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Does contract farming affect technical efficiency? Evidence from soybean farmers in Northern Ghana

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Abstract

Understanding how and the extent to which contract farming arrangements impact agricultural productivity is important to ensuring that policies are designed to maximize the likelihood of success. Using cross-sectional data from 516 soybean farmers in Northern Ghana, we provide empirical evidence that contract farming increases soybean productivity and technical efficiency in Northern Ghana. We use propensity score matching to reduce bias from observables, and then estimate a stochastic production frontier model that addresses selection bias arising from unobservable variables. We find that the technical efficiency levels of contract farmers are 77 percent compared with 69 percent for non-contract farmers. We also find that access to credit, extension contact, and farmer group membership are key determinants of participating in contract farming.

Keywords: Contract farming, Propensity score matching, Stochastic frontier analysis, Technical efficiency

Introduction

Increasing the productivity of smallholder farmers[1] through the use of external inputs, such as fertilizer and improved seed, has been the priority of major agricultural development policies in Ghana over the last three decades (Houssou et al. 2017; Tanko et al. 2019). However, the strategy has resulted in mixed outcomes on poverty alleviation (Houssou et al. 2017). Though Ghana has made substantial gains in reducing the national poverty rate in half, from 56.5 to 23.4% between 1992 and 2018, a high incidence of poverty still exists in the three northern regions where it is between 54.8 and 70.9% (Ghana Statistical Service (GSS) 2018). This has led to a renewed interest in an alternative strategy to develop the rural areas that focus on market-oriented agriculture (MoFA 2015). Contract farming has been touted as an approach that has the potential to provide smallholder farmers with credits, inputs, and transfer improved technologies (Oya 2012; Otsuka et al. 2016).

[1] Smallholder farmers are characterized as those who cultivate less than 2 hectares of land, and approximately 90% of all soybean farmers in Ghana are classified as smallholders (MoFA).

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In the past three decades, contract farming has emerged as the most dominant institutional arrangement linking smallholder farmers to agricultural value chains (Barrett et al. 2012) and commercial markets both domestically and internationally (Kirsten and Sartorius 2002; Da Silva and Rankin 2013). Smallholder farmers with low education and limited access to land, credit, technical advice, and current information on market prices can benefit from contracting with large professional agribusiness firms through the reduction in transaction costs and risk (Barrett et al. 2012; Cahyadi and Waibel 2016; Ruml et al. 2021). These contractual arrangements have led to higher productivity for smallholder farmers in many less developed countries (LDCs) (Wang et al. 2014; Henningsen et al. 2015). Given the effort of policymakers in the drive toward achieving increased agricultural productivity and welfare through contractual arrangements, this study seeks to examine the impact of contract farming participation on the productivity of smallholder soybean farmers in northern Ghana.

Early studies on contract farming focused on examining its impact on household welfare. Empirical evidence from these studies revealed that participating in contract farming increased household income (Miyata et al. 2009; Rao and Qaim 2011; Jones and Gibbon 2011), increased farm profitability (Mishra et al. 2016), increased household productive asset holdings (Michelson 2013), improved household food security and nutrition (Bellemare and Novak 2017; Debela et al. 2022) and improved subjective well-being (Dedehouanou et al. 2013). A common theme among these papers is that improving productivity can often lead to improved household welfare. However, there is a large amount of heterogeneity due to weaknesses in empirical approaches and widely different contexts (Bellemare and Bloem 2018). In the Ghanaian context, there is some evidence that contract farming in Maize did not lead to poverty alleviation or greater welfare as the higher input costs outweighed the benefits of greater yields (Ragasa et al. 2018). This shows that higher productivity is not a sufficient condition for improving overall welfare and that simply having a contract may not lead to poverty reduction. Nevertheless, improving overall productivity is still an important element, and a better understanding of the nature of and the extent to which contract farming can improve soybean output is one of the steps to a more-effective pro-poor strategy.[2]

Technical efficiency (TE) refers to the extent to which input usage in the production of a given set of outputs is minimized, or obtaining maximum output from a given set of inputs (Kumbhakar et al. 2015). Having knowledge of the TE levels offers several benefits. Firstly, it can be used to rank producers and to identify under-performing producers or those performing near the efficient frontier. This is useful in designing agricultural development programs or subsidy programs aimed at improving the overall productivity levels of farmers, which can assist with government targeting programs. Secondly, further investigation can reveal drivers of higher performance among these producers. This helps to identify appropriate government policies and responses or identify processes and improved technologies that can be introduced to less efficient farmers (Kumbhakar et al. 2015).

[2] In this specific project, farmers were provided inputs at subsidized cost. Therefore, an examination of the welfare effects of contract farming in this context would be in appropriate as it is unlikely that the government would be able to provide inputs at such cost at a larger scale and for a prolonged period of time.

In Ghana, soybean is a key cash crop with vast potential to improve household nutrition, decrease poverty, and reduce of the vulnerability of smallholder farmers to cash income constraints (Dogbe et al. 2013; Osman et al. 2018). Additionally, the crop can make positive contributions to the development of the health, agricultural, and industrial sectors of the Ghanaian economy (MoFA 2020). The production of soybeans has been increasing for more than two decades as it has become a key raw ingredient for industrial purposes and a more important source of food for humans, livestock, and aquaculture (Gage et al. 2012; MoFA 2020). Unfortunately, these increases in soybean production have been largely due to the expansion of land area rather than increases in yields, a situation that limits the potential of the country to become self-sufficient in soybean production (MoFA 2020).

Contract farming has the potential to improve the productivity of the soybean sector in Ghana. As has been shown in other settings, contract farming can lead to greater access to knowledge and improved technologies, productivity-enhancing inputs, credit, more stable output prices, and guaranteed market access (Henningsen et al. 2015; Meemken et al. 2020).

Research on the impact of contract farming on TE has shown a positive effect in crops (González-Flores et al. 2014; Ragasa et al. 2018) and livestock (Simmons et al. 2005; Begum et al. 2013). However, there is significant heterogeneity across studies, which may be due to the modeling approach or institutional differences across countries and commodities (Wang et al. 2014). Another issue that can have an effect on the results is the presence of observable and unobservable biases when using a stochastic frontier model. González-Flores et al. (2014) show that unobserved factors in contract farming participation correlate with the white noise of the stochastic frontier model. Given that farmers self-select to participate in contract farming, this implies that productivity and TE outcomes can be subject to sample selection bias. Several recent studies have employed the sample selection SPF approach to examine the impact of technology adoption in Zambia and the Philippines (Abdulai and Abdulai 2017; Villano et al. 2015), evaluate project participation impact in the Ecuadorean Sierra (Gonzalez-Flores et al. 2014), as well as evaluate the effect of farmer groups on yields and efficiency of a rice farmers in northern Ghana (Abdul-Rahaman and Abdulai 2018).

In this study, we investigate the impact of a large-scale contract farming program implemented by the Ghanaian government on the soybean sector in Northern Ghana. This research has important implications for the empirical literature. It investigates if contract farming, as an approach through which credit, inputs, and markets are easily accessible to the farmers, has an impact on the technical efficiency of smallholder soybean producers in developing nations. In addition to the novel empirical setting, we contribute to the literature by accounting for bias from both observable and unobservable factors using a two-stage approach. First, we use propensity score matching to reduce bias from observables; second, we estimate a stochastic production frontier model that addresses selection bias arising from unobservable variables.

The contract farming scheme

The contract farming scheme described in this study was implemented by the Ghana Commercial Agriculture Project (GCAP) which started in 2012 and ended in 2020. The GCAP received $145 million USD from USAID and the World Bank and was led by the Government of Ghana through the Ministry of Food and Agriculture (MoFA). The project promoted inclusive commercial farming through improved access to agricultural input and output markets for smallholder farmers through contract farming arrangements. Under this project, smallholder farmers are provided with tractor services, improved seeds, agrochemicals, extension services, and fertilizers at a subsidized (50%) cost. Crop output acted as collateral for these non-cash-based contract schemes, and farmers are free to join or exit the contract scheme at the end of production season. Soybeans farmers under contract cannot leave the scheme after having received the inputs. The project engaged 11 soybean contract providers (also referred as "nucleus farmers" in the program). In total, nearly 1500 smallholder soybean farmers were engaged in smallholder farmer–nucleus farmer arrangements.

In the arrangement, the nucleus farmer agrees to purchase all the output produced by the smallholder farmer per the terms of the contract at a fixed price without any quality restrictions. Therefore, in addition to receiving the services described above, participating smallholder farmers also benefit from having a guaranteed buyer and a stable price. The decision to participate in contract farming in this case is a simple binary one, as smallholder farmers cannot contract out a portion of their production (or allocate only a portion of their land to soybean production). In other settings, producers may opt to contract out a portion of their output where the contract can act as a partial insurance mechanism (Bellemare et al. 2021).

Empirical approach

Contract farming participation decision

Following Bellemare (2012) and Mishra et al. (2018), we assume that a smallholder farmer makes the decision to engage in contract farming or not by comparing the expected utility gain from participating versus not participating. The farmer will choose contract farming if the utility from contract farming (U_{CF}) is greater than the utility from being a non-contract farmer (U_{NF}), or if $U_{CF} - U_{NF} > 0$. Demographic and socioeconomic attributes of the farmer and farm also play a role in the decision such that a model for the decision to participate in contract farming can be expressed as:

$$C_f^* = \lambda Z_i + e_i \tag{1}$$

where

$$C_f = \begin{cases} 1 \text{ if } U_{\mathrm{CF}} - U_{\mathrm{NF}} > 0 \\ 0 \text{ if } U_{\mathrm{CF}} - U_{\mathrm{NF}} \leq 0 \end{cases} \tag{2}$$

C_f^* is a latent variable representing the propensity that an individual farmer chooses to participate in contract farming. The observed dependent variable refers to contract farming status C_f, where $C_f = 1$ for contract farmers and $C_f = 0$ for non-contract farmers; Z_i is a vector of independent variables (e.g., the farmer's experience, education, age, gender, etc.); λ is a vector of parameters to be estimated; and e_i is an error term that we assume to be normally distributed with zero mean.

Stochastic production frontier model

This study uses a stochastic production frontier (SPF) model and makes the simplifying assumption that the smallholder farmer either produces soybeans exclusively as contract farmers or non-contract (independent) farmers. The yield model can be expressed as:

$$y_{ij} = f\left(R, C_f\right) + v_{ij} + u_{ij} \tag{3}$$

where y_{ij} is the yield (kilograms per hectare) of the ith farmer, R is a vector of inputs and other explanatory variables, C_f is a dummy variable that equals one for contract farmers,v_{ij} is a two-sided error term, and u_{ij} is a one-sided error that captures efficiency. The subscript j indexes for contract farmers (CF) and non-contract farmers (NF).

Correction of self-selection bias in stochastic production frontier

In this study, sampled farmers were not randomly assigned but rather self-selected themselves into participating in contract farming. First, to control for possible biases based on unobservable characteristics, we implement a method introduced by Greene (2010). This model assumes that the unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier. Greene (2010) frames his model by noting that Heckman's (1999) original sample selection approach was developed for linear models and is not applicable for nonlinear cases such as the SPF. Thus, Greene proceeds to develop a SPF with sample selection, which can be expressed as:

$$\begin{array}{ll}
\text{Sample selection:} & d_i = 1\left[\alpha' z_i + w_i > 0\right], w_i \sim N[0,1] \\
\text{SFP :} & \quad y_i = \beta' x_i + \varepsilon_i, \varepsilon_i \sim N\left[0, \sigma_\varepsilon^2\right] \\
 & \quad \left(y_i, x_i\right) \text{observed only when } d_i = 1 \\
\text{Error structure:} & \varepsilon_i = v_i - u_i \\
 & u_i = |\sigma_u U_i| = \sigma_u |U_i| \text{where } U_i \sim N[0,1] \\
 & v_i = \sigma_v V_i \text{where } V_i \sim N[0,1] \\
 & (w_i, v_i) \sim N_2\left[(0,1), \left(1, \rho\sigma_v, \sigma_v^2\right)\right]
\end{array} \tag{4}$$

where d_i is a binary variable equal to one for contract farmers and zero for non-contract farmers, z_i is a vector of explanatory variables included in the (binary) sample selection model, and w_i is the unobservable error term. Furthermore, y_i is output, x_i is a vector of inputs in the production frontier, and ε_i is the composed error term. The coefficients α and β are parameters to be estimated, while the elements in the error structure correspond to those included in the stochastic frontier formulation. The parameter ρ indicates the presence or absence of selection bias associated with unobserved attributes. In particular, if it is significant, it indicates the presence of selection bias on unobserved attributes (Greene 2010). On the other hand, if it is insignificant, it implies the absence of selection bias and reduces to that of the maximum simulated likelihood estimator of the standard frontier model.

In analyzing the impact of contract farming on TE, it is also important to correct for possible biases that may result from observable factors. To mitigate the effects of this bias, we employ a matching technique using propensity scores generated from a probit model to control for possible biases in the covariates of contract farmers and non-contract farmers. This also provides a statistical basis for estimating the sample selection SPF model and average treatment effects of contract farming participation on TE. Following Bravo-Ureta et al. (2012), we use the PSM method to account for selection bias arising from observed attributes, and Greene's (2010) SPF sample selection model to correct for selection bias due to unobserved attributes. Using the PSM method, we construct a counterfactual group of farmers with similar time-invariant characteristics as those who participate in contract farming. It is important to mention that in implementing the PSM involves fitting a binary choice (in this case probit) model to generate propensity scores for contract and non-contract farmers. These propensity scores, which represent the probability of participating in contract farming, are used to match contract farmers with non-contract farmers, based on the observed time-invariant characteristics.

Model specification

The two most common functional forms in productivity and efficiency analysis are the Cobb–Douglas and translog (Bravo-Ureta et al. 2007). We estimate the translog functional form, which nests the Cobb–Douglas, to represent the production structure after a likelihood ratio test rejected the Cobb–Douglas function as the appropriate functional form. Following Coelli et al. (2005), the translog functional form can be specified as follows:

$$\ln y_i = \beta_0 + \sum_{j=1} \beta_j \ln x_{ij} + \frac{1}{2}\sum_{j}\sum_{k} \beta_{jk} \ln x_{ij} \ln x_{ik} + v_i - u_i \tag{5}$$

where y_i represents the output of the ith farm; x_{ij} is the quantity of the jth input; β and γ are parameters to be estimated; v_i is white noise; and u_i is the technical inefficiency term.

To correct for selection bias due to unobserved factors, we follow Greene's (2010) sample selection stochastic frontier framework that assumes that the unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier. First, we estimate a selection equation for contract farming participation using the probit model as follows:

$$C_i^* = \phi_0 + \sum_{j=1} \phi_i x_i + \tau_i \tag{6}$$

where C_i^* is a binary variable capturing the farmer's participation in contract farming ($C = 1$ for contract farmers, and 0 for non-contract farmers);x_i is a vector of farmer specific characteristics, household, and farm-specific factors as well as institutional factors; ϕ_i is a vector of parameters to be estimated; and τ_i is the error term. In the second stage, we estimate the SPF model with ρ (selection hazard) generated from the probit model as an additional regressor to account for selection bias. A statistically significant ρ is evidence that selection bias in unobservables is present.

Data and description of variables

Data used in this study were collected from 531 soybean farmers in the Northern and Upper East Regions of Ghana, between November and December 2019 using a structured questionnaire. The two regions accounted for about 85 percent of the total soybeans produced in 2017 in Ghana. A multi-stage sampling technique was employed to select the respondents for the study. Specifically, a simple purposive sampling approach was used to select 4 districts (Karaga, Binduri, Bawku West, and Nanumba South), while a stratified random sampling design with proportional allocation was employed to select 235 contract farmers from 8 GCAP beneficiary communities. A simple random sample was used to select 296 non-contract farmers from 11 non-GCAP beneficiary communities.

The main reason for the selection of non-contract farmers from non-GCAP beneficiary communities is to avoid possible spillover effects and contamination of project areas. The sampling of contract farmers was done using a list of outgrowers from the GCAP project, whereas the sampling of non-contract farmers in the non-GCAP communities was done using a list of soybean farmers from the MoFA offices in the selected districts. The non-contract farmers were selected based on answering "no" to the following questions: (1) Have you ever participated in any outgrower scheme or contract farming for any crop with aggregator, company, buyer under GCAP? (2) Are there any other schemes that you know of but that you were not part of? (3) Do you know or heard of any outgrower scheme or contract farming for any crop? If the answers to these questions are no, then the sampled farmers qualify as a control group and will be selected.

The data collection was carried out during face-to-face interviews with the smallholder soybean farmers using a structured questionnaire. The dataset includes information on personal and household socioeconomic characteristics, production factors, risk aversion behavior, climate shocks, adoption of improved agricultural technologies, and contract farming participation (Table 1).

Table 2 reports the summary statistics of key variables used in the study as well as the results of *t* tests of the differences in mean characteristics between contract and non-contract soybean farmers. The mean values of twelve covariates (gender, household size, land size, household assets index, farmer specialization, off-farm income activities, labor, extension contacts, farmer-based organization (FBO) membership, credit access, drought occurrence, and the regional dummy) significantly differ between contract farmers and non-contract farmers. The differences in these observable factors between contract farmers and non-contract farmers provide some justification for the application of a matching method and sample selection procedure to account for biases resulting from these differences.

Given that the focus of this study is to examine the drivers of participation in contract farming, as well as the factors through which contract farming affects TE, we draw on the existing literature on contract farming to select our explanatory variables (Miyata et al. 2009; Wang et al. 2014; Dubbert 2019). The results revealed that the proportion of women participating in contract farming is significantly lower compared to non-contract farmers. Moreover, contract farmers are significantly more experienced in soybean production, owned larger quantities of land, and belong to larger household sizes than non-contract farmers. Also, contract farmers are more specialized in soybean production, more likely to belong to farmer groups, and experience more occurrence of drought than non-contract farmers. However, non-contract farmers are more likely to participate in off-farm employment than contract farmers.

Table 1 Description of variables

Variable	Unit	Description
Dependent variable in Probit (selection) Equation		
Contract farming participation	Dummy	1 indicates a soybean farmer with a contract; 0 otherwise
Explanatory variables for matching and contract farming participation		
Gender	Dummy	1 indicates a male farmer; 0 otherwise
Basic education	Dummy	1 indicates a farmer having basic education; 0 otherwise
Secondary education	Dummy	1 indicates a farmer having secondary education; 0 otherwise
Tertiary education	Dummy	1 indicates a farmer having tertiary education; 0 otherwise
Household size	People	number of people in the household
Soy farming experience	Years	number of years in soybean production
Land size	Hectares	the total size of land under food crop production
Household assets	Index	household asset abundance scale
Farmer specialization	Ratio	the proportion of soybean income to total farm income
Off-farm activities	Dummy	1 indicates a farmer who has an off-farm job; 0 otherwise
Labor	Person days	number of the workforce employed in soybean production
Extension contacts	Visits	number of extension visits to the farmer's soybean farm
Credit access	Dummy	1 indicates a farmer credit beneficiary; 0 otherwise
FBO membership	Dummy	1 indicates a member of an FBO; 0 otherwise
Distance to district market	Kilometers	number of kilometers from house to district market
Occurrence of drought	Dummy	1 if household encountered drought
Risk aversion	Dummy	1 indicates a farmer with low farm investment; 0 otherwise
Region	Dummy	1 indicates a farmer in Upper East Region; 0 otherwise
Dependent variable in the production function		
In_Yield	Kg/ha	log of normalized output per unit area
Input variables (and other explanatory variables) in the production functions		
In_Labor	Person days	log of normalized labor used for soy production
In_Fertilizer	Kg	log of normalized fertilizer used for soy production
In_Seed	Kg	log of normalized seed used for soy production
In_Pesticides	Liters	log of normalized pesticides used for soy production
Power tillage	Dummy	1 indicates a farmer who uses mechanized services during land preparation; 0 otherwise
Districts	Categorical	District indicates the specific location of a farmer (1 = Bawku West, 0 = otherwise; 1 = Binduri, 0 = otherwise; 1 = Nanumba South, 0 = otherwise; 1 = Karaga, 0 = otherwise)

Table 2 Summary statistics

Variable	Pooled		Contract farming		Non-contract farming		*t*-ratio
	Mean	SD	Mean	SD	Mean	SD	
Gender of the farmer	0.65	0.48	0.60	0.49	0.69	0.46	− 2.06**
Basic education	0.23	0.42	0.24	0.43	0.23	0.42	0.32
Secondary education	0.13	0.34	0.14	0.35	0.12	0.32	0.9
Tertiary education	0.07	0.25	0.06	0.23	0.07	0.26	− 0.88
Household size	7.54	5.18	8.43	6.88	6.82	3.09	3.59***
Soy farming experience	12.94	8.78	13.13	10.1	12.79	7.58	0.45
Land size	3.08	2.95	3.54	3.71	2.72	2.09	3.2***
Household asset index	0.003	2.00	− 0.33	1.83	0.26	2.10	− 3.37***
Farmer specialization	3.44	7.03	4.66	9.46	2.48	3.97	3.59***
Off-farm activities	0.41	0.49	0.36	0.48	0.46	0.50	− 2.2**
Labor (person days)	66.45	35.01	72.43	36.0	61.71	33.48	3.54***
Extension contacts	2.08	1.66	2.70	1.38	1.59	1.70	8.13***
Credit Access	0.38	0.49	0.42	0.49	0.34	0.48	1.81*
FBO membership	0.50	0.50	0.59	0.49	0.44	0.50	3.5***
Distance to market	5.72	10.27	6.32	13.6	5.24	6.47	1.21
Occurrence of drought	0.02	1.19	0.20	1.34	− 0.13	1.03	3.29***
Risk aversion	0.65	0.48	0.68	0.47	0.62	0.49	1.5
Regional dummy	0.51	0.50	0.42	0.49	0.58	0.49	− 3.70***

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively

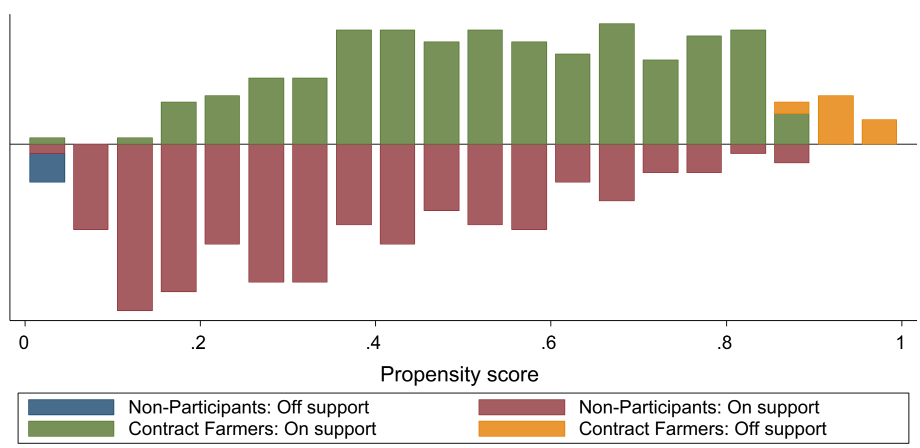

Fig. 1 Propensity score distribution and common support for propensity score estimation

Empirical results

Assessment of matching quality

PSM was used to estimate the average treatment effects of contract farming participation on soybean yields and other production variables. In matching covariates of contract and non-contract farmers using kernel matching and nearest-neighbor estimators approaches, we also check for the region of common support in the matching procedure. The region of common support was imposed on the matching process to eliminate treatment observations whose propensity scores are higher than the maximum or lower than the minimum propensity scores of the controls. Fourteen of the contract farmers and six

Table 3 Probit results of contract farming participation

Explanatory variables	Unmatched sample			Matched sample		
	Coeff.	Z-stat	Marginal effect	Coeff.	Z-stat	Marginal effect
Gender of the farmer	− 0.184	− 1.36	− 0.073	− 0.181	− 1.33	− 0.071
Basic education	0.265*	1.68	0.105	0.269*	1.66	0.106
Secondary education	0.369*	1.82	0.146	0.369*	1.81	0.146
Tertiary education	0.173	0.63	0.069	0.184	0.67	0.073
Household size	0.037***	2.56	0.014	0.031**	2.01	0.012
Soybean farming experience	0.019**	2.42	0.008	0.019**	2.32	0.007
Land size	0.051*	1.76	0.020	0.044	1.34	0.017
Household assets Index	− 0.167***	− 3.43	− 0.065	− 0.158***	− 3.00	− 0.062
Farmer specialization	0.023*	1.87	0.009	0.021	1.33	0.008
Off-farm activities	0.033	0.25	0.013	0.023	0.17	0.009
Labor	0.001	0.55	0.000	0.001	0.66	0.001
Extension contacts	0.254***	6.13	0.100	0.249***	5.93	0.097
Credit access	0.225*	1.81	0.089	0.224*	1.79	0.088
Farmer groups	0.265**	2.04	0.104	0.264**	2.03	0.103
Distance to district market	0.005	0.96	0.002	0.005	0.94	0.002
Occurrence of drought	0.109*	1.94	0.043	0.106*	1.84	0.041
Risk aversion	0.227*	1.69	0.088	0.219	1.63	0.085
Regional dummy	0.005	0.03	0.002	0.005	0.03	0.002
Constant	− 1.966	− 7.3		− 1.895	− 6.77	
Wald chi^2(18)	120.66***			97.03***		
Pseudo-R^2	0.179			0.147		
Count R^2	67.80%			66.93%		
Log pseudo-likelihood	− 299.286			− 298.222		
No. of observations	531			511		

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively

of the non-contract farmers were dropped in the matching process (Fig. 1) The number of lost households in the matching process is small, so the effect on the consistency of the matching results should be minimal (Bryson et al. 2002). The distribution of propensity scores and the region of common support in the matching procedure imply that the average treatment effect can be estimated for households that fall within the common support region (Caliendo and Kopeinig 2005).

Determinants of contract farming participation

The results of the first-stage probit model on factors affecting contract farming participation are presented in Table 3. Using the unmatched sample, the results show that contract farming participation increases with education (mainly at the basic or secondary level), household size, soybean farming experience, land size, farmer specialization, credit access, extension contacts, membership of FBO, occurrence of drought, and risk aversion behavior but decreases with household assets. We find similar results using the matched sample, except that now land size, farmer specialization, and risk aversion behavior are not statistically significant. Farmers who have basic or secondary education and those with larger household members are more like to participate in contract farming.

Farmers who have access to credit, more extension contacts, and belong to farmer groups also have a greater probability of participating in contract farming. These findings are in line with Bellemare (2012) and Abdul-Rahaman and Abdulai (2018). Participation in a farmer group facilitates farmers to obtain farm-related information and also acts as a channel of distribution for government support such as farm subsidies, farm machinery, and training programs (Rondhi et al. 2018). Farmers may also have an improved bargaining position by being a member of a group (Abdul-Rahaman and Abdulai 2018).

Access to credit has positive and significant marginal effect value on contract farming participation. This may be due to several factor; first, credit tends to minimize smallholder farmers cash constraints which affords them the opportunity to purchase their own production inputs. Additionally, access to financial services enhances the efficiency of input use and can facilitate the purchase of machinery and equipment to support high-value production and crop diversification. This can improve farmers' ability to market and transport their products. In total, access to credit is essential to transforming peasant agriculture into commercialized agriculture.

Households with bigger land sizes, more experience, and that are specialized in soybean farming are more likely to become contract participants. A plethora of empirical studies have found a significant and positive effect of farm size on contract farming participation (e.g., Dubbert (2019) and Rondhi et al. 2020). Lastly, the results also show that farmers who are risk-averse concerning farm investments and encounter more drought are more likely to become contract participants.

Stochastic production frontier results

Table 4 presents results from the conventional and sample selection SPF models for the matched samples. The estimated correlation coefficients for contract farmers ($\rho = 0.959$) and non-contract ($\rho = 0.967$) were significant at the 1% level. This indicates that there is a significant sample selection bias due to unobserved factors, which justifies the use of the sample selection stochastic frontier model for estimating the stochastic frontier model of contract and non-contract farmers. The estimated coefficients of the transformed conventional factor inputs are all positive with the exception of herbicide, which implies that the monotonicity condition is (globally) fulfilled. The results show that the elasticity of scale for contract farmers (0.778) is slightly higher than for non-contract farmers (0.770), but both estimates are less than one (see Table 4[3]). This implies that both groups of farmers operate under decreasing returns to scale.

From the conventional SPF model using pooled samples, labor, fertilizer, seed, and herbicides are significant factors in explaining soybean yields at the 1% level. Results from the sample selection SPF model for contract farmers also reveal that yields significantly increase with labor, fertilizer, and seed and reduce with herbicide application. In the non-contract farmers model, labor and seed are found to increase yields, whereas herbicide application is found to reduce yields. The observed negative effect of herbicide on soybean yield could be due to the over-application of herbicide to the extent that output is adversely affected. The positive effect of labor, fertilizer, and seed agrees with

[3] SPF models using the unmatched sample can be found in Appendix 1.

Table 4 SPF estimates using matched sample

Variables	Conventional SPF						Sample selection correction SPF			
	Pooled		Contract farmers		Non-participants		Contract farmers		Non-participants	
	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat
Constant	0.029	0.37	− 0.118	− 0.94	0.126	1.23	− 0.336**	− 2.22	0.011	0.1
Labor	0.275***	4.46	0.251**	2.49	0.299***	3.79	0.252**	2.11	0.280**	2.45
Fertilizer	0.039***	3.08	0.052**	2.47	0.028*	1.8	0.049*	1.8	0.024	1.3
Seed	0.571***	3.7	0.522**	2.04	0.637***	3.25	0.579**	2.37	0.647**	2.4
Herbicide	− 0.136***	− 3.25	− 0.198***	− 2.67	− 0.131**	− 2.56	− 0.210***	− 2.59	− 0.125**	− 2.04
$Labor^2$	0.206***	3.76	0.273***	2.75	0.181***	2.69	0.237**	1.99	0.207***	2.64
$Fertilizer^2$	0.001	1.62	0.001	1.1	0.001	1.1	0.002	1.46	0.0003	0.32
$Herbicide^2$	− 0.025***	− 2.69	− 0.021	− 1.13	− 0.025**	− 2.38	− 0.017	− 0.9	− 0.035***	− 3.5
$Seed^2$	0.019	0.36	0.160	1.48	− 0.017	− 0.26	0.169	1.39	− 0.035	− 0.47
Labor × Fertilizer	− 0.013*	− 1.71	− 0.017	− 1.38	− 0.010	− 1.02	− 0.012	− 0.91	− 0.012	− 1.11
Labor × Herbicide	− 0.023	− 1.18	− 0.050	− 1.49	− 0.005	− 0.23	− 0.059	− 1.63	− 0.014	− 0.52
Labor × Seed	− 0.209***	− 3.13	− 0.166*	− 1.68	− 0.227**	− 2.37	− 0.120	− 0.79	− 0.271**	− 2.04
Fertilizer × Herbicide	− 0.001	− 0.2	− 0.0003	− 0.07	− 0.001	− 0.36	− 0.0001	− 0.02	0.002	0.5
Fertilizer × Seed	− 0.005	− 0.85	− 0.011	− 1.15	− 0.002	− 0.24	− 0.015	− 1.06	− 0.003	− 0.3
Herbicide × Seed	0.042	0.8	− 0.047	− 0.43	0.054	0.89	− 0.077	− 0.7	0.104	1.62
Power Tillage	0.098**	2.36	0.183***	3.03	0.033	0.57	0.140**	2.08	0.015**	0.24
Bawku West District	0.154**	2.47	0.175*	1.77	0.150*	1.86	0.139	1.28	0.147	1.5
Nanumba South District	0.209***	3.16	0.217**	2.09	0.185**	2.15	0.167	1.53	0.144	1.33
Karaga District	0.126*	1.84	0.048	0.46	0.173*	1.93	− 0.024	− 0.21	0.122	1.18
Variance	0.500***	5.17	0.487***	4.65	0.510***	9.06				
Lambda	0.988***	8.45	0.816***	6.42	1.263***	7.28				

Table 4 (continued)

Variables	Conventional SPF						Sample selection correction SPF			
	Pooled		Contract farmers		Non-participants		Contract farmers		Non-participants	
	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat
Sigma (u)							0.488***	6.09	0.509***	8.57
Sigma (v)							0.487***	10.12	0.384***	11.71
Rho(ρ)							0.959***	10.92	0.967***	15.68
Log-likelihood ratio	− 273.911		− 122.187		− 143.025		− 299.045		− 298.054	
Returns to scale (RTS)	0.743		0.748		0.782		0.778		0.770	
No. of observations	511		221		290		221		290	

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively

Table 5 *T* tests of technical efficiency using matched samples

Variable	Conventional SPF				Sample selection SPF			
	Mean TE	SD	Min	Max	Mean TE	SD	Min	Max
Unmatched sample								
Pooled	0.76	0.08	0.38	0.92				
Contract farmers (CF)	0.78	0.07	0.51	0.91	0.77	0.08	0.42	0.91
Non-participants (NP)	0.73	0.10	0.30	0.93	0.69	0.14	0.23	0.91
Difference (contract farming–NP)	0.05***				0.09***			
Matched sample								
Pooled	0.76	0.08	0.40	0.92				
Contract farmers (CF)	0.79	0.06	0.53	0.91	0.77	0.07	0.50	0.92
Non-participants (NP)	0.74	0.10	0.31	0.93	0.71	0.12	0.34	0.91
Difference (contract farming–NP)	0.05***				0.06***			

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively

studies by Villano et al. (2015) and Henningsen et al. (2015), while the negative effect of herbicide application on yields aligns with findings by Azumah et al. (2016).

The estimated parameters in the pooled model show that users of tractor services experienced a positive and significant effect for both contract farmers and non-contract farmers. This result agrees with the findings of Tun and Kang (2015) and Chidambaram (2013) who reported a positive association between farm mechanization and agricultural production in Bangladesh. Farmer locations also have a significant and positive effect on soybeans yield. The results show that farmers in the Bawku West and Nanumba South Districts of Northern Ghana have higher yields compared to farmers in Binduri District. However, the effect of farmers' location on yields was not significant in the sample selection SPF for both contract farmers and non-contract farmers. The yield differences between districts are significantly reduced due to the correction for observed and unobserved biases.

Impact of contract farming participation on technical efficiency

Our results show that contract farmers have higher TE than non-contract farmers using both the unmatched and matched samples (Table 5). The mean TE for the pooled estimates is 76% using both the unmatched sample and the matched sample. For the unmatched samples, the estimated TE of contract farmers ranges from 51 to 91% with a mean of 78%, while the estimated TE for non-contract farmers ranges from 30 to 93% with a mean of 73% using the conventional SPF model. After correcting for sample selection bias, the mean estimated TE reduces marginally from 78 to 77% for contract farmers and from 73 to 69% for non-contract farmers. Similarly, the mean estimated TE decreases from 79 to 77% for contract farmers and from 74 to 71% for non-contract farmers when sample selection bias is corrected using the matched samples (See Table 5). After controlling for biases resulting from both observed and unobserved factors, we can conclude that smallholder farmers producing under contract

Table 6 Determinants of technical efficiency

Variable	Pooled		Contract farmers		Non-contract farmers	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Gender of the farmer	− 0.133	− 0.51	− 0.303	− 0.56	− 0.155	− 0.5
Basic education	0.157	0.57	0.225	0.45	0.1594	0.47
Secondary education	− 1.293**	− 2.03	− 2.236	− 1.12	− 1.134*	− 1.64
Tertiary education	− 0.420	− 0.7	− 0.519	− 0.45	− 0.966	− 1.11
Household asset index	− 0.245*	− 1.84	− 0.253	− 0.91	− 0.300**	− 2.08
Off-farm activities	0.438*	1.66	0.866**	2.41	0.127	0.43
Dependency ratio	0.524	1.13	0.109	0.13	0.625	1.13
Access to training	− 0.570**	− 1.99	− 0.254**	− 2.15	− 0.866**	− 2.37
Farm size	0.089	0.55	− 0.241	− 0.6	0.338	1.39
Adoption of IPT	− 0.031	− 0.31	− 0.108	− 0.5	− 0.086	− 0.72
Constant	− 1.995	− 3.9	− 2.240	− 2.22	− 1.698	− 2.92

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively

are substantially more technically efficient than their non-contract counterparts. This result is consistent with others in the literature, such as Mishra et al. (2016) and Mishra et al. (2018).

We further categorize the estimated TE scores for contract farmers and non-contract farmers using the unmatched and matched samples. When comparing TE scores, about 75% of the contract farmers achieve efficiency scores of 0.70–0.90, while 55–60% of non-contract farmers achieved efficiency scores of 0.70–0.90 using both the unmatched and matched samples (Fig. 2). The observed positive effect of contract farming participation on the TE of soybean farmers is likely due to differences in knowledge transfer and training on-farm management practices that diffuse to farmers, and the access to inputs such as fertilizers and seed. As discussed earlier, contract farmers benefit from training in on-farm management practices and knowledge transfer in improved agricultural technologies (Oya 2012; Otsuka et al. 2016). While we are unable to pinpoint the specific mechanism from our data, these findings show that contract farming has the potential to increase the overall productivity of the soybean sector by increasing the TE of non-contract smallholder farmers.

Determinants of technical efficiency

The results of the determinants of TE in soybean production are presented in Table 6. Please note that in the SPF estimation, the dependent variable in the second stage (or inefficiency effects components) of the model is the inefficiency level. Therefore, a negative sign on the coefficient here is interpreted as indicating a negative effect on inefficiency, or a positive effect on efficiency (Coelli et al. 2005). In general, the signs on the factors of TE are as expected. The results show that secondary education, household assets, off-farm activities, and access to training on-farm management practices are significantly and positively related to TE. We further find that access to training on farm

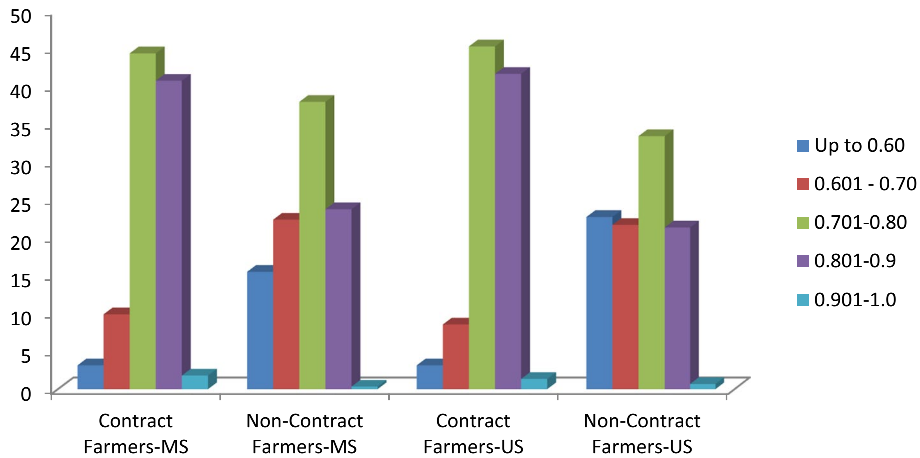

Fig. 2 TE scores for contract farmers and non-contract farmers. Note: US denotes the unmatched sample, while MS denotes the matched sample

management practices is positively correlated with the TE of both contract farmers and non-contract farmers, with the effect being larger for non-contract farmers. This difference may be attributable to the smaller (marginal) impact of additional training on farmers who would have already received some training as a result of being under contract. Furthermore, this may speak to the outsized role of access to training when inputs are not provided, as was the case for non-contract farmers in this dataset. Off-farm employment is correlated with a decrease in the TE of soybean farmers. The most likely explanation for this result is that participation in the off-farm labor market takes away labor from the farm, which reduces farm productivity and efficiency. This result is consistent with several empirical studies that found a negative relationship between off-farm work and TE (e.g., Mayen et al. 2010; Chang and Wen 2011; Chang and Mishra 2011; Sabasi et al 2019).

Conclusion

Increasing the productivity and efficiency of soybean production continues to be a challenge in Ghana and many LDCs (FAO 2017). Contract farming is one potential solution and has been used to increase productivity and facilitate the integration of smallholder farmers into commercial value chains (Ragasa et al. 2018). This paper contributes to the current debate by examining the factors that influence soybean farmers' decisions to participate in contract farming and its impacts on TE. The study combines an emerging framework of combining a selection corrected SPF model with PSM to estimate the impact of contract farming on soybeans farmer's efficiency levels in Ghana.

Our main results show that farmers participating in a contract farming scheme have higher levels of TE. We find that higher levels of key purchased inputs—seed, labor, and fertilizer—are positive and statistically significant contributors to greater soybean yield. The GCAP provided the smallholder farmers in the treatment group with these key inputs as part of the contract terms, and our results show that these were important factors in achieving higher productivity. The other key result we find is that access to training has a larger effect (in terms of magnitude) on the TE of non-contract farmers than contract farmers, which suggests that future projects may not have to provide inputs at highly subsidized prices and could instead focus on training and knowledge transfer if funds are limited. This is contrast to most results that find knowledge transfer on its own often has no positive impact on outcomes (e.g., Bellemare (2010), Jones and Kondylis (2018) and Arouna et al (2021a)) though Arouna et al. (2021b) find that personalized extension services have a positive effect.

While we find that contract farming in our dataset has a positive effect on productivity in the form of higher TE levels, there are several limitations we need to acknowledge. First, our results do not provide any evidence on the effectiveness of contract farming as a poverty reduction strategy. A well-known criticism of contract farming is that farmers are sometimes forced to purchase expensive inputs and do not experience sufficiently large increases in revenue to compensate for the higher costs (Bellemare and Bloem 2018; Ragasa et al. 2018). This was not an issue in this particular project but is worth mentioning. In addition, it is not always clear if the most impoverished farmers are the ones who benefit from contract farming as there is evidence that farmers with larger landholdings and greater wealth are more likely to participate in contract farming (Michelson 2013). Lastly, it is inherently risky to rely on a single crop as crop failure due to external forces such as pests and inclement weather is always a possibility. Greater crop diversification would enhance overall farmer resilience to negative shocks, and should be considered as a part of the contract farming arrangement. In spite of these risks and limitations, there remains much optimism for the impact that contract farming can have on improving the agricultural sector (Otsuka et al. 2016). It will be imperative, however, that the contracts do not focus exclusively on the wealthiest farmers and that the terms of the contracts do not impose additional financial burdens.

Given the important role that contract farming plays in improving the TE of smallholder farmers, it is important that there continues to be support from governments, development organizations, and private agribusinesses in implementing agricultural and value chain development activities through contract farming. This will help address the multiple production and marketing problems faced by smallholder producers. Further, policies aimed at integrating smallholder farmers into the modern agricultural value chain through contract farming must be accompanied by complementary factors such as access to production credit, formal education, and FBO membership. The government of Ghana, through the MoFA, should continue to invest in the human capital of farmers through training in the form of farmer demonstrations and farmer field schools to increase productivity and efficiency levels.

Appendix 1

(See Table 7)

Table 7 SPF estimates using unmatched sample

Variables	Conventional SPF						Sample selection correction SPF			
	Pooled		Contract farmers		Non-participants		Contract farmers		Non-participants	
	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat
Constant	0.036	0.46	− 0.116	− 0.96	0.127	1.24	− 0.299**	− 2.11	− 0.014	− 0.12
Labor	0.290***	4.77	0.266***	2.73	0.318***	4.02	0.239**	2.42	0.291**	2.26
Fertilizer	0.041***	3.27	0.053***	2.65	0.030*	1.94	0.057**	2.31	0.027	1.37
Seed	0.567***	3.71	0.509**	2.04	0.630***	3.20	0.567***	2.75	0.644**	2.16
Herbicide	− 0.143***	− 3.47	-0.206***	− 2.93	− 0.136***	− 2.67	− 0.211***	− 3.10	− 0.128**	− 1.96
Labor^2	0.218***	4.02	0.289***	3.00	0.194***	2.86	0.258***	2.60	0.196**	2.45
Fertilizer^2	0.001*	1.85	0.001	1.38	0.001	1.26	0.002*	1.77	0.001	0.96
Herbicide^2	− 0.024***	− 2.64	− 0.021	− 1.13	− 0.025**	− 2.35	− 0.020	− 1.25	− 0.028***	− 2.66
Seed^2	0.025	0.48	0.150	1.49	− 0.007	− 0.11	0.148	1.45	− 0.029	− 0.36
Labor × Fertilizer	− 0.012	− 1.57	− 0.015	− 1.24	− 0.008	− 0.89	− 0.016	− 1.41	− 0.010	− 0.94
Labor × Herbicide	− 0.020	− 1.05	− 0.049	− 1.49	− 0.002	− 0.09	− 0.042	− 1.39	− 0.010	− 0.35
Labor × Seed	− 0.216***	− 3.26	− 0.164*	− 1.70	− 0.239**	− 2.48	− 0.173	− 1.48	− 0.254*	− 1.80
Fertilizer × Herbicide	− 0.001	− 0.55	− 0.002	− 0.52	− 0.002	− 0.47	− 0.002	− 0.56	− 0.001	− 0.39
Fertilizer × Seed	− 0.005	− 0.92	− 0.011	− 1.25	− 0.002	− 0.27	− 0.011	− 0.89	− 0.001	− 0.13
Herbicide × Seed	0.033	0.64	− 0.053	− 0.50	0.048	0.80	− 0.064	-0.69	0.073	1.06
Power Tillage	0.089**	2.20	0.169***	2.93	0.028	0.48	0.163***	2.94	0.018	0.29
Bawku West District	0.151**	2.47	0.179*	1.88	0.150*	1.88	0.194**	2.11	0.149	1.51
Nanumba South District	0.211***	3.26	0.234**	2.35	0.180**	2.10	0.242***	2.63	0.167	1.53
Karaga District	0.118*	1.75	0.048	0.47	0.168*	1.89	0.058	0.62	0.144	1.38
Variance	0.504***	7.38	0.487***	4.86	0.517***	6.45				
Lambda	1.031***	8.9	0.863***	5.09	1.308***	7.47				

Table 7 (continued)

Variables	Conventional SPF						Sample selection correction SPF			
	Pooled		Contract farmers		Non-participants		Contract farmers		Non-participants	
	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat	Coeff.	Z-stat
Sigma (u)							0.414***	4.51	0.537***	7.62
Sigma (v)							0.377***	7.56	0.384***	10.66
Rho							0.775***	2.63	0.925***	8.19
Log-likelihood ratio	-283.275		-126.887		-147.556		-317.068		-315.771	
Returns to scale (RTS)	0.970		0.748		0.800		0.732		0.770	
No. of observations	531		235				235		296	

Legends: ***, **, * represent significance levels at 1%, 5% and 10%

Abbreviations

FBO	Farmer-based organization
GCAP	Ghana Commercial Agriculture Project
GSS	Ghana Statistical Service
FAO	Food and Agriculture Organization
LDC	Less developed country
MoFA	Ministry of Food and Agriculture
PSM	Propensity score matching
SPF	Stochastic production frontier
TE	Technical efficiency

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Declarations

Competing interests
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