AfJARE African Journal of Agricultural and Resource Economics

African Journal of Agricultural and Resource Economics Volume 16 Number 2 pages 140-154

Gender-differentiated stochastic meta-frontier analysis of production technology heterogeneity among smallholder cassava farmers in Ghana

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Abstract

This paper assesses the differences in technical efficiency of, and the cassava production systems employed by, male-managed (MMF) and female-managed (FMF) cassava farms in the Fanteakwa District of Ghana. The study employs the translog stochastic meta-frontier model to analyse data obtained from 300 randomly selected smallholder cassava farmers and finds an average meta-frontier technical efficiency (MTE) of 0.06 and 0.03 among MMF and FMF respectively. The technology gap ratios (TGR) are 0.25 and 0.04 for the MMF and FMF respectively. The results suggest that both MMFs and FMFs are technically inefficient. However, the production technology operated on MMFs is relatively superior to that operated on FMFs, as shown by the relatively higher TGR for MMFs. The results also reveal that proximity to markets, extension access, off-farm economic activities and formal education are the major contributors to the technical efficiency of the farmers.

Key words: gender; technical efficiency; cassava; stochastic meta-frontier; Ghana

1. Introduction

Cassava is the fourth most important food crop globally, after maize, rice and wheat, in terms of quantity produced (Food and Agriculture Organization [FAO] 2019). In Africa, it is a source of calories for two-fifth of the population, as it is consumed daily, and at times more than once a day. Cassava is cultivated predominantly by resource-poor smallholder farmers. It is often hailed as an excellent crop for resisting the negative repercussions of climate change. It also serves as a source of income through its sale and processing, thereby helping in the fight against hunger and food insecurity (Mupakati & Tanyanyiwa 2017).

In Ghana, cassava is the most important staple in terms of per capita consumption and calorie intake. According to the new food balance sheet of FAOSTAT, the crop provides 688 kilocalories per capita each day, accounting for about 30% of daily calorie intake (FAO 2019). Furthermore, the crop is cultivated in all 16 regions of Ghana, making it an important food security crop (Ministry of Food and Agriculture [MoFA] 2017). Relative to maize, cassava contributes about 22% to the agricultural gross domestic product (AGDP) and is cultivated by an estimated 70% of smallholder farmers (Poku *et al*. 2018). Although Ghana is Africa's third-largest producer, the current yield of 20 million metric tons per hectare (MT/ha) falls below the country's potential yield of 28 million MT/ha annually (FAO

2018). The low yields have been attributed to inadequate access to improved inputs emanating from credit constraints, low soil fertility and suboptimal farm management practices (Senkoro *et al*. 2018). There is empirical evidence to support the assertion that, when individual characteristics and access to inputs are controlled, female-managed farms (FMF) perform just as well as, and sometimes better than, male-managed farms (MMF) in terms of efficiency in resource use (Dimelu *et al*. 2009; Makombe *et al*. 2011; Koirala *et al*. 2015; Dossah & Mohammed 2016; Oyakhilomen *et al*. 2017; Seymour 2017; Gebre *et al*. 2019). However, evidence of this assertion in Ghana is non-existent. In a World Bank (2009:2) document, entitled *Gender in Agriculture Sourcebook,* it was stated that the "failure to recognize the roles, differences and inequities between men and women poses a serious threat to the effectiveness of the agricultural development agenda". The International Fund for Agricultural Development (IFAD) has also stated that, even though female farmers primarily are contributors to food production and security globally, their roles are most of the time underestimated in developmental strategies. This further highlights the consensus that the lack of attention being paid to gender inequalities, and gender in general, in agricultural development leads to lower productivity, income loss and increased poverty levels. Therefore, understanding the differences in resource-use efficiency between MMF and FMF is imperative for the agricultural development of Ghana. The findings of this study will inform policymakers in the design of gender-specific strategies and policies to boost cassava production in the country. It will also contribute to the discourse on the role of gender in agricultural development and the overall economic development of countries in sub-Saharan Africa (SSA).

This stochastic meta-frontier method was employed to investigate the technical efficiency and technological differences between MMF and FMF in Ghana. A meta-production function, as described by Hayami (1969), is an envelope of all individual production functions. The approach allows the estimation of technology gap ratios (TGRs), which show how far or how close the individual production technologies are to the best possible production technology (the meta-frontier) (Villano *et al*. 2010).

The rest of the paper is organised as follows: Section 2 presents the methods and comprises an overview of the stochastic meta-frontier approach, the empirical models, and the data sources; while section 3 presents a discussion of the results. The paper ends with conclusions and the policy implications of the results.

2. Methods and data

2.1 Analytical framework

The stochastic meta-frontier relaxes the assumption that firms in an industry face the same production technology. It therefore allows a formal statistical test (likelihood ratio test) to ascertain whether there are any technological differences.

Assuming *n* firms (I = 1, 2…n), each with an input vector, X_i, and a vector of unknown parameters, β, then a conventional stochastic frontier with cross-sectional data is given by (Battese *et al*. 2004):

$$Y_i = f(x_i, \beta)\exp\,(v_i - u_i), \tag{1}$$

where Y_i is the yield of the ith firm and $(v_i - u_i)$ is a composite error term, with V_i representing white noise (the stochastic error term) and u_i being a one-sided error representing the firm's technical inefficiency. Both $v_i \sim iidN(0, \sigma_v^2)$ and $u_i \sim iidN^+(0, \sigma_u^2)$ are assumed to be independent of each other. Equation (1) is used to estimate the technical efficiency (TE) of each firm, with the assumption that all the firms use a similar production technology and/or operate in the same environment (Orea

& Kumbhakar 2004). Such an assumption ignores the possible presence of any technology difference and so clouds the actual differences in technical efficiencies.

Representing gender as j, and following Moreira and Bravo-Ureta (2009), a gender-differentiated stochastic frontier is defined as:

$$Y_i^j = f^j\left(x_i^j, \beta_i^j\right)\exp\left(v_i^j - u_i^j\right) \quad \forall i = 1, 2, \dots, n \text{ and } j = 1, 2, \tag{2}$$

where Y_i^j represents the yield of ith firm operated by the jth gender, and x_i^j is the vector of inputs of the ith firm, operated by the jth gender. As stated above, $v_i^j \sim N(0, \sigma_{v_j}^2)$, while $u_i^j \sim N^+\left(0, \sigma_{u_j}^2\left(Z_i^j\right)\right)$. u_i^j also represents a non-negative unobservable random error connected with the ith firm's technical inefficiency, with Z_i^j representing the determinants of technical inefficiency (Battese *et al*. 2004); and β_i^j represents the vector of unknown parameters to be estimated for the ith firm operated by the jth gender. The TE of firm *i* relative to the jth gender is given by O'Donnell *et al*. (2008):

$$TE_i^j = \frac{Y_i^j}{f^j\left(x_i^j, \beta^j\right)\exp\left(v_i^j\right)} = \frac{f^j\left(x_i^j, \beta^j\right)\exp\left(-u_i^j\right)}{f^j\left(x_i^j, \beta^j\right)} = \exp\left(-u_i^j\right). \tag{3}$$

Following Huang *et al*. (2014), the stochastic meta-frontier function, represented by MM' in Figure 1, envelopes all the production frontiers of the J gender. It is given by:

$$\hat{f}^j\left(x_i^j, \beta^j\right) = f^M\left(x_i^M, \beta^M\right)\exp\left(-u_{ij}^M\right), \quad \forall\ j, i, \tag{4}$$

where u_{ij}^M is non-negative, while subscript M represents "meta-frontier".

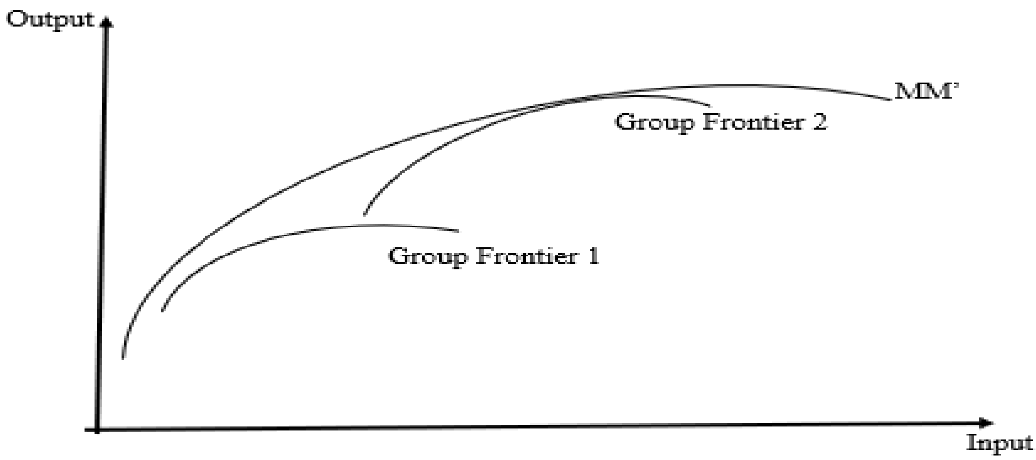

Figure 1: Meta-frontier production model
Adapted from Wang *et al.* (2013)

In equation (4), $\hat{f}^j\left(x_i^j, \beta^j\right)$ is obtained by stacking the vectors of the gender-specific frontiers. Given input level x_i^j, the meta-technical efficiency (MTE) of the ith firm operated by the jth gender, that is the observed yield Y_i^j of the ith firm in relation to the meta-frontier, comprises three components (Huang *et al*. 2014):

$$MTE_i = \frac{Y_i^j}{f^M\left(x_i^j \beta^j\right)} = TGR_i^j \times TE_i^j \times \exp\left(v_i^M\right), \tag{5}$$

where TGR_i^j is the technology gap ratio, TE_i^j is the firm's TE, and $\exp(v_i^M)$ is the random noise of the meta-frontier.

The gender-specific TGR is computed from the ratio of the gender-specific frontier and the meta-frontier (Huang *et al*. 2014). That is:

$$TGR_i^j = \frac{f^j\left(x_i^j, \beta^j\right)}{f^M\left(x_i^j \beta^j\right)}, \tag{6}$$

where $0 \leq TGR_i^j \leq 1$. The technology gap arises from the technology choice and therefore is both gender- and firm-specific (Huang *et al*. 2014).

The meta-frontier is estimated in two steps. First, a group-specific frontier (i.e. Equation (7)) is estimated, and then estimates from the J groups are pooled or stacked to estimate the meta-frontier (i.e. Equation (8)).

$$lnY_i^j = f^j\left(x_i^j, \beta^j\right) + v_i^j - u_i^j \quad \forall i = 1, 2, \ldots, N_j \tag{7}$$

$$ln\hat{f}^j\left(x_i^j, \beta^j\right) = f^M\left(x_i^j, \beta\right) + v_i^M - u_i^M, \ \forall i = 1, 2, \ldots, J \tag{8}$$

2.2 Empirical model

Following Alem *et al*. (2019), a translog stochastic production function was used to estimate cassava farmers' technical efficiency:

$$lnY_i^j = \beta_0^j + \sum_{k=1}^{5} \beta_k^j \, lnx_{ik}^j + 0.5 \sum_{k=1}^{5} \beta_{kk}^j \, (lnx_{ik}^j)^2 + \sum_{k=1}^{5} \sum_{l=2}^{5} \beta_{kl}^j lnx_{ik}^j lnx_{il}^j + (\, v_i^j - u_i^j) \tag{9}$$

lnY_i^j is the natural log of cassava yield produced by farmer i of the jth gender, measured in kilograms per hectare; x_{ik}^j is a vector of k inputs (i.e. labour, seed, weedicides and pesticides) used by farmer i of the jth gender. As before, βs are the parameters to be estimated, v_i^j represents the stochastic error term, assumed to be *i.i.d.* normal (i.e. $v_i^j \sim N(0, \sigma_v^{2j})$), while u_i^j is a one-sided error that denotes farmer i's technical inefficiency of the jth gender and is distributed as $u_i^j \sim N^+\left(0, \sigma_u^{2j}\left(Z_i^j\right)\right)$, with Z_i^j representing the determinants of technical inefficiency.

The inefficiency model is specified as:

$$u_i^j = \delta_0 + \sum_{k=1}^{5} \delta_k \, Z_{ik}^j, \tag{10}$$

where μ_i is the inefficiency component of the stochastic frontier and the Zs represent the vector of farm-level, socioeconomic and institutional factors hypothesised to influence inefficiency, and δ the vector of unknown parameters to be estimated. The variables incorporated in this model include household size, education, experience in cultivation, income from off-farm economic activity, credit access, extension access, distance to the nearest market, membership of a farmer-based organisation, and land tenure system.

2.3 Data sources

2.3.1 Study area

This study was conducted in the Fanteakwa District in the Eastern region of Ghana. The district is located at longitude 0°10’ East and latitude 6°15’ North. The vegetation comprises savanna scrub and wet semi-deciduous rain forests, with bimodal rainfall. The mean annual rainfall varies between 1 500 mm and 2 000 mm, while the population of the district is about 121 714 people (Ghana Statistical Service (GSS) 2013). The district is primarily agrarian, with more than 50% of the population engaged in crop farming. Cassava is one of the staples in the area, with over 50% of the population engaged in its cultivation (GSS 2013).

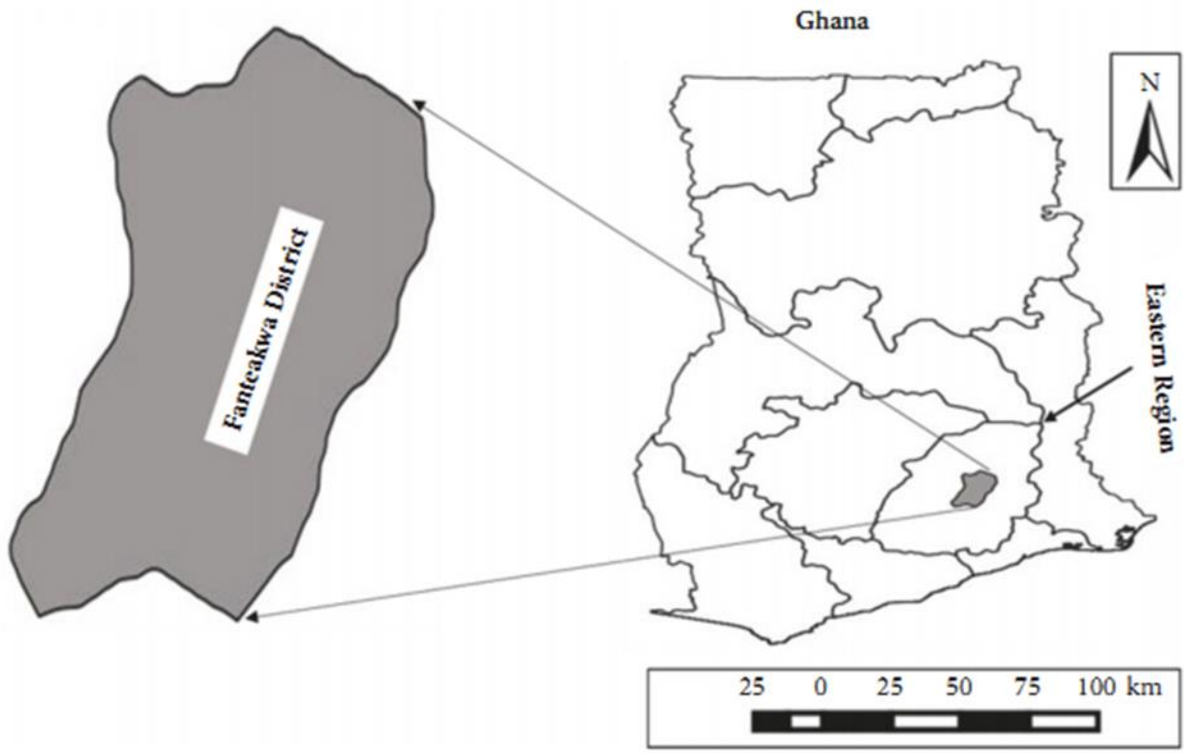

Figure 2: A map of Ghana showing the location of Fanteakwa District

2.3.2 Data and sampling procedure

Primary data was collected on farmers’ socio-economic and farm-specific characteristics, such as age, gender, education, household size, farm size, output and input quantities, extension access, land tenure system, membership of farmer-based organisations (FBOs), engagement in off-farm economic activities, and experience in cassava cultivation. The direct elicitation method of data collection was employed. Accordingly, semi-structured interviews were conducted with the help of agricultural extension agents, who served as enumerators. The questionnaires were designed on the basis of the literature, thus all information required for the survey was captured.

The study used a multistage sampling technique to obtain the sample. The first stage was a purposive selection of five cassava-producing communities in the Fanteakwa District, namely Ahomahomasu, Obuoho, Feyiase, Akoradarko and Begoro. This was done following information obtained from the agricultural extension office of the Fanteakwa District assembly. A list of smallholder cassava farmers in each of the five communities was then acquired from the district office. In the second stage, a simple random sampling technique was used in each of the five communities using the list as a sampling frame. The random selection of the farmers was carried out using the random numbers technique. In this technique, random numbers are assigned to each farmer on the list, and the first 60 cassava farmers are selected. This was done for each of the five communities. Potential data problems, such as incomplete questionnaires and missing data, were catered for by selecting five additional respondents in each community to arrive at a total of 325 respondents. After data cleaning, the final sample size used for analysis was 300 smallholder cassava farmers.

2.4 Hypothesis testing

The study tested three hypotheses. The first one was used in the choice of the functional forms of the production function. The null hypothesis was that the coefficients of the interaction variables in the translog production function are zero (i.e. $H_0: \beta_{jk} = 0$), so that the best specification is the Cobb-Douglas production function. The generalised likelihood ratio test rejected the null hypothesis ($df = 14$; $p < 0.05$), implying that the translog was the most appropriate functional form for each gender category, as well as for the pooled sample.

The second hypothesis tested for the presence of inefficiency in the gender-differentiated models, as well as in the pooled model. The null hypothesis for absence of technical inefficiency was stated as $H_0: \gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \cdots = \delta_n = 0$. The generalised likelihood ratio test could not sustain the null hypothesis ($df = 20$ and $p < 0.05$), implying the presence of inefficiency effects in the models. The final hypothesis tested whether or not the two groups of cassava farmers operated the same cassava-production technology. The generalised likelihood ratio test rejected the null hypothesis that the two groups operated the same technology ($p < 0.05$). This implies that the stochastic frontier for the pooled model would not be appropriate to compare the technical efficiencies of the two groups, thereby justifying the meta-frontier approach.

3. Results and discussion

3.1 Descriptive statistics

Of the 300 smallholder cassava farms, 217 (or 72.3%) were male-managed. This suggests that cassava farming in Fanteakwa District is male-dominated. About two-thirds of the farmers had attained at least primary formal education, with the rest having no formal education. The average age of the MMFs was 44 years, against 42 years for the FMFs. However, the average income from non-farm economic activities was approximately 986 Ghana cedis (~USD 197) for FMFs compared to 445 Ghana cedis (~USD 89) for MMFs, producing a mean difference of 541 Ghana cedis (~USD 108) ($p < 0.01$). This suggests that non-farm economic activities are more lucrative for females than they are for males.

The average farm size cultivated by MMF and FMF was 3.8 and 3.3 acres respectively, with no statistically significant differences between them. Furthermore, in terms of institutional factors such as credit access, extension access and membership of FBOs, there were no statistically significant differences between MMF and FMF in the Fanteakwa District. However, on average, FMF live relatively closer to market areas (2.8 km) compared to MMF, who on average live 5.9 km from market areas ($p < 0.01$). The mean cassava yield was significantly different between the MMF and FMF ($p < 0.05$). In the same light, there were significant differences in the quantities of inputs used by the MMF and FMF on average ($p < 0.1$).

Table 1: Summary statistics of socio-demographic characteristics

Variable	Pooled	MMF (n = 217)	FMF (n = 83)	Mean difference	Test statistic
Socio-demographic data					
Household size (number of members)	4.80 (0.12)	4.86 (0.15)	4.62 (0.25)	-0.24 (0.28)	-0.82^{t}
Education (years)	6.12 (0.27)	6.27 (0.33)	5.71 (0.49)	-0.57 (0.61)	-0.92^{t}
Experience (years)	10.61 (0.44)	11.16 (0.57)	9.16 (0.57)	-2.00 (0.98)	-2.05^{t}**
Income (Ghana cedis)	595.23 (36.33)	445.51 (26.94)	986.68 (99.07)	541.17 (75.06)	7.21^{t}***
Age (years)	44.00 (0.60)	44.41 (0.75)	42.94 (0.97)	-1.47 (1.35)	-1.09^{t}
Farm-specific characteristics					
Yield (kg/ha)	1 855.41 (90.45)	1 949.13 (111.53)	1 610.37 (145.46)	-338.75 (201.58)	-1.68^{t}**
Farm size (acres)	3.64 (0.16)	3.77 (0.20)	3.27 (0.28)	-0.51 (0.36)	-1.40^{t}*
Institutional factors					
[d] Land tenure					
Secure	81.00	54.00	27.00		1.74^{x}
Insecure	219.00	163.00	56.00		
[d] Credit access					
Yes	126	96.0	30.0		1.63^{x}
No	174	121.0	53.0		
Institutional factors					
[d] Extension access					
Yes	130.00	76.00	54.00		22.07^{x}***
No	170.00	141.00	29.00		
[d] FBO membership					
Yes	114.00	74.00	40.00		4.98^{x}**
No	186.00	143.00	43.00		
Market access (km)	4.48 (0.12)	4.69 (0.14)	3.95 (0.19)	-0.73 (0.26)	-2.85^{x}***

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$; ^{t} t-statistic; ^{x} Chi-square statistic; Standard errors in parentheses. [d] Dummy variable
Source: Survey data (2019)

3.2 Gender-differentiated translog stochastic frontier estimates

Table 2 presents the maximum likelihood (ML) estimates of the gender-specific translog production functions for cassava farmers in the Fanteakwa District of Ghana. According to Dawson (1990), the frontier estimates only help in the calculation of the measures of technical efficiency (TE). Therefore, the predictive power of the model should be considered, rather than the frontier estimates, if the main aim is to measure TE (Wilson *et al*. 1998; Otieno *et al*. 2011). On that note, the discussion of the frontier estimates will be brief. Lambda is significantly different from zero in all the models, suggesting that the recorded variations in yield are not as a result of randomness and unobserved heterogeneities, but due to farmers' inefficiencies in resource use.

In the MMF model, the output elasticities are positive and statistically significant, except for pesticide, which is negative and statistically insignificant. The positive output elasticities are consistent with the production regularity condition of monotonicity (Sauer *et al*. 2006; Moreira & Bravo-Ureta 2010), and imply that a 1% increase (decrease) in the quantity of one input, *ceteris paribus*, will increase (decrease) yield by the magnitude of the output elasticity. For instance, the elasticity of yield to *Seed* (cassava stem cuttings) is 0.50, and is the largest contributor to cassava yield. Accordingly, a 1% increase in the current level of labour will lead to a 0.50% increase in cassava yield.

Table 2: ML estimates of translog stochastic frontier models for MMFs and FMFs

Variable	MMF model		FMF model		Pooled model	
	Coef.	Z-statistic	Coef.	Z-statistic	Coef.	Z-statistic
Pesticides	-0.01 (0.10)	-0.05	0.19 (0.24)	0.77	-0.02 (0.08)	-0.05
Weedicides	0.31 (0.40)	2.22**	0.40 (0.25)	1.64	0.41 (0.13)	2.22***
Labour	0.38 (0.14)	2.60***	-0.25 (0.23)	-1.10	0.23 (0.13)	2.60*
Seed	0.50 (0.11)	4.55***	0.34 (0.16)	2.15**	0.46 (0.09)	4.55***
Labor2	1.78 (0.46)	3.89***	-0.09 (0.48)	-0.19	1.41 (0.38)	3.89***
Seed2	0.38 (0.23)	1.64	0.20 (0.27)	0.72	0.39 (0.19)	1.64**
Pest2	-0.06 (0.13)	-0.42	0.41 (0.51)	0.81	-0.01 (0.13)	-0.42
Weeds2	1.43 (0.43)	3.37***	-0.15 (0.67)	-0.22***	1.41 (0.37)	3.37***
SeedxLabour	-0.56 (0.36)	-1.58	-0.89 (0.64)	-1.37	-0.63 (0.32)	-1.58**
SeedxPesticides	0.78 (0.28)	2.75***	-0.45 (0.34)	-1.35	0.51 (0.24)	2.75**
PestxLabour	1.40 (0.47)	2.99***	0.53 (0.83)	0.64	1.21 (0.37)	2.99***
WeedsxLabour	-1.06 (0.57)	-1.86*	-2.06 (0.98)	-2.10**	-1.11 (0.59)	-1.86*
WeedsxSeed	-0.62 (0.40)	-1.56	-1.43 (0.80)	-1.78*	-0.77 (0.37)	-1.56**
WeedsxPest	-0.14 (0.44)	-0.32	1.84 (0.87)	2.13**	0.06 (0.36)	-0.32
Constant	1.88 (0.23)	8.15***	0.37 (0.10)	3.81***	1.50 (0.22)	8.15***
Lambda	0.24***		0.33***		0.14***	
Log-likelihood	-172.45		-45.50		-251.34	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$; Robust standard errors are in parentheses
Source: Survey data (2019)

In the FMF model, *Seed* (cassava stem cuttings) is the second-largest and the only statistically significant contributor to cassava yield, with an estimated elasticity of 0.34. The implication is that a 1% increase in the current levels of cassava stem cuttings employed by FMFs will lead to a 0.34% increase in yields. It points to the fact that stem cuttings are fundamental to cassava production for both groups. Surprisingly, the elasticity of yield to labour is negative in the FMF model, suggesting that a 1% increase in the quantity of labour employed by FMFs will cause yields to fall by 0.25%, although it is statistically insignificant. Labour is the second-largest contributor to cassava yield among MMFs, with an elasticity of 0.38. This implies that a 1% increase in the current level of labour employed by MMFs will lead to an increase of about 0.38% in yields. The positive contributions of labour and seed to cassava yield in this study is similar to the findings of Ali *et al*. (2019) and Danso-Abbeam and Baiyegunhi (2020). The fact that some inputs are statistically significant in one model and insignificant in the other is also an indication that resource use varies across the two groups (MMF and FMF) and confirms the possibility of different production technologies.

The second-order terms (interaction terms) represent the second-order derivatives of the translog production function. A positive coefficient suggests incremental changes in the marginal physical product (MPP) with every 1% increase in factor levels and vice versa, *ceteris paribus* (Bai *et al*. 2019). The result shows the squared term of labour (*Labor2)* to be positive and statistically significant ($p < 0.01$) in the MMF model, but negative and statistically insignificant in the FMF model (Table 2). The implication is that the current level of labour employed by MMF is sub-optimal. In production theory, MMF would be said to be operating in stage I, where the MPP of labour is still rising. Therefore, it is advisable for MMF to increase the units of labour they employ, *ceteris paribus*. In the rural parts of Ghana, the primary source of labour for smallholder farmers is their family members. They could increase the level of labour by hiring from outside the household.

The second-order derivative for weedicides (*Weeds2*) is positive in the MMF model ($p < 0.01$). However, it is negative and statistically significant in the model for FMF ($p < 0.01$) (Table 2). The positive coefficient suggests that the MPP of weedicides will continue to rise with every 1% increase in weedicide levels; therefore, it is wise for MMF to increase their use of weedicides, *ceteris paribus.* The negative coefficient of *Weeds2* in the FMF model suggests that the MPP weedicides will fall with every additional unit they employ. thereby having detrimental effects on total cassava yield. This suggests that FMFs are overusing or incorrectly applying weedicides, and could be due to the low access to agricultural extension services among FMF (Table 1). Extension agents are the primary source of information on and training in new agricultural technologies in the district; therefore, inadequate access to such information may lead to the misapplication or misuse of such technologies.

3.3 Technical efficiency and technology gap ratio for cassava farmers

The technology gap ratios were calculated with equation (6) using the estimated TE scores. The results are presented in Table 3. A higher TGR implies a smaller gap between the gender-specific production system and the meta-frontier, and vice versa. A TGR of 1.00 suggests that the frontier of the individual groups lies on the meta-frontier, therefore the best possible technology available (Ng'ombe 2017).

Table 3: Gender-differentiated technical efficiency and technology gap ratios

Group	Variable	Mean	Standard deviation	Minimum	Maximum
MMF	TE	0.23	0.07	0.13	0.53
	TGR	0.25	0.05	0.17	0.39
	MTE*	0.06	0.02	0.03	0.15
FMF	TE	0.92	0.17	0.28	0.99
	TGR	0.04	0.05	-0.07	0.17
	MTE*	0.03	0.04	-0.06	0.17
Pooled	TE	0.32	0.08	0.16	0.64

TE is technical efficiency based on the group-specific technology; TGR is the technology-gap ratio; MTE* presents the TGR-corrected technical efficiency/meta-technical efficiency
Source: Survey data (2019)

The overall mean TE, irrespective of gender, is 0.32. This suggests that cassava farmers in the district are currently producing only 32% of the potential output given the input levels, and could increase their yield by 68% without changing the input quantities. However, the gender-differentiated TE scores show that FMFs are more technically efficient compared to MMFs, with average technical efficiencies of 0.92 and 0.23 respectively (Table 3). This means that, on average, FMFs produce 92% of their potential yield, depicting a relatively more efficient use of resources compared to MMFs, who are able to produce only 23% of the potential yield. These figures, however, fail to paint an accurate picture of the technical efficiencies of the two groups, since the underlying assumption in their calculation is that both groups are using the same production system and/or have the same environmental conditions. These findings contradict those of Danso-Abbeam *et al*. (2020), who studied the gender differentials in technical efficiency of cocoa farmers in Ghana and found that female-managed plots were on average less technically efficient compared to male-managed cocoa farms. They attributed the variations observed in the technical efficiencies to differences in resource endowments. Similarly, this result is contrary to that of Gebre *et al*. (2019), who studied the effect of gender differences on the technical efficiency of maize farmers in Southern Ethiopia and found that male farmers are relatively more productive than female farmers.

As can be seen from Table 3, the average TGR for MMFs is 0.25, while it is 0.04 for FMFs. This suggests that the efficacy of the production technology employed by MMFs is 25% compared to the best possible cassava production technology, and that of the FMFs is 4% when juxtaposed with the meta-frontier. The implication is that the production system operated by MMFs is superior to that of the FMFs. Therefore, the TGR-corrected technical efficiencies (i.e. meta-technical efficiency [MTE*]) of the two groups show the performance of each group's production system relative to the best possible production system (meta-frontier). The results show that, given the specific production system employed by MMFs, they are producing only 6% of their potential yield. The implication here is that they are technically inefficient in relation to the meta-frontier. Similarly, FMFs are able to produce only 3% of their potential yield given their specific cassava-production technology (Table 3). This also means that they are technically inefficient in terms of the meta-frontier. A possible explanation for the low technical efficiencies observed in this study is that farmers are also engaged in the cultivation of other crops, thus are diverting their already scarce resource of time and/or financial resources that could otherwise be invested in cassava cultivation. The picture this paints is that, in terms of resource use, FMFs are relatively more efficient; however, their efficiency is limited by the production technology they employ. This further supports the point that female-managed farms are just as good as, and sometimes better than, male-managed farms in terms of resource-use efficiency.

3.4 Pairwise comparisons of mean TGRs

Table 4 presents a pairwise comparison of the mean technology gap ratios of MMFs and FMFs across the five selected communities. The goal of this comparison is to check whether there are any differences in the production systems within each group. Among FMFs, the statistically significant differences are recorded between Feyiase and Ahomahomasu, Feyiase and Obuoho, Feyiase and Begoro, and Feyiase and Akoradarko. This result indicates that the technology employed by MMFs in Feyiase is significantly superior, by 6%, to that employed by MMFs in Ahomahomasu. Compared to those at Obuoho, the difference is 75. A similar result is obtained from the comparisons among FMF. The results reveal that the technology employed by FMFs in Feyiase is 7% superior to that of FMFs in Ahomahomaso.

Table 4: Pairwise comparison of mean technology gap ratios by farm location

Comparison	MMF		FMF	
	Contrast	Scheffe test	Contrast	Scheffe test
Obuoho vs. Ahomahomasu	-0.00	-0.10	0.01	0.66
Begoro vs. Ahomahomasu	-0.01	-1.54	-0.01	-0.91
Feyiase vs. Ahomahomasu	0.06	6.72***	0.07	5.18***
Akoradarko vs. Ahomahomasu	0.01	1.12	0.02	1.74
Begoro vs. Obuoho	-0.01	-1.53	-0.02	-1.39
Feyiase vs. Obuoho	0.06	7.26***	0.06	3.91***
Akoradarko vs. Obuoho	0.01	1.29	0.01	0.87
Feyiase vs. Begoro	0.07	8.77***	0.08	5.37***
Akoradarko vs. Begoro	0.02	2.78	0.03	2.37
Akoradarko vs. Feyiase	-0.05	-5.79***	-0.04	-3.32**

Notes: *** $p < 0.01$; ** $p < 0.05$
Source: Survey data (2019)

The differences observed in the TGRs point to the fact that the location of the farm has significant influence on the technical efficiencies of the farmers. The heterogeneities observed may be ascribed to the differences in climatic and edaphic factors, and farm management practices. These findings corroborate those of Kuwornu *et al*. (2013) and Ng'ombe (2017).

3.5 Factors influencing technical inefficiency

Table 5 summarises the factors that influence the technical inefficiency of the cassava farmers in the Fanteakwa District. In the MMF model, all the regressors met the *a priori* expectations, except for experience (proxy for age of the farmer). Furthermore, only the coefficients of extension access and distance to market centres were statistically significant at the 1% level. The coefficient of extension access was negative, which implies that access to agricultural extension services leads to a reduction in the farmers' technical inefficiency. This finding is intuitive, since agricultural extension agents are one of the primary sources of information for farmers, particularly in the rural parts of Ghana, as far as new and improved agricultural technologies are concerned. Extension agents provide training and guidance for farmers on the best farm management practices. Therefore, farmers who are in constant touch with agents tend to be more efficient in their resource use. This finding is consistent with that of Addai and Owusu (2014), who found that access to extensions services improves the technical efficiency of smallholder maize farmers in Ghana. It is also in line with the findings of Ali *et al*. (2019), who reported that extension services positively affect the technical efficiency of hybrid maize growers in Pakistan.

Table 5: Determinants of farmers' technical inefficiency

Variable	**MMF model**		**FMF model**		**Pooled model**	
Socio-demographic factors	Coef.	Z-stat	Coef.	Z-stat	Coef.	Z-stat
Household size	-0.11 (0.09)	-1.27*	0.42 (0.33)	1.27	-0.13 (0.07)	-1.78*
Education (1 = Yes)	-0.02 (0.08)	-0.24	-1.33 (0.42)	-3.20	0.16 (0.07)	-2.29**
Experience	0.06 (0.05)	1.25	-0.03 (0.31)	-0.09	-0.01 (0.05)	-0.12
Off-farm income	-0.05 (0.04)	-1.17	0.44 (0.22)	1.98**	-0.03 (0.04)	-0.74
Institutional factors						
Credit access (1 = Yes)	-0.08 (0.07)	-1.04	0.76 (0.54)	1.39	-0.04 (0.07)	-0.67
Extension access (1 = Yes)	-0.24 (0.10)	-2.47***	-2.15 (0.48)	-4.51***	-0.20 (0.08)	-2.50***
Distance to market	0.40 (0.10)	3.93***	0.78 (0.40)	2.16**	0.35 (0.09)	3.94***
Group membership (1 = Yes)	-0.08 (0.09)	-0.95	-0.26 (0.24)	-1.07	0.02 (0.08)	0.26
Land tenure (1 = Secure)	-0.05 (0.09)	-0.48	-0.03 (0.31)	-0.09	-0.13 (0.08)	-1.73*
Constant	1.42 (0.30)	-34.83***	-3.45 (0.70)	-5.70**	1.34 (0.30)	4.47***

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Robust standard errors are in parentheses
Source: Survey data (2019)

The coefficient of *distance to market* is positive in the MMF model. The connotation is that farms in close proximity to market centres are relatively more technically efficient. In other words, the further away an MMF is from the market centre, the less technically efficient the farm is. This may be attributed to the fact that farmers in close proximity to market centres have the advantage of easy and timely access to essential inputs, all other factors held constant. On the other hand, farmers staying further from the market centres may incur extra costs in acquiring certain inputs, which may deter these farmers from making such investments, thereby affecting their technical efficiency. This finding is consistent with that of Musa *et al*. (2015). They found that proximity to market areas significantly improved the technical efficiency of maize farmers in Ethiopia.

In the FMF model however, all covariates met their respective *a priori* expectations, with the exception of *household size*, *income from off-farm economic activities*, and *credit access*. Furthermore, only the coefficients of *extension access* and *distance to market centres* were statistically significant in the MMF model, at the 1% level. Furthermore, access to agricultural extension services was negative and statistically significant at 1%. This means that extension access significantly improves the technical efficiency of FMFs. Similarly, proximity to market centre significantly improves the technical efficiency.

The coefficient of off-farm income was positive and statistically significant at the 5% level. This means that female cassava farmers who engage in off-farm economic activities are relatively more technically inefficient. This result is surprising, since a number of studies have reported that engagement in off-farm economic activities provides farmers with extra sources of income, which aid their adoption of new productivity-enhancing technologies (Zhang *et al*. 2016; Ahmed & Melesse 2018; Danso-Abbeam *et al*. 2020). The positive relationship observed between off-farm income and the technical inefficiency of FMFs may be attributed to the fact that off-farm economic activities also require time resources and, according to utility maximisation theory, individuals are more likely to invest their time resources in activities that reap the highest returns. Therefore, the more income women obtain from off-farm economic activities, the more time and effort they would apportion to such activities. Eventually, less time and effort are invested in the cassava farm, making them relatively more technically inefficient (less technically efficient).

4. Conclusions

This study sought to compare the cassava production technologies and technical efficiency of male- and female-managed cassava farms. This is of relevance, since cassava as crop has the potential to propel households out of food insecurity and poverty and identifying such differences would inform policy makers in the formulation of agricultural policies targeted at enhancing productivity. Using the stochastic meta-frontier approach, we observed that MMF and FMF operate different production technologies and that there are significant differences in their technical efficiency and technology gap ratios. Using the TGR-corrected technical efficiency scores, both groups were found to be technically inefficient. However, MMFs have an average TE of 23% compared to that of FMFs, even though the former have a relatively higher TGR. The results further suggest that, irrespective of gender, farmers operated sub-optimally given the meta-frontier. The average TE score given by the meta-frontier is 88%. The implication of this is that yield could be increased by 12% without making changes to the quantities of the input – if farmers employed the best possible production technology. Among MMFs, membership in farmer groups is beneficial to their resource-use efficiencies. Among FMFs, formal education, experience in cassava cultivation, access to credit, proximity to market and secure land tenure are the major contributing factors to their resource-use efficiency. Furthermore, the cassava production systems vary in both groups of farmers across the five selected communities in the study.

5. Policy implications

The findings of this study have implications for policy. Firstly, the results show that the farmers are technically inefficient. There is a need for farmers' attention to be drawn to their inefficiencies. Sensitisation of farmers on efficient cassava cultivation practices therefore is imperative if productivity is to be enhanced. The Ministry of Food and Agriculture, through the Farmer-based Organisations Secretariat, should organise training workshops for cassava farmers, educating them on the best cassava production practices and efficiency-enhancing technologies. Secondly, the fact that FMFs have relatively higher technical efficiency but lower TGR is an indication that FMFs require relatively more attention regarding cassava production technologies. There is a need for more gender-tailored, wholistic training programmes on cassava production systems. The right production system with higher technical efficiency will lead to the much-needed enhancement in cassava productivity. With that, socioeconomic barriers that are gender-related could be addressed by implementing policies that promote gender equality in terms of access to economic resources, particularly credit, and agricultural information to help boost women's efficiency in cassava cultivation. Also, considering the fact that cassava stem cuttings contribute immensely to yield, the study recommends the reinforcement of programmes such as the Planting for Food and Jobs (PFJ) programme and the West Africa Agricultural Productivity Programme (WAAPP) to enhance farmers' access to improved seeds. In addition, the scope and mode of delivery of extension services, particularly in rural areas, should be enhanced to accelerate technology adoption among rural female smallholder cassava producers.

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