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Article

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GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

Impact of contract farming on rice farm performance: Endogenous switching regression

John Kanburi Bidzakin^{1*}, Simon C. Fialor², Dadson Awunyo-Vitor² and Iddrisu Yahaya¹

Abstract: Contract farming (CF) is increasing been used as a strategy in rice production in Ghana while there is no empirical data supporting it. This study investigated the importance of CF in rice production. Cross-sectional farm household level data collected from 350 rice farmers randomly selected across the rice production areas of Ghana was used. The adoption and casual impact of CF was estimated using endogenous switching regression and propensity score matching methods. Results revealed positive and significant relationship between CF and farm performance measures (yield and gross margins). Results indicate that, CF increases yield and gross margins significantly. It further identified educational level, rice farm size and ISFM as positive determinants of contract participation. This evidence provides strong support for efforts to promote CF in Ghana. Educated farmers should be targeted for CF participation because their propensity to participate in CF is high. Sensitising our illiterate farmers to participate in CF should be vigorously pursued. CF should also be encouraged as a means to promote the adoption of ISFM technology. CF is recommended as a good tool for developing the local rice value chain in Ghana.

Subjects: Agriculture; Microeconomics; Econometrics; Economic Forecasting; Development Economics

Keywords: contract farming; impact; rice; endogenous switching regression

ABOUT THE AUTHOR

John Kanburi Bidzakin BIDZAKIN is an Agricultural Economist and works with Council for Scientific and Industrial Research (CSIR)-Savanna Agricultural Research Institute (SARI) in Ghana. He has carried evaluations of several projects, Designed and Implemented Project Monitoring and Evaluation Plans, Carried out Analysis of commodity value chains and developed upgrading strategies. He worked on a project that introduced CF as an intervention to deal with production and marketing challenges. This study is part of an evaluation of the project, which is seeking to empirically establish the role of CF in rice value chain development in Ghana. It will seek to advise on whether we should continue to promote contract farming or we should stop. This study was carried out jointly with Professor Simon C. Fialor, Dr Dadson Awunyo-Vitor and Dr Iddrisu Yahaya all Agricultural Economist.

PUBLIC INTEREST STATEMENT

Contract farming (CF) is regarded as a strategy for agricultural transformation in developing countries because it has the potential to solve agricultural marketing and production problems of smallholder farmers simultaneously. Even though many studies identify positive effects of CF on the livelihood of farmers, CF is still controversial. It is predicted that CF would not likely work for traditional staple commodities like rice, soybean, maize, etc. because spot markets would be the most efficient. With the increasing trend of rice CF in Ghana it is very critical to empirically establish its role in rice production in Ghana hence the need for the study. The study concluded that CF increased yield and gross margins significantly. It is therefore recommended that CF is a good tool to enhance rice production in Ghana hence farmers should be encouraged to participate in CF.

1. Introduction

Small-scale farmers in many developing countries face a number of production and marketing constraints, such as limited access to services, including effective extension and rural credit, which are crucial pre-conditions for upgrading commodity value chains (Wiggins et al., 2010). Low fertilizer use intensity has been cited as one of the main factors limiting rice productivity growth in Sub-Sahara Africa (SSA) (Fuglie et al., 2013; Koji, 2009). Smallholder rice farmer's poor access to credit is induced by their lack of collateral or by the high interest rates demanded by financial institutions (Jan et al., 2012; Barrett et al., 2012; Deb & Suri, 2013; Oya, 2012).

There are a number of new technologies available to boost rice production but just a few farmers are aware of these technologies. This gap is largely due to poor extension farmer ratio, which is estimated to be about 1:1000 in Ghana (MoFA, 2014). There is also poor access to market and lack of economies of scale (Rehber, 1998; Simmons, Winters, & Patrick, 2005). The few who have knowledge of the technologies often also lack the capacity to adopt the new and improved technologies due to cost associated with it. Contract farming (CF) is seen as a strategy that can address these deficiencies.

CF has long been prevalent in developed countries and in recent times has spread widely in developing countries (Wong, Darachanthara, & Soukhamthath, 2014). CF is perceived as a strategy for agricultural transformation in developing countries because of its potential to address agricultural marketing and production challenges concurrently. Little and Watts (1994); Simmons et al. (2005); Christensen, Sayāmwalā, and Witchayānon (1993); and Ton et al. (2007) has argued that CF can benefit farmers directly through access to credit, inputs, remunerative markets and improved technology, thus increasing their productivity and income. CF also improves access to capital and credit (Hudson, 2000). The engagement of smallholder farmers in CF will result in proper co-ordination and allocation of resources, goods and services thereby reducing poverty and improving the livelihoods of farm households (Jari & Fraser, 2009) hence the need for CF.

Even though many studies identify positive effects of CF on the livelihood of farmers such as Porter and Phillips-Howard (1997); Warning and Key (2002); Minten, Randrianarison, and Swinnen (2009); Bolwig, Gibbon, and Jones (2009) and Bellemare (2012) who identified income and productivity gains from CF in Africa. It is also argued that CF can lead to risk-sharing between the producer and the agribusiness firm hence it can reduce price and income volatility (Key & Runsten, 1999). Warning and Key (2002); Govere and Jayne (2003); Minten et al. (2009); Bellemare (2012) showed that CF reduced market imperfections by providing credit, inputs, technology and information and hence lowered transaction costs (Deininger, Ali, & Alemu, 2011; Grosh, 1994; Key & Runsten, 1999). Other studies described CF as a tool for agribusiness firms (contractors) to cheat farmers (Little & Watts, 1994; Porter & Phillips-Howard, 1997; Singh, 2002). Ragasa, Lambrecht, and Kufoalor (2017) showed that CF in the Upper West region of Ghana contributed to technology adoption and productivity growth, but did not result in high profitability because production cost was too high relative to non-contract farmers in their maize CF study. Abdulai and Al-hassan (2016) also concluded that participation in CF does not necessarily improve smallholder farmers' income despite productivity gains in their soybean CF study in Ghana.

Information on CF is relatively not available in staple food chains. Theoretical considerations have shown that there are challenges in employing CF in staple food chains (Swinnen & Maertens, 2007). Some of the challenges includes contract enforcement would be particularly difficult because the value of the chain is low and the opportunities for quality improvement are limited and this will impede the use of a price premiums as a strategy for contract enforcement; secondly, the presence of a large number of small buyers in the value chain and the fact that the commodities are often bulky and also not highly perishable, further increases the risk of opportunistic sales and breach of contract. Hence, it is predicted that CF would not likely work for traditional staple commodities like rice, soybean, maize, etc. because spot markets would be the most efficient system (Berdegué &

Escobar, 2002; Hellin, Lundy, & Meijer, 2009; World Bank, 2014). From literature, most studies conducted on CF impact on farm performance often use indicators like, income and yield with very little (just about 6%) on profitability. However, profitability is a critical farm measures because farms may have high yields and may still be unprofitable. Yield is an important farm measure but not sufficient to give as a comprehensive performance status of the farm and its effect on livelihood, hence the need to include gross margins as a performance measure.

The findings of the study will go a long way to contribute to the development of the local rice value chain. It will also test the hypothesis that CF will not work with traditional non-differentiated crops like rice. It will also contribute to farm performance assessment literature using gross margin (profit) as a farm performance measure, which is rarely done. The study will also conclude on whether CF is a viable strategy in developing the local rice value chain.

The objective of the study is to assess the factors influencing rice farmers CF participation decision and its impact on yield and gross margins in Ghana.

The following hypotheses are tested:

- There is no relationship between CF participation and rice yields
- There is no relationship between CF participation and rice gross margins

2. Materials and methods

2.1. The study area

This study covered Northern, Upper East and Volta Regions of Ghana basically because of their rice production potential, which is mainly savannah. About 80% of total rice production in Ghana comes from these three regions.

2.2. Sampling strategy and sample frame

Stratified sampling technique was use to sample representative of smallholder rice farmers in Northern, Upper East and Volta Regions. The three regions were purposively selected based on their rice production potential. Each region was further classified into the two main production ecologies (irrigation and rain-fed ecologies). The production ecologies were further classified into Contract production and non-contract production. Farmers were then randomly selected from the CF and NCF stratum. Stratified random sampling is to guarantee representation of the specific sub-groups or strata of this study. The stratified sample formula is specified as:

$$n = \frac{N}{p} Y \quad (1)$$

Where;

n = Sample size of the stratum

N = Estimated total sample size

P = Total population size

Y = Estimated stratum size

The population of interest for the study included small-scale rice farmers working under irrigation and rain-fed production ecology in Northern, Upper East and Volta Regions of Ghana. A total of 350 farmers were selected from the three regions for the study. The sample distribution by each stratum is shown in [Table 1](#).

Table 1. Number of farmers sampled

Region	Production Ecology	Management System	Est. Farmer Population	No. of Farmers Sampled
NR	Irrigation	CF ^a	371	13
		NCF ^b	1086	38
	Rain fed	CF	914	32
		NCF	1914	67
UER	Irrigation	CF	429	15
		NCF	829	29
	Rain fed	CF	857	30
		NCF	2171	76
VR	Irrigation	CF	1086	38
	Rain fed	CF	343	12
Total			10000	350

^a CF = Contract farmers.

^b NCF = Non-contract farmers.

2.3. Types and sources of data

The study employed primary data as the main data source for this study. This was collected through farmer survey. Secondary data was gathered from sources like books, journals and research reports.

The study used different data tools, which included quantitative data tools (questionnaires) and qualitative data tools (focus group discussions and key informant's interviews). Focus group discussions were carried out with randomly selected rice FBOs working within the project districts. Ten focus group sessions were conducted which covered the three regions. This was aimed at collecting qualitative data to support the data gathered by the household questionnaire and also serve as a means of triangulation to ensure that the data is of good quality. Key informant's interviews were also conducted, basically engaging in a conversation with key stakeholders in the district such as MoFA crop officers, scientist from SARI, processors and aggregators.

Semi-structured questionnaires were administered to randomly selected farmers to enable us obtain data on their livelihoods, which includes, production, marketing, credit access, adoption of ISFM practices, income status, contract participation, food security situation, farm and farm household characteristics, rice production status, etc., the questionnaires were administered through face to face interview with the farmers.

3. Analytical framework

In examining the impacts of CF on yield and gross margin, it will be too simplistic and biased to just attribute the differences in yields and gross margins between the two groups to CF. When we are dealing with experimental data in which the counterfactual situation is known the problem of causal inference is not an issue (Miguel et al., 2004). However, when dealing with a cross sectional survey data such as this, where the counterfactual situation is not known, then the causal inference will be a big issue. As argued by Dehejia et al. (2002), this problem can be resolved by investigating the impact of CF participation by analysing the differences in outcomes among farm households participating in CF and those not participating using econometric models.

Some of the models include propensity score matching approach proposed by Rosenbaum et al. (1983), which has been widely employed to examine the impacts of technology adoption on farm outcomes and household welfare, particularly when self-selection is an issue. However, propensity score estimation tries to balance the observed distribution of covariates across the groups of

Table 2. Variables of the models and their hypothesized relationships

Variable Label	Description	Unit	Expected Signs (ESRM)		
			GM	Yield	CF
	Household and farmer characteristics				
Gender	Gender of HHH is a dummy variable (male = 1, female = 0)	Dummy	+	+	-
Education	Education of household head is measured	Years	+	+	+
Production ecology	Production been under rain fed or irrigation Dummy variable (irrigation = 1, rain fed = 0)	Dummy	+	+	+
Crop Variety	The type of rice variety used (1 = improved, 0 = local)	Dummy	+	+	+
Age	Age of household head	Years	+	±	±
Farmer Experience	Number of years household head has been in crop production	Years	+	+	+
HH size	Total number of household members	Numbers	-	+	+
Total acres	Total household land holding	Acres	±	±	+
FBOP	Farmer base organization participation. Dummy variable (member of FBO = 1, otherwise = 0)	Dummy	+	+	+
Management system	Contract farming (CF) (CF = 1, Non-CF = 0)	Dummy	+	+	
Wealth	Total wealth of the farm household	GHS	+	+	-
	Output				
Yield	Yield/Ha	(kg)			
Gmargin	Gross margin/Ha	GHS			
	Inputs				
Farm Size	Farm size	Ha	+	+	±
Labour	Labour used	Number	-	+	+
Fertilizer	Fertilizer applied	kg	-	+	+
	Input prices				
FertCost	Fertilizer price	GHS	+	-	-
LabourCost	Labour wage	GHS	+	-	-
SeedCost	Seed price	GHS	+	-	-

adopters and non-adopters. Hence, the probit or logit estimates obtained in the estimation cannot be considered as determinants of adoption.

Another model is the endogenous switching regression approach, which was developed by Lee (1982) as a general model of the Heckman's selection correction model. It can account for selection bias by treating selectivity as an omitted variable problem (Heckman, 1979). In contrast to the Heckman model, farm outcomes such as yields and gross margins can be observed for the whole sample of CF and NCF. Thus, in the switching regression approach, the farmers are partitioned according to their classification as CF and NCF in order to capture the differential responses of the two groups.

Given our interest in examining the determinants of yield and gross margins, as well as the impact of CF participation, we employ the endogenous switching regression model to account for selection bias in our estimation of the impact of CF participation on farm outcomes (Yield and Gross margin) and also the determinants of yields and gross margin. The PSM will also be used to allow for assessing the robustness of the impact results. The variables of the models and their hypothesized relationships are shown in Table 2.

3.1. Specification of propensity score matching model (PSM)

The PSM is a non-parametric technique and hence do not require specification of a functional form and distribution assumptions. The method is naturally attractive as it is simply to apply. It compares the observed outcomes of the adopters with those of the non-adopters (Heckman, Ichimura, & Todd, 1998). The basic idea of the PSM method is to match observations of adopters and non-adopters according to the predicted propensity of adopting a superior technology (Asfaw, Shiferaw, Simtowe, & Lipper, 2012; Heckman et al., 1998; Rosebaum et al., 1983; Wooldridge, 2002). The main attribute of the matching procedure is the creation of the conditions of randomized experiment in order to evaluate a causal effect as in a controlled experiment.

Let G_i denotes a dummy variable such that $G_i = 1$ if the i^{th} individual participates in CF and $G_i = 0$ otherwise. Similarly let Y_{1i} and Y_{2i} denote potential observed welfare outcomes for CF participants and non-participants respectively. Then $\Delta = Y_{1i} - Y_{2i}$ is the impact of CF on the i^{th} individual, usually called treatment effect. As we observe $Y = G_i Y_{1i} + (1 - G_i) Y_{2i}$ rather than Y_{1i} and Y_{2i} for the same individual, we are unable to compute the treatment effect for every unit. The primary treatment effect of interest that can be estimated is therefore the Average impact of Treatment on the Treated (ATT) given by

$$\pi = E(Y_{1i} - Y_{2i} / G_i = 1) \quad (2)$$

Following Rosenbaum and Rubin (1983), the propensity score can be estimated as

$$P(X) = P(G_i = 1/X) \quad (3)$$

Given the assumptions that

- (1) $Y_{1i}, Y_{2i} \perp G_i/X$, that is the potential outcomes are independent of CF participation given as X , this imply $E(Y_{2i}/G_i = 1, P(X)) = E(Y_{2i}/G_i = 0, P(X))$
- (2) $0 < P(X) < 1$, that is for all X there is a positive probability of either adopting ($G = 1$) or not adopting ($G = 0$), this guarantees every adopter a counterpart in the non-adopter population,

The ATT can then be estimated as

$$\begin{aligned} \pi &= E(Y_{1i} - Y_{2i} / G_i = 1) \\ &= E[E(Y_{1i} - Y_{2i} / G_i = 1, P(X))] \\ &= E[E(Y_{1i} - Y_{2i} / G_i = 1, P(X)) - E(Y_{2i} / G_i = 0, P(X))] \end{aligned} \quad (4)$$

The propensity score is a continuous variable and there is no way to get adopter with the same score as its counterfactual(s). Thus, estimation of the propensity score is not sufficient to compute the average treatment effect given by equation (4). We need to search for counterfactual(s) that matches with each adopter depending on its propensity score. Different matching methods are used in the literature (Smith & Todd, 2005). We use the Nearest-Neighbour Matching Method (NMM) to pick comparison groups. The method could also be applied with or without replacement where the former allows a given non-adopter to match with more than one adopter (Becker & Ichino, 2002; Dehejia & Wahba, 2002). As discussed earlier, the observed outcome variable used are yield and gross margins of smallholder rice farmers.

3.2. Specification of endogenous switching regression model (ESRM)

CF participation as indicated earlier is modelled under the Random utility Theory (RUT) which says that farmers will choose between CF participation and non-participation based on the utility they will receive. It is assumed that farmers are risk neutral, and their decision to participate in CF will be influenced by the utility they will derive from CF participation. Rice farmers are therefore assumed to choose the management option that will provide them the maximum benefits (Abdulai & Huffman, 2014). Under the assumptions that, the utility (yield and gross margin) farmers derives from CF participation is Y_{JCF} , and the utility from non-adoption represented as Y_{JNCF} .

The two regimes can be specified mathematically as:

$$Y_{JCF} = X_J \beta_{CF} + u_{JCF} \quad (5)$$

and

$$Y_{JNCF} = X_J \beta_{NCF} + u_{JNCF} \quad (6)$$

Where X_J is a vector of variable factor prices, independent factors of farm and household characteristics; β_{CF} and β_{NCF} are the parameter estimates for CF and NCF respectively; u_{JCF} and u_{JNCF} are the error terms, which are assumed to be i.i.ds. Every rational farmer will chose the technology with the highest utility and it is expressed as, $Y_{JCF} > Y_{JNCF}$ (Pitt, 1983).

Preferences such as perceived net benefit of CF are not known to the researcher, however farmer and community attributes are observed during the data collection. The perceived benefits of CF derived can be represented by a latent variable D_J^* , which can be expressed as a function of the observed characteristics and attributes, denoted as Z , in a latent variable model as follows:

$$D_J^* = z_J \gamma + \varepsilon_J; D_J = 1 \text{ if } D_J^* > 0; D_J = 0 \text{ if } D_J^* \leq 0 \quad (7)$$

D_J is a dummy variable that equals 1 for farmers who participated in CF, and zero otherwise. γ represents the parameter to be estimated. A farmer will only participate in CF only if the perceived net benefits are positive. The error term ε with zero mean and variance σ^2_ε captures measurement errors and factors unobserved to the researcher but known to the farmer. Variables in Z include factors that influence the CF participation, such as farm-level household and community characteristics.

Given that farmers choose to either participate or not participate in CF, the observed net benefits take the following values:

$$\text{Regime 0 (NCF)} : Y_{JNCF} = X_J \beta_{NCF} + u_{JNCF} \text{ if } D_J = 0 \quad (8)$$

$$\text{Regime 1 (CF)} : Y_{JCF} = X_J \beta_{CF} + u_{JCF} \text{ if } D_J = 1 \quad (9)$$

Where Y_{JCF} and Y_{JNCF} are the outcome variables (yield and gross margin) for CF and NCF respectively, X_J is a vector of variable factor prices, independent factors of farm-level and household characteristics. The vectors β in equation (9) and γ in equation (8) are the associated parameters that have to be estimated.

For easy identification of the covariates of equation (9) and (8) it is suggested that at least one variable in Z does not appear in X . Self-selection occurs in CF participation decisions and may lead to non-zero covariance's between the error terms of CF participation decision equation and the outcome equations. The three error terms u_{CF} , ε , and u_{NCF} are assumed to have a trivariate normal distribution with mean vector zero and the following covariance matrix:

$$\text{Cov}(u_A, \varepsilon, \text{ and } u_N) = \Sigma = \begin{bmatrix} \sigma_A^2 & \sigma_{AN} & \sigma_{A\varepsilon} \\ \sigma_{AN} & \sigma_N^2 & \sigma_{N\varepsilon} \\ \sigma_{A\varepsilon} & \sigma_{N\varepsilon} & \sigma_\varepsilon^2 \end{bmatrix} \quad (10)$$

Where; $A = CF$; $N = NCF$

$$\text{Var}(u_A) = \sigma_A^2; \text{Var}(u_N) = \sigma_N^2; \text{Var}(\varepsilon) = \sigma_\varepsilon^2;$$

$$\text{cov}(u_A, u_N) = \sigma_{AN}; \text{cov}(u_A, \varepsilon) = \sigma_{A\varepsilon}; \text{cov}(u_N, \varepsilon) = \sigma_{N\varepsilon}$$

For this reason, the error terms in equation (10), conditional on the sample selection criterion, have non-zero expected values and ordinary least squares estimates of coefficients β_{CF} and β_{NCF}

also will suffer from sample selection bias (Lee, 1982). According to Johnson and Kotz (1970) the values of the truncated error term ($u_{CF}|D = 1$) and ($u_{NCF}|D = 0$) are then given as;

$$(u_{NCF}|D = 0) = E(u_{NCF}|\varepsilon \leq -z'\gamma) = \sigma_{NCF\varepsilon} \frac{-\vartheta\left(\frac{z'\gamma}{\sigma}\right)}{1 - \vartheta\left(\frac{z'\gamma}{\sigma}\right)} \equiv \sigma_{NCF\varepsilon}\lambda_{NCF} \quad (11)$$

and

$$(u_{CF}|D = 1) = E(u_{CF}|\varepsilon > -z'\gamma) = \sigma_{CF\varepsilon} \frac{\vartheta\left(\frac{z'\gamma}{\sigma}\right)}{1 - \vartheta\left(\frac{z'\gamma}{\sigma}\right)} \equiv \sigma_{CF\varepsilon}\lambda_{CF} \quad (12)$$

Where ϑ and ϑ are the probability density and cumulative distribution function of the standard normal distribution respectively. The ratio of ϑ and ϑ evaluated at $z'\gamma$ is referred to as the inverse Mills ratio λ_{CF} , λ_{NCF} (selectivity terms). The selectivity terms are incorporated into equation (11 and 12) to account for selection bias.

Where σ represents the covariance of the error terms, λ_{CF} and λ_{NCF} represents the inverse mills ratios of CF and NCF respectively. In estimating the impact of CF participation on yield and gross margins, it is important to note that if self-selection is based on comparative advantage, $\sigma_{CF\varepsilon} - \sigma_{NCF\varepsilon}$ would be positive, indicating that CF participation would result in higher yields and gross margins than under random assignment (Maddala, 1983). As indicated earlier, propensity score matching approach has been widely employed to estimate the average treatment effect. However, its strong assumption of confoundedness¹ makes it a restrictive approach.

The estimation of the model proceeds in two stages. The first stage involves a probit regression to determine the probability of CF participation and thus estimation of the parameter γ given in equation (8). These estimates are then used to calculate the selectivity terms (λ_{CF} , λ_{NCF}) according to equations (11) and (12). The limitation of this two-step approach is that it generates residuals that are heteroskedastic² and as a result cannot be used to obtain consistent standard errors without complex adjustments (Lokshin & Sajaia, 2004). The full information maximum likelihood method suggested by Lokshin and Sajaia (2004) overcomes the problem through a simultaneous estimation of the two equations, that is, the participation and outcome equations.

The areas of keen interest are the signs and significance levels of the correlation coefficients (ρ) from the estimates. As indicated previously, these are the correlations of the error terms of the outcome and treatment equations ($\text{cor}(\varepsilon, u) = \rho$). Specifically, there is endogenous switching, if either $p_{CF\varepsilon}\left(\frac{\sigma_{CF\varepsilon}}{\sigma_{CF}\sigma_{\varepsilon}}\right)$ or $p_{NCF\varepsilon}\left(\frac{\sigma_{NCF\varepsilon}}{\sigma_{CF}\sigma_{\varepsilon}}\right)$ is significantly different from zero, which would result in selection bias. If $\rho > 0$, this would mean negative selection bias, meaning that farmers with below average yields or gross margins are more likely to participate in CF. On the other hand, if $\rho < 0$ it means positive selection bias, suggesting that farmers with above average yields or gross margins are more likely to participate in CF.

Since impact of CF on farm outcomes (yield and gross margin) is of interest to the study we will assess the treatment and heterogeneity effects on yield and gross margins. An efficient way to estimate endogenous switching regression model is by the Full Information Maximum Likelihood (FIML) estimation method (Lee & Trost, 1978; Lokshin & Sajaia, 2004). The FIML method simultaneously estimates the probit criterion or selection equation and the regression equations to yield consistent standard errors. Given the assumption of trivariate normal distribution for the error terms. The FIML method, estimates the parameters of the Endogenous Switching Regression model using the **movestay** command in STATA (Lokshin & Sajaia, 2004).

3.3. Estimating treatment and heterogeneity effects on yield and gross margin

The endogenous switching regression model discussed can be used to compare the expected crop yields and gross margins of the farm households that participated in CF as shown in equation (12) and those that did not participate as shown in equation (13), and to estimate the expected yields and gross margins in the counterfactual hypothetical cases in equation (14) that the CF farm households did not participate in CF, and equation (15) that the NCF participated in CF. The conditional expectations for our outcome variables in the four cases are presented in Table 3 and also defined.

Where equation (13) and equation (14) represent observed expected crop yield and gross margin; equations (15) and (16) represent counterfactual expected crop yield and gross margins.

$D_i = 1$ if farm households participated in CF; $D_i = 0$ if farm households did not participate in CF;

Y_{jCF} = crop yield and gross margins if the farm households participated in CF

Y_{jNCF} = crop yield and gross margins if the farm households did not participate in CF

TT = the treatment effect of CF on the treated (i.e. farm households that participated);

TU = the treatment effect of CF on the untreated (i.e. farm households that did not participate);

BH = the base heterogeneity effect of farm households that participated (BH_{CF}), and did not participate (BH_{NCF});

TH = TT-TU, that is transitional heterogeneity

$$E(Y_{jCF}|D = 1) = X\beta_{jCF} + \sigma_{CF\varepsilon}\lambda_{CF} \quad (13)$$

$$E(Y_{jNCF}|D = 0) = X\beta_{jNCF} + \sigma_{NCF\varepsilon}\lambda_{NCF} \quad (14)$$

$$E(Y_{jNCF}|D = 1) = X\beta_{jCF} + \sigma_{NCF\varepsilon}\lambda_{CF} \quad (15)$$

$$E(Y_{jCF}|D = 0) = X\beta_{jNCF} + \sigma_{CF\varepsilon}\lambda_{NCF} \quad (16)$$

Cases [13] and [14] of Table 3 represent the actual expectations observed in the sample. Cases [15] and [16] represent the counterfactual expected outcomes. In addition, following Heckman and Vytlacil (2001), we calculate the effect of the treatment on the treated (TT) as the difference between equations (13) and (15).

$$TT = E[Y_{jCF}|D = 1] - E[Y_{jNCF}|D = 1] = X(\beta_{jCF} - \beta_{jNCF}) + (\sigma_{CF\varepsilon} - \sigma_{NCF\varepsilon})\lambda_{CF} \quad (17)$$

Which represents the effect of CF participation on the rice farm yield and gross margin of the farm that actually adopted the technology. Similarly, we can calculate the impact of the treatment on

Table 3. Treatment and heterogeneity effects

Sub-samples	Decisions Stage		Treatment Effects
	To Adopt	Not to Adopt	
Farm households that participated in CF	[13] $E(Y_{jCF} D = 1)$	[15] $E(Y_{jNCF} D = 1)$	TT
Farm households that did not participate CF	[16] $E(Y_{jCF} D = 0)$	[14] $E(Y_{jNCF} D = 0)$	TU
Heterogeneity effects	BH_{CF}	BH_{NCF}	TH

the untreated (TU) for farms that actually did not participate in CF as the difference between equation (16) and (14).

$$TU = E[Y_{jCF}|D = 0] - E[Y_{jNCF}|D = 0] = X(\beta_{jCF} - \beta_{jNCF}) + (\sigma_{CF\epsilon} - \sigma_{NCF\epsilon})\lambda_{NCF} \quad (18)$$

The difference between equations (13) and (16) will give us the heterogeneity effects. This refers to differences in the outcome due to their inherent differences such rice producing experience and not that of the treatment.

Carter and Milon (2005) define heterogeneity effect for the CF group as the difference between equation (13) and equation (16),

$$BH_{CF} = E[Y_{jCF}|D = 1] - E[Y_{jCF}|D = 0] = \beta_{jCF}(X_{jCF} - X_{jNCF}) + (\lambda_{CF} - \lambda_{NCF})\sigma_{CF\epsilon} \quad (19)$$

and that of the NCF group as the difference between equation (15) and equation (14)

$$BH_{NCF} = E[Y_{jNCF}|D = 1] - E[Y_{jNCF}|D = 0] = \beta_{jNCF}(X_{jCF} - X_{jNCF}) + (\lambda_{CF} - \lambda_{NCF})\sigma_{NCF\epsilon} \quad (20)$$

Finally, transitional heterogeneity (TH) is estimated, as if the effect of participating in CF is larger or smaller for the farm households that actually participated in CF or for the farm household that actually did not participate in the counterfactual case that they did participate, that is the difference between equations (17) and (18) ((TT) and (TU)).

4. Results and discussion

4.1. Farmer characteristics

The mean age difference between contract farmers and non-contract farmers is about 3 years and is significant at 1% level see Table 4. This implies farmer's age has a positive correlation with contract participation. It also implies most contract farmers are older and the NCF are youthful. However, there is no significant difference between the contract farmers farming experienced and that of non-contract farmers experience in rice production. Contract farmers are richer than non-contract farmers and this is significant at 1%. There is no difference in the household size and also the available arable lands of the two groups.

From Table 5, the mean difference of rice farm size of contract farmers and non-contract farmers is about 0.35 ha and significant at 1% significance level. The mean difference of fertilizer use, seed use, labour used are 122 kg/acre, 28 kg/acre and 5 persons/acre respectively, which are all significant at 1% level of significance. There is no difference in the prices of fertilizer and labour used. Seed price was significant at 1% with mean difference of -0.12 GHS, which implies non-contract farmers bought their seed at relatively cheaper price than contract farmers. This could be that farmers bought grain and used it as seed because of the relative high cost certified seed. Yield is an important variable in assessing farm level performance and it is evident that contract farmers have higher yields than their non-contract farmer colleagues with difference of 1,090 kg per acre. Total output of contract farmers was far more than the output of non-contract farmers with about 3,360 kg of paddy rice. Output price was also significant indicating contract farmers earn 0.15 GHS/kg more than their non-contract farmer counterparts. This implies their farm revenues will also be higher with a significant mean difference of 1,792 GHS. Cost of production of contract farmers is far more than that of non-contract producers with mean difference of 170 GHS. Gross margins mean difference is 1,622.00 GHS indicating contract farmers earn more profit than their non-contract counterparts.

4.2. Impact of CF on rice yields and factors influencing rice yield

The estimates of impact of CF participation on rice yields and determinants of yields are presented in Table 6. CF participation equation, which represents the determinants of CF participation are presented in columns 2 and 3 and the determinants of yield for CF participants and non-participants are

Table 4. Farmer characteristics of contract and non-contract participants

Farm Household Characteristics	CF (n = 140)	NCF (n = 210)	Mean Difference	t-Statistic
	Mean	Mean		
Age of HHH	46.41	43.22	3.19 ***	2.701,642
Farmer experience	22.94	24.20	(1.25)	-1.145
Wealth of farm HH GHS	8,256.64	3,214.71	5,041.93 ***	4.643,198
Household Size	7	7	0.35	1.1456
Total household arable land	5.07	5.65	(0.58)	-1.52

*** 1% level of significance; **5% level of significance; *10% level of significance

Table 5. Farm characteristics of CF and NCF

Variables	CF (n = 140)	NCF (n = 210)	Mean Difference	t-Statistic
	Mean	Mean		
Rice farm size (ha)	1.31	1	0.31***	4.5
Fertilizer used (kg)	314.43	192.20	122.23***	5.33
Seed used (kg)	90.03	61.61	28.41***	2.82
Labour used	13	8	5.0***	4.9
Fertilizer price (GHS)	1.11	1.81	-0.70	-1.57
Seed price (GHS)	0.57	0.70	-0.12***	-2.84
Labour price (GHS)	36.28	43.07	-6.79	-1.41
Yield/ha	1,743.08	652.99	1090.09***	10.56
Total output (kg)	4,880.41	1,520.11	3360.30***	10.75
Output price/kg (GHS)	1.46	1.31	0.15***	5.1
Total revenue (GHS)	2,642.00	850.08	1791.91***	10.17
Total cost of prod. (GHS)	584.98	414.91	170.07***	4.7
Gross margins/ha (GHS)	2,057.01	435.17	1621.84***	10.32

*** 1% level of significance; **5% level of significance; *10% level of significance

presented in columns (4 and 5) and (6 and 7) respectively. The coefficients are interpreted as normal probit coefficients.

4.2.1. Factors influencing rice yields

From the results, the Wald test is highly significant indicating the goodness of fit of our endogenous switching regression model. This implies there is an endogeneity problem hence the use of the endogenous switching regression model is justified. From the likelihood ratio test of independence of the selection and outcome equations indicate that we can reject the null hypothesis of no correlation between CF participation and rice yields. This implies CF participation is positively correlated with rice yields.

The results in Table 6 indicate that the positive and significant determinants of yield are; production ecology, wealth of farm households, total household arable land, fertilizer used, seed used and labour used. Irrigation production has positive effect on yields of rice farms. Rice is a water loving plant and hence the positive effect of irrigation on its yield was expected and it

Table 6. Endogenous switching regression results for CF participation and its impact on yield

	CF Participation		Yield			
			CF		NCF	
Variables	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Production ecology	0.049	0.167	228.269	143.197	152.024***	46.549
Crop variety	-0.186	0.354	260.569	326.192	-64.464	111.611
Gender	-0.265	0.373	197.671	360.499	-1.026	114.101
Age of farmer	-0.001	0.009	12.019	7.793	-1.677	2.400
Education level	0.047**	0.019	-4.738	15.274	-0.418	6.219
Farmer experience	0.005	0.009	-9.445	8.296	0.152	2.481
Wealth of farm HH	0.000	0.000	0.036***	0.008	0.004	0.009
Household size	0.035	0.032	-38.062*	27.277	5.208	8.693
Total household arable land	-0.070*	0.039	56.113*	39.770	7.197	10.483
Rice farm size	0.142*	0.090	-285.018***	64.727	-54.623*	29.931
Fertilizer used			1.050**	0.492	0.534***	0.150
Seed used			1.289*	0.919	-0.022	0.339
Labour used			-5.435	6.727	7.472*	4.544
ISFM	2.33***	0.26				
Constant	1.292*	0.905	1712.830**	687.418	493.295**	216.485
/lns1	6.747	0.084				
/lns2	5.724	0.051				
/r1	-1.235	0.225				
/r2	0.101	0.311				
sigma_1	851.625	71.378				
sigma_2	306.008	15.636				
rho_1	-0.844	0.065				
rho_2	0.101	0.308				
Log likelihood	-2719.36					
Wald test χ^2 (14)	125.27					

LR test of independent equations χ^2 (1) 14.40 ***

*** 1% level of significance; **5% level of significance; *10% level of significance

agrees with the work of Bidzakin, Fialor, Awunyo-Vitor, and Yahaya (2018) and Nonvide (2018). Wealth has positive influence on yields of CF participants. Wealth increases the purchasing power of the household, which helps them to buy farm inputs like fertilizers, which provides nutrients to the plant and hence influences yield positively (Ekbo, 1998). Total arable land has positive effect on yields of CF participants because land can be a proxy for wealth and from our focus group discussions we realized CF participants who had more lands were more resourceful. This is in line with the wealth variable. Farmers who use more fertilizer obtain higher yields for both adopters and non-adopters. Seed has positive effect on yields of only adopters.

The negative and significant determinants of yields are household size, rice farm size and labour used. Household size of adopters has negative influence on yields. Households with large household members have lower yields. Large rice farms have lower yields compared to smaller rice farms. Igweoscar (2014) work on cassava also identified farm size and labour cost as determinants of yield. Farm size has a negative effect on crop yields, representing diseconomies of scale Blanc, Lepine, and Strobl (2016), which is in sync with our findings. Maniriho and Bizoza (2018) also showed that crop production was positively correlated with labour, fertilizers, seeds and pesticides used.

4.2.2. Impact of CF on yields

The results of the impact of CF participation on yield are presented in Table 6 columns (4–5) and (6–7) for participants and non-participants of CF respectively. The estimates show the impact of household and farm level characteristics on rice yields of CF and NCF. The likelihood ratio test for the joint independence of the three equations is shown on Table 4. The test shows that the three equations are dependent on each other.

The signs and significance of the covariance terms (ρ_1 and ρ_2) show that covariance term of the adopters is statistically significant, indicating that self-selection occurred in CF participation. This implies CF may not have the same effect on the NCF if they choose to participate (Abdulai & Huffman, 2014). The negative sign indicates a positive bias, suggesting that farmers with above average yields have a higher probability of participating in CF. This finding is consistent with earlier studies by Abdulai and Binder (2006) and Abdulai and Huffman (2014) but in contrasts with the findings of Kabunga, Dubois, and Qaim (2012). The statistically insignificant covariance estimate for NCF suggests that in the absence of CF, there would be no significant difference in the average yields of the two categories of farmers caused by unobservable factors. The necessary conditions for consistency are also fulfilled, since $\rho_1 < \rho_2$ indicating that CF obtain higher yields than they would if they did not participate in CF (Lokshin & Sajaia, 2004).

4.3. Impact of CF participation on gross margins and factors influencing gross margins

The estimates of the impact of CF participation on rice gross margins and determinants of gross margins are presented in Table 7. The Full Information Maximum Likelihood (FIML) approach was used to estimate the CF participation equation and yield equations simultaneously for CF and NCF. From Table 7 the CF participation equation, presents the determinants of CF participation and the results are presented in columns (2 and 3) and the determinants of yield for CF participants and non-participants are presented in columns (4 and 5) and (6 and 7) respectively. The coefficients are interpreted as normal probit coefficients.

4.3.1. Factors influencing gross margins

From the results, the Wald test is highly significant indicating the goodness of fit of our endogenous switching regression model. This implies there is an endogeneity problem hence the use of the endogenous switching regression model is justified. From the Wald test of independence of the CF participation and gross margins equations indicate that we can reject the null hypothesis of no correlation between CF participation and rice gross margins. This implies CF is positively correlated with rice gross margins.

The results in Table 7 indicate that the positive and significant determinants of gross margins of CF participants are; age of farmer and wealth of farm households. For NCF, it is only irrigation that had positive effect on their gross margins. Wealth has positive impact on gross margins of CF participants. The positive relationship of age of the household with that of gross margin is in line with findings of Olayiwolaa (2008). It was expected that the younger and more energetic farmers would report higher gross margins than the older ones due to their ability to comprehend new technologies because they are more educated. Wealth of farm households was expected to influence gross margins positively because they have the ability to procure fertilizers and also pay for farm labour where necessary and this is expected to increase yield and hence gross

Table 7. Endogenous switching regression results for CF and its impact on gross margins

Variables	CF Participation		Gross Margin			
			CF		NCF	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Production ecology	0.020	0.165	233.191	230.279	109.765**	54.833
Crop variety	−0.193	0.350	520.735	519.936	−99.966	131.555
Gender	−0.275	0.370	760.166	571.595	19.328	134.306
Age of farmer	−0.005	0.009	22.301*	12.503	−2.097	2.837
Education level	0.038**	0.018	−23.595	24.696	−1.344	7.134
Farmer experience	0.007	0.009	−18.224	13.280	−2.643	2.924
Wealth of HH	0.000	0.000	0.054***	0.012	0.010	0.011
Household size	0.040	0.031	−76.781*	43.212	4.105	10.151
Total HH arable land	−0.056*	0.038	64.303	60.499	7.680	12.227
Rice farm size	0.136*	0.088	−377.892***	101.736	13.161	35.202
Fertilizer cost			147.024	182.013	−1.632	4.087
Seed cost			−888.360*	560.857	80.841	100.783
Labour cost			−5.170*	2.916	−0.393	0.618
ISFM	2.331***	0.265				
Constant	1.994**	0.891	2286.998**	1088.91	476.03*	255.664
/lns1	7.234	0.078				
/lns2	5.888	0.050				
/r1	−1.347	0.193				
/r2	0.091	0.286				
sigma_1	1386.056	108.783				
sigma_2	360.695	18.158				
rho_1	−0.873	0.046				
rho_2	0.091	0.284				
Log likelihood	−2820.78					
Wald test χ^2 (14)	90.76					
LR test of independent equations χ^2 (1) 21.28***						

*** 1% level of significance; **5% level of significance; *10% level of significance

margins. They may also have the ability to negotiate for better prices. Even though fertilizer is not significant, the sign agrees with similar works of Reardon et al., (1997); Olubanjo and Oyebojo (2005); Ahmad and Bakhsh (2006) who found that fertilizer contributes positively to profitability of agricultural production.

The negative and significant determinants of gross margins of CF are; household size, rice farm size, seed cost and labour cost. Household size of CF has negative influence on gross margins. Households with large household members have lower gross margins the observed relationship may be due to the fact that in some instances, despite the relatively larger household size, most members spend their time on other activities such as alcohol consumption and others may be in school and thus may not be readily available labour force. This result is inconsistent with findings of Sulumbe, Iheanacho, and Mohammed (2010). Farm size has an inverse relationship with gross margins one would expect a positive relationship due to economies of scale; however, the observed relationship might have been due to inefficiencies in production and possibly poor land management and improvement systems. Seed cost and labour cost all negatively influence gross margins of CF, this is in line with theory whereby cost is inversely related to gross margins. Seed

and labour cost increase total variable cost which is subtracted from total revenue to yield gross margins. Samboko (2011) revealed that land ownership, household size are important determinants of profitability.

4.3.2. Impact CF on gross margins

The results of the impact of CF on gross margins are presented in Table 7 columns (4 and 5) and (6 and 7) for CF and NCF respectively. The estimates show the impact of household and farm level characteristics on gross margins of CF and NCF. The likelihood ratio test for the joint independence of the three equations is shown in Table 7. The test shows that the three equations are dependent on each other.

The signs and significance of the covariance terms (ρ_1 and ρ_2) show that covariance term of the CF participation in Table 5 is statistically significant, indicating that self-selection occurred in CF participation decision. This implies CF participation may not have the same effect on NCF if they choose to participate in CF (Abdulai & Huffman, 2014). The negative sign indicates a positive bias, suggesting that farmers with above average gross margins have a higher probability of participating in CF. This finding is consistent with earlier studies by Barrett et al. (2012); Abdulai and Binder (2006); Abdulai and Huffman (2014) but contrasts with the findings by Kabunga et al. (2012).

The statistically insignificant covariance estimate for NCF suggests that in the absence of CF, there would be no significant difference in the average gross margins of CF and NCF caused by unobservable factors. The necessary conditions for consistency are also fulfilled, since $\rho_1 < \rho_2$ indicating that CFs obtained higher gross margins than they would have if they did not participate in CF (Lokshin & Sajaia, 2004). Igweoscar O., (2014) and Chang, Chen, Chin, and Tseng (2006) work also agrees with this findings where CF increase profits.

4.4. Determinants of CF participation

The significant and positive determinants of contract participation decision are educational level, farm size and ISFM adoption. The significant and negative factor influencing contract participation is total household arable land. The farmer who is more educated is more likely to participate in contract production than a farmer who is not educated because they may have better understanding of the concept and also better negotiation ability than their illiterate colleagues. It also plays an important role in determining the allocative ability of farmer (Caswell et al., 2001; Bachke, 2010; Narayanan, 2011; Onphanhdala, 2009).

Farmers who practice ISFM technology have a higher probability of participating in contract production. ISFM requires the use of improved seed and organic and inorganic fertilizers, which is made possible through contract arrangements. Land is an important resource base of the farmer in the production process. The economic and social progress of farmers mostly depends on the size of their operational holdings (Shah, 2013). Farmers with bigger household arable land are less likely to participate in CF (Just et al., 1983) which is in line with the findings of this study.

Farm size denotes intensity of crop cultivation. This variable is expected to have positive influence in probability of participation in CF. The size of the farm denotes higher investments, thus farmers shall like to reduce their risk coverage by participating in contact. This agrees with the findings of the study.

4.5. Estimates of impact of CF on yield and gross margin

4.5.1. Endogenous switching regression model impact estimates

The estimates for the average treatments effects on the treated (ATT), average treatments effects on the untreated (ATU) and the heterogeneity effect (HE) which show the impact of CF on rice yields and gross margins and also the effect due to their inherent characteristics on yields and gross margins, are presented in Table 8. Unlike the mean differences presented in Table 3, which

Table 8. Impact of CF on yield and gross margins using ESRM

Farm Outcomes	Adoption Status	Predictions		Treatment Effect	t-Value
		CF	NCF		
(1) Yield/ha	ATT (CF)	2243.91	1743.08	500.83***	4.1
	ATU (NCF)	2199.03	652.99	1546.03***	21.9
	Heterogeneity effect	44.88	1090.09		
(1) Gross margins/ha	ATT (CF)	2887.05	2151.84	735.21***	4.19
	ATU (NCF)	2777.11	435.17	2341.94***	30.25
	Heterogeneity effect	109.94	1716.67		

may confound the impact of CF participation on yields and gross margins, The ESR estimates of ATT and ATU account for selection bias arising from the fact that CF and NCF may be systematically different.

The results revealed that CF participation significantly increases yields and gross margins of CFs and also had the potential to increase that of the NCFs. Specifically, the causal effect of CF for participants is about 500 kg of paddy, representing a 27% increase in yields of CF participants. The causal effect of CF for non-participants is about 1546 kg of paddy if they practice it, representing a 240% increase in yield. Similarly, the CF increased gross margins by 34.2%, from GHS 2151.84 to GHS 2887.05 for CF participants. However, the potential causal effect of CF for non-participants is about 2341.94 GHS, representing a 538% increase in gross margins for non-participants. These findings are consistent with the view that CF participation has the potential to improve farm yields and profits significantly (Minten *et al.*, (2008); Men *et al.* (2013); Koji (2009); Cai, Ung, Setboonsarng, and Leung (2008); Gustaf (2011); Nham (2012).

The effect of CF participation will have considerable impact on current non-participants if they participate in CF. They can increase their yields by 240% averagely and also increase their gross margins by 538% averagely.

4.5.2. Propensity score matching impact estimates

Results for the casual impact of CF on yield and gross margin are consistent with those of the ESRM. The overall average gain of CF participation on yield is about 502 kg for PSM logit model and the result is highly significant as shown in Table 9. The estimates from the ESRM and PSM are very consistent.

5. Conclusions and recommendation

5.1. Estimates of impact of CF on yield and gross margin

The results reveal that CF participation significantly increases yields and gross margins of farmers who participated in CF and has the potential to increase yield and gross margins of those who did not. Specifically, the causal effect CF on yield of CF participants is about 500 kg per hectare of

Table 9. Impact of CF on yield and gross margin using PSM method

Model	Outcome	Treat Effect	Coef.	Std. Err.
Logit	Yield	ATT	502.151***	100.814
	GM	ATT	691.657***	123.146

paddy, representing a 27% increase in yields for CF. The potential causal effect of CF on yields of non-participants is about 1546 kg per hectare of paddy, representing a 240% increase in yields for non-participants. Similarly, CF participation increased gross margins by 34.2%, from GHS 2151.84 to GHS 2887.05 per hectare for CF participants and for non-participants its potential effect is about 2341.94 GHS, representing a 538% increase in gross margins for non-participants. These are similar to the results from the PSM technique as shown in [Table 7](#).

5.2. Impact of CF on yield and its determinants

The results reveal that CF participation is positively correlated with rice yields. Self-selection occurred in CF participation and this implies CF participation may not have the same effect on non-participants if they choose to adopt (Abdulai & Huffman, 2014). Farmers with above average yields have a higher probability of participating in CF. Rice yields can be achieved by encouraging farmers to produce more under irrigation, and resource poor households should be encouraged to participate in CF. Farmers should be encouraged to use fertilizer and improved seed to increase their production. Farmers should also be encouraged to cultivate smaller farm sizes they can effectively manage to ensure good yields. A large family size does not necessarily imply available labour, Hence funds should be provided to pay for hired labour to support the family labour when necessary.

5.3. Impact of CF on gross margins and its determinants

The results show that CF participation is positively correlated with rice gross margins. Self-selection occurred in CF participation and this implies CF participation may not have the same effect on the non-participants if they choose to participate in CF (Abdulai & Huffman, 2014). The negative sign indicates a positive bias, suggesting that farmers with above average gross margins have a higher probability of participating in CF. The positive and significant determinants of gross margins are production ecology, age of farmer and wealth of farm households. The negative and significant determinants of gross margins are household size, rice farm size, seed cost and labour cost.

5.4. Policy recommendations

In order to sustain and improve rice production in Ghana the following policy recommendations are drawn from the study;

- (1) Government and her development partners should continue and intensify the introduction of CF as a management strategy to boost rice production and hence improve livelihood of farmers.
- (2) Government should introduce CF in its planting for food and jobs program to attract more participation in CF for improved yield and gross margins.
- (3) Older farmers should be targeted for CF as they have higher propensity to participate in CF.
- (4) Educated farmers should be targeted for CF participation because their propensity to participate in CF is high.
- (5) Sensitizing our illiterate farmers to participate in CF should be vigorously pursued.
- (6) CF should also be encouraged as a means to promote the adoption of ISFM technology.

5.5. Recommendations for future study

The study focused on farm level performance assessing indicators like efficiency, yield and gross margins, we recommend future studies should go beyond farm level performance to look at impact on welfare indicators like food security. The study focused on only the demand side of CF (the farmer) without looking at how it affects the supply side of CF (the agribusiness firm). CF may be beneficial to the supply side and may not be beneficial to the demand side and vice versa, hence it is recommended for an assessment of the supply side of CF in future studies.

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Notes

1. It implies that once observable factors are controlled for, technology adoption is random and uncorrelated with the outcome variables. As argued by Smith and Todd (2005), there may be systematic differences between adopters' and non-adopters' outcomes even after conditioning, because selection is based on unmeasured characteristics.
2. This refers to the circumstance in which the variability of a variable is unequal across the range of values of a second variable that predicts it.

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