



Research article

Gender differentials in technical efficiency of Ghanaian cocoa farms

Gideon Danso-Abbeam^{a,b,c,*}, Lloyd J.S. Baiyegunhi^c, Temitope O. Ojo^{d,e}^a Department of Agricultural and Resource Economics, University for Development Studies, Tamale, Ghana^b African Centre for Crop Improvement, University of KwaZulu-Natal, Pietermaritzburg, South Africa^c Discipline of Agricultural Economics, University of KwaZulu-Natal, Pietermaritzburg, South Africa^d Department of Agricultural Economics, Obafemi Awolowo University, Nigeria^e Disaster Management Training and Education Centre for Africa, University of the Free State, Bloemfontein, South Africa

ARTICLE INFO

Keywords:

Cocoa
Gender decomposition
Neumark approach
Technical efficiency
Double-bootstrapped DEA procedure
Agricultural economics
Agricultural policy
Agricultural technology
Environmental economics
Economics

ABSTRACT

This study considers the presence of a gender gap in technical efficiency in Ghana's cocoa production sector. The two-stage double bootstrap data envelopment analysis (DEA) procedure was applied to estimate the bias-corrected technical efficiency scores for male and female cocoa farm managers. The results indicate that there is a potential for male and female cocoa farm managers to increase output without altering the quantities of inputs employed. Applying the extended version of the Blinder-Oaxaca (B-O) decomposition approach, the findings suggest that female plot managers are, on average, less technically efficient compared to their male counterparts. This gap could be linked to differences in their resource endowments. Nevertheless, there are still significant unobservable factors that contribute to the gender efficiency gap. A comprehensive decomposition examination indicates that differences in educational attainment, engagement in non-farm activities, and farm size may contribute to the unexplained technical efficiency gap. The study recommends that female-sensitive programmes that seek to encourage the participation of non-farm activities and provide access to education and land utilization are essential in reducing the gender gap in technical efficiency.

1. Introduction

Cocoa production is a vital industry not only for producing countries but for the economy of the consuming nations. The crop contributes significantly to foreign exchange earnings of the economies of Ghana, Ivory Coast, Nigeria, and Cameroon. Cocoa is estimated to contribute to about 60–90% of the income of producers in West and Central Africa. Africa supplies about 76% of the global cocoa output with Cote d'Ivoire and Ghana, producing about 36–42% and 18–21%, respectively, over the last decade (International Cocoa Organization (ICCO), 2017). Moreover, cocoa provides livelihoods for the other sectors (e.g., manufacturing and services) of the world economy.

In Ghana, cocoa production is critical for macroeconomic balances and is tied to the livelihoods of many people. Ghana's cocoa sector contributes about 1.8% to GDP and provides a source of livelihoods to nearly four million households (Ghana Statistical Service [GSS], 2018). The crop is a principal contributor (about 80%) to the country's agricultural export (Institute of Statistical, Social and Economic Research (ISSER), 2017). Irrespective of the significant contributions of the cocoa sector to the Ghanaian economy, the production of cocoa is threatened by lots of

challenges, among which are small farm holdings and low productivity. The yield of cocoa in Ghana is low compared to other cocoa-producing countries like Cote d'Ivoire and Brazil (International Cocoa Organization (ICCO), 2017). Ghanaian cocoa farmers operate on small-scale, family-run farms of about 2–4 ha, with an average yield of 250 kg/ha – 478 kg/ha compared with prospective productivity of about 1000 kg/ha (International Institute of Tropical Agriculture (IITA) 2009; World Cocoa Foundation (WCF) 2014; International Cocoa Organization (ICCO) 2017). Other challenges in the industry include declining soil nutrients, high incidence of pests and diseases, inadequate financial capital, weak institutions, and poor access to information on good agronomic practices. Nevertheless, it is doubtful that these are the only factors that contribute to low productivity of cocoa farms in Ghana. One of the keys, yet unrecognized and undervalued in most constraint analyses in Ghana's cocoa sector is the differences in gender productivity.

Women contribute significantly to the amount and quality of cocoa produced in West Africa. They are involved in a wide-ranging of production activities spanning from the sowing of seeds to the carting of cocoa beans from the farm to the drying spot. The World Cocoa Foundation and KIT (2017) reports that wives of cocoa farmers are actively

* Corresponding author.

E-mail addresses: dansoabbeam@uds.edu.gh, dansoabbeamG@ukzn.ac.za (G. Danso-Abbeam).

involved in 12 of 19 critical stages in cocoa production. Unfortunately, men take charge of the income when the crop enters into the high-valued export market. Women not only contribute to the labour force but own cocoa farms as well. In Ghana and Cote d'Ivoire, 25% of cocoa farmers are women and contribute to about 68% of the labour force in the industry (African Development Bank, 2015). Apart from the dwindling supply of cocoa in West Africa, the quality level is one of the critical challenges to industrial players such as processors, grinders, and manufacturers. In most cash crop production, including cocoa, buyers are happy with women because they produce quality products compared with men when given the needed support (Chan, 2015). This suggests that women are central to the growth and sustainability of the sector as well as to secure the future of the rural cocoa farm household. However, women face some barriers in the cocoa sector. Notable among these barriers is the growing perception that cocoa farming is not "a woman thing", limiting their aspirations and opportunities for them in the industry, particularly access to land. Moreover, women are expected to take care of their young siblings and perform all kinds of household chores from tender age to their old age, crowding out the opportunity to acquire cocoa farming skills or engage in any farm-related activities to earn income for themselves.

As a result, probably, women are less productive in managing farms compared with their men counterparts across Sub-Saharan Africa in most crops, including cocoa (FAO, 2011; World Cocoa Foundation and KIT, 2017). This gap in productivity could be attributed to inefficient over-allocation of farm resources to men, which may result in productivity losses (Akresh, 2005). Women have limited access to productive farm resources, technical training in modern technologies, credit facilities, membership of cooperatives, and markets, resulting in productivity and income inequality between themselves and their male counterparts (Murugani et al., 2014; Kilic et al., 2015; Sharaunga and Mudhara, 2016; Mangheni et al., 2019). Hence, bridging the gap in women access to productive and financial resources has become a critical strategy for increased productivity in the agricultural industry, including the cocoa sub-sector. The FAO reports that bridging the gender gap could expand farm output in developing economies by 2.5% – 4% while reducing undernourishment by 12% – 17% (FAO, 2011). Thus, empowering women in an economic and social sense is healthy for agricultural productivity as it helps communities to lift themselves from the whips of poverty.

In response to the widespread gender disparity concerning access to productive resources and income inequality, many international organizations have introduced gender intervention programmes in an attempt to close this gap in the immediate future. In the West African cocoa industry, many women-sensitive projects have been implemented, while others are on-going to empower women in the cocoa sector to wake up from their slumber. Some of these projects include fair labour associations that map women in Nestle cocoa supply chain in Cote d'Ivoire and Nigeria's cocoa communities with Oxfam. In Ghana, the Mondelez International Cocoa Life in partnership with other NGOs and organizations such as Kuapa-Kokoo are taking steps to build the capacity of women through pilots such as Barry Callebaut's tree nursery and farmer training as well as the World Cocoa Foundation's use of video clubs to reach women cocoa farmers. It is, therefore, expected that the deficit in women's access to resources would decline and subsequently lead to a reduction in the productivity gap. However, bridging the productivity differences means that women ought to optimize their resource use or be technically efficient. The technical efficiency of any production unit is a measure of how well it employs production inputs to optimize output, compared with its maximum potential indicated by the production possibility frontier (Coelli et al., 2002). Thus, the technical efficiency of a cocoa managed plot is its ability to transform multiple inputs into output (Coelli et al., 2002).

Analysis of gender productivity gaps has taken different approaches. Some approaches involve inter-household studies where the mean yield gap between plots managed by men and women are estimated and then test whether the gap could be attributed to differences in resource endowment.¹ In technical efficiency analysis concerning gender, most studies (e.g., Kinkingninhou-Medagb et al., 2010; Yiadom-Boakyee et al., 2012) estimate the technical efficiency of men and women-headed households (not managed plots) using stochastic frontier and test for a statistical difference in mean technical efficiency. Various inputs (land, seeds, fertilizer, labour, etc.) and socioeconomic characteristics (age, household size, education, extension services, access to credit, membership of farmer organizations, etc.) are accounted for in the analysis. One drawback of this gender differential in the technical efficiency approach is that it does not estimate the individual contributions to endowment differences relative to the differences in technical efficiency. A comprehensive decomposition of the gender-efficiency gap would be appropriate and insightful for designing programmes oriented towards bridging the inequality between men and women. Another limitation is the use of male-headed and female-headed households as units of analysis rather than male and female plot managers. Since the use of male and female-headed families is relevant in its rights in farm-level policy, it is essential to distinguish the inter-household gender gap from the overall gender gap (Ali et al., 2015). This is because the majority of women-managed plots in African settings are confined within male-headed households. Thus, the structure of male-female headed homes is different from that of male-female managed plots. In the family structure of Africa, particularly Ghana, women-headed households are found in situations where they are widows, migrant husbands, or polygamous marriages where the husband is a member of a different home. Hence, analysis using male-female-headed households draw inappropriate inferences for policy recommendations.

This study contributes to the body of literature by bringing a shred of new evidence on gender gaps in technical efficiency and attempts to address the two concerns in three ways. First, we use farm manager level data for the analysis to enable us to come out with technical efficiency gaps between cocoa farms managed by men and those managed by women in the presence of both the man and the woman. Second, a two-stage double bootstrap data envelopment analysis developed by Simar and Wilson (2007) was employed to analyze the technical efficiencies of male and female-managed plots in Ghana's cocoa production sector. Finally, an extended version of the well-known Blinder-Oaxaca (B-O) gender decomposition (Blinder, 1973; Oaxaca, 1973) developed by Bauer and Sinning (2008) that account for the differences in technical efficiency between males and females was applied. The conventional version of the B-O decomposition, which was also generalized by Neumark (1988) and Oaxaca and Ransom (1988, 1994) can only be applied on linear dependent variables using the Ordinary Least Square (OLS) estimator. The extended version developed by Bauer and Sinning (2008) can be applied to non-linear dependent models such as probit/logit, Poisson, and Tobit, among others. The B-O framework decomposes the gap into two components: endowment effect and structural effect. The endowment effect emanates from the inequality concerning access to and use of inputs as well as other characteristics of the households, while the structural effect is attributable to the gender differences in the return to such factors. From a farm-level policy perspective, estimating the technical efficiency in the Ghanaian cocoa farms from the dimensions of men and women, and identifying the drivers of the gender efficiency gap provides a guide for the design and implementation of more gender-sensitive interventions.

2. Methodology

2.1. The study area and data collection procedure

The data for this study is based on a farm household survey conducted in Ghana between October and December 2016. The sampling frame

¹ Readers can consult Peterman et al. (2011) and Quisumbing (1996) for a review of the literature on gender decomposition.

covered Western, Brong-Ahafo, Eastern, and Ashanti regions, where cocoa is predominantly produced in Ghana. The four regions were pre-defined for the study because their combined cocoa output is about 90% of the total national output for the past decade (COCOBOD, 2019). The cocoa-producing areas within the selected regions are predominantly rural. Cocoa farming and its related activities are the primary sources of livelihood.

We followed a multi-stage sampling procedure in selecting the districts from each region. A list of cocoa-producing districts and villages was obtained from the offices of COCOBOD. In the first stage, we randomly selected three districts each from the Brong-Ahafo, Ashanti, and Eastern regions, except for the Western region. In the Western region, four districts were selected. This is because the region produces about 50% of Ghana's cocoa (COCOBOD, 2019). Second, three to four communities were selected through a simple random procedure. In each village, cocoa farming households were identified and stratified into households with men and women cocoa farm managers. This was done with the assistance of agricultural extension officers who are periodically in contact with the farm households. Finally, 10–16 farm plot managers were selected from each community. In summary, 183, 121, 110, and 91 farm managers from Western, Brong-Ahafo, Ashanti, and Eastern regions, respectively, were used in the study. Accordingly, a total sample size of 505 (411 male plot managers and 94 female plot managers) were included in the sample. In a typical crop production system in most African communities, particularly Ghana, husband and wife in the same household do not usually have separate farms. In this case, the spouse mostly responsible for the management of the farm was identified as the plot manager and interviewed using a well-structured questionnaire. The information collected included household characteristics, membership of farmer groups, access to supply-side variables, inputs used in cocoa production, cocoa production output, and other socioeconomic characteristics.

2.2. Empirical methodology

The study followed two estimation techniques to achieve its objectives. First, we employed a two-stage double bootstrapped procedure to estimate efficiency scores as well as identifying the sources of efficiency differentials. Second, we applied the extended version of the Blinder-Oaxaca (B-O) to disaggregate efficiency scores between male farm managers and female farm managers. Sections 2.2.1 and 2.2.2 discuss the estimation techniques of the double bootstrap data envelopment analysis (DEA) procedure and B-O gender decomposition, respectively.

2.2.1. Technical efficiency estimation with DEA approach

Technical efficiency is a common practice used to assess the performance of a decision-making unit (DMU) relative to a best-practice frontier. Efficiency scores are performance measures or success indicators by which production units are evaluated. Two estimation techniques exist in the literature for calculating technical efficiency: the non-parametric DEA and the parametric stochastic production frontier (SPF). In the DEA technique, we use linear programming to estimate the efficiency of the farm units (DMU) in a way that makes the observed input-output factors wrapped as firmly as it can be (Lee et al., 2009). The stochastic production frontier model measures the ratio of the actual to the expected maximum output, given input levels and the existing technology, otherwise referred to as technical inefficiency. The stochastic frontier model also acknowledges that variations in maximum output could be attributed to random shocks such as climatic conditions outside the control of the production units. The differences in production could also be ascribed to farm households operating at various levels of inefficiency due to weak incentives, mismanagement, inappropriate input levels or imperfect competition (Battese and Rao, 2002).

This study adopts the non-parametric linear programming frontier procedure against the parametric statistical method for two reasons. First, the DEA avoids the problem of misspecification of the production

function. Second, the double bootstrap DEA² approach proposed by Simar and Wilson (1998, 2000, and 2007) enables the statistical properties of non-parametric frontier estimators to be determined.

Two primary types of DEA exist in literature: input-oriented and output-oriented. For the assumed input and output levels, the output-oriented maximizes the output without further expansion in inputs, while the input-oriented minimizes the input levels to achieve the same level of output. Our unit of analysis is cocoa producers who have more control over inputs used in production as against output: hence, we apply the input-oriented procedure to measure the efficiency scores of the farm units. The decision to use an input-oriented procedure was also motivated by Coelli et al. (2005), who indicated that the orientation to use should be premised on the part of the production system the unit of analysis has more control over. Many empirical studies (e.g., Ogada et al., 2014; Rahman and Awerije, 2015) have employed the input-oriented procedure to estimate farm-level performance in Sub-Saharan Africa. In the Ghanaian cocoa sector, Danso-Abbeam and Baiyegunhi (2020) applied the input-oriented DEA to estimate the technical efficiency among cocoa farm households. However, their study did not correct for biases in measuring technical efficiency scores through the use of the double-bootstrap DEA procedure³. Hence, the estimated efficiency scores are likely to be overestimated.

The study, therefore, follows the studies of Cooper et al. (2007) and Poudel et al. (2015) to estimate technical efficiency using the DEA approach, which can be expressed as follows:

Minimize θ subject to;

$$\begin{aligned} \theta Z'_j - Z' \lambda &\geq 0 \\ Y' \lambda &\geq Y_j \\ \lambda &\geq 0 \end{aligned} \quad (1)$$

Following Simar and Wilson (2007), the efficient level of input $\theta Z'_j$, is defined as the projection of a j^{th} cocoa farm manager on the efficient frontier. The scalar, θ denotes the efficiency score of the j^{th} cocoa farmer, which satisfies the condition: $\theta \leq 1$, and λ denotes the $I \times 1$ vector of constant.⁴ The $z \times n$ and $m \times n$ indicate the input (Z') and output matrix (Y'), respectively. Z_j denotes a vector of inputs employed, and Y_j is the output of the j^{th} cocoa farm. Eq. (1) represents the constant return-to-scale (CRS), also known as overall technical efficiency (OTE_{CRS}), suggesting that farmers operate on an optimal scale. The OTE_{CRS} consists of two components: the pure technical efficiency (PTE), which represents the management practices under the assumption of variable return-to-scale (VRS), hence denoted as PTE_{VRS} and the residual called the scale efficiency (SE) (Latruffe et al., 2008; Ullah and Perret, 2014)⁵. Following Banker et al. (1984), the addition of the constraint $\sum \lambda_j = 1$ to Eq. (1) gives rise to the VRS frontier. SE is the ratio of OTE to PTE ($SE = OTE/PTE$) and measures the scale of operations of the farm.⁶ Nevertheless, farms usually experience increasing or decreasing return-to-scale (IRS or DRS, respectively). Hence, Cooper et al. (2007) proposed a non-increasing return-to-scale (NIRS) model where a constraint $\sum \lambda \leq 1$ is added to Eq. (1). Comparing OTE_{CRS} and TE_{NIRS}

² Bootstrapping enable us to assign measures of accuracy with regards to biases, variances, confidence intervals, and prediction errors to sample estimates.

³ It is also worth mentioning that although the same set of data was used in this study and that of Danso-Abbeam and Baiyegunhi (2020), the objectives, concepts, dynamics, and approaches are entirely different.

⁴ Here θ is independent of input prices.

⁵ We also call the OTE 'CCR-model' named after the initials of Charnes et al. (1978). PTE is also named after the initials of Banker et al. (1984), hence, called BCC-model.

⁶ In this study, we use OTE_{CRS} and PTE_{VRS} to refer to technical efficiency under the assumption of CRS (overall technical efficiency) and technical efficiency under the assumption of VRS (pure technical efficiency), respectively.

indicates whether a farm unit is experiencing IRS or DRS. If $1 > OTE_{CRS} = TE_{NIRS}$, then a cocoa farm is considered inefficient, where the inefficiency is due to IRS. In contrast, if $1 > OTE_{CRS} < TE_{NIRS}$, then the farm's inefficiency emanates from the DRS (Wossink and Denaux, 2006).

However, the focus of the DEA technique is to measure the efficiency of the DMUs. It does not explain the efficiency differentials. In other words, DEA does not estimate factors that might be responsible for differences in the technical efficiency scores across the DMUs. Hence, a second-stage approach needs to be employed where the estimated efficiency scores ($\hat{\theta}$) are regressed on a vector of explanatory variables as applied in many studies (Sharma et al., 1999; Wadud and White, 2000; Dhungana et al., 2010). Many empirical studies (Wossink and Denaux, 2006; Gómez-Limón et al., 2012; Mohapatra and Sen, 2013; Poudel et al., 2015) in farm efficiency analysis have used Tobit regression for the second stage of the DEA, with the assumption of censored distribution error terms since the dependent variable ($\hat{\theta}$) ranges between zero (0) and one (1). Nevertheless, this famous approach has been criticized because of the potential bias in the efficiency scores. While the DEA analysis assumes no statistical noise, there is uncertainty because efficiency scores are sensitive to measurement and sampling errors. There is potential sampling error due to the fact that DEA constructs the frontier from the sample rather than the population. Moreover, Simar and Wilson (2007) noted that the efficiency scores estimated from the DEA strongly depend on one another; hence, they may violate the underlying assumption of regression models, making censored regression models inappropriate. Simar and Wilson (2007), therefore, suggested a statistically grounded double bootstrapped estimation procedure that enables consistent inferences while concurrently producing standard errors and confidence intervals for the efficiency scores. The notion for bootstrapping is to mimic the true sampling distribution by simulating the data generating-process (Latruffe et al., 2008). Greene et al. (2008) emphasized that bootstrapping is a necessary condition in the "absence of a statistical underpinning." The study, therefore, employed a double bootstrap estimation procedure, where the error terms are not censored but truncated.

Following Simar and Wilson (2007) double bootstrapping procedure, the truncated maximum likelihood (ML) can be expressed as follows:

$$\hat{\theta}_j = z_j\beta + \varepsilon_j \quad (2)$$

where $\hat{\theta}$ represents the efficiency score of each DMU, z_j denotes the vector of explanatory variables, β is the set of unknown parameters, and ε_j is the error term $N(0, \sigma^2)$ with left-truncated $1 - z_j\beta^7$.

Previous studies such as Färe et al. (1994), Davidova and Latruffe (2003), Krasachat (2004), Reig-Martinez and Picazo-Tadeo (2004), and recent studies such as Abou-Ali and El-Ayouti (2014), and Poudel et al. (2015) modelled efficiency under the assumption of CRS. This is not tenable in this study because cocoa production is influenced by many external factors such as weather, economic shocks, and supply-side policy variables, among others. Hence, our dependent variable was the bias-corrected PTE_{VRS} scores. Nevertheless, results and discussions on OTE_{CRS} and SE are also provided.

2.2.2. Blinder-Oaxaca (B-O) decomposition for Tobit models

To date, decomposition methods proposed by Blinder (1973) and Oaxaca (1973), and extended by Neumark (1988), Juhn et al. (1991), and Oaxaca and Ransom (1988, 1994) have been widely used in linear regressions. The B-O theory allows the decomposition of the differences in an outcome variable between two groups into a part that is attributed

⁷ The detailed description of the bootstrapped truncated regression for the second stage of DEA can be found in Simar and Wilson (2007), Barros and Garcia-del-Barrio (2011) and Badunenko and Tauchmann (2018).

to differences in the observed characteristics of these two groups and the part that is ascribed to differences in the estimated coefficients of these groups. Fairlie (1999, 2003) made an extension to the B-O framework for limited dependent variables. Our dependent variable (PTE_{VRS}) estimated from the DEA approach is constrained between zero (0) and one (1), which in many cases necessitates the application of the Tobit regression model because the OLS estimator may provide biased and inconsistent results. Hence, we apply the B-O gender decomposition for Tobit model to compare the technical efficiency differential between male and female cocoa farm managers.⁸

Consider the standard B-O framework in a linear regression model, which is estimated separately for the groups; $g = m, f$; where m and f denote male and female managers, respectively, can be expressed as;

$$Y_g^* = X_g\beta_g + \varepsilon_g \quad (3)$$

where Y_g^* is a continuous dependent variable explained by a vector of independent variables X_g . β_g denotes the corresponding estimates, and ε_g is the random error term. The total difference in the outcome variable defined as the mean gap between the two groups, Y_m^* and Y_f^* can be expressed as:

$$\bar{Y}_m - \bar{Y}_f = (\bar{X}_m - \bar{X}_f)\hat{\beta}_m + (\hat{\beta}_m - \hat{\beta}_f)\bar{X}_f \quad (4)$$

where $\bar{Y}_g = N_g^{-1} \sum_{i=1}^{N_g} Y_{ig}$ and $\bar{X}_g = N_g^{-1} \sum_{i=1}^{N_g} X_{ig}$. From Eq. (4), the mean gap in Y^* is the sum of the characteristics effect and the coefficient effects. The first term $(\bar{X}_m - \bar{X}_f)\hat{\beta}_m$ relates to differences ascribed to observable characteristics (endowment effect), whereas the second term $(\hat{\beta}_m - \hat{\beta}_f)\bar{X}_f$ estimates the differences in the return to these characteristics (structural effect). The structural effect can be sub-divided into two components, namely, male structural advantage and female structural disadvantage. The male advantage measures the deviation of the coefficient of the male model from the combined sample, while the female disadvantage estimates the deviation of the female model from the combined sample.

Oaxaca and Ransom (1994) proposed a matrix of weights that can be used to decompose $\bar{Y}_m - \bar{Y}_f$. This can be expressed in Eq. (5) as

$$\bar{Y}_m - \bar{Y}_f = (\bar{X}_m - \bar{X}_f)\beta^* + \bar{X}_m(\beta_m - \beta^*) + \bar{X}_f(\beta^* - \beta_f) \quad (5)$$

$$\beta^* = \Omega\beta_m + (I - \Omega)\beta_f$$

In Eq. (5), I and Ω are the identity matrix and the matrix of weight, respectively. The generalized equation proposed by Blinder (1973) and Oaxaca (1973) represents a particular case in which Ω is the null matrix or is equal to I . However, other assumptions about the form of Ω have been proposed. For instance, Reimers (1983) and Cotton (1988) considered Ω as a scalar matrix. Reimers (1983) treated the weighting matrix $\Omega = (0.5)I$, whereas Cotton (1988) proposed the weighting matrix as $\Omega = sI$, where s represents the relative sample size of the majority group (Bauer and Sinning, 2008)⁹. Moreover, Neumark (1988) and Oaxaca and Ransom (1994) suggested the estimation of a pooled model to derive the counterfactual coefficient vector, β_g .

The application of Eq. (4) to non-linear models such as Tobit (in our case)¹⁰ is not appropriate because the conditional expectation $E(Y_{ig}/X_{ig})$

⁸ Note that this is different from the argument made earlier regarding the use of bootstrapped truncated regression model instead of Tobit. The two estimators work differently and the 'nldecompose' STATA command employed to fit gender decomposition model was bootstrapped.

⁹ The number of male farm managers in our sample is 411 representing approximately 81% of the sample. Hence, the $s = 0.81$.

¹⁰ The formulations of Tobit model equation have been omitted because it is common in many empirical studies. However, readers can refer to Bauer and Sinning (2010) for further information.

Table 1. Descriptive statistics of farm managers by gender.

Variables	Male plot managers		Female plot Managers		Pooled sample		t-value
	mean	SD	Mean	SD	Mean	SD	
Output of cocoa beans (kg)	1484.615	70.251	1023.496	102.15	1398.78	60.75	2.98 ^a
Quantity of labour (person-days)	535.25	37.19	476.27	76.26	524.27	33.42	0.69
Quantity of fertilizer (kg)	470.44	41.58	420.29	27.65	461.01	23.80	0.82
Quantity of pesticides (litres)	6.52	1.22	5.48	0.44	5.67	0.45	0.96
<i>Demographic factors</i>							
Marital status (married = 1)	0.925	0.264	0.585	0.495	0.861	0.346	6.44 ^a
Educational attainment (years)	6.708	5.147	5.128	4.866	6.414	5.128	2.81 ^a
Number of years in cocoa farming (years)	23.170	10.324	20.702	9.050	22.711	10.136	2.32 ^b
Household size (count)	6.111	2.824	6.150	2.764	6.121	2.809	0.15
Engagement in non-farm activities (Yes = 1)	0.491	0.500	0.223	0.419	0.442	0.497	5.38 ^a
<i>Farm-specific factors</i>							
Farm size (hectares))	3.33	0.509	2.503	0.192	2.922	0.094	3.87 ^a
Age of cocoa farm (years)	15.588	7.556	15.532	6.963	15.578	7.439	0.07
<i>Institutional/policy factors</i>							
Access extension services (Yes = 1)	1.608	1.898	0.819	1.191	1.461	1.813	5.11 ^a
Visit demonstration farms (Yes = 1)	0.406	0.783	0.330	0.767	0.392	0.779	0.87
Membership of FBOs (Yes = 1)	0.538	0.514	0.255	0.438	0.485	0.512	5.45 ^a
Access Agricultural credit (Yes = 1)	0.459	0.498	0.596	0.493	0.485	0.500	2.41 ^b

SD denotes standard deviation, a and c denote significance levels at 1% and 10%, respectively.

may be different from $\widehat{X}_g \widehat{\beta}_g$. Therefore, to obtain the general version of the B-O decomposition in terms of conditional expectation, we re-expressed Eq. (4) as follows:

$$\Delta_f^{Tobit} = [E_{\beta_m, \sigma_m}(Y_{im}/X_{im}) - E_{\beta_f, \sigma_f}(Y_{if}/X_{if})] + [E_{\beta_m, \sigma_f}(Y_{if}/X_{if}) - E_{\beta_f, \sigma_f}(Y_{if}/X_{if})] \tag{6}$$

$$\Delta_m^{Tobit} = [E_{\beta_m, \sigma_m}(Y_{im}/X_{im}) - E_{\beta_m, \sigma_m}(Y_{if}/X_{if})] + [E_{\beta_m, \sigma_m}(Y_{if}/X_{if}) - E_{\beta_f, \sigma_f}(Y_{if}/X_{if})] \tag{7}$$

where $E_{\beta_g, \sigma_g}(Y_{ig}/X_{ig})$ denotes the conditional expectation of Y_{ig} evaluated at the parameter vector β_g and the standard error σ_g . In Eqs. (6) and (7), the first part on the right-hand side indicates the differences in the outcome variable (in our case PTE_{VRS} scores) between male and female managers, which is attributable to differences in the characteristics, X_{ig} . The part of the differential that is due to differences in the coefficient forms the second term on the right-hand side of the two equations. The decompositions described in Eqs. (6) and (7) may differ if variances of the error terms between the two groups are large. However, it is worth mentioning that using σ_f as in Eq. (6) to estimate the counterfactual part is similar to the OLS version of the B-O framework described in Eq. (4). This is because the counterfactual part differs from $E_{\beta_f, \sigma_f}(Y_{if}/X_{if})$ only by employing the parameter for the male group, β_m instead of using the parameter and standard error of the female group.

Moreover, Daymont and Andrisani (1984) suggested an extension to the B-O decomposition, which is a threefold option. The threefold option permits the decomposition of the mean differential in the outcome variable into three components. The third component is the interaction term. This extension can be expressed as

$$\bar{Y}_m - \bar{Y}_f = (\bar{X}_m - \bar{X}_f)\beta_m + \bar{X}_m(\beta_m - \beta_f) + (\bar{X}_m - \bar{X}_f)(\beta_m - \beta_f) = E + C + CE \tag{8}$$

where E denotes the part of the raw differential that is ascribed to differences in endowment, C represents the part due to differences in coefficient, and CE denotes the part that is explained by the interaction between C and E .

3. Results and discussions

3.1. Summary statistics of variables

The study collected a wide array of data on farmers and farm-specific characteristics, institutional variables, output, and input, including cocoa production in kilograms, labour, fertilizer, and pesticide applications, among others. Table 1 reports the summary statistics for the full sample and by gender disaggregation of all the variables used in the models. The last column is the t-statistic that indicates whether the differences in mean characteristics between plots managed by men and women are statistically significant.¹¹

The table shows that men obtain a significantly higher output of cocoa beans (1484.65 kg) than their women counterparts (1023.5 kg). Other previous studies (Kilic et al., 2015; Oseni et al., 2015) have shown that female plot managers tend to have a lower output than male plot managers. The output for the full sample was 1398.78 kg.

Although men used more quantities of inputs (labour, fertilizer, and pesticides) as compared to women, no statistical differences exist. Also, women cultivate less cocoa farmland (about 2.5 ha compared with about 3.3 ha for men), and this is statistically significant. Thus, apart from land, there is limited evidence that women have limited access to and used less productive resources than men. These results are in line with those reported by Alene et al. (2008) in western Kenya, where women used inputs as intensively as men. About 86% of the respondents (full sample) were married. However, only 58.5% of the women were married, which is significantly lower than the percentage of men who are married (about 93%). The table further shows that women are less educated, have less experience in cocoa farming, and are less engaged in non-farm activities.

Some studies (Doss, 2001, Sharaunga and Mudhara, 2016) have argued that differences in access to supply-driven variables such as access to extension services, and agricultural credit have undermined the productivity of women. The results of the study show a significant difference in access to extension services, membership of FBOs, and access to agricultural credit between men and women farm managers.

¹¹ Two-sample t-test with unequal variance was used.

Table 2. Summary results of the original DEA and bias-corrected estimates.

	Technical Efficiency Estimates								
	Non-bias scores			bias-corrected scores			Confidence		Bias
	Mean	Min	Max	Mean	Min	Max	LB	UB	
<i>A. Overall technical efficiency (OTE_{CRS})</i>									
Male Managers	0.50	0.07	1	0.42	0.06	0.86	0.37	0.49	0.09
Female Managers	0.35	0.05	1	0.28	0.04	0.85	0.26	0.34	0.07
Full sample managers	0.44	0.04	1	0.37	0.03	0.87	0.35	0.42	0.06
<i>B. Pure technical efficiency estimates (PTE_{VRS})</i>									
Male Managers	0.81	0.21	1	0.77	0.20	1	0.69	0.81	0.04
Female managers	0.70	0.18	1	0.64	0.18	1	0.61	0.70	0.06
Full sample managers	0.71	0.17	1	0.68	0.16	1	0.65	0.70	0.02
<i>C. Scale efficiency score (SE)</i>									
Male Managers	0.62	0.09	1	0.56	0.081	1			
Female managers	0.53	0.05	1	0.44	0.041	0.88			
Full sample managers	0.52	0.05	1	0.45	0.041	1			
<i>D. Return-to-scale for original OTE_{CRS}</i>									
	CRS	DRS	IRS						
Male managers	9.57	25.79	64.64						
Female managers	2.43	21.22	76.35						
Full sample managers	2.38	21.38	76.24						
<i>E. Share of farms with efficiency score of 1 (%)</i>									
	OTE		PTE						
	OS	BCS	OS	BCS					
Male managers	9.57	-	48.94	17.02					
Female managers	2.43	-	14.11	6.08					
Full sample managers	2.38	-	13.27	5.94					

LB, UB, OS, and BC denote lower bound confidence interval, upper bound confidence interval, original score, and bias-corrected score, respectively.

3.2. DEA analysis of efficiency scores

The technical efficiency distributions across the male and female managers as well as the pooled sample are presented in Table 2. Any farm manager with an efficiency score of less than one (1) is said to be relatively inefficient. Sections A, B, and C of Table 2 present both the original and bias-corrected scores of OTE_{CRS} and PTE_{VRS}, respectively, across the two types of management and the full sample. In both cases, the bias-corrected scores are less than the original scores, suggesting that the original efficiency scores were overestimated, which in turn, leads to bias results.¹² The OTE_{CRS} for male managers ranges from 0.06 to 0.86, with an average efficiency of 0.42, while that for the female managers ranges from 0.04 to 0.85, with a mean score of 0.28. Thus, there is a significant difference between the mean OTE_{CRS} of male and female producers. The mean OTE_{CRS} suggests that male and female managers can produce the same level of output with the current technology by downsizing their input levels by 58% and 72%, respectively. Alternatively, there is a potential for men and women to increase their output level by 2.38 times (1/0.42) and 3.57 (1/0.28), respectively, without altering the quantities of inputs employed. With regard to the pooled sample, cocoa farmers have the ability to produce about 2.27 times more than their current production, with almost no change in inputs. Table 2 further shows that the estimates of the PTE_{VRS} are significantly higher than the scores from the OTE_{CRS}. This is so because, technically, the data generating process for the PTE_{VRS} scores envelopes the data points more closely than the process of generating the OTE_{CRS} scores (Kumar and Gulati, 2008). Again, the difference between PTE_{VRS} scores of male managers is higher than that of female managers (0.77 versus 0.64), suggesting that more inefficient farms are

¹² Discussions regarding OTE_{CRS} and PTE_{VRS} are based on the bias-corrected estimates.

managed by women than men. The PTE_{VRS} estimate for the full sample is 0.68, which is a significant improvement on the OTE_{CRS} scores.

One of the critical concerns of every production unit is to maximize profit by producing at the optimum level. Sections C and D of Table 2 report the different types of return-to-scale under both male and female plot management and the pooled sample. The two groups of farm managers have scaling challenges in their production, with average SE scores of 0.62 and 0.53 for men, and women, respectively. The proportion of male managers operating under CRS, DRS, and IRS are 9.57%, 25.79%, and 64.64%, respectively. However, 2.43%, 21.22%, and 76.35% of female managers operate under CRS, DRS, and IRS, respectively. Thus, only 9.57% of male producers and 2.43% of female producers are considered efficient under CRS. These managers are managing their employed resources productively, and are referred to as peers. Their management style or practices serve as a guide for their inefficient neighbours to replicate or follow. Overall, approximately 2.38%, 21.38%, and 76.24% of the sampled farmers (pooled) operated under CRS, DRS, and IRS, respectively. Nevertheless, the proportion of farmers who are efficient increased considerably under the assumption of PTE_{VRS}, even when the estimates were bias-corrected (section E column 4).

Thus, the relatively low proportion of farmers under OTE_{CRS} could be attributed to the incongruous size of operations other than managerial inefficiency. Cocoa farm managers experiencing IRS are working below their optimal scale size, and could, therefore, improve their level of efficiency by increasing their scope of operations. However, the plausible option for those operating under DRS is to downsize their scale of operation to enhance their level of efficiency.¹³ In summary, the

¹³ However, as a result of only two primary categories - male and female - construction of frontier plot was problematic to present the gender distribution of the efficiency scores.

Table 3. Baseline determinants of technical efficiency (PTE_{VRS}) across gender plot management.

Variables	Male managers		Female Managers		Pooled Sample	
	Coeff.	BSE	Coeff.	BSE	Coeff.	BSE
Gender	-	-	-	-	0.12282 ^a	0.04209
Marital status	0.47362	0.06217	-0.04603	0.06489	0.03635	0.04399
Educational attainment	0.00005	0.00310	0.00449	0.00581	0.00211	0.00286
Number of years in farming	-0.00002	0.00176	0.00693 ^c	0.00406	0.00181	0.00163
Household size	-0.01613 ^a	0.00628	0.01237	0.01125	-0.0123 ^b	0.00577
Engagement in non-farm activities	0.11713 ^a	0.03650	0.16235 ^c	0.09348	0.13812 ^a	0.03432
<i>Farm-specific factors</i>						
Age of cocoa farm	0.00662 ^a	0.00227	0.00314	0.00484	0.00602 ^a	0.00219
<i>Institutional/policy factors</i>						
Access extension services	-0.00492	0.00889	-0.05960	0.03288	0.00570	0.00848
Visit demonstration farms	-0.01764	0.02307	-0.03895 ^a	0.00587	0.03881 ^c	0.02162
Membership of FBOs	0.06629 ^c	0.03563	0.08826 ^a	0.02344	0.07128 ^b	0.03382
Access Agricultural credit	-0.10809 ^a	0.03622	0.01409	0.05944	-0.08371 ^a	0.03118
Constant	0.33321 ^a	0.08329	0.00125	0.13642	0.23978	0.06551
<i>Sigma</i>	0.25212 ^a	0.01496	0.21924	0.02522	0.25543	0.01435

BSE denotes bootstrap standard errors. a, b, and c denote significance levels at 1%, 5%, and 10%.

efficiency indicators show that men are better managers than women, as reported by many empirical studies.

3.3. The base determinants of technical efficiency

Following Simar and Wilson (2007), Table 3 reports the results from the truncated regression model employed to identify the determinants of PTE_{VRS} under both male and female farm management as well as the pooled sample. The variable gender was included in the pooled model, where the direction and significance were tested to serve as a baseline for the subsequent gender decomposition analysis. The estimated coefficient of gender is positive and significant at 1% level of significance, which aligns with our *a priori* expectation. The positive coefficient of the gender variable suggests that technical efficiency is oriented toward male managers than female managers. This result, not in favour of women, could not be attributed to the fact that they are women but probably, the unequal allocation of productive resources and limited access to farm services such as extension, demonstration farms, agricultural credit, among others. Our results agree with many empirical studies (Adesina and Djato, 1997; Doss, 2001; Yiadom-Boakyee et al., 2012) that farm plots managed by women are less productive than plots managed by men. However, other studies such as Saito et al. (1994) and Adeleke et al. (2008) argued that women as farm managers are as efficient as men.

Household size negatively affects both the male sample and pooled sample. Thus, a household with more members is less efficient compared with a family with small members, probably because more members exert pressure on the limited resources available and seem to aggravate the incidence of poverty and food insecurity. Moreover, more members compete for cash resources available for farm operations, leading to small or no allocations of productivity-enhancing inputs and subsequently result in inefficiency. This result is in line with a study on the technical efficiency of smallholder farmers in Zimbabwe by Mango et al. (2015). However, it is in agreement with the study by Wang et al. (1996), who noted that household size enhances efficiency in the Chinese agricultural sector.

Extant of literature (Akaakohol and Aye, 2014; Wan et al., 2016; Batool et al., 2017; Chirwa et al., 2017) have reported the positive and significant influence of non-farm activities on agricultural productivity. Income from non-farm economic activities boosts farmers' financial capacity to purchase productivity-enhancing inputs such as fertilizer and pesticides, and also enables farmers to hire labour for their farm operations. The significant effect of non-farm activities on technical efficiency, as revealed by our study confirmed the findings of the previous

studies. Thus, both male and female producers who engage in non-farm activities are better managers than those who solely depend on agriculture as their only source of income.

A visit to cocoa demonstration farms had no significant influence on male-managed farms, but had a positive and significant effect on the pooled sample, and a negative influence on female-managed farms. Demonstration farms provide an opportunity for farmers to learn from the field some of the good farm management practices, which will enhance their technical and managerial skills and subsequently improve their efficiency. It is, therefore, no surprise that farmers who visited demonstration farms are more efficient than those who either did not get the chance or seize the opportunity. However, women usually lack access to some of these opportunities to learn new ways of farming techniques. This is because women are usually busy with their household chores or nursing of babies; hence, they have little time to participate in these programmes. These impediments to women limit their managerial skills and adversely affect their farm efficiency. Membership of social groups such as FBOs is positive and significant under both male and female management as well as the pooled sample. Social groups in farming communities in Ghana are usually self-help groups, which serve as a rotational farm labour and sometimes a source of credit among farmers, particularly women. Thus, with FBOs, farmers can lessen labour constraints with regard to cost and availability, leading to the purchase of other inputs to boost production. Participation in FBOs also serves as a source of information concerning farming practices, which may lead to the efficient management of farms. Access to agricultural credit is significant among the male farm managers and the pooled sample. Thus, farmers who accessed credit are less technically efficient than farmers who needed credit but did not get the opportunity to access it. This could be because credit acts as a push factor driving farm managers to diversify into non-farm activities, which may lead to less intensification of farm operations. On the other hand, agricultural credit could also lead to the over-application of farm resources. Our results agree with the findings of Ogada et al. (2014), who reported a negative correlation between technical efficiency and access to credit among crop farmers in Kenya.

3.4. Gender decomposition in technical efficiency: the B-O approach

The B-O analysis is employed to estimate the fraction of the technical efficiency difference that could be ascribed to: (i) differences in average characteristics of PTE_{VRS} generating factors (endowment effect), and (ii) gender differences in the returns to those factors (structural effect). Table 4 reports the aggregate decomposition results following the

Table 4. Oaxaca-Blinder: Aggregate decomposition of the efficiency (PTE_{VRS}) gap.

Results	$\Omega = 1$ (Daymont and Andriasani)		$\Omega = 0.5$ (Reimers)		$\Omega = 0.81$ (Cotton)		$\Omega =$ Neumark	
	Coeff.	%	Coeff.	%	Coeff.	%	Coeff.	%
Endowment effect	0.0487 (0.0239) ^b	37.54	0.0458 (0.0177) ^b	35.26	0.0475 (0.0201) ^b	36.59	0.0605 (0.0151) ^a	46.59
Male structural advantage	0.0000 (0.0011)	0.00	0.0445 (0.0171) ^a	34.28	0.0173 (0.0065) ^a	13.28	0.0129 (0.0046) ^a	9.94
Female structural disadvantage	0.8116 (0.0372) ^b	62.46	0.0396 (0.0186) ^a	30.47	0.0651 (0.0302) ^b	50.12	0.0565 (0.0207) ^a	43.47
Raw differential	0.1299 (0.0279) ^a	100	0.1299 (0.0279) ^a	100	0.1299 (0.0279) ^a	100	0.1299 (0.0279) ^a	100

Ω denotes omega. a, b, and c represent significant levels at 1%, 5%, and 10%, respectively. Standard errors are reported in parentheses.

methodology originally developed by Oaxaca (1973) and later extended by Daymont and Andriasani (1984), Reimers (1983), Cotton (1988), and Neumark (1988). The table reveals a gender PTE_{VRS} gap of about 13% (indicated in the last row), which is positive and statistically significant at 1%, suggesting that male farm managers outperform female farm managers by 13%. The 13% mean gender gap is then split into the endowment effect and the structural effect. The endowment effect as discussed earlier, is the explained portion of the gender PTE_{VRS} gap. The structural effect (unexplained part of the mean PTE_{VRS} gap) has two components: male advantage and female disadvantage.

The first set of results presented in columns 2 and 3 followed a methodology extended by Daymont and Andriasani (1984), where the weighting matrix was set to one (1). From the Daymont and Andriasani (1984) results, 37.5% (4.9 percentage points) of the PTE_{VRS} gap is explained by the gender differences in the endowment of productive resources.

The structural effect accounted for the remaining 62.5% representing 81.2 percentage points, which is due to differences in return to productive resources or unobservable terms. Reimers (1983) opposed the original matrix formulation proposed by Oaxaca (1973), where the weighting matrix was set as $\Omega = I$. Instead, Reimers (1983) suggested a weighting matrix of $\Omega = 0.5(I)$, where the no-discrimination efficiency function lies somewhere between male and female managers. With this decomposition approach, about 35% of the difference in PTE_{VRS} between men and women could be attributed to the explained part, while the structural effects accounted for the remaining 65%. With 65%, male advantage accounted for about 34% (i.e., 4.5 percentage points), while the female disadvantage contributed about 30.5% (i.e., 4 percentage points). Cotton (1988) extended the notion of no-discrimination by Reimers (1983) and set the weighting matrix according to the proportion of the majority group in the sample. It can be observed from the table that this had a significant influence on the unexplained part (structural effect) of the gender PTE_{VRS} gap. While the male advantage accounted for only 13% (i.e., 1.7 percentage points), the female disadvantage contributed to about 50% (i.e., 6.5 percentage points) of the unexplained portion. Finally, Neumark (1998) and Oaxaca and Ransom (1994) proposed that a pooled model should be estimated in deriving the counterfactual coefficient vector. This approach is considered more rigorous and comprehensive than the other methods discussed (Sebagala, 2007).¹⁴ The results from the Neumark methodology indicate that the endowment factor or the explained portion accounted for approximately 46.6% of the PTE_{VRS} gap (representing about 6 percentage points), while the unobserved components control the remaining 53.4%.

The male advantage is responsible for just about 10% (representing 0.5 percentage points), and the disadvantage that women experience explain as high as 43% of the unexplained gap. Given that the explained part (endowment effect) of the mean PTE_{VRS} gap is smaller across all the methodologies than the unexplained portion (structural effect) suggests that even if male and female farmers have equal access to productive resources, significant differences in their PTE_{VRS} levels will continue to exist.

Table 5 reports a detailed gender decomposition for a given set of covariates¹⁵. A positive coefficient suggests that the factor widens the gender gap in technical efficiency, while a negative coefficient narrows the gap. Educational attainment increases the differences in the PTE_{VRS} by about 0.3 percentage points through female disadvantage. Farmers' involvement in non-farm activities is another significant factor that explains the endowment effect. The gender gap in productivity increases with farmers' engagement in non-farm activities, contributing about 8 percentage points to widening the gender gap. Farm-specific characteristics such as the size of land under cocoa production and age of cocoa farms also contribute significantly to the PTE_{VRS} difference between men and women. Many empirical studies (Slavchevska, 2015; Oseni et al., 2015; Aguilar et al., 2015) have argued that land is a critical factor that seems to widen the gender gap in productivity and, subsequently efficiency. The results revealed that land contributes about 9 percentage points to the endowment effect. Similarly, the age of cocoa farms positively affects the endowment effect. Thus, the rate of return favours male managers, probably because old cocoa farmlands are mostly bequeathed to male children.

Table 5 further reveals that policy-driven variables (demonstration farms, membership of FBOs, and agricultural credit) are all statistically significant and have negative effects on the explained part of the gender gap. This suggests that these policy variables help to decrease the gender gap in technical efficiency. Thus, a visit to cocoa demonstration farms, FBO membership, and access to agricultural credit reduce the PTE_{VRS} gap by about 3.6, 6 and 8 percentage points, respectively. The results could be attributed to the recent gender-sensitive intervention programmes being implemented in cocoa-growing communities in Ghana. For example, the Ghana cocoa board in collaboration with Solidaridad (an international NGO) has a programme called Women in Cocoa and Chocolate Network (WINCC). This network creates a platform for women engaged in cocoa production and its related activities to learn new farm management practices, share knowledge, connect, and become inspired to take on a leadership role.

The quantity of labour used (both family and hired) and fertilizer applied on cocoa farms tend to marginally decrease the PTE_{VRS} gap by about 2 and 3 percentage points, respectively. This is somehow in line with many empirical studies (Quisumbing et al., 2001; Peterman et al., 2011) that differences in the intensity of use of productive resources narrowly explain gender differentials in agricultural productivity.

For the structural effect, the study is being cautious in its interpretation since the coefficients cannot be interpreted casually (Quisumbing, 1996; Peterman et al., 2011; Aguilar et al., 2015). The structural effect of the decomposition indicated in Eq. (4) is the differences emanating from unequal returns to inputs. Nevertheless, these characteristics might be inaccurate in the presence of unobservable heterogeneity (Aguilar et al., 2015). This, however, does not suggest that the results from the structural effect are meaningless or should be underestimated. The results are recommended as guides for farm-level intervention policies and further studies. The primary factors that significantly explain male structural

¹⁵ To reiterate our unit of analysis, we stick to plots managed by men and women, and not household heads.

¹⁴ The Neumark methodology was used to generate the results in Table 5.

Table 5. Detailed gender decomposition using the Neumark approach.

Variables	Endowments effect		Male Advantage		Female disadvantage	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
<i>Farmer demographic characteristics</i>						
Marital status	0.03579	0.03458	0.04282	0.05054	-0.00871	0.04889
Educational attainment	0.00106	0.00226	-0.00117	0.00252	0.00346 ^b	0.00454
Farming experience	0.00145	0.00125	0.00002	0.00139	0.00586	0.00288
Household size	-0.00504	0.00447	-0.00709	0.00507	0.00567	0.00880
Engagement in non-farm activities	0.08505 ^a	0.02706	0.06479 ^b	0.02941	0.13704 ^c	0.07305
<i>Farm-specific characteristics</i>						
Farm size	0.08672 ^a	0.01806	0.07281 ^a	0.02011	0.04875	0.04232
Age of cocoa farm	0.15016 ^a	0.05490	0.19246 ^a	0.06047	-0.02781	0.11945
<i>Institutional/policy variables</i>						
Extension services	-0.00305	0.00645	-0.00254	0.00683	-0.03643 ^c	0.02201
Visit to cocoa demonstration farms	-0.03580 ^b	0.01627	-0.01980	0.01801	-0.05878	0.04069
Membership of FBOs	-0.06009 ^b	0.02729	0.05399 ^c	0.02970	0.05474	0.06575
Agricultural credit access	-0.08108 ^a	0.02485	-0.10639 ^a	0.02812	-0.00031	0.04616
<i>Farm productive resources</i>						
Labour	-0.01903 ^b	0.00893	-0.02814 ^a	0.00974	0.03078	0.02190
Fertilizer applications	-0.02729 ^a	0.00946	-0.02309 ^b	0.01038	-0.02305	0.02059
Pesticides application	-0.00093	0.00198	-0.00039	0.00217	-0.00102	0.00435
Constant	0.19491	0.07260	0.24729	0.08725	0.16609	0.14534
<i>sigma</i>	0.24801	0.00818	0.25010	0.00918	0.19889	0.01491

Coeff., Std. Err. represent the coefficient and standard errors, respectively. a, b, and c denote significance levels at 1%, 5%, and 10%, respectively.

advantage are engagement in non-farm activities, farm size, age of cocoa farm, membership of FBOs, access to agricultural credit, labour, and fertilizer application. For female structural disadvantage, educational attainment, engagement in non-farm activities, and extension services are factors that significantly explain the differences in the gender PTE_{VRS} gap.

4. Conclusions and recommendations

Assessing the presence of gender efficiency gaps in cocoa production is essential, not because it differs from the production of other crops, but because it is a cash crop that holds significant potential means by which rural households in the southern part of Ghana can enhance their livelihoods. The study has examined the gender differences in technical efficiency in Ghanaian cocoa farms. The results from the DEA analysis indicated that the use of the double bootstrap technique as a benchmark to set up frontier farmers for a given sample is an important approach. This is because the bias-corrected scores for all the efficiency indicators were less than the original scores, indicating that the original efficiency scores were biased upwards. From the analysis, male plot managers recorded a mean bias-corrected PTE_{VRS} of 77%, while the average PTE_{VRS} of cocoa farms managed by women was 64%. The efficiency of the pooled sample was 68%. Thus, males outperformed females plot managers by 13%. Also, while about 65%, 26%, and 10% of male farm managers experienced IRS, DRS, and CRS, respectively; about 70%, 17%, and 3% of female farm managers exhibited IRS, DRS, and CRS, respectively. When both male and female sub-samples were put together, about 76%, 22%, and 2% of cocoa producers experienced IRS, DRS, and CRS, respectively. The study identified some factors such as household size, farmers' level of experience in cocoa production, engagement in non-farm activities, age of cocoa farms, membership of FBOs, and access to agricultural credit to have a significant influence on PTE_{VRS} .

The extended version of the B-O approach was employed to measure and decompose the gender PTE_{VRS} gap into two parts: endowment and structural effects. Using a different weighting matrix, the endowment effect portion accounted for a range of 35–47% of the gender PTE_{VRS} gap,

while the remaining 53–65% was associated with the structural effect. The larger structural effect suggests that policymakers trying to establish equality between men and women concerning access to resources will not necessarily narrow the gap in technical efficiency. Factors that significantly contribute to the endowment effect include engagement in non-farm activities, farm size, membership of FBOs, farmers' visit to cocoa demonstration farms, access to agricultural credit, and amounts of labour and fertilizer employed. As for the structural effect, the returns to factors contributing to technical efficiency are different for male and female managers; hence, the study finds it challenging to explain this situation. Further studies are recommended to come out with a well-informed policy direction for this situation.

The results of this study provide some avenues for policy implications. First, the results affirmed the existence of inefficiency in cocoa production in Ghana, which farmers should be aware of this situation. Creating awareness of the inefficient management of farms is a necessary condition for improving productivity. If cocoa producers are made aware of how inefficient they are in the management of their resources, they could consciously and effectively combine inputs to optimize their output. Second, the results call for the actions of policymakers to help improve farm-level efficiency of both male and female farmers by encouraging them to engage in non-farm income activities, strengthening the formation and implementations of farmer groups, and implementing credit schemes. Engagement in non-farm employment could be incorporated into effective extension service delivery so that while farmers are trained in farm management practices, they are also encouraged to engage in other sources of alternative livelihoods. In this case, income from non-farm activities could be invested in their farm operation through the purchase of the right quantities of inputs at the right time to increase farm efficiency. The positive and significant contribution of FBOs to the endowment effect suggests that gender-sensitive groups such as Women in Cocoa and Chocolate Network implemented in Ghana's cocoa industry could be a potential women's farmer group to inspire them to be more productive. For women farmers, who by socio-cultural norms are at a more considerable disadvantage, FBOs offer mutual support and solidarity, which enhances women to grow their social capital, and boosts

their self-esteem and self-reliance. With FBOs, women can collectively have easy access to productive resources and other services such as credit, capital, and other financial services. Also, an effective credit scheme programme where farmers are given inputs (not cash to avoid diversion) could ease financial constraints and help farmers apply the right quantities of resources at the right time. Third, the fact that men and women have different observed characteristics and the more substantial portion of the PTE_{VRS} gap is explained by unobserved covariates calls for “a best-fit” farm-level strategy rather than “one size fits all” strategy. The “one size fits all” farm-level policies implemented mostly by state institutions, particularly MoFA, where no gender-specific projects within the policies are designed to encourage the participation of women in agricultural activities is problematic and needs critical attention. For instance, a study conducted by Mabe et al. (2018) on the assessment of the on-going Planting for Food and Jobs (PFJ) programme in Ghana that is geared to increase crop productivity and make Ghana self-sufficient revealed low (15%) participation of women as against men. This is so, probably because the PFJ programme had no special package to encourage women to participate in the programme. Implementing “a one size fits all” farm-level policies in countries like Ghana, where access to land and other productive resources are customarily in the hands of men put women in a disadvantaged position, which aggravates the gender gap in productivity. The study, therefore, recommends that separate farm-level programmes for men and women may be needed to minimize (if not completely eliminate) the gender gap in farm-level efficiency and subsequently boost cocoa production.

Declarations

Author contribution statement

Gideon Danso-Abbeam: Conceived and designed the experiment; analysed and interpreted the data; contributed reagents, materials, analysis tools or data; wrote the paper.

Lloyd J.S. Baiyegunhi: Analysed and interpreted the data; contributed reagents, materials, analysis tools or data.

Temitope O. Ojo: Conceived and designed the experiment; analysed and interpreted the data; wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

The authors are grateful to the farmers who sat hours to answer all the questions. We also acknowledge the work of all the anonymous reviewers and the editor for the constructive feedback.

References

Abou-Ali, H., El-Ayouti, H., 2014. Nile water pollution and technical efficiency of crop production in Egypt: an assessment using spatial and non-parametric modelling. *Environ. Ecol. Stat.* 21, 221–238.

Adesina, A.A., Djato, K.K., 1997. Relative efficiency of women as farm managers: profit function analysis in Côte d'Ivoire. *Agric. Econ.* 16, 47–53.

Adeleke, O.A., Adesiyun, O.I., Alaniyi, O.A., Adelalu, K.O., Mantanni, H.M., 2008. Gender differentials in the productivity of cereal crop farmers: a case study of maize

farmers in the Oluyole local government area of Oyo State, Nigeria. *Agric. J.* 3 (3), 193–198.

African Development Bank, 2015. Economic Empowerment of African Women through Equitable Participation in Agricultural Value Chains.

Aguilar, A., Carranza, E., Goldstein, M., Kilic, T., Oseni, G., 2015. Decomposition of gender differentials in agricultural productivity in Ethiopia. *Agric. Econ.* 46, 311–334.

Akaakohol, M.A., Aye, G., 2014. Diversification and farm household welfare in Makurdi, Benue state, Nigeria. *Dev. Stud. Res.* 1 (1), 168–175.

Akresh, R., 2005. Understanding Pareto inefficient intrahousehold allocations. Working Paper, Department of Economics, University of Illinois at Urbana-Champaign.

Alene, A.D., Manyong, V.M., Omany, G.O., Mignouna, Bokanga Mpoko, Odhiambo, G.D., 2008. Economic efficiency and supply response of women farm managers. Comparative evidence from western Kenya. *World Dev.* 36 (7), 1247–1260.

Ali, D.A., Bowen, D., Deininger, K., Duponchel, M.F., 2015. Investigating the Gender gap in Agricultural Productivity: Evidence from Uganda. World Bank Policy Research Working Paper, # 7262.

Badunenko, O., Tauchmann, H., 2018. Simar and Wilson Two-Stage Efficiency for Stata. Friedrich-Alexander University Erlangen-Nuremberg, Institute for Economics. FAU Discussion Papers in Economics. No. 08/2018.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models in estimating technical and scale efficiencies in Data Envelope Analysis. *Eur. J. Oper. Res.* 2, 429–444.

Barros, C.P., Garcia-del-Barrio, P., 2011. Productivity drivers and market dynamics in the Spanish first division football league. *J. Prod. Anal.* 35, 5–13.

Batool, S., Babar, A., Nasir, F., Iqbal, S.Z., 2017. Income diversification of rural households in Pakistan. *Int. J. Econ. Manag. Sci.* 6 (6).

Battese, G.E., Rao, D.S.P., 2002. Technology gap, efficiency, and a stochastic metafrontier function. *Int. J. Bus. Econ.* 1 (2), 87–93.

Bauer, T.K., Sinning, M., 2008. An extension of the Blinder–Oaxaca decomposition to nonlinear models. *Adv. Stat. Anal.* 92, 197–206.

Bauer, T., Sinning, M., 2010. Blinder-Oaxaca decomposition for Tobit models. *Appl. Econ.* 42, 1569–1575.

Blinder, A.S., 1973. Wage discrimination: reduced form and structural estimates. *J. Hum. Resour.* 8, 436–455.

Chan, Man-Kwun, 2015. Improving Opportunities for Women in Smallholder-based Supply Chains: business case and practical guidance for international food companies. Methodological issues and empirical evidence. *World Dev.* 24 (10), 1579.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision-making units. *Eur. J. Oper. Res.* 2, 429–444.

Chirwa, C.W., Makoka, D., Maonga, B.B., Ng'ong'ola, D.H., 2017. Impact of Malawi's Closing the Gender Gap for Development. FAO and Agriculture Organization of the United Nations, Rome, Italy.

COCOBOD (Ghana Cocoa Board), 2019. https://cocobod.gh/weakly_purchase.php.

Coelli, T.J., Rahman, S., Thirtle, C., 2002. Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a non-parametric approach. *J. Agric. Econ.* 33, 605–624.

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. *An Introduction to Efficiency and Productivity Analysis*. Springer, New York.

Cooper, W.W., Seiford, L.M., Tone, K., 2007. *Data Envelopment Analysis: a Comprehensive Text with Models, Applications, References and DEA-Solver Software*, second ed.s. Springer Science, Business Media, LLC, New York.

Cotton, J., 1988. On the decomposition of wage differentials. *Rev. Econ. Stat.* 70, 236–243.

Danso-Abbeam, G., Baiyegunhi, L.J.S., 2020. Do farm-level technical efficiency and welfare complement each other? Insight from Ghana's cocoa industry. *J. Econ. Struct.* 9 (23).

Davidova, S., Latruffe, L., 2003. Technical efficiency and farm financial management in countries in transition. In: Institut National del recherche Agronomique Working Paper series 03–01 (December), 03 - 01, pp. 1–35.

Daymont, T.N., Andrisani, P.J., 1984. Job preferences, college major, and the and the gender gap in earnings. *J. Hum. Resour.* 19, 408–428.

Dhungana, B., Sugimoto, Y., Yamamoto, N., Kano, H., 2010. Technical efficiency analysis of vegetable farms in the mid-hill region of Nepal-an approach using data envelopment analysis. *Jpn. J. Food Agric. Resour. Econ.* 60 (2), 27–37.

Doss, C.R., 2001. Designing agricultural technology for African women farmers: lessons from 25 years of experience. *World Dev.* 29, 2075–2092.

Fairlie, R.W., 1999. The absence of the African-American owned business: an analysis of the dynamics of self-employment. *J. Labor Econ.* 17, 80–108.

Fairlie, R.W., 2003. An Extension of the Blinder–Oaxaca Decomposition Technique to Logit and Probit Models. Yale University Economic Growth Center, pp. 1–11. Discussion Paper No. 873.

FAO, 2011. The State of Food and Agriculture 2010–11. Women in Agriculture: Closing the Gender gap for Development. Retrieved from. <http://www.fao.org/docrep/013/i2050e/>.

Färe, R., Grosskopf, S.S., Lovell, C.A.K., 1994. *Production Frontiers*. Cambridge University Press, Cambridge.

Ghana Statistical Service [GSS], 2018. Provisional 2017 Annual Gross Domestic Product. GSS April 2018 Edition, Accra, Ghana. www.statsghana.gov.gh.

Gómez-Limón, J.A., Picazo-Tadeo, A.J., Reig-Martínez, E., 2012. Eco-efficiency assessment of olive farms in Andalusia. *Land Use Pol.* 29, 395–406.

Greene, W.H., 2008. The econometric approach to efficiency analysis. In: Fried, C.A.H., Lovell, K., Schmidt, S. (Eds.), *The Measurement of Productive Efficiency and Productivity Growth*. Oxford University Press, Oxford, UK, pp. 92–250.

Institute of Statistical, Social and Economic Research (ISSER), 2017. State of the Ghanaian Economy. Institute of Statistical, Social and Economic Research, University of Ghana, Legon.

- International Cocoa Organization (ICCO), 2017. ICCO Quarterly Bulletin of Cocoa Statistics. XLIII (2).
- International Institute of Tropical Agriculture (IITA), 2009. The Productivity of Cocoa Systems in West Africa. Accra-Ghana. In: 7th Regional Executive Committee Meeting, October 25th – 28th, 2009, Accra, Ghana.
- Juhn, C., Murphy, K.M., Pierce, B., 1991. In: Koster, M.H. (Ed.), *Accounting for the Slowdown in Black-White Wage Convergence in Workers and Their Wages: Changing Patterns in the United States*. American Enterprise Institute, Washington.
- Kilic, T., Palacios-Lopez, A., Goldstein, M., 2015. Caught in a productivity trap: a distributional perspective on gender differences in Malawian agriculture. *World Dev.* 70, 416–463.
- Kinkingninhou-Medagb, F.M., Diagne, A., Simtowe, F., Agboh-Noameshie, A.R., Adegbola, P.Y., 2010. Gender discrimination and its impact on income, productivity, and technical efficiency: evidence from Benin. *Agric. Hum. Val.* 27 (1), 57–69.
- Krasachat, W., 2004. Technical efficiencies of rice farms in Thailand: a non-parametric approach. *J. Am. Acad. Bus. Camb.* 4 (1 - 2).
- Kumar, S., Gulati, R., 2008. An examination of technical, pure technical and scale efficiencies in Indian Public sector Banks using Data Envelopment Analysis. *Eurasian J. Bus. Econ.* 1 (2), 33–69.
- Latruffe, L., Davidova, S., Balcombe, K., 2008. Application of a double bootstrap to the investigation of determinants of technical efficiency of farms in Central Europe. *J. Prod. Anal.* 29 (2), 183–191.
- Lee, C., Lee, J., Kim, T., 2009. Defence acquisition innovation policy and dynamics of productive efficiency: a DEA application to the Korean defence industry. *Asian J. Technol. Innovat.* 17 (2), 151–171.
- Mabe, F.N., Danso-Abbeam, G., Ehiakpor, D.S., 2018. Assessment of Implementation of Planting for Food and Jobs (PFJ) Programme: Lessons and Ways Forward. In: Alhassan, A., Agbenorhevi, A., Ibrahim, A. (Eds.), *Agriculture in Ghana Today: Some Critical Topics for Policy Making*. Faculty of Agribusiness and Communication Sciences, University for Development Studies, Ghana, pp. 35–56.
- Mangheni, M.N., Tufan, H.A., Nkengla, L., Aman, B.O., Boonabaana, B., 2019. Gender norms, technology access, and women farmers' vulnerability to climate change in sub-Saharan Africa. In: *Agriculture and Ecosystem Resilience in Sub Saharan Africa*. Springer, Cham, pp. 715–728.
- Mango, N., Makate, C., Hanyani-Mlambo, B., Shephard Siziba, S., Lundy, M., 2015. A stochastic frontier analysis of technical efficiency in smallholder maize production in Zimbabwe. The post-fast-track land reform outlook. *Cogent Econ. Finance* 3, 1117189.
- Mohapatra, R., Sen, B., 2013. Technical, allocative and economic efficiency in sugarcane production: a non-parametric approach. *Int. J. Adv. Res.* 1, 366–374.
- Murugani, V.G., Thamaga-Chitja, J.M., Kolanisi, U., Shimelis, H., 2014. The role of property rights on rural women's land uses security and household food security for improved livelihood in Limpopo Province. *J. Hum. Ecol.* 46 (2), 205–221.
- Neumark, D., 1988. Employers' discriminatory behaviour and the estimation of wage discrimination. *J. Hum. Resour.* 23, 279–295.
- Oaxaca, R.L., 1973. Male-female wage differentials in urban labor markets. *Int. Econ. Rev.* 14, 693–709.
- Oaxaca, R.L., Ransom, M., 1988. Searching for the effect of unionism on the wages of union and non-union workers. *J. Labor Res.* 9, 139–148.
- Oaxaca, R.L., Ransom, M., 1994. On discrimination and the decomposition of wage differentials. *J. Econom.* 61, 5–21.
- Ogada, M.J., Muchai, D., Mwabu, G., Mathenge, M., 2014. Technical efficiency of Kenya's smallholder food crops farmers: do environmental factors matter? *Environ. Dev. Sustain.* 16, 1065–1076.
- Oseni, G., Corral, P., Goldstein, M., Winters, P., 2015. Explaining gender differentials in agricultural production in Nigeria. *Agric. Econ.* 46 (3), 285–310.
- Peterman, A., Quisumbing, A.R., Behrman, J., Nkonya, E., 2011. Understanding the complexities surrounding gender differences in agricultural productivity in Nigeria and Uganda. *J. Dev. Stud.* 47 (10), 1482–1509.
- Poudel, K.L., Yamomota, N., Johnson, T.G., 2015. Comparing the technical efficiency of organic and conventional coffee farms in the rural hill region of Nepal using data envelopment analysis (DEA) approach. *Org. Agric.* 5, 263–275.
- Quisumbing, A.R., 1996. Male-female differences in agricultural productivity: methodological issues and empirical evidence. *World Dev.* 24 (10), 1579–1595.
- Quisumbing, A., Payongayong, E., Aidoo, J.B., Otsuka, K., 2001. Women's land rights in the transition to individualized ownership: implications for the management of tree resources in western Ghana. *Econ. Dev. Cult. Change* 50 (1), 157–182.
- Rahman, S., Awerije, B.O., 2015. Technical and scale efficiency of cassava production system in Delta State, Nigeria: an application of the two-stage DEA approach. *J. Agric. Rural Dev. Tropics Subtropics* 116 (1), 59–69.
- Reig-Martínez, R., Picazo-Tadeo, A.J., 2004. Analysing farming systems with data envelopment analysis: citrus farming in Spain. *Agric. Syst.* 82, 17–30.
- Reimers, C.W., 1983. Labor market discrimination against Hispanic and black men. *Rev. Econ. Stat.* 65, 570–579.
- Saito, K., Mekonnen, H., Spurling, D., 1994. Raising the Productivity of Women Farmers in Sub-saharan Africa. The World Bank, Washington, DC, USA. Discussion Paper 230.
- Sebagala, R., 2007. Wage determination and gender discrimination in Uganda. *Econ. Res. Pol. Cent. Research Series* No. 50.
- Sharaunga, S., Mudhara, M., 2016. Factors influencing water-use security among smallholder irrigating farmers in Msinga, KwaZulu-Natal Province. *Water Pol.* 18, 1209–1228.
- Sharma, K.R., Leung, P., Zalleski, H.M., 1999. Technical, allocative, and economic efficiencies in swine production in Hawaii: a comparison of parametric and non-parametric approaches. *Agric. Econ.* 20, 23–35.
- Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Manag. Sci.* 44, 49–61.
- Simar, L., Wilson, P.W., 2000. Bootstrapping in non-parametric frontier models. *J. Appl. Stat.* 27, 779–802.
- Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. *J. Econ.* 136, 31–64.
- Slavchevska, V., 2015. Gender differences in agricultural productivity: the case of Tanzania. *Agric. Econ.* 46, 335–355.
- Ullah, A., Perret, S.R., 2014. Technical and environmental efficiency analysis of irrigated cotton-cropping systems in Punjab, Pakistan using Data Envelopment Analysis. *Environ. Manag.* 54, 288–300.
- Wadud, A., White, B., 2000. Farm household efficiency in Bangladesh: a comparison stochastic frontier and DEA methods. *Appl. Econ.* 32, 1665–1673.
- Wan, J., Li, R., Wang, W., Liu, Z., Chen, B., 2016. Income diversification: a strategy for rural region risk management. *Sustainability* 8 (10), 1064.
- Wang, J., Cramer, G.L., Wailes, E.J., 1996. Production efficiency of Chinese agriculture: evidence from rural household survey data. *Agric. Econ.* 15, 17–28.
- World Cocoa Foundation and KIT, 2017. *The Gender and Cocoa Livelihood Toolbox: removing barriers for women to access and benefit from services*. <http://genderandcocoalivelihoods.org/fact/removing-barriers/>.
- World Cocoa Foundation (WCF), 2014. *World cocoa foundation market update report*. www.worldcocoafoundation.org/wp-content/uploads/Cocoa-Market-Update.pdf.
- Wossink, A., Denaux, Z.S., 2006. Environmental and cost efficiency of pesticide use in transgenic and conventional cotton production. *Agric. Syst.* 90, 312–328.
- Yiadom-Boakye, Y., Ebenezer Owusu-Sekyere, E., Nkegbe, P.K., Ohene-Yankyer, K., 2012. Gender, resource use and technical efficiency among rice farmers in the Ashanti region, Ghana. *J. Agric. Econ. Dev.* 2 (3), 102–110.