricultura e Segurança Alimentar* (MASA)] has conducted several studies and implemented comprehensive plans to boost agricultural production, most recently with the conclusion of the National Agricultural Investment Plan [*Plano de Investimento no Sector Agrário* (PNISA)] implemented from 2013 to 2017, under the decade-long *Plano Estratégico para o Desenvolvimento do Sector Agrário* (PEDSA: 2010–2020) (MASA 2017a).

According to pillar (i) of PEDSA, "Agricultural Production, Productivity and Competitiveness" (MASA 2017b), productivity is one of the plan's four primary targets. However, apart from official reporting, there has been limited rigorous investigation of agricultural productivity in Mozambique (Uaiene 2008; Farahane 2009; Cunguara 2011). Thus, an examination of existing production systems to track total factor productivity (TFP) and technical efficiency (TE) makes an important contribution to the literature. This type of targeted study of smallholder production systems provides useful information to policymakers and key stakeholders. At a time when production and productivity growth figure significantly in critical policy aims, there is a great demand for analysis from diverse stakeholders to develop future strategies, particularly in the light of global climate change and the ongoing COVID-19 pandemic (Barrett 2020). Moreover, greater domestic production constitutes a well-established strategy to mitigate food security risks stemming from climatic adversity (e.g. drought), which is a major concern in Mozambique (World Bank 2011; Arndt & Thurlow 2015; Salazar-Espinoza *et al*. 2015; CIAT & World Bank 2017; Ahmadalipour *et al*. 2019; Salazar *et al*. 2019).

Household (HH) strategies to expand production fall into two general categories: extensification and intensification. Cropland in Mozambique reaches 5.9 million hectares (ha), with 4.7 million ha (80%) farmed (FAOSTAT 2019); therefore, extensification is a longstanding strategy to increase domestic production (e.g. Tschirley & Benfica 2001). In the past, the traditional practices and land tenure policies that were implemented following independence and the long period of civil war made it challenging for smallholders to increase the area under production and for outside interests to capitalise on large tracts of open agricultural land (Arndt *et al*. 2000; DeBrauw 2015). Over recent decades, state institutions have worked to reduce constraints to land access and to provide additional support to smallholders on the land they currently farm (Hanlon 2004). These programmes have explicitly targeted intensification based on evidence of significant productivity gains from improved management (MASA 2017a). In particular, investments in agricultural research and extension services have been made to increase agricultural productivity and total domestic production (Cunguara & Moder 2011). Correspondingly, a joint approach of extensification and intensification has been adopted to increase output. Given these aims, additional research on agricultural productivity in Mozambique is warranted. Thus, this study focuses on a sample of groundnut farmers in the North-eastern provinces of Cabo Delgado and Nampula to examine smallholder productivity.

Groundnuts have received attention from various stakeholders as a highly nutritious foodstuff that contributes to a diverse crop portfolio and enhances soil health and fertility when used in rotations and intercropping (CNFA & USAID 2010; Waha *et al*. 2013; Salazar-Espinoza *et al*. 2015). Notably, groundnuts are a source of zinc and protein, essential nutrients that appear to be declining in the food supply due to increased atmospheric carbon dioxide (CO_2) (Wessells & Brown 2012; Myers *et al*. 2015; Medek *et al*. 2017; Beach *et al*. 2019). Leguminous crops like groundnuts have been promoted, given the limited availability of chemical fertiliser and the low adoption rates of the crop in the region (2% to 3%) (Benson *et al*. 2012). Furthermore, these crops are projected to benefit from increased atmospheric CO_2, with greater yield and nitrogen fixing in the soil (Burkey *et al*. 2007; Rogers *et al*. 2009). Risk from disease (e.g. groundnut rosette virus), low output-to-seed ratio, and complexity of cultivation compared to other crops have worked against the decision to grow groundnuts (Naidu *et al*. 1999, DeBrauw 2015). Groundnuts are grown by 32% of HHs on 390 000 ha in Mozambique, primarily for home consumption, with the greatest production levels in Nampula province (MASA 2017b).

Productivity measurement and analysis in agriculture have consistently revealed the importance of decision-making by farm managers who seek to maximise output, given their technology, input set and environment (Bravo-Ureta *et al*. 2007). TFP and TE measures provide useful benchmarks to compare potential output with realised production levels across farm samples. In contrast to simple production metrics (e.g. output and yield), TFP and TE indicators allow stakeholders to plan and implement effective strategies to generate productivity growth. For instance, high mean TE may suggest that the best strategy for productivity growth is to invest in research and development that generates new technologies and spurs technological change. In SSA, research on TFP and TE has included over 400 studies published from 1984 to 2013 (Bravo-Ureta & Pinheiro 1993; Bravo-Ureta *et al*. 2007; Ogundari 2014; Bravo-Ureta *et al*. 2017). These studies demonstrate the importance of measurement to track and develop strategies to further enhance productivity growth. Moreover, given the wide heterogeneity across farming systems and geographical locations, it is critical to develop productivity measurements that are country- and even site-specific.

In Mozambique, several studies over recent decades incorporate groundnuts into their analysis or list them as an important staple crop (Tschirley & Benfica 2001; Carter *et al.* 2014; DeBrauw 2015; Salazar-Espinoza *et al*. 2015; Deininger & Xia 2016; Benfica *et al*. 2017). However, productivity analysis in these studies rely on simple measures, mainly yield and total value of output. We only found a single case that applies stochastic production frontier methodology to examine farm-level TE (Uaiene 2008) in Mozambique, while a few studies have used country-level data to examine aggregate TFP growth (e.g. Nkamleu 2004; Coelli & Rao 2005; Avila & Evenson 2010). Hence, given the dearth of micro-productivity analyses for Mozambique, additional research is warranted. The rationale for this paper was therefore to generate new evidence that may be used to motivate future research and interventions by policymakers and funding agencies. The remainder of this paper is structured as follows: the methods section describes the econometric framework, data and estimation strategy used in the analysis; then we present the results and discussion; and, finally, the summary and conclusions.

2. Methods

2.1 Econometric framework

We consider a production model in which traditional agricultural inputs – land, labour and seeds – are combined to produce groundnuts. The main approach to productivity analysis taken here assumes that firms maximise expected profits, which provides the rationale for estimating production frontier models where inputs are predetermined, thus avoiding the simultaneity bias issue (Zellner *et al*. 1966; Karagiannis & Kellermann 2019; Bravo-Ureta *et al*. 2020). Maximum likelihood estimation (MLE) is the preferred methodology used to fit stochastic production frontiers (SPFs) (Greene 2003). The SPF model has gained great popularity in various economic sectors (Greene 2008), including agriculture (Ogundari 2014). More recently, stochastic production frontiers have been used by a number of authors in the measurement and decomposition of TFP, including O'Donnell (2016), Njuki *et al*. (2018), and Julien *et al*. (2019).

This paper assumes a Cobb-Douglas (C-D) functional form for all models estimated below. The C-D is selected because it is a good approximation of the unknown true production function and it satisfies theoretically based curvature properties globally (O'Donnell 2016, 2018). Furthermore, the 'proper' TFP index developed by O'Donnell (2016), used here, is based on the C-D. More flexible functional forms like the transcendental logarithmic (translog) are less restrictive (e.g. variable elasticities of substitution), but violate global curvature properties. In addition, C-D and translog estimates typically provide similar TE estimates (Baccouche & Kouki 2003; Ogundari 2014; Bravo-Ureta *et al.* 2020).

The general C-D SPF model for cross-sectional data can be expressed as follows (Aigner *et al.* 1977):

$$Y_i = f(X_i) + v_i - u_i, \tag{1}$$

where Y_i is the natural log of observed output, X_i are natural logs of inputs, v_i is the standard normally distributed error term, $N(0, \sigma_v^2)$, and u_i is the one-sided term representing technical inefficiency. The literature includes alternative specifications for the distribution of u_i, although the half-normal distribution is the most popular option (Coelli *et al.* 2005). For the half-normal distribution, the expected value of u_i, conditional on the composed error term $\varepsilon_i = v_i - u_i$, is:

$$E[u_i|\varepsilon_i] = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi(\varepsilon_i\lambda|\sigma)}{\Phi(-\varepsilon_i\lambda|\sigma)} - \frac{\varepsilon_i\lambda}{\sigma}\right], \tag{2}$$

where $\sigma = [\sigma_u^2 + \sigma_v^2]^{1/2}$, $\lambda = {}^{\sigma_u}/_{\sigma_v}$, $\phi(\cdot)$ is the density of the standard normal distribution, and $\Phi(\cdot)$ is the cumulative density function (Jondrow *et al.* 1982). The TE of the i^{th} unit, HHs in our case, is defined as the ratio of observed (Y_i) and frontier (Y^*) output, given by:

$$TE_i = exp(-u_i). \tag{3}$$

Another important productivity indicator, shown in equation 4, is TFP. In general, TFP is defined as the ratio of total outputs to total inputs, which for HH i can be expressed as:

$$TFP_i = \frac{Y_i}{X(X_i)}, \tag{4}$$

where Y_i is total output and $X(X_i)$ is aggregate input. Parameter estimates from the C-D SPF are used as weights to aggregate inputs. Another critical advantage of the C-D functional form is that it satisfies axiomatic properties associated with TFP indexes that allow for consistent comparisons between HHs (O'Donnell 2018). Based on our model, the TFP for HH i and m regressors is denoted as:

$$TFP^M(y_i, x_i) = \left[\prod_{m=1}^{M}\left(x_{mi}^{\beta_{mi}-b_m}\right)\right] \times [exp(u_i)] \times [exp(v_i)]. \tag{5}$$

The first right-hand-side (rhs) term in equation (5) measures output-oriented scale and mix efficiency, capturing fluctuations in TFP due to economies of scale and input adjustments. The second component measures output-oriented TE, which measures productivity change due to movements toward or away from the frontier. The last component is statistical noise, which accounts for errors and other unknown factors. The TFP index (TFPI) is then calculated by dividing TFP$_i$ by a reference TFP value r from the sample, i.e. TFPI$_i$ = TFP$_i$ / TFP$_r$. If the HH with maximum TFP is used as the reference point, i.e. TFPI$_i$ = TFP$_i$ / TFP$_{max}$ (as in equation 6), then TFPI values fall into the [0, 1] interval. The TFPI for our model is denoted as (O'Donnell 2016, 2018):

$$TFPI^M(y_i, y_r, x_i, x_r) = \left[\prod_{m=1}^{M}\left(\frac{x_{mi}^{\beta_{mi}-b_m}}{x_{mr}^{\beta_{mr}-b_m}}\right)\right] \times \left[\frac{exp(u_i)}{exp(u_r)}\right] \times \left[\frac{exp(v_i)}{exp(v_r)}\right], \tag{6}$$

where the rhs components are sub-indices representing output-oriented scale and mix efficiency, output-oriented TE and statistical noise, respectively.

2.2 Controlling for spatial heterogeneity with 'true' fixed effects

Heterogeneity between HHs is driven by observable and unobservable factors. In a 'pooled' model (see equation 8), these factors are captured by an intercept term and white noise (v_i) in the composed error. In certain cases, it is possible to exploit the data structure to capture unobserved heterogeneity by incorporating time and/or spatial effects. Below we incorporate fixed effects into an SPF model as an alternative to a 'pooled' specification, which is referred to as the true fixed effects (TFE) model, and disaggregate the intercept term to capture unobserved heterogeneity. Given the cross-sectional nature of our data, we control for spatial heterogeneity between i HHs in l regions. The TFE model includes a dummy variable for each district to capture unobserved heterogeneity (e.g. climate, leadership, infrastructure). Note that equation (7), the TFE version of (1), incorporates district dummy variables (F_l), while v_{il} and u_{il} are HH (i) and district (l) specific, and is expressed as:

$$Y_{il} = f(X_{il}, F_l) + v_{il} - u_{il}. \tag{7}$$

The TFE is estimated using MLE according to the methodology in Greene (2005). The TFE estimator is 'distribution free' – an appealing characteristic. A drawback of earlier FE estimators used in TE analysis (e.g. Schmidt & Sickles 1984) is that TE comparisons between individual units were based on the best-in-sample value as a reference point. The TFE model handles this drawback by incorporating the inefficiency term u_{il} in the frontier structure. A possible concern with TFE estimation is the incidental parameters problem (Greene 2005), which arises from inconsistent variance estimates, which are critical in post-estimation of the inefficiency term (Belotti & Ilardi 2018). However, this is typically an issue for short panels and is therefore not of concern given our data.

2.3 Data

The data used in this study were collected as part of ongoing multi-country efforts supported by the United States Agency for International Development (USAID) to enhance the productivity of agricultural systems in least developed countries. Under the Feed the Future initiative, USAID Innovation Labs have targeted multiple crops depending on site-specific characteristics while aiming to enhance food security. The Peanut and Mycotoxin Innovation Lab (PMIL) was in operation from 2012 to 2017 following prior efforts to support peanut (i.e. groundnut) growers under the USAID Peanut Collaborative Research Support Program (CRSP) from 1996 to 2012 (Hoisington 2018). Participating PMIL countries included Haiti, Ghana, Malawi, Mozambique and Zambia. Partner agencies, usually under the respective national ministries of agriculture, provided institutional support and facilitated engagement with key stakeholders, including universities, research centres, agricultural producers and local consultants, particularly for in-country data collection.

PMIL activities varied by country, with initiatives including research on good management practices to enhance yield and reduce the likelihood of fungal contamination (i.e. formation of harmful aflatoxins); plant breeding to generate new varieties that are high yielding, drought and disease resistant, while maintaining other desirable characteristics that are likely to affect HH adoption and marketability; human capacity building by funding research and graduate students at partner agencies and universities, as well as providing training via agricultural extension, including expert visits and farmer field trials; and data collection for areas identified by experts as critical to the project mission (Hoisington 2018 and https://ftfpeanutlab.caes.uga.edu).

For this study, partners at the Mozambique Agricultural Research Institute (MARI), also known as *Instituto de Investigação Agrária de Moçambique (IIAM)*, facilitated the collection of primary data from groundnut producers in Northern Mozambique. Researchers have highlighted the low availability of inputs, which is a primary constraint to agricultural productivity North of the Zambezi

River due to the lack of infrastructure (e.g. roads), which greatly limits access to markets in the South (Cirera & Arndt 2008; Mabiso *et al*. 2014). The Northern region was selected by local experts because of the large proportion of HHs that grow groundnuts and a lack of available data for this population. A version of the survey instrument, adapted from an earlier study conducted in Ghana, was distributed prior to in-country meetings in early June 2016. During these June meetings, the research team reviewed and adjusted the instrument according to expert opinion and pilot testing with local producers. A team of trained enumerators conducted the survey in North-eastern Mozambique in June and July 2016.

Researchers at MARI selected two provinces, Nampula and Cabo Delgado, as the study location. In Mozambique, provinces are divided into districts, which are further split into administrative posts, followed by localities and villages (or communities). The sampling unit in this study is a HH located in a given village. Additional village information was collected using a separate questionnaire administered by the field supervisor to village leaders. Given resource availability, a multistage approach for sample selection was taken, randomising at the district, locality and village levels. The sample design consisted of four districts, two per province; sixteen localities, four per district; and thirty-two villages, two per locality. Given the target of 400 HH interviews, 12 or 13 HHs were surveyed in each village, with 25 surveyed per locality. Data were cross-checked by a field supervisor during the survey visit. The final sample used for the analysis includes 232 HHs that reported all the data required for the estimation of the groundnut production models. In terms of geography, the final sample is evenly distributed among the provinces, districts, localities and villages, with 50.4% of the sample located in Nampula province (22.8% in Memba and 27.6% in Mogovolas district). The remaining 49.6% of the sample comes from Cabo Delgado province (24.6% in Chiure and 25% in Balama district) (Table 1).

Table 1: Household and production variables: Definitions and type

Variable	Definition	Type	Mean
Demographic			
AGE	HHH age	Discrete	38.7
SEX	HHH sex (0 = male, 1 = female)	Dummy	0.11
MSTAT	HHH marital status (1 = single, 2 = married, 3 = widowed, 4 = divorced)	Dummy	
1			0.03
2			0.90
3			0.04
4			0.04
EDU	HHH education (1 = no formal, 2 = primary, 3 = primary+)	Dummy	
1			0.32
2			0.62
3			0.06
SIZE_HH	HH members	Discrete	5.16
SIZE_AE	HH adult male equivalents (0.5 = child; 0.8 = ad. female; 1 = ad. male)	Continuous	3.48
DIST	District (1 = Memba, 2 = Mogovolas, 3 = Chiure, 4 = Balama)	Dummy	
1			0.228
2			0.276
3			0.246
4			0.250
Production			
Y	Groundnut production output (kg)	Continuous	474.4
YIELD	Groundnut yield (kg/ha)	Continuous	681.4
FARMSIZE	Farm area (ha)	Continuous	2.70
X1	Groundnut area (ha)	Continuous	0.71
X2	Groundnut labour (MHr)*	Continuous	149.6
X3	Groundnut seed planted (kg)	Continuous	21.7
N = 232			

* Calculated using adult male equivalents

2.4 Descriptive statistics

Table 1 presents HH demographic and production statistics for the sample of smallholders analysed in this study. Household heads (HHHs) in the sample were on average 38.7 years old; 88.8% were male and 11.2% female; 89.6% were married and the remaining 10.4% were either single (2.6%), widowed (3.9%) or divorced (3.9%). No formal education was reported by 32.3% of HHHs, while the remaining 67.7% of HHHs indicated a minimum of primary education (62.1%) or greater (5.6%). Average HH size was 5.16 members, composed of 3.48 adult male equivalents, derived by assigning weights to HH members based on their age and gender to get an idea of labour availability. The weights used are: adult males (16 years or more) = 1.0; adult females (16 years or more) = 0.8; and children (younger than 16 years) = 0.5 (Dillon & Hardaker 1989).

Total groundnut output (Y) ranged from 50 to 3 450 kg, with a mean of 474 kg (Table 1), and yield ranged from 171 to 1 767 kg/ha, with an average of 681 kg/ha. Farm size ranged from 0.4 to 15.25 ha, with a mean of 2.69 ha. Area planted with groundnuts ($X1$) averaged 0.713 ha. Labour was measured in hours of adult male equivalents (MHr), calculated as explained above and summed over all activities. Average HH labour input for groundnut farming ($X2$) was 149.65 MHr. On average, HHs use 21.72 kg of groundnut seed ($X3$).

2.5 Empirical model

The empirical C-D model is specified as total groundnut output (Y_i) for HH i as a function of a set of m traditional inputs (X_{mi}), namely groundnut area (ha), labour (MHr), and seed planted (kg). The estimates from the C-D were compared with those obtained from translog estimates and the results support the C-D.[1] Comparisons of restricted and unrestricted versions of the model (the latter includes additional covariates) show that the restricted specification is preferred based on statistical tests.[2] Given the underlying structure of the data, standard errors are clustered at the village for all models to control for intra-village similarities between HHs (Moulton 1990).

The first empirical specification is a pooled C-D SPF model, denoted as:

$$ln(Y_i) = \alpha_0 + \sum_{m=1}^{M} \beta_m lnX_{mi} + v_i - u_i, \tag{8}$$

where the following parameters were estimated: intercept α_0, β_m for traditional inputs, and the error term composed of white noise, v_i, and the inefficiency term u_i. As is well known, the β_m parameters from a C-D production frontier are partial elasticities of production. The calculations of TE and TFP are based on the general expressions shown in equations (3) and (5) respectively.

The next model includes fixed effects, F_l, to account for regional heterogeneity at the district level, and the expression for the C-D SPF true fixed effects specification is:

$$ln(Y_{il}) = \sum_{m=1}^{M} \beta_m lnX_{mil} + \theta_l F_l + v_{il} - u_{il}. \tag{9}$$

The 'pooled' intercept α_0 in equation (8) is dropped, and the TFE parameters θ_l are estimated for each of the l districts. TE is again calculated according to equation (3), and TFP is given by:

$$TFP^M(y_{il}, x_{il}) = \left[\prod_{m=1}^{M} \left(x_{mil}^{\beta_{mil} - b_m}\right)\right] \times [exp(\phi_{il})] \times [exp(u_{il})] \times [exp(v_{il})], \tag{10}$$

[1,2] Results available upon request.

where the additional second right-hand-side component, $[exp(\phi_{il})]$, measures fluctuations in TFP due to HH district-level heterogeneity (O'Donnell 2016). Finally, the selection of the preferred C-D SPF model relies on likelihood ratio tests and the Akaike information criterion (AIC), where lower AIC values indicate a better model fit (Lai & Huang 2010).

3. Results and discussion

Estimates for the C-D SPF models are presented in Table 2. The two models generate similar results for each of the conventional production inputs – groundnut area ($X1$), labour ($X2$) and seed ($X3$). The coefficients for the conventional inputs are all positive, less than one, and statistically significant at the 1% level. Estimated coefficients for the pooled SPF and TFE are, respectively, 0.298 and 0.328 for groundnut area; 0.169 and 0.170 for labour; and 0.555 and 0.520 for seed. The relative importance of the primary inputs to groundnut production have been well documented by agronomists (CNFA & USAID 2010). Groundnuts are considered a low-input crop that requires relatively little labour to achieve modest yields. Even under adverse growing conditions where other crops may fail, groundnuts tend to produce, so it is an important food security crop (Valentine *et al*. 2016). Notably, groundnut seed weighs most heavily on predicted output, i.e. the partial elasticity of production is greater than groundnut area and labour, with a value exceeding 0.5. Furthermore, the partial elasticities of production for the two most productive inputs (i.e. seed and groundnut area) add up to 0.83. Thus, seeding rate (kg of seed per ha) stands out as a critical factor for predicted groundnut production. We also observe that the average seeding rate for the sample is about a third of the recommended 100 kg/ha. The differential in seeding rates is consistent with the 70% yield gap between the average farmer in the sample and results from agronomic field trials (CNFA & USAID 2010). Even the highest yield in the sample is about half of that from agronomic trials.

Table 2: Cobb-Douglas stochastic production frontier models: Pooled and true fixed effects

SPF	**Pooled**		**True fixed effects (TFE)**	
Variable	Coefficient	*SE*	Coefficient	*SE*
$X1$	0.298***	*0.057*	0.328***	*0.054*
$X2$	0.169***	*0.050*	0.170***	*0.045*
$X3$	0.555***	*0.057*	0.520***	*0.045*
Constant	4.112***	*0.203*	Suppressed	
DIST_1			4.298***	*0.217*
DIST_2			4.145***	*0.195*
DIST_3			4.153***	*0.222*
DIST_4			4.233***	*0.209*
σ_v^2	0.033		0.033	
σ_u^2	0.291		0.276	
$\lambda\ (= \sigma_u/\sigma_v)$	2.975***	*0.110*	2.884***	*0.481*
N	232		232	
Log Likelihood	-90.61		-86.74	
AIC	193.3		191.5	

Note: Standard errors (SEs) clustered at village level in all cases

The sum of the partial elasticities of production, a measure of economies of scale, is 1.02 for both models, suggesting mildly increasing returns (Table 2). However, a Wald test fails to reject the null hypothesis of constant returns to scale (CRS) for both cases, which prevails when the sum of the coefficients is equal to 1. The coefficient of the intercept term is positive and significant (1%) in the pooled SPF model. In the TFE model, the constant is suppressed and each of the district coefficient estimates are significant (1%). The estimated AIC values for the alternative model specifications are 193.3 (pooled) and 191.5 (TFE), so the TFE model is preferred over the pooled specification. Table 2 presents the results for both models and the estimates are consistent. We find no significant differences in the mean TFPI or TE estimates, as well as for maximum and minimum values and standard deviations.

The results for TFPI and TE are summarised in Table 3. The mean TFPI ranges from 0.305 (pooled) to 0.336 (TFE), with a minimum-maximum range of 0.05 to 1.00 (Table 3). These figures indicate that the average farm is about a third as productive as the top farm in the sample. This gap reveals a significant opportunity to expand output through productivity gains. Although very few studies in the region have conducted similar TFP analysis, our results are consistent with recent farm-level estimates for smallholders in three nearby countries – Malawi, Tanzania and Uganda (Julien *et al.* 2019). The findings show that productivity gains can be achieved by increasing TE. For the sample, mean TE ranges from 0.677 (pooled) to 0.682 (TFE). The minimum and maximum values range from 0.354 to 0.926 (pooled) and 0.356 to 0.931 (TFE) between the models. Thus, we find evidence that, under current technology, managerial improvements can play an important role in increasing productivity. Again, these results are in line with values for the region as summarised in available meta-analyses of TE in SSA (Bravo-Ureta *et al.* 2007; Ogundari 2014; Bravo-Ureta *et al.* 2017).

Table 3: Summary of total factor productivity index and technical efficiency estimates

Model	Mean	St. dev.	Min	Max
TFPI				
Pooled	0.305	0.172	0.048	1.000
TFE	0.336	0.188	0.049	1.000
TE				
Pooled	0.677	0.162	0.354	0.926
TFE	0.682	0.160	0.356	0.931

Note: TFPI and TE calculations based on C-D SPF estimates

As discussed, the Wald test supports CRS, so changing the scale of production is expected to have no effect on productivity in this case. On the other hand, an adjustment in the input mix to recommended seeding rates is an important consideration for increasing productivity. Finally, the district fixed effects that account for unobservables have a clear effect on productivity. Hence, the TFE model is not only the preferred option in this study, but also has the advantage of controlling for unobserved heterogeneity at the district level. The net result is a better estimation of the frontier that generates slightly higher TFP and TE estimates.

4. Summary and concluding remarks

Our work uses microlevel data to examine household productivity for groundnut production, an important crop in Mozambique as well as in other sub-Saharan Africa countries. The productivity literature for Mozambique is thin, with no micro-studies found that focus on total factor productivity and very few that examine technical efficiency. Therefore, this paper contributes to the literature by providing productivity analyses for farmers in the Northern region of the country. Estimates from alternative Cobb-Douglas stochastic production frontier models are well behaved, with positive and statistically significant parameters for the conventional inputs (land, labour and seed). We find that seed use has the highest elasticity of production, and this is consistent with the sub-optimal seeding rates observed in the sample. The results from the preferred true fixed effects model reveal a mean total factor productivity index and technical efficiency score equal to 33.6% and 68.2%, respectively. This indicates ample room for productivity growth under current technologies, which can be achieved through improved management. Furthermore, our findings are generally consistent with earlier studies from the region (Bravo-Ureta *et al.* 2007; Ogundari 2014; Bravo-Ureta *et al.* 2017; Julien *et al.* 2019).

The abundance of arable land in Mozambique, along with our empirical findings supporting constant returns to scale, suggests that further analysis of extensification designed to increase domestic output is warranted. Given that 95% of domestic output comes from smallholders, it is possible to achieve meaningful increases in production through smallholder extensification. Furthermore, successful extensification efforts would require complementary measures to intensify production through the adoption of good management practices and technologies.

Groundnut experts have identified several approaches to increase yields in SSA, such as early planting, following recommended seeding rates, additional weeding, adoption of regionally adapted high-yielding drought- and disease-resistant seed varieties, and locally available low-cost soil amendments and pest control. The potential of these various actions is reflected in yield gaps between sample mean and field trials that exceed 70% (CNFA & USAID 2010). A key factor in narrowing this yield gap is the development and implementation of targeted agronomic training for smallholders, including well-designed demonstration and outreach activities. Another essential ingredient to encourage the adoption of productivity-enhancing practices is to adequately fund institutions that support smallholder producers as they seek to upgrade their farming skills and technologies. Groundnuts are a promising crop with the potential to enhance the diversity and productivity of smallholder production portfolios in the face of increasing atmospheric carbon dioxide, while providing essential nutrients to food-insecure households. We find that the potential for agricultural productivity gains among smallholder groundnut farmers in Mozambique is substantial.

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