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Participation in contract farming and farm performance: Insights from cashew farmers in Ghana

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Abstract

The global demand for cashew nuts continues to increase steadily. However, many African countries face difficulties in marketing and adding value to the product. Using recent survey data of 391 cashew farmers in Ghana, this paper contributes to the growing evidence on the significance of contract farming (CF) in improving the welfare of rural households in developing countries. Specifically, the paper analyzes the factors that influence cashew farmers' decisions to participate in CF, and the impact of participation on farmers' performance. We employ a recently developed switching regression model with endogenous explanatory variables and endogenous switching to control for selection bias caused by observable and unobservable factors. The empirical results show that participation in CF significantly increases labor productivity and price margins, as well as cashew yields, and net revenues. A disaggregated analysis of the sample into farm size categories reveals that small-sized cashew farms tend to benefit more through CF, compared to medium- and large-sized farms.

KEYWORDS
Africa, cashew, contract farming, impact assessment, value chain

JEL CLASSIFICATION
C34, J24, L24, O13, Q13

1 | INTRODUCTION

The need for higher levels of managed coordination has grown due to rapid changes in global food markets (Minot & Sawyer, 2016). Rather than relying on commodities purchased at farm gate or spot markets, buyers rely more on complex supply chains. Nevertheless, smallholder farmers were hindered from innovating and participating in those agrifood value chains, due to the low investments in market systems and infrastructure in the past (Dendena & Corsi, 2014).

In order to facilitate smallholder farmers' participation in managed agrifood value chains, contract farming (CF) has received much attention in recent years (Ragasa, Lambrecht, & Kufoalor, 2018; Reardon, Timmer, Barrett, & Berdegue, 2003). CF plays an increasingly important role in developing countries, as it addresses constraints related to inadequate access to credit and extension services, market failures, risk, and high transaction costs (Miyata, Minot, & Hu, 2009). Moreover, CF allows farmers to overcome market entry barriers and provides smallholder farmers access to modern technologies, quality control, and marketing (Mishra, Kumar, Joshi, & D'Souza, 2018b).

Several studies have analyzed the impact of CF on smallholder farmers in developing countries on various crops. Most of these studies show positive impacts of CF on welfare indicators such as household income, farm productivity, and food security (Bernard, Hidrobo, Le Port, & Rawat, 2019; Harou, Walker, & Barrett, 2017; Maertens & Velde, 2017; Mishra et al., 2018b; Miyata et al., 2009). However, the empirical evidence on this topic remains inconclusive in the development debate (Bellemare & Bloem, 2018). In particular, some argue that companies take advantage of cheap labor and transfer production risk to farmers and thus making farmers worse off (Miyata et al., 2009). CF can even contribute to increased inequality within regions, as buyers often buy from areas with better roads, easier access to water, or from support areas of NGOs and other donors (Barrett et al., 2012). Moreover, income from labor markets and nonfarm business might get sacrificed due to CF (Bellemare, 2018).

Very few studies have extended their analysis on how factors like output prices and labor inputs contribute to the improvement of smallholders welfare through CF (Bellemare, 2018; Benali, Brümmer, & Afari-Sefa, 2018; Mishra, Kumar, Joshi, & D'Souza, 2018a). Participation in CF generally evolves in response to market imperfections particularly that of labor inputs due to moral hazard and high monitoring costs in developing countries (Casaburi, Kremer, & Mullainathan, 2016). The present study therefore contributes to the debate on welfare impacts of CF by examining the potential of CF for job creation and income generation. More specifically, we look at whether participation in CF increases labor productivity, off-farm income, and price margins of smallholder farmers. We use recently collected household data of 391 Ghanaian cashew farmers from Brong-Ahafo and Northern regions. These regions are Ghana´s major areas of cashew production (African Cashew Initiative, 2010). Cashew is the second most important smallholder cash crop in terms of export value in Ghana. Despite the central role of cashew for the Ghanaian economy, there is a lack of knowledge about how CF shapes cashew production and incomes.

Another aspect of our analysis is the introduction of heterogeneity in impacts by scale of operation. This enables us to show whether the effects of CF is uniform across different farm size categories. The significance in this also has to do with our ability to show at what levels of operation CF plays complementary role to off-farm income, and at what level it could negatively, if any, affect off-farm income. This will be very important in designing policies that aim at supporting CF and off-farm employment by knowing which segment of farmers to target. Likewise, it will provide policy makers with insights into the multidimensional effects of participation in CF, as well as enhance the understanding of the mechanisms through which CF affects welfare (Bellemare & Bloem, 2018; Upton & Lentz, 2017).

However, a major problem in examining the effects of CF is that participation in CF is not randomly assigned across farm households, because farmers may self-select into CF. Therefore, the estimation must consider unobserved heterogeneity that could simultaneously affect the CF decision and the dependent variables. The limitation in approaches used in past studies has been noted by Bellemare and Bloem (2018) and Ton, Vellema, Desiere, Weituschat, and D'Haese (2018). Most studies have either used instrumental variable (IV) approach (Simmons, Winters, & Patrick, 2005), or propensity score matching (PSM) technique (Mishra et al., 2018b) to account for selection bias. The issue of instrument relevance and validity in the context of highly heterogeneous dependence effects of CF in our context, make the IV approach alone not suitable. A well-known shortcoming of PSM is its inability to account for unobservable factors among farmers such as innate skills and risk preferences, which may result in biased and inconsistent estimates (Ma & Abdulai, 2016).

We use a control function approach combined with IV estimation following Murtazashvili and Wooldridge (2016) to estimate both, the participation decision and the outcomes. Different to applying IV methods directly, the control function accounts for the correlation of endogenous explanatory variables with the endogenous switching indicator, which is CF participation in our case. This makes the control function approach for linear models more consistent, than only applying IV methods. As a result, we are able to account for potential endogeneity, many sources of heterogeneity, and self-selection based on both observable and unobservable factors.

The remainder of this paper is structured as follows: Section 2 gives an overview of the development of the cashew sector in Ghana. Section 3 describes the data used in the analysis. Section 4 outlines the empirical framework employed in the analysis and presents the details of our estimation and identification strategy. Section 5 presents the empirical results, while conclusions of our study are presented in the final section.

2 | THE CASHEW MARKET IN GHANA

Cashew trees grow in most tropical countries around the world, with production more than doubling in the last 16 years to almost 5 million tons in 2016. West Africa produces together with South-Eastern Asia, about 90% (45% each) of the world's raw cashew nuts (Rabany, Rullier, & Ricau, 2015). In 2014, cashew became the second main cash crop in terms of export value behind Cocoa in Ghana (MoFA, 2017). Cashew cultivation is a major source of income for about 75,000 Ghanaian smallholder farmers. Since the harvest of the nuts takes place during the lean season, it ensures their livelihood by generating additional income. Therefore, cashew can assume a crucial role in food and nutrition security (Heinrich, 2012). As the cashew tree is drought-resistant and

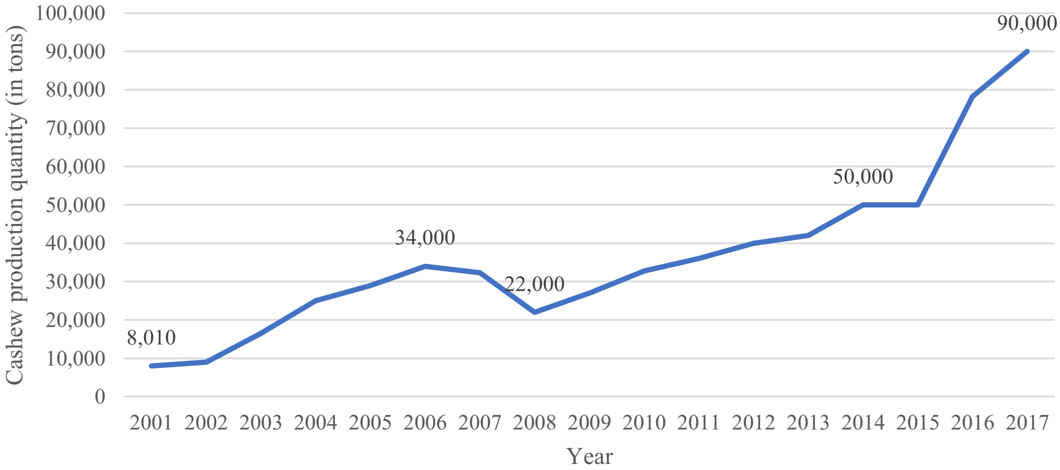

FIGURE 1 Development of raw cashew production quantity in Ghana (in tons) (FAO, 2018) [Color figure can be viewed at wileyonlinelibrary.com]

requires low production inputs, it can also serve as an adaptation strategy to reduce the adverse impacts of climate change.

Cashew cultivation in Ghana started in the 1960s with sporadic plantings in the Central and Greater Accra Regions, and later spread to Brong-Ahafo and Northern Regions. In the 1970s, the industry suffered a setback due to issues such as low producer prices, underdeveloped market structures, and inadequate information regarding appropriate husbandry practices which led to low interest in the crop, with many established cashew plantations abandoned. With the introduction of the Economic Recovery Program in 1983, cashew was identified as one of the major nontraditional crops to be developed as part of the Government's efforts to diversify the country's export base. Commodity markets were therefore liberalized, thus providing opportunities for farmers to sell raw cashew nuts. As a result, cashew farmers reinvested resources to rehabilitate some of the abandoned farms. Increasing trade between Asia and Africa and strong global demand for cashew boosted this new sector, and offered new opportunities for smallholder farmers who massively invested in cashew farming (Rabany et al., 2015).

About 88% of cashew farmers in Ghana are smallholders, with farms ranging in size from 0.8 to 3 hectare (ha). Only 12% are large plantations, with farm sizes between 4 and 40 ha (Wongnaa & Awunyo-Vitor, 2013). Figure 1 shows that raw cashew nut production in Ghana more than tripled over a period of 10 years from about 30,000 tons in 2007 to 90,000 tons in 2017 (FAO, 2018). Moreover, production is projected to increase to about 225,000 tons in 2025 (Rabany et al., 2015). Average yield levels of raw cashew nuts vary between 350 and 650 kg/ha. This reveals potential for higher output under required production conditions and labor input (African Cashew Initiative, 2010).

The development of the cashew sector in Ghana has given birth to numerous functional farmer associations, processing plants, and traders linked to the industry. Ghana´s access to the sea and a relatively well-developed major road network across the country provides ideal conditions for cashew processing. Value addition is an important issue in order to generate jobs and to obtain higher prices, as the country still earns only a fragment of the cashew nut value chain. However, in comparison with other West African countries such as Ivory Coast or Benin, Ghana's cashew sector is a relatively small player and less advanced in fulfilling its potential in production and marketing. It is only responsible for about 2.6% of global raw cashew nut production (FAO, 2018; Heinrich, 2012; Rabany et al., 2015).

3 | DATA AND DESCRIPTIVE STATISTICS

The data used in the present study come from a household survey that was conducted from August to October 2017 in the Brong-Ahafo and Northern regions of Ghana. A multistage random sampling procedure was used to select farm households for the interviews. First, Brong-Ahafo region and Northern region were purposively selected, based on the national intensity of cashew production. In a second step, four districts with intensive cashew cultivation were chosen. These include Nkoranza, Techiman, and Wenchi districts in Brong-Ahafo region, as well as Bole district in the Northern region. We next randomly selected four communities per district (in Bole eight communities), using a sampling frame provided by cashew buyers and community chiefs. Finally, contract farmers and noncontract farmers were proportionately selected from each community randomly.

The data set consists of 391 cashew farming households from 20 villages, of which 177 are participants in CF and 214 are nonparticipants. Identified farmers answered a detailed questionnaire on individual sociodemographic data; farm and plot-level characteristics that cover the management of the cashew farm, marketing of cashew nuts, contract relations with buyers, farmer's perceptions of cashew business and CF, as well as nonincome wealth indicators.

Smallholder cashew farmers in our sample produce and supply raw cashew nuts to buyers, using contracts or spot market transactions. These buyers are private companies, aggregators, traders, and processors[1]. The sample consists of 45% contract farmers. Almost all contracts (97.6%) are verbal agreements between the farmer and the buyer, with only 2.4% of written contracts. The main provisions that are included in the contracts are grading and quality requirements (nut size and weight), and the harvest time. The majority of contract farmers (92%) report cashew farming as their primary source of income, while 83% of noncontract farmers declare cashew farming as their most important income activity.

Table 1 presents the descriptive statistics of differences in characteristics between contract and noncontract farmers. Given that the focus of this study is to examine the drivers of participation in CF, as well as the factors through which CF affects farm productivity and incomes, we draw on existing literature on CF to identify explanatory variables (Miyata et al., 2009; Wang, Wang, & Delgado, 2014). Table 1 reveals that the proportion of women participating in CF is significantly lower compared to noncontract farmers. Moreover, contract farmers are significantly older, and they own significantly larger and older cashew farms than noncontract farmers.

Table 2 presents the descriptive statistics for incomes and agricultural productivity used as outcome variables in this study. It shows that cashew yields, net revenues, and farm incomes are significantly higher for contract farmers, while their off-farm income is significantly lower compared to noncontract farmers. For instance, cashew yields of contract farmers are on average 523 kg/ha, which is above the national average cashew yield of 500 kg/ha (MoFA, 2017). The higher yields obtained by cashew farmers could suggest their access to better information about cultivation of the crops, as well as access to production inputs. The effect of participation in CF on off-farm work is not clear-cut, since participation in the off-farm labor market may restrict production and decision-making activities, thereby decreasing farm productivity. On the other hand, increased off-farm work reduces financial constraints, particularly for resource-poor farmers, and thus enables them to purchase productivity enhancing inputs (Abdulai & Huffman, 2000; Benali et al., 2018).

As indicated earlier, participation in CF typically arises in response to market imperfections particularly that of labor inputs due to moral hazard and high monitoring costs in developing countries (Casaburi et al., 2016; Wendimu, Henningsen, & Czekaj, 2017). To gain some insights into the impacts of CF on farm performance and household welfare, we extend our analysis to capture the impact of CF on labor productivity and price margins. Labor productivity measures the quantity of harvested cashew nuts in kilograms per total labor days of family and hired workers. Price margins is the difference of received cashew prices per kg minus the production input costs per kg output. Cashew generally does not require much input for operation, once the trees are matured. However, to reduce losses associated with rotting, collection of cashew nuts on time is very important. Ensuring the required amount of labor input at the appropriate time is therefore necessary. Thus, we expect that participation in CF give farmers the income and guarantee to engage more hired labor to carry out the needed activities at the appropriate time.

In summary, Tables 1 and 2 suggest that contract and noncontract farmers are systematically different across observable characteristics and output variables. This implies that participation in CF is characterized by potential selectivity concerns. The simple comparison of mean differences across contract farmers and noncontract farmers does not account for unobservable factors and could be biased. We therefore employ econometric analysis to disentangle the bias driven by selection in CF and to examine the impact of CF on the indicated welfare measures.

4 | EMPIRICAL FRAMEWORK

In this section, we present the theoretical and empirical framework. In particular, we begin with the description of a farmer's decision to participate in CF. This is followed by the presentation of the control function approach to estimate a switching regression with endogenous explanatory variables and endogenous switching.

The conceptual framework employed in this study considers the expected net returns R_C^* from participation in CF and the expected net returns R_N^* from nonparticipation, with R representing net returns. Defining the difference between the expected net returns from participating in CF and not participating as R^*, that is, $R^* = R_C^* - R_N^*$, a farmer will choose to participate in CF if the net returns from participation is greater than the net returns from nonparticipation; that is, $R^* > 0$. However, R^* is latent and thus not observable. Only the choice of CF participation (D_i) can be observed and can be expressed as a function of observable elements in the following latent variable model:

$$R^* = Z_i\beta + \mu_i, \qquad \text{with } D_i = 1 \qquad \text{if } R^* > 0, \tag{1}$$

where D_i is the CF participation indicator that takes the value of one, if the household participates in CF, and zero

[1] Examples of the private companies that contract with smallholder cashew farmers in Ghana include Olam International, Rajkumar Impex Ghana Ltd., Unicom Commodities Ghana Ltd., and Mim Cashew & Agricultural Products Ltd.

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TABLE 1 Household characteristics of contract and noncontract farmers

Variable	Definition of variables	Contract ($N = 177$)	No contract ($N = 214$)	Mean diff.
Age	Age of household head (years)	54.864 (13.717)	52.177 (14.401)	2.687*
Female headed HH	1 if household head is female, 0 otherwise	0.198 (0.399)	0.312 (0.465)	−0.115***
Education	1 if a farmer's level of education is at least primary school (≥6 years), 0 otherwise	0.616 (0.488)	0.542 (0.499)	0.074
Household size	Number of persons living in the household	7.762 (3.446)	7.748 (3.877)	0.015
Farm size	Total cashew area (ha)	3.995 (2.966)	3.163 (2.335)	0.832***
Soil type	1 if fertile soil, 0 otherwise	0.384 (0.488)	0.402 (0.491)	0.018
Farm age	Age of cashew farm (years)	12.850 (6.360)	11.100 (5.914)	1.751***
Farm records	1 if farmer keeps farm records, 0 otherwise	0.147 (0.355)	0.056 (0.231)	0.091***
Market	1 if community has market, 0 otherwise	0.282 (0.451)	0.238 (0.427)	0.044
Farmer group	1 if farmer is farm group member, 0 otherwise	0.299 (0.459)	0.257 (0.438)	0.042
Labor	Total labor used in cashew production (days/ha)	50.888 (40.356)	52.414 (35.977)	−1.526
Family labor	Family labor used in cashew production (days/ha)	32.329 (27.525)	37.217 (29.193)	−4.888*
Hired labor	Hired labor used in cashew production (days/ha)	18.559 (23.901)	15.197 (16.936)	3.362
Mobile phone	1 if farmer owns mobile phone, 0 otherwise	0.706 (0.457)	0.790 (0.408)	−0.083*
Motorbike	1 if farmer owns motorbike, 0 otherwise	0.373 (0.485)	0.266 (0.443)	0.107**
Farm radius	Number of cashew farmers living in a 3 km radius around farmhouse	15.469 (12.633)	12.431 (9.114)	3.037***
Access to credit	1 if farmer asked for and received sufficient credit, 0 otherwise	0.406 (0.490)	0.381 (0.482)	0.025
Extension service	1 if farmer received extension services (last 3 years), 0 otherwise	0.542 (0.500)	0.519 (0.501)	0.024
Nkoranza	1 if farm household is located in Nkoranza district, 0 otherwise	0.232 (0.423)	0.177 (0.383)	0.054
Bole	1 if farm household is located in Bole district, 0 otherwise	0.384 (0.488)	0.397 (0.490)	−0.013
Wenchi	1 if farm household is located in Wenchi district, 0 otherwise	0.192 (0.395)	0.215 (0.412)	−0.023
Techiman	1 if farm household is located in Techiman district, 0 otherwise	0.192 (0.395)	0.210 (0.408)	−0.018

Note. $N = 391$.
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.
Standard deviation in parentheses.

if otherwise; Z_i is a vector of observable household and farm-level characteristics (such as age, gender, education, and farm size) expected to influence the participation decision; β is a vector of parameters to be estimated. The error term μ_i is assumed to be normally distributed with zero mean and constant variance (σ^2). As stated before, selection into CF is not random. Farmers choose to participate or not to participate in CF based on expected net returns that are subjective and based on their inherent characteristics and experiences. This may be driven by unobserved intrinsic characteristics such as farming skills, risk preferences, or motivation. These characteristics are likely to affect the CF participation

TABLE 2 Cashew production costs and revenues of contract and noncontract farmers

Variable	Definition of variables	Contract ($N = 177$)	No contract ($N = 214$)	Mean diff.
Farm income	Income from farm work (GHS/ha)	3,480.719 (3,014.245)	2,957.861 (2,462.562)	522.9*
Off-farm income	Income from off-farm work (GHS/ha)	1,618.967 (1,584.18)	2,237.427 (1,952.107)	−618.5***
Yield	Harvested cashew nuts (kg/ha)	522.975 (477.620)	411.181 (363.886)	111.0***
Quantity sold	Total quantity of cashew nuts sold (kg)	1,631.42 (1,470.168)	1,164.797 (1,201.306)	466.6***
Price	Average Price (GHS/kg)	5.963 (0.671)	5.844 (0.548)	0.040
Gross revenue	Gross revenue from cashew sales (GHS/ha)	2,950.885 (2,702.906)	2,420.414 (2,317.602)	530.5**
Production costs	Total input costs for cashew production (GHS/kg)	1.907 (1.902)	2.151 (3.552)	−0.234
Net revenue	Gross revenue minus costs for agricultural inputs and labor (GHS/ha)	2,332.053 (2,531.876)	1,873.791 (2,060.555)	458.3**

Note. $N = 391$.
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.
Standard deviation in parentheses. The figures refer to cropping season 2016/2017.

decision and farmers' productivity and incomes simultaneously, leading to potential endogeneity problem, since the covariance between the decision to participate and the error term in Equation (1) will not be equal to zero. As such, causal identification of participation requires an instrument that is strongly correlated with the participation decision, but does not directly affect the outcomes. We will discuss the applied instrument later in this section.

Following Equation (1), we express the probability of participation in CF as:

$$\Pr(D_i = 1) = \Pr(R^* > 0) = \Pr(\mu_i > Z_i\beta) = 1 - F(-Z_i\beta), \tag{2}$$

where F is the cumulative distribution function for μ_i.

In order to link CF participation decision to the potential outcomes, we follow the approach by Ma and Abdulai (2016) and express the maximum net returns as

$$R^*_{\max} = PQ_i\left(W, Z_i\right) - C_iW, \tag{3}$$

where P is the output price per kg, Q_i is the cashew yield in kg, W is a vector of input prices, C_i is a vector of input quantities (e.g., fertilizer, pesticides, and labor), and Z_i is a vector of farm- and household-level characteristics. Following Equations (1) and (3), we express net returns (R) as a function of input and output prices, the choice of CF participation (D_i), and farm- and household-level characteristics as follows:

$$R = R(P, C_i, D_i, Z_i). \tag{4}$$

Also applying Hoteling's lemma directly to Equation (3) yields a reduced form of the following cashew output supply function:

$$Q = Q(P, C_i, D_i, Z_i). \tag{5}$$

Equations (4) and (5) suggest that net returns from cashew production (R) and cashew yields (Q) are influenced by the input and output prices, the choice of participation in CF, and farm- and household-level characteristics. Following Ito, Bao, and Su (2012), we decompose net farm income into labor (L) productivity (Q/L) and price margin ($P - CW/Q$) in order to evaluate the differential impact of these variables on CF.

As indicated earlier, we are not only interested in farmer's decisions on participation in CF, but also in the impact of participation on cashew yields, net revenues, labor productivity, price margins, as well as off-farm income. If we define X as a vector of farm and household characteristics, we can express the link between the CF participation decision with the outcome variables.[2] Therefore, we assume that the vector of outcome variables is a linear function of a vector of explanatory variables that include the participation decision, as well as farm- and household-level features, specified as:

$$y_i = X_i\gamma + D_i\eta + u_i, \tag{6}$$

where y_i represents a vector of outcome variables such as cashew yields, net revenues, labor productivity, price margins,

[2] Z_i contains an instrument that is excluded in X_i for identification.

and off-farm income; X_i is a vector of explanatory variables such as household characteristics (e.g., age, education, and household size), farm and location characteristics, and financial and institutional variables (e.g., extension service and access to credit); D_i represents the CF participation dummy as defined above; γ and η are parameters to be estimated, and u_i is the error term.

Given that farmers self-select into participating in CF, selection bias may arise due to observed and unobserved attributes. Therefore, ordinary least square (OLS) method might generate biased and inconsistent estimates. In the present study, we employ the control function approach proposed by Murtazashvili and Wooldridge (2016) to estimate an endogenous switching regression model with endogenous explanatory variables. The control function approach is combined with IV estimates. This enables us to allow for more than one continuous endogenous explanatory variable. Different to applying IV methods directly, the control function accounts for the correlation of endogenous explanatory variables with exogenous variables. This makes the control function approach more consistent and efficient than only applying IV estimation.

Specifically, the approach involves estimating a control function of a probit model in the first-stage and two-staged least squares (2SLS) of the outcome models in the second stage. Following our participation equation (1), we express the first-stage probit of CF participation as:

$$D_i = 1[Z_i\beta + \mu_i > 0]. \tag{7}$$

In order to ensure identification and exclusion restriction, we need to have an instrument that is correlated with the CF participation decision at the first stage, but does not directly correlate with the outcome variables in the second stage. Thus, we use farm radius as an instrument (see Table 1). The variable farm radius measures the number of other cashew farmers living in a 3 km radius around the farm household. This is a valid and relevant instrument because we expect that CF participation informs the extent to which farmers are clustered in a given location. When the level of clustering is high, farmers are more likely to interact among themselves making information externalities about themselves high and vice versa in the case of less clustered locations (Michelson, 2017). In addition, companies will be more likely to engage farmers who are more clustered. A higher cluster density enhances access to farmers and aggregation of output at relatively lower cost, compared to locations where cashew farmers are less populated and companies have to invest more time and resources in locating farmers (Barrett et al., 2012). The benefits of clustering in CF accrue more to the buying companies since they tend to enjoy lower transportation and search costs. Therefore, we do not expect it to affect the outcomes directly. However, if one argues that the proximity of farmers to each other influences their participation in CF, then, for example in the case of extreme weather events, the yields of all farmers living in the area can be influenced. Following Ma and Abdulai (2016), we account for this by including district fixed effects in our model, since climatic conditions stay constant over time. As evident from Appendix B, the employed instrument is uncorrelated with the outcome variables.

We estimate the probit of CF participation and obtain the generalized residuals, which are then used in the second stage to account for sample selection and issues of unobserved heterogeneity. We then insert the residuals and their interactions with the CF variable into Equation (6) to account for sample selection and unobserved heterogeneity as follows:

$$\begin{aligned} y_i = {} & \beta_0 + D_i\beta_D + X_i\beta_1 + D_iX_i\beta_2 + m_i\beta_m + D_im_i\beta_{Dm} \\ & + \widehat{gr}_i\rho_0 + D_i\widehat{gr}_i\rho_1 + v_i, \end{aligned} \tag{8}$$

with $E(v_i|D_i, Z_i) = 0$, where D_i represents the CF participation and is the endogenous switching indicator, which is also interacted with all other variables in the model in this approach. Thus, X_i is a vector of exogenous covariates and D_iX_i is the interaction of CF participation and these exogenous covariates, $\widehat{gr}_i$ is the generalized residual from the first-stage CF participation probit, and $D_i\widehat{gr}_i$ is the interaction between the endogenous switching indicator and the generalized residuals. ρ_0 and ρ_1 are coefficients of the variables meant to account for unobserved heterogeneity and self-selection issues. The coefficients of the generalized residuals (ρ_0) and the interacted generalized residuals (ρ_1) have econometric interpretations. First, if ρ_0 or ρ_1 are statistically significant, this would indicate the presence of selection bias arising from unobservable factors. Hence, taking into account both observable and unobservable factors is a prerequisite to derive consistent estimates of treatment effects. Second, if ρ_0 or ρ_1 have alternative signs, it means that farmers choose to participate in CF based on their comparative advantage, that is, participants have above average outcomes, compared to nonparticipants, independent of the CF decision. Third, $\rho_1 > 0$ implies negative selection bias, suggesting that farmers who have lower than average outcomes are more likely to choose to participate in CF. Conversely; $\rho_1 < 0$ would suggest positive selection bias. Given that the outcome variables are all continuous, we use 2SLS method to estimate Equation (8).

An issue that needs to be addressed in estimating the participation decision and the outcome equations is the potential endogeneity of the variables access to credit and extension contact. These are denoted as m in Equation (8). Access to credit is potentially endogenous because farmers who participate in CF are more likely to have higher incomes and guaranteed market prices, which in turn improves the credit worthiness of these farmers, and as such their access to credit. Extension contact on the other hand could be potentially endogenous because some companies provide extension services to farmers and as a result, such farmers would have more extension contacts compared to other farmers who are noncontract farmers. To control for the potential endogeneity of these variables in the CF participation equations (Equations (1) and (7)), we use the control function approach.

Therefore, we estimate first-stage probit models of access to credit and extension contacts, using farmers' own perception of their liquidity status and the perception of extension service, respectively, as instruments. Expectations and perceptions are useful predictors of economic behavior. However, their validity depends on the methods used for eliciting such information and may raise concerns of possible reverse causality (Delavande, Giné, & McKenzie, 2011). In fact, both perception variables for liquidity status and extension service were determined prior to harvest season. As such, it is certain that the respondents stated their perceptions on credit availability and extension service based on their experience in cashew farming from the previous year. Moreover, as evident from Appendix C, the employed instruments are uncorrelated with CF participation. Therefore, we do not expect these variables to influence the decision to participate in CF directly.

The generalized residuals from these probit models together with the observed access to credit and access to extension variables are then included in the specification for CF participation. To account for the potential endogeneity of these two variables in the outcome equation, we use the predicted values of the variables from the first stage in the second-stage outcome equation. The estimation takes places in a 2SLS framework. To the extent that the two-step approach used in the model could result in inefficient estimates, we bootstrapped our standard errors. This is to ensure they are robust to uncertainties associated with the first-step estimates being treated as variables in the second step.

TABLE 3 First-stage estimates: Determinants of contract farming participation

	Contract farming participation	
Variables	**Coeff.**	**Std. Err.**
Age	0.010*	0.005
Female headed HH	−0.260	0.173
Education	0.282	0.193
Household size	−0.020	0.020
Farm size	0.099***	0.034
Soil type	−0.151	0.150
Farm age	0.014	0.013
Farm records	0.637**	0.258
Market	0.002	0.030
Farmer group	0.045	0.182
Labor days	0.001	0.002
Mobile phone	−0.574***	0.181
Motorbike	0.249	0.156
Nkoranza	0.336	0.281
Bole	−0.001	0.265
Wenchi	−0.033	0.224
Credit	−0.259	0.604
Extension service	−0.019	0.271
Farm radius	0.021***	0.380
Res (Credit)	0.131	0.187
Res (Extension service)	−0.125	0.007
Constant	−1.105**	0.540

Note. $N = 391$.
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level; the reference district is Techiman.
Standard errors are bootstrapped, Log likelihood = −239.089; LR chi^2 = 60.36 (p-Value = .000).

5 | EMPIRICAL RESULTS

In this section, we present the estimates of the factors that influence a farmer's decision to participate in CF and the impact of participation in CF on the outcome variables, namely, cashew yields, net revenues, off-farm incomes, as well as labor productivity, and price margins. We first discuss the first-stage probit estimation for the determinants of participation in CF in Section 5.1. Section 5.2 discusses the determinants of our outcome variables. The average treatment effects (ATE) of participation in CF for all the outcomes are presented in Section 5.3.

5.1 | Determinants of participation in CF

Table 3 shows the results of the determinants of CF participation as in Equations (1) and (7). The model is statistically significant as revealed by the LR-chi-squared (p = .000) which suggests that our variables jointly and significantly explain participation in CF. The estimates show that the residuals of our two potentially endogenous variables (i.e., access to credit and extension service) are not significantly different from zero, suggesting that these variables are not endogenous in the model. Our identification instrument, farm radius, positively affects participation and is statistically significant at the 1% level. The chi-square test between the CF dummy variable and farm radius variable reveals a p-value of .002, indicating that the instrument farm radius is significantly different from zero in the first stage. We further performed the estimation using the IV approach for our outcome variables as robustness check. The results are presented in Appendix A. The estimates show that the F-statistic is statistically significant and confirms that farm radius is a valid instrument. This suggests that an increase in the number of neighboring cashew farmers living in 3 km radius of a farmer's farmhouse significantly increases the likelihood of participating in CF.

Table 3 shows that the coefficient of the variable representing gender is negative and statistically significant, suggesting that male farmers are more likely to participate in CF than their female counterparts. This finding is in line with other studies that document that women are less likely to participate in CF (Wang et al., 2014). The coefficients of the variables farm size and farm records are positive and significantly different from zero, indicating that farmers cultivating larger farms and those who keep farm records are more likely to participate in CF. Mobile phone ownership appears to have a negative effect on the decision to participate in CF. The usage of mobile phones is widely considered to help in reducing marketing, search and transportation costs, and as such simplify participation in markets. Although, interpersonal communication is often favored when it comes to building on business relationships and transactions. This underlines the significance of CF as a marketing strategy especially for farmers without access to mobile phones (Mittal & Tripathi, 2009; Molony, 2006). Motorbike ownership appears to have significant and positive effect on the choice of CF, suggesting that farmers with access to motorized transportation are more likely to participate in CF.

5.2 | Determinants of CF on outcome variables

Table 4 reports the estimates for the outcome variables as in Equation (8). The first set of estimates are the effects of the various variables, noninteracted, on outcomes and the second set contains the estimates of these variables interacted with the switching indicator, CF participation.

The lower part of Table 4 shows the estimated correlation coefficients (ρ_0 or ρ_1) of covariance terms between the error term of the first-stage probit model (Equation (7)) of CF participation and the second stage (Equation (8)). The results show significance of ρ_1 in the cashew yield equation, suggesting the existence of self-selection in the participation decisions. This implies that unobservable factors that influence farmers' decisions to participate in CF also affect cashew yields. Thus, participation in CF may not produce the same yield impact on noncontract farmers, if they choose to participate (Lokshin & Sajaia, 2004). The signs of ρ_1 are negative, suggesting positive selection bias. This implies that farmers with above than average yields and are more likely to participate in CF.

Farm age is an important determinant of cashew yields, net revenues, and labor productivity. An additional year obtained by the farm significantly increases cashew yields of noncontract farmers, but significantly reduces cashew yields, net revenues, and labor productivity of contract farmers. This finding is expected because on average, contract farmers have older farms than noncontract farmers (see Table 1) and is in line with the notion that older farms become less productive than newer ones due to increasing age of trees (Onumah, Al-Hassan, & Onumah, 2013). Farm size has a negative and significant effect on cashew yields and labor productivity of contract farmers, suggesting that contract farmers with larger farms obtain lower cashew yields and are less productive. This inverse relationship between farm size and productivity is in line with findings obtained by Ali and Deininger (2015) and Casaburi et al. (2016) who show for Rwanda and Kenya, respectively, that small-sized farms are more productive than large-sized farms.

Mobile phone ownership exerts a positive and significant effect on cashew yields of contract farmers. This confirms the findings by Lio and Liu (2006) who found that information and communication technology (ICT)-based systems support the exchange of information and lead to increased agricultural productivity. The district fixed effects variables show that contract and noncontract farmers especially from Bole area tend to obtain lower yields and net revenues relative to their counterparts in Techiman district. This suggests that cashew farmers from the Northern region obtain significantly lower net revenues and are less productive, compared to cashew farmers from Brong-Ahafo region.

5.3 | ATE of CF participation

Equation (8) provides the estimates of the ATE of CF on the outcome variables (Murtazashvili & Wooldridge, 2016). The ATE estimates are used to compute the marginal effects that are reported in Table 5. Unlike the simple mean differences, we obtain the ATE after accounting for confounders due to both observable and unobservable characteristics.

The impact of CF is positive and significantly different from zero for all outcomes except off-farm income. Specifically, a farmer who participates in CF is able to obtain on average 37% higher cashew yields compared to the mean of cashew farmers. Similarly, participation in CF would increase net revenues by almost 36% compared to the average net revenue of cashew farmers. These findings are consistent with those by Barrett et al. (2012), that participation in CF increases farm productivity.

As stated earlier, we also examine the impact of CF participation on labor productivity and price margins. We find that CF participation significantly increases labor productivity by 61%, and price margins by 45%, compared to the average labor productivity and price margins obtained by cashew farmers. The impacts on labor productivity and price margins can be attributed to efficient use of labor associated with the use of more hired labor by contract farmers and guaranteed prices, respectively. This finding is in line with Benali et al. (2018), who showed for vegetable farmers in Tanzania that participation in modern supply chains increases the likelihood to hire labor.

In terms of labor, we also observe in Table 1 that contract farmers use more hired labor than noncontract farmers. The

TABLE 4 Second-stage estimates: Impact of contract farming on outcome variables

Noncontract farmers	Cashew yields (kg/ha) log		Cashew net revenues (GHS/ha) log		Off-farm incomes (GHS/ha) log		Labor productivity (kg/labor day) log		Price margins (GHS/kg) log	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	0.011***	0.004	0.004	0.005	0.004*	0.002	0.007**	0.003	0.001	0.002
Female headed HH	−0.010	0.115	0.206	0.144	0.079	0.065	0.005	0.085	0.068	0.059
Education	0.127	0.148	−0.062	0.150	−0.137	0.086	0.125	0.104	−0.002	0.060
Household size	0.006	0.015	0.029*	0.015	−0.001	0.010	0.006	0.012	0.004	0.006
Farm size	−0.015	0.031	−0.091**	0.044	−0.239***	0.026	0.054**	0.023	−0.031**	0.015
Soil type	0.216**	0.093	0.196	0.134	0.058	0.055	0.105	0.087	0.049	0.047
Farm age	0.055***	0.013	0.057***	0.016	−0.012**	0.006	0.043***	0.009	0.001	0.004
Farm records	0.626**	0.263	0.449	0.314	0.252	0.206	0.517***	0.190	0.041	0.096
Market	−0.022	0.020	−0.006	0.034	0.006	0.012	−0.019	0.015	0.011	0.010
Farmer group	−0.389***	0.121	−0.477***	0.122	0.038	0.080	−0.353***	0.087	−0.156***	0.050
Labor days	0.008***	0.001	0.005**	0.002	0.005***	0.001	−0.006***	0.001	−0.001	0.001
Mobile phone	−0.125	0.196	0.236	0.228	0.063	0.089	−0.127	0.121	0.095	0.101
Motorbike	0.078	0.128	−0.084	0.175	0.097	0.074	0.052	0.114	−0.021	0.048
Nkoranza	−0.484***	0.185	−0.728**	0.314	0.006	0.121	−0.351**	0.160	−0.078	0.100
Bole	−0.811***	0.169	−0.705***	0.229	−0.093	0.092	−0.569***	0.128	0.033	0.073
Wenchi	−0.166	0.142	−0.064	0.284	−0.041	0.094	−0.179	0.125	0.073	0.078
Credit (pr)	−0.161	0.124	−0.057	0.161	−0.112	0.097	−0.089	0.095	0.028	0.068
Extension service (pr)	0.137***	0.051	0.217***	0.059	0.037	0.029	0.104***	0.034	0.047**	0.023
Contract farmers										
Age	−0.012*	0.007	−0.003	0.010	0.000	0.004	−0.008	0.005	−0.004	0.003
Female headed HH	−0.104	0.240	−0.458	0.287	0.015	0.112	−0.045	0.191	−0.119	0.115
Education	−0.428	0.268	−0.122	0.251	0.080	0.124	−0.388**	0.171	−0.022	0.104
Household size	0.021	0.022	−0.007	0.025	−0.015	0.013	0.029	0.023	−0.001	0.008
Farm size	−0.093**	0.040	−0.042	0.058	0.054*	0.030	−0.083**	0.032	0.003	0.021
Soil type	−0.085	0.168	0.046	0.228	−0.006	0.069	−0.025	0.143	0.061	0.071
Farm age	−0.046***	0.017	−0.053***	0.019	0.002	0.007	−0.028*	0.016	0.000	0.007
Farm records	−0.844**	0.333	−0.791**	0.371	−0.271	0.216	−0.772***	0.264	−0.115	0.134
Market	0.003	0.026	0.002	0.041	−0.009	0.016	−0.008	0.024	−0.004	0.015
Farmer group	0.174	0.164	0.154	0.194	−0.075	0.114	0.133	0.147	0.048	0.074
Labor days	−0.002	0.003	−0.001	0.004	−0.001	0.001	−0.001	0.002	0.000	0.001
Mobile phone	0.425*	0.256	0.095	0.374	0.098	0.129	0.324	0.217	−0.072	0.143
Motorbike	−0.173	0.173	0.026	0.217	−0.122	0.082	−0.226	0.166	0.008	0.070
Nkoranza	−0.349	0.326	−0.201	0.418	0.058	0.173	−0.323	0.258	−0.092	0.144
Bole	−0.415	0.303	−0.573	0.430	0.215	0.146	−0.529*	0.282	−0.218*	0.118
Wenchi	0.082	0.208	0.101	0.391	−0.095	0.123	0.139	0.192	−0.099	0.111
Credit (pr)	0.168	0.196	−0.020	0.254	0.220**	0.112	0.031	0.189	−0.057	0.091
Extension service (pr)	−0.057	0.075	−0.092	0.113	−0.044	0.050	−0.008	0.063	−0.012	0.036
Constant	4.832***	0.340	6.066***	0.490	7.674***	0.193	2.051***	0.245	1.432***	0.160
Generalized residuals (ρ_0)	0.408	0.407	−0.330	0.568	−0.091	0.224	0.431	0.262	−0.176	0.166
Interacted generalized residuals (ρ_1)	−0.910*	0.540	−0.582	0.683	0.128	0.318	−0.678	0.421	−0.099	0.218
Wald χ^2 statistic	3,253.58***		1,785.48***		4,911.16***		1,237.85***		186.78***	

Note. $N = 391$.

*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

The reference district is Techiman. Standard errors are bootstrapped.

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TABLE 5 Average treatment effects of contract farming on outcomes

Outcome variables	Mean outcome	ATE	z-Value	Change (%)
Cashew yields (kg/ha)	5.782 (0.718)	2.144	2.99***	37.06
Net revenues (GHS/ha)	7.157 (1.154)	2.569	2.23**	35.85
Off-farm incomes (GHS/ha)	7.251 (0.449)	−0.163	−0.36	−2.25
Labor productivity (kg/labor day)	2.230 (0.665)	1.373	2.06**	61.57
Price margins (GHS/kg)	1.597 (0.343)	0.734	2.14**	45.96

Note. $N = 391$.
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.
Bootstrapped standard errors in parentheses.

latter use more family labor than the former. This implies that contract farmers are able to engage more hired labor and are able to carry out the required farming activities in less days and under supervision. This is further justified by the fact that noncontract farmers use more days of labor than contract farmers (see Table 1). Hence, this shows that contract farmers are more efficient in labor use, since they are able to engage hired labor through incomes from CF and cash saved from provision of advanced inputs. Thus, this enhances efficiency and effectiveness in operation into more timely harvest.

Contract farmers also attain higher price margins because of the guarantee and certainty in prices, which is not susceptible to wide seasonal variations. Usually, given that most cashew farmers are smallholders who are generally price takers, these farmers tend to get lower prices during very good harvest. Hence, this protects contract farmers from lower prices during harvest, where the supply of cashew is normally very high. To investigate possible trade-off effects due to CF participation, we also look at off-farm income. We find a negative, but statistically insignificant impact of CF on off-farm income. While Bellemare (2018) found a significantly negative effect of participation in CF on income from nonfarm businesses of smallholder farmers in Madagascar, our findings are in line with Benali et al. (2018) who did not find a statistically significant effect for vegetable farmers in Tanzania.

To provide some insights into how scale effects on farm performance differ among contract farmers, we also analyzed the impact of CF according to farm size. Table 6 represents the ATE estimates by three farm size categories, which include small (less than 1.5 ha), medium (1.5–4 ha), and large (more than 4 ha) scales, since farms larger than 4 ha are considered as large cashew plantations (African Cashew Initiative, 2010).[3]

The estimates show that participation in CF significantly increases cashew yields by 35%, 30%, and 25% for farmers with small, medium, and large farm sizes, respectively, compared to the average yield of a cashew farmer. We also find that participation in CF tends to significantly increase net revenues by 41%, 32%, and 29% for small-, medium-, and large-sized farms, respectively. With respect to labor productivity, Table 6 shows that relative to other cashew farmers, participation in CF is associated with a significant increase in labor productivity by almost 67% for small farms, and 50% for medium farms, while the coefficient for large-sized farms is also positive, but not statistically significant. We further find that participation in CF significantly increases price margins, albeit more favorable for small farms. In particular, cashew farmers with small farms experience significant gains in price margins by 59%, while medium and large farms obtain 45% and 41% increases in price margins, respectively.

Interestingly, the disaggregated estimates on off-farm income show that the effects are not uniform across farmers, but differ based on scale of the operation. Specifically, participation in CF significantly increases off-farm income of small-sized cashew farmers by almost 7%, while it decreases off-farm income of medium- and large-sized farms, though, not statistically significant. This is not surprising because of the difference in time requirement by the scale of operation.

In effect, the findings indicate that there is substantial heterogeneity in the impact of CF across scale of operation and that smaller cashew farms tend to benefit more from CF compared to medium- and large-sized farms. This finding is in line with findings by Casaburi et al. (2016) on sugarcane CF schemes in Kenya. Also, the results, put together support the inverse farm size relationship as smaller farmers benefit more from CF than medium and larger farms (Carletto, Savastano, & Zezza, 2013; Henderson, 2015; Khataza, Hailu, Doole, Kragt, & Alene, 2019). This is because small farms have advantages in labor supervision and knowledge. Smallholder farmers accumulate knowledge over generations, which can offset their difficulty in accessing capital and insurance. Nevertheless, the findings should be interpreted with caution. For instance, Muyanga and Jayne (2019) looked at a wider range of farm sizes in Kenya and find a U-shaped relationship between farm size and productivity. Even though the inverse relationship holds for very small farms (0–3 ha), farms between 20 and 70 ha are substantially more productive due to mechanization and reduced labor

[3] The definition of farm size groups is based on the farm size cashew farmers had before participating in CF.

TABLE 6 Average treatment effects of contract farming on outcomes disaggregated by farm sizes

Outcome variables	Mean outcome		ATE	z-Value	Change (%)
Cashew yields (kg/ha)					
Small Farm (≤1.5 ha)		(0.674)	2.024	3.00***	35.05
Medium Farm (1.5–4 ha)	5.782	(0.647)	1.749	2.70***	30.24
Large Farm (>4 ha)		(0.680)	1.501	2.21**	25.95
Net revenues (GHS/ha)					
Small Farm (≤1.5 ha)		(1.092)	2.942	2.69***	41.17
Medium Farm (1.5–4 ha)	7.157	(1.021)	2.310	2.26**	32.28
Large Farm (>4 ha)		(0.971)	2.110	2.17**	29.62
Off-farm income (GHS/ha)					
Small Farm (≤1.5 ha)		(0.304)	0.507	1.67*	6.99
Medium Farm (1.5–4 ha)	7.251	(0.324)	−0.109	−0.34	−1.50
Large Farm (>4 ha)		(0.326)	−0.396	−1.25	−5.46
Labor productivity (kg/labor day)					
Small Farm (≤ 1.5 ha)		(0.629)	1.502	2.39**	67.35
Medium Farm (1.5–4 ha)	2.230	(0.640)	1.134	1.77*	50.85
Large Farm (>4 ha)		(0.695)	0.932	1.34	41.79
Price margin (GHS/kg)					
Small Farm (≤1.5 ha)		(0.310)	0.949	3.06***	59.42
Medium Farm (1.5–4 ha)	1.597	(0.297)	0.721	2.42**	45.15
Large Farm (>4 ha)		(0.308)	0.656	2.13*	41.08

Note. $N = 391$.
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.
Bootstrapped standard errors in parentheses.

input per hectare. Moreover, the studies by Carletto, Gourlay, and Winters (2015) and Dillon and Rao (2018) show that self-reported farm sizes, as in our case, can lead to land measurement bias. Small farmers tend to overestimate, whereas large farmers tend to underestimate their land sizes (Carletto et al., 2013).

6 | CONCLUSIONS AND POLICY IMPLICATIONS

Given the challenges smallholder farmers face in marketing their products, particularly with the emergence of supermarkets, CF has been widely identified as a means of helping smallholder farmers to participate in value chains. This paper contributes to the debate by examining the factors that influence cashew farmers' decisions to participate in CF and the impacts of participation on labor productivity, price margins, as well as household welfare indicators such as yields, net revenues, and off-farm income. We use household-level data of 391 cashew farmers from Brong-Ahafo and Northern regions of Ghana.

Simple comparisons of household welfare indicators between contract and noncontract farmers revealed some significant differences between the two groups. However, since these average differences do not account for the confounding effects of other individual characteristics such as risk preferences, farming ability, or motivation, we employed a control function approach to estimate a switching regression model that accounts for endogeneity and selection bias of observed and unobserved characteristics.

The empirical results revealed that CF contributes to the enhancement of agricultural productivity as well as improvement of income of cashew farmers in Ghana. In particular, the estimates show a positive and statistically significant relationship between participation in CF and labor productivity, price margins, as well as cashew yields, and net revenues. Specifically, farmers who participate in CF significantly increased labor productivity by 62% and price margins by 46%. The estimates also showed that participation in CF resulted in significant increases in cashew yields by 37% and net revenues by 36%.

The estimates of CF impact across farm sizes revealed that cashew yields, net revenues, labor productivity, and price margins of contract farmers were significantly higher for smaller farms (less than 1.5 ha), compared to medium (1.5–4 ha), and large-sized farms (more than 4 ha). An important finding revealed by this analysis across farm size is that the impact of CF on off-farm income is not uniform across farmers but varies with the scale of operation. If one considers the impact in a more differentiated way, it shows that participation in CF complements off-farm income for farmers with small farm sizes but reduces off-farm incomes when the level of operation is large.

Returning to the issues raised in the introduction of this paper, evidence has been generated that CF could prove useful in advancing productivity and utilizing labor resources in the cashew sector more effectively. Policies should therefore focus on attracting investment higher up in the value chain (cashew processing) and introduce appropriate production and processing technologies. The positive impact of CF on labor productivity is especially interesting and suggests that labor engagement through incomes from CF is one of the key ways through which CF affects cashew revenues and yields. This is important and implies that policy makers can use CF in cashew production to augment labor demand. Policies should incentivize these jobs, which can help to reduce rural–urban migration.

Improvement of infrastructure is another important aspect, since contracting is usually concentrated in easily accessible areas. This is also the case in Ghana, where farmers from the Northern regions tend to face structural disadvantages compared to farmers from the more favored Brong-Ahafo region. In order to align regions, policies need to improve roads and public transport, as well as access to airports and harbors. This will not only reduce migration from the Northern regions of Ghana to the South where the main cities are located, it is also important when it comes to stronger commercialization of Ghana's cashew sector.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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APPENDIX A: IV APPROACH: IMPACT OF CONTRACT FARMING ON OUTCOME VARIABLES

	Cashew yields (kg/ha) log		Cashew net revenues (GHS/ha) log		Off-farm incomes (GHS/ha) log		Labor productivity (kg/labor day) log		Price margins (GHS/kg) log	
Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
CF	0.997**	0.496	1.946***	0.842	0.144	0.270	0.584	0.389	0.508*	0.268
Age	0.003	0.004	0.000	0.006	0.004*	0.002	0.002	0.003	−0.001	0.002
Female headed HH	0.026	0.105	0.148	0.178	0.104*	0.057	0.044	0.082	0.051	0.057
Education	−0.115	0.116	−0.172	0.197	−0.125**	0.063	−0.072	0.091	−0.019	0.063
Household size	0.024**	0.011	0.036*	0.019	−0.009	0.006	0.024***	0.009	0.006	0.006
Farm size	−0.088***	0.023	−0.140***	0.039	−0.218***	0.013	−0.011	0.018	−0.035***	0.013
Soil type	0.185**	0.082	0.202	0.140	0.064	0.045	0.105	0.065	0.072	0.044
Farm age	0.030***	0.008	0.028**	0.013	−0.013***	0.004	0.027***	0.006	0.001	0.004
Farm records	−0.055	0.180	−0.202	0.307	0.046	0.098	−0.090	0.142	−0.046	0.098
Market	−0.020	0.016	−0.002	0.027	0.002	0.009	−0.023*	0.013	0.009	0.009
Farmer group	−0.320***	0.102	−0.434**	0.173	0.000	0.056	−0.303***	0.080	−0.132**	0.055
Labor days	0.006***	0.001	0.004**	0.002	0.004***	0.001	−0.008***	0.001	−0.001*	0.001
Mobile phone	0.229	0.141	0.450*	0.240	0.170**	0.077	0.142	0.111	0.087	0.077
Motorbike	−0.046	0.094	−0.106	0.160	0.017	0.051	−0.069	0.074	−0.021	0.051
Nkoranza	−0.656***	0.161	−0.848***	0.273	−0.006	0.088	−0.491***	0.126	−0.132	0.087
Bole	−0.956***	0.141	−0.930***	0.239	0.004	0.077	−0.741***	0.110	−0.054	0.076
Wenchi	−0.076	0.123	0.060	0.209	−0.063	0.067	−0.082	0.097	0.043	0.067
Credit (pr)	−0.061	0.103	−0.057	0.174	−0.003	0.056	−0.045	0.081	0.002	0.056
Extension service (pr)	0.091**	0.044	0.153**	0.075	0.021	0.024	0.083**	0.035	0.034	0.024
Constant	5.131***	0.266	6.237***	0.451	7.639***	0.145	2.243***	0.209	1.513***	0.144
Wald χ	300.82***		105.35***		1,288.15***		282.10***		21.22	
F-value	9.380***		9.380***		9.380***		9.380***		9.380***	

Note. $N = 391$.
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.
The reference district is Techiman.

APPENDIX B: CORRELATION BETWEEN INSTRUMENTAL VARIABLE FARM RADIUS AND OUTCOMES VARIABLES

Dependent variable	Instrumental variable	Correlation	*p*-Value
Cashew yields	Farm radius	.059	.242
Cashew net revenues		.083	.102
Off-farm incomes		.097	.055
Labor productivity		−.007	.886
Price margins		.102	.045

APPENDIX C: CORRELATION BETWEEN CF PARTICIPATION VARIABLE AND INSTRUMENTAL VARIABLES

Dependent variable	Instrumental variable	Correlation	*p*-Value
Contract farming	Farmers' perception of liquidity status	−.028	.579
	Farmers' perception of extension service	−.037	.463