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Farmer groups, collective marketing and smallholder farm performance in rural Ghana

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Abstract

Purpose – Rapid transformation of agrifood value chains because of population growth, urbanization, rising consumer incomes and increased demand for food quality and safety has resulted in the need for smallholder farmers to coordinate horizontally through group formation and collective marketing to improve farm performance in developing countries. This paper aims to examine the factors that influence farmer group membership and collective marketing decisions and their impacts on smallholder farm performance in rural Ghana.

Design/methodology/approach – Using data from a recent survey of 447 rice farmers in rural Ghana, an endogenous switching regression model is employed to account for selection bias arising from both observable and unobservable farmer attributes.

Findings – The data reveal that group members and collective marketing participants obtained higher prices and also incurred lower input costs. The econometric estimates show that age, access to credit, mobile phone ownership, distance to market and road status are the main drivers of group membership and collective marketing decisions. The authors also find positive and significant impacts of farmer group membership and collective marketing on farm net revenues.

Research limitations/implications – The findings from this study suggest that government and donor support for the formation of farmer groups during implementation of agriculture and value chain interventions should as well incorporate strategies to facilitate collective marketing.

Originality/value – To the best of the authors' knowledge, this study is the first to examine the role farmer groups and collective marketing play in improving smallholder farm performance.

Keywords Farmer groups, Collective marketing, Farm net revenue, Endogenous switching regression model

Paper type Research paper

1. Introduction

Over the past few decades, the contribution of smallholder agriculture to economic transformation and poverty reduction in developing countries has received considerable attention in research and development (Markelova *et al.*, 2009; Verhofstadt and Maertens, 2014). Nonetheless, several challenges still impede smallholder farmers from effectively participating in both input and output markets. The main challenges include high transaction costs due to poor infrastructure and market imperfections and limited access to credit and extension services (Mojo *et al.*, 2017; Kaganzi *et al.*, 2009; Fischer and Qaim, 2012). These challenges have resulted in increased development efforts in developing countries to improve both production capacities and access to markets (Markelova *et al.*, 2009; Devaux *et al.*, 2018).

The rapid transformation in agrifood value chains stemming from rising consumer incomes, urbanization and increasing consumer demand for food safety has resulted in the need for actor coordination to improve smallholder farm performance in developing countries

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(Reardon *et al.*, 2009). Effective organization of smallholders into groups to undertake production and marketing activities would help strengthen their position in the agrifood value chain. Farmer group formation has been recognized as one of the development strategies for promoting collective action and facilitating market linkages in agrifood chains (Bernard and Spielman, 2009). It effectively contributes to reducing transaction costs, enhancing bargaining power to ensure higher output prices and possibly lower input prices, fostering risk sharing and ensuring economies of scale (Bijman *et al.*, 2006; Francesconi and Wouterse, 2015). African governments and non-governmental organizations (NGOs) are keenly interested in promoting the formation of farmer groups as the first step to implementing agriculture and value chain development initiatives. For example, the Ghana Ministry of Food and Agriculture (MoFA) in collaboration with donor agencies has intensified efforts to promote farmer group formation as a means of improving farm performance and rural livelihoods (Salifu *et al.*, 2012).

The implications of farmer groups in developing countries have been greatly contested across various strands of the literature. Some studies reveal that farmer groups enhance smallholders' agrifood value chain participation and welfare. The study by Fischer and Qaim (2012) showed that in Kenya, participation in banana farmer groups resulted in price advantages and increased household income. A recent study by Mojo *et al.* (2017) found that Ethiopian coffee farmer groups experienced positive gains in household incomes and assets of members. Ito *et al.* (2012) found that belonging to a farmer group contributes significantly to improving the economic status of smallholder farmers in China. Using an endogenous switching regression approach, Mishra *et al.* (2018a) reveal that farmer group membership enhances value chain participation and food security through white onion contract farming in India. A plethora of other studies also found that smallholder participation in agrifood value chains though farmer groups improves farm yields, household income and net farm income (e.g., Maertens and VandeVelde, 2017; Mishra *et al.*, 2018b), prices received by group members, farm profit and gross income (e.g., Ma and Abdulai, 2017) and land and labor redistribution (e.g., Henderson and Isaac, 2017).

By contrast, the findings from other studies suggest that farmer groups performed poorly, and in some cases, led to dissolution of the groups (Markelova *et al.*, 2009; Kaganzi *et al.*, 2009; Francesconi and Wouterse, 2015). For example, Bernard *et al.* (2008) found that farmer groups in Ethiopia failed to improve their level of commercialization, while a study by Nkhoma and Conforte (2011) on Malawi reported that farmer groups could not enhance their welfare, which they attributed to ineffective governance and management of the groups. The study by Mwambi *et al.* (2016) did not find sufficient improvement in household, farm and avocado income through smallholder participation in agrifood value chains in Kenya. In the upper west region of Ghana, organizing farmers into groups for participation in maize value chains has a negative effect on profitability even when input diversion is accounted for (Ragasa *et al.*, 2018).

These mixed findings justify efforts in further exploring conditions that trigger successful operations of farmer groups, agrifood value chain participation, as well as mechanisms under which substantial benefits accrue to group members. Collective marketing undertaken by farmer groups is one of the important ways of ensuring sustainability of farmer groups, as it helps in reducing transaction costs, ensuring higher output prices and lower input prices (Fischer and Qaim, 2012). In their study on Kenya, Fischer and Qaim (2012) found that about 40 percent of the banana group members who did not participate in collective marketing, but engaged buyers on individual basis, experienced lower household incomes. This suggests that the use of farmer groups in agricultural development interventions is as important as facilitating collective marketing within such groups to ensure economic transformation and poverty reduction in developing countries.

However, an issue of great interest from rural development perspective is whether or not members of farmer groups are willing and committed to participating in collective marketing. It is worth noting that some members of farmer groups do not participate in collective marketing due to a myriad of reasons, including, but not limited to difficulties in meeting quality requirements, lack of trust for group leaders, as well as the notion that they receive satisfactory prices by selling individually. Moreover, some group members live relatively far from the agreed paddy collection centers or in some cases, in different communities, thus making paddy bulking a challenge for such category of farmers. Thus, an issue that has not received much attention, particularly in the empirical literature, is the extent to which farmer groups commit members to collective marketing and how collective marketing impacts on farm performance. Most of the studies mentioned earlier focused on the determinants of farmers' participation intensity in farmer groups (e.g., Gyau *et al.*, 2016). The study by Fischer and Qaim (2012), which employed the propensity score matching (PSM) approach to examine the effects of banana groups on household welfare, disaggregated by collective marketing found that, for banana production in Kenya, belonging to a farmer group improves household income through collective marketing participation. But, a widely known weakness of the PSM method is its failure to account for farmer unobserved attributes such as farmer's innate skills, motivation and risk perception. However, the fact that group membership and collective marketing participation decisions are not randomly assigned, but involves farmers' self-selection, means that unobserved attributes still play a role in the decision process, which could bias the PSM estimates (Smith and Todd, 2005). Therefore, group membership and collective marketing decisions for improved farm performance in smallholder agriculture still require further assessment.

This study contributes to the growing literature on the role of farmer groups on farm performance in two ways. First, we explore the factors that influence farmers' decisions to join farmer groups and to participate in collective marketing. Second, we investigate the impact of group membership and collective marketing on farm performance, such as farm net revenues. The study uses recent cross-sectional data from 447 smallholder farmers in five selected districts of northern Ghana. We employ a bivariate probit model to assess the relationship between farmer group membership and collective marketing decisions, as well as factors that influence both decisions among smallholder rice farmers (Greene, 2012). An endogenous switching regression (ESR) model is then used to examine the impact of group membership and collective marketing on farm net revenues (Lokshin and Sajaia, 2004) and to account for observable and unobservable factors that could bias the coefficients of the estimates.

The rest of this paper proceeds as follows: Section 2 presents a brief review of farmer groups in rural Ghana. Section 3 describes the analytical framework employed to guide the empirical analysis. The specification of the empirical model is contained in Section 4, followed by the presentation of data and descriptive statistics of the variables used in the analysis in Section 5. Section 6 discusses the empirical results, while conclusions and policy implications are presented in the final section.

2. Farmer groups in rural Ghana

The Government of Ghana in collaboration with NGOs and donor agencies has in recent times implemented a series of agriculture and value chain development programs aimed at promoting the formation of farmer groups. One of such programs involved a five year US$241m agricultural development program launched in 2007 and funded by the Millennium Challenge Cooperation (MCC) of the USA and implemented by the Millennium Development Authority (MiDA) under the Millennium Challenge Account (MCA) Ghana compact program. The program was aimed at enhancing smallholder competitiveness in high-value markets through increased productivity and quality of agrifood crops (MiDA, 2013). About 1,242 farmer groups operating in the cereals, legumes, fruits and vegetables value chains were recruited and registered with both MiDA and MoFA under the commercial development of farmer organizations (CDFO) component of the program. These groups were trained on organizational, business and technical capacity development modules prior to the commencement of their various agribusiness activities.

Overall, the MiDA project contributed to significant returns on investments in a transformed and competitive agricultural sector, enhanced speedy growth of the rural economy and a lowered poverty incidence among beneficiary smallholder farmers in Ghana. However, the program had a limited impact on farmer value chain integration and the promotion of collective investments by farmer groups. The attributed reasons were that collateral security for financial credit acquisition from financial institutions by farmer groups was provided by MiDA rather than orientating them to develop collective entrepreneurship spirit and their own financial capital formation, which denied majority of the farmer groups access to credit and also resulted in high loan default rate (ISSER, 2012).

The agriculture component of the Feed the Future (FtF) program, an ongoing five-year (2013–2018) US Agency for International Development (USAID)-funded program, is another important program that is heavily investing in the formation and capacity-building of farmer groups to enhance technology adoption, market access and overall livelihoods of smallholders in Ghana. The program aims at improving productivity, competitiveness and incomes of smallholder farmers in the rice, soybeans and maize value chains, as well as nutrition and resilience of vulnerable populations in northern Ghana. Several NGOs also work with farmer groups in northern Ghana to promote smallholder market access. Among others include Technoserve, Agricultural Cooperative Development International and Volunteers Overseas Cooperative Assistance (ACDI/VOCA), Market Development for Northern Ghana (MADE), International Fertilizer Development Center (IFDC), German Agency for International Cooperation (GIZ), Adventist Development and Relief Agency (ADRA), The Netherlands Development Organization (SNV), Action Aid Ghana and Association of Church Development Projects (ACDEP).

The capacity-building and orientation of farmer groups is gradually enhancing their commitment to participating in collective activities and performance in the agrifood chain. For example, a survey of 501 farmer groups in Ghana revealed that only about 13 percent of them participated in collective marketing (Salifu *et al.*, 2012). This suggests that more development efforts are still required to enhance the level of collective marketing participation for improved smallholder farm performance in Ghana.

3. Analytical framework

In this section, we present an analytical framework that is based on the assumption that rice farmers make two binary decisions: to join farmers' groups or not to join and to participate in collective marketing or not to participate. To simplify the framework, we assume that a rice farmer is risk neutral and compare the benefits (D_M^*) generated from rice production and marketing as a group member or collective marketing participant to the benefits (D_N^*) from non-group membership or non-collective marketing participation. A farmer will choose to be a group member or collective marketing participant if the net benefits (D_i^*) from group membership and non-membership or collective marketing participation or non-participation is positive, i.e. $D_i^* = D_M^* - D_N^* > 0$. However, as D_i^* is unobserved, we express it as a function of observable characteristics in a latent variable framework as:

$$D_i^* = Z_i\gamma + \varepsilon_i, \; D_i = 1\left[D_i^* > 0\right], \tag{1}$$

where D_i is the group membership or collective marketing participation indicator, assigned a value of 1, and 0 otherwise; γ denotes a vector of parameters to be estimated; ε_i is the error term assumed to be independently and identically distributed with mean zero, and variance σ_ε^2; and Z_i is a vector of observable factors such as household and farm-level factors influencing group membership or collective marketing participation decisions. These factors include farmer's age, education, gender, farm size, access to credit, mobile phone, radio set, bicycle ownership, distance to market, road status, market perception and location variables. The choice of these variables for the present study is based on the review of relevant literature (e.g., Meinzen-Dick and Zwarteveen, 1998; Fischer and Qaim, 2012; Akar *et al.*, 2016; Mojo *et al.*, 2017: Zanello, 2012). The probability of a farmer being a group member or collective marketing participant is expressed as:

$$\Pr(D_i = 1) = \Pr\left(D_i^* > 0\right) = \Pr(\varepsilon_i > -Z_i\gamma) = 1 - F(-Z_i\gamma) \tag{2}$$

where F denotes the cumulative distribution function for ε_i. Given the relation among group membership, collective marketing participation and farm net revenues, we assume that farmers maximize net revenues from rice production and marketing, which can be expressed as:

$$\pi_{max} = [PQ(\omega, Z) - W\omega] \tag{3}$$

where P is the price of output, Q is the expected output level, ω is the vector of input quantities, Z is a vector of farm- and household-level factors, W is a vector of input prices. Equation (3) implies that the farm net revenue from rice production and marketing can be expressed as a function of variable input quantities, input and output prices, farm- and household-level characteristics, group membership and collective marketing participation decisions D. This is specified as:

$$\pi = \pi(W, P, D, Z) \tag{4}$$

For any well-specified normalized profit function, applying Hotelling's lemma directly to equation (3) results in a reduced form of the following rice output supply specification:

$$Q = Q(W, P, D, Z) \tag{5}$$

Notice that equations (4) and (5) suggest that input and output prices, farm-level and household characteristics, group membership and collective marketing participation decisions tend to influence the farm net revenues received by farmers.

Given our interest in investigating the impact of group membership and collective marketing participation on farm net revenues, we specify farm net revenues as a linear function of group membership or collective marketing participation and a vector of variables representing farm and household characteristics as:

$$Y_i = X_i\beta + D_i\delta + \mu_i \tag{6}$$

where Y_i represents farm net revenue of farmer i; X_i denotes a vector of farm, household and transaction costs characteristics; D_i is a vector of dummy variables representing group membership and collective marketing participation decisions as defined earlier; β and δ represent unknown parameters to be estimated; and μ_i denotes a random error term. To the extent that farmers self-select into group membership or collective marketing participation, using the ordinary least squares (OLS) method to estimate equation (6) may result in biased and inconsistent estimates, because the error term (ε_i) in equation (1) and the error term (μ_i) in equation (6) may be correlated, leading to selection bias. Some studies have employed quasi-experimental methods such as PSM, treatment effects model or ESR to account for potential selection bias (e.g., Ma and Abdulai, 2017). However, as stated earlier, the major weakness of the PSM approach is that it only accounts for selection bias due to observable attributes. This study employs an ESR approach to jointly estimate the impact of group membership and collective marketing participation on farm net revenues while accounting for selection bias due to both observable and unobservable attributes.

4. Empirical specification

This study also aims at investigating the interrelationship between group membership and collective marketing decisions to provide insight as to whether farmers who are group members are more or less likely to also participate in collective marketing. For some farmer groups that undertake collective marketing of their paddy, some members of such groups do not participate in such a group activity, attributable to some reasons mentioned earlier. However, some farmers who are not members of farmer groups also have the opportunity to participate in collective marketing, especially in situations where group members are unable to meet the quantity requirements. This makes group membership and collective marketing decisions potentially jointly determined. Therefore, we employ a bivariate probit model to analyze the joint determination of group membership and collective marketing decisions and the related drivers of both decisions. The approach involves a specification of a two-equation model that captures farmers' decisions to belong to farmer groups and to participate in collective marketing (see online Appendix).

To analyze the impact of group membership and collective marketing on farm net revenues, we employ the ESR method, which is a two-stage procedure that involves first estimating a selection equation (eq. 1) to examine the factors influencing farmer group membership or collective marketing decision. In the second stage, the impact of group membership or collective marketing on farm net revenues is estimated by specifying two regimes of outcome equations for group members and non-members or collective marketing participants and non-participants as follows:

$$\text{Regime 1}: Y_{1i} = X_{1i}\beta_1 + \mu_{1i} \text{ if } D_i = 1 \tag{7a}$$

$$\text{Regime 2}: Y_{2i} = X_{2i}\beta_2 + \mu_{2i} \text{ if } D_i = 0, \tag{7b}$$

where Y_i denotes the farm net revenue per hectare for group membership and non-membership or collective marketing participation and non-participation regimes, X is the vector of farm and household characteristics, β is a vector of unknown parameters to be estimated and μ is the random error term.

It is significant to note that the variables in X account for potential selection bias, taking into account only observed factors. However, because selection bias still persists due to unobserved factors such as farmer innate skills and motivation, this leads to possible correlation between the error terms in the group membership or collective marketing choice equation (1) and net revenue equations (7a) and (7b), i.e. $corr(\varepsilon_i, \mu_i) \neq 0$. The ESR model accounts for this potential selection bias as an omitted variable problem. Following Heckman (1979), we compute the inverse mills ratios for group members or collective marketing participants (λ_{i1}) and non-members or collective marketing non-participants (λ_{i2}) and the covariance terms $\sigma_{\mu 1}$ and $\sigma_{\mu 2}$, after estimating the selection equation (1), which are then included in the outcome equations (7a) and (7b) as follows:

$$Y_{i1} = X_{i1}\beta_1 + \sigma_{\mu 1}\lambda_{i1} + \xi_{i1} \; if \; D_i = 1, \tag{8a}$$

$$Y_{i2} = X_{i2}\beta_2 + \sigma_{\mu 2}\lambda_{i2} + \xi_{i2} \; if \; D_i = 0, \tag{8b}$$

where λ_{i1} and λ_{i2} are the selectivity correction terms used to control for selection bias caused by unobserved attributes; ξ_{i1} and ξ_{i2} are the random error terms with conditional zero means. As proposed by Lokshin and Sajaia (2004), the full information maximum likelihood (FIML) is employed to simultaneously estimate the selection equation (1) and the outcome equations (7a) and (7b).

Next, we derive the average treatment effects on the treated (ATT) by comparing the expected farm net revenues from group members or collective marketing participants to the expected farm net revenues of the counterfactual hypothetical cases that they did not belong to farmer groups or marketed and sold their paddy individually, respectively. In particular, the expected net revenues of group members or collective marketing participants and non-group members or collective marketing non-participants, respectively, are expressed as:

$$E[Y_{i1}|D=1] = X_{i1}\beta + \sigma_{\mu 1}\lambda_{i2} \tag{9a}$$

$$E[Y_{i2}|D=1] = X_{i2}\beta + \sigma_{\mu 2}\lambda_{i2} \tag{9b}$$

The ATT for group membership and collective marketing participation is computed as the difference between equations (9a) and (9b), expressed as:

$$ATT = E[Y_{i1}|D=1] - E[Y_{i2}|D=1] = X_i(\beta_{i1} - \beta_{i2}) + \lambda_{i1}\left(\sigma_{\mu 1} - \sigma_{\mu 2}\right) \tag{10}$$

Identification of the model requires that at least one variable (known as an instrument) in Z from equation (1) should not feature in X. The identifying instrument should characteristically influence group membership or collective marketing participation decision, but not farm net revenues.

5. Data and descriptive statistics

This study uses recent farm household data gathered from June to August 2016 in five selected districts of northern Ghana: Tolon, Kumbungu, Sagnarigu districts, Savelugu Nanton Municipal and Tamale Metropolitan area. The sample for the study was drawn using a multi-stage sampling approach. Purposive sampling method was first employed to select the five study districts because of their geographic accessibility and the intensive rice production in these areas. After purposive sampling of the districts, series of consultations were held with the agricultural extension agents (AEAs) of the MoFA and other officials of ongoing donor-funded projects (e.g. Ghana-USAID/FtF) to randomly select about two to three communities from each study district. Finally, smallholder rice farmers were sampled in proportion to the farmer population in each area. In total, we sampled 477 smallholder rice farmers, including group members and non-members, and engaged them in face-to-face interviews using a structured questionnaire. The information elicited during the survey was related to 2015 growing season and focused on household and farm-level characteristics, asset ownership as well as production and marketing activities. The data were collected with the help of trained research assistants.

The definition and descriptive statistics of variables used in the analysis are reported in Table 1. The dependent variables are farm group membership, collective marketing and farm net revenues. Group membership is captured as a dummy and assigned a value of 1 if the famer belongs to a farmer group, and 0 otherwise. As shown in Table 1, 42 percent of the rice farmers interviewed belong to farmer groups. Collective marketing is also captured as a dummy variable, where 1 is assigned to the case where a farmer participated in collective marketing in the past 12 months prior to the survey, and 0 otherwise. In this context, collective marketing refers to a case where members market and sell paddy rice through a group. About 19 percent of farmers in the sample participated in collective marketing. This

Variable	Definition	Mean (SD)
Dependent variables		
Group membership	1, if farmer belongs to rice farming group; 0, otherwise	0.42 (0.49)
Collective marketing	1, if farmer participated in collective marketing; 0, otherwise	0.19 (0.39)
Farm net revenue	Gross farm revenue from rice production minus variable input cost (GH¢)	457.72 (638.27)
Transaction costs variables		
Mobile phone	1, if farmer owns mobile phone; 0, otherwise	0.45 (0.49)
Radio set	1, if farmer owns radio set; 0, otherwise	0.56 (0.49)
Distance to market	Distance to market (km)	6.54 (4.08)
Bicycle	1, if a farmer owns bicycle; 0, otherwise	0.70 (0.45)
Road status	1, if market road if motorable; 0, otherwise	0.73 (0.44)
Household characteristics		
Age	Age of respondent (years)	37.45 (11.72)
Education	Education of respondent (years)	2.02 (3.98)
Gender	1, if farmer is male; 0, otherwise	0.88 (0.32)
Market perception	Farmer perception of market demand (1 = high, 0 = low)	0.32 (0.46)
Farm characteristics		
Farm size	Size of farm (hectares)	1.14 (1.27)
Access to credit	1, if farmer has access to enough credit and not credit-constrained; 0, otherwise	0.40 (0.49)
Average price per kg	Average selling price of paddy (GH¢/kg)	1.19 (0.27)
Gross farm revenue	Total value of paddy output per hectare (GH¢)	799.42 (810.00)
Yield	Quantity of rice output per hectare (kg)	665.78 (634.56)
Fertilizer and chemical costs	Expenditure on fertilizer and chemicals (GH¢)	171.89 (164.04)
Location dummies		
Sagnarigu	1, if farmer is located in Sagnarigu district; 0, otherwise	0.12 (0.33)
Tolon	1, if farmer is located in Tolon district; 0, otherwise	0.22 (0.41)
Kumbungu	1, if farmer is located in Kumbungu district; 0, otherwise	0.23 (0.42)
Savelugu Nanton	1, if farmer is located in Savelugu Nanton Municipal; 0, otherwise	0.20 (0.40)
Tamale	1, if farmer is located in Tamale metropolitan area; 0, otherwise	0.21 (0.40)

Note(s): GH¢ is Ghanaian currency (US$1 = GH¢ 4.19), SD: standard deviation

Table 1.
Variable definition and summary statistics

suggests that majority of the farmers in the study area still conduct marketing and sales of their produce individually, which may influence output prices and farm net revenues. The outcome variable is farm net revenue, which is generated from rice production and marketing, and is computed as the difference between gross farm revenue per hectare less variable costs.

As shown in Table 1, an average farmer is 37 years old, has completed about two years of formal education, cultivates about 1.14 ha of rice farm and generates a farm net revenue of Gh ¢457.72 per hectare. Table 2 reports the mean differences by group membership and collective marketing participation for the variables used in the analysis, as well as the statistical t-test results of these differences. As reported in Table 2, group members constitute a greater proportion of farmers who participate in collective marketing. Specifically, about 27 and 14 percent of the group members and non-members, respectively, participated in collective marketing. We also find that group members obtain higher yields, receive higher prices and generate higher gross farm revenues, resulting in significantly higher farm net revenues than non-members. On average, group members appear older and constitute a higher proportion of farmers who are not credit constrained relative to non-members. In addition, group members

Table 2. Differences in farmer characteristics by group membership and collective marketing participation

Variable	Group membership: Members Mean	SD	Non-members Mean	SD	Diff. (*t*-statistic)	Collective marketing: Participants Mean	SD	Non-participants Mean	SD	Diff. (*t*-statistic)
Age	40.17	11.88	35.48	11.21	4.25***	37.38	11.21	37.47	11.86	−0.06
Education	1.95	4.01	2.07	3.96	−0.31	2.07	4.08	2.01	3.96	0.13
Gender	0.87	0.32	0.88	0.31	−0.33	0.93	0.25	0.87	0.33	1.60
Mobile phone	0.63	0.48	0.32	0.46	6.87***	0.74	0.44	0.37	0.48	6.39***
Radio set	0.64	0.47	0.50	0.50	3.12***	0.71	0.45	0.52	0.50	3.33***
Farm size	1.08	0.98	1.19	1.44	−0.88	1.15	1.22	1.14	1.28	0.04
Access to credit	0.57	0.49	0.27	0.44	6.82***	0.50	0.50	0.37	0.48	2.21**
Distance to market	7.04	4.10	6.17	4.03	2.23**	5.72	3.19	6.74	4.25	2.11**
Bicycle	0.65	0.47	0.73	0.44	−1.80*	0.74	0.44	0.68	0.46	0.95
Market perception	0.46	0.49	0.22	0.41	5.48***	0.48	0.50	0.28	0.45	3.61***
Road status	0.84	0.36	0.65	0.47	4.57***	0.85	0.35	0.70	0.45	2.83***
Sagnarigu	0.29	0.45	0.01	0.10	9.55***	0.11	0.31	0.13	0.34	−0.54
Tolon	0.25	0.43	0.20	0.40	1.23	0.25	0.44	0.21	0.40	0.93
Kumbungu	0.21	0.41	0.25	0.43	1.03	0.42	0.49	0.18	0.39	4.81***
Savelugu Nanton	0.08	0.27	0.28	0.45	−5.37***	0.10	0.30	0.22	0.41	−2.64***
Tamale	0.15	0.36	0.24	0.43	−2.24**	0.10	0.30	0.23	0.42	−2.84***
Farm net revenue	634.51	854.88	329.39	367.74	5.12***	751.55	1,068.78	384.67	447.77	4.98***
Average price per kg	1.27	0.37	1.13	0.13	5.59***	1.30	0.43	1.16	0.20	4.54***
Gross farm revenue	981.58	1,092.99	667.32	476.04	4.12***	1109.39	1357.68	722.45	579.14	4.10***
Yield	773.03	841.14	587.93	410.86	3.07***	–	–	–	–	–
Fertilizer and chemical costs	154.66	175.50	184.40	154.34	−1.89**	–	–	–	–	–
Sample size	188		259			89		358		

Note(s): *, **, *** represent significance at 10, 5 and 1 percent levels, respectively mostly own mobile phones, radio sets, live in communities with motorable roads, travel longer distances to markets as well as possess perception of high rice market demand. With regard to differences in the characteristics by collective marketing participation, Table 2, reveals that farmers who participate in collective marketing mostly access credit and are not credit constrained, own mobile phones and radio sets as well as live in communities with motorable roads. However, collective marketing participants receive significantly higher paddy prices and gross farm revenues than non-participants, probably contributing to the significantly higher farm net revenues than those farmers who marketed and sold paddy individually.

6. Empirical results and discussion

6.1 Bivariate probit results: group membership and collective marketing decisions

Table 3 shows the estimation results for the bivariate probit model on group membership and collective marketing participation decisions. The correlation coefficient ρ is found to be positive and significant, implying that group membership and collective marketing participation decisions are not independent. This suggests that employing a univariate probit regression would generate biased and inconsistent estimates. Before we begin discussion of the drivers of group membership and collective marketing decisions, it is significant to point out that some smallholder farmers in northern Ghana join farmer groups with the motive of accessing credit to undertake and/or expand their farming operations. Moreover, farmers who accessed enough credit for the growing season are also motivated to market and sell collectively with the notion of generating satisfactory farm revenues for the

Table 3.
Maximum likelihood estimates of bivariate probit model for group membership and collective marketing

Variable	Membership Coefficient	SE	Collective marketing Coefficient	SE	Marginal effects (in %) Coefficient	SE
Constant	−3.301***	0.567	−1.886***	0.591		
Age	0.022***	0.008	−0.002	0.008	0.000	0.001
Education	0.028	0.020	−0.025	0.021	−0.001	0.002
Gender	0.087	0.290	0.243	0.309	0.033	0.019
Mobile phone	0.643***	0.158	0.920***	0.171	0.145***	0.023
Radio set	0.244	0.164	0.430**	0.172	0.064***	0.023
Farm size (log)	0.045	0.136	−0.195	0.147	−0.020	0.019
Access to credit	0.761***	0.153	0.040	0.156	0.047**	0.021
Distance to market(log)	0.423**	0.164	−0.146	0.165	0.021	0.022
Bicycle	−0.456**	0.193	−0.034	0.192	−0.029	0.029
Road status	0.467**	0.195	0.656***	0.219	0.104***	0.029
Market perception	0.499***	0.167	0.273 *	0.164	0.060***	0.022
Tolon	0.219	0.267	0.628**	0.305	0.086**	0.040
Sagnarigu	1.799***	0.390	0.365	0.341	0.143***	0.046
Kumbungu	−0.273	0.222	0.880***	0.253	0.089***	0.032
Savelugu Nanton	−0.359	0.265	−0.003	0.309	−0.020	0.040
Residual (credit)	0.672	1.243	−2.080	1.300	−0.210	0.174
ρ	0.182*	0.103				
Log-likelihood-374.19, $p = 0.000$						
Wald chi-sq(df =32) 193.23						
Wald test of $\rho = 0$ ($df = 1$) 3.027, $p = 0.081$						
Murphy's score test: chi-sq (9) = 8.99, $p(X^2) = 0.437$						
Sample size	447					

Note(s): *, **, *** represent significance at 10, 5, and 1 percent levels, respectively credit repayment. This makes access to credit potentially endogenous in both specifications, which when unaccounted for, could result in biased coefficient estimate. We address this potential endogeneity by employing the control function approach (Wooldridge, 2015). In doing so, we estimate a probit model in the first stage with access to credit as dependent variable and including distance to credit institution as an instrument, which influences access to credit (see Table A1 in online Appendix), but not group membership or collective marketing. The observed access to credit variable and the predicted residuals are incorporated into the bivariate probit model in the second stage. The *t*-statistic of credit residual coefficient indicates that we fail to reject the null hypothesis that access to credit is exogenous (Tables 3–5).

Next, we discuss the marginal effects of the exogenous variables on the probability of collective marketing participation, conditional on group membership. Table 3 reveals that, given group membership, farmers who have access to credit and are not credit-constrained have about 4.7 percent higher probability of participating in collective marketing. Participation in collective marketing has a higher likelihood of ensuring guaranteed markets for smallholder farmers, especially in situations where farmer groups have established purchase agreements with buyers. Guaranteed markets could possibly encourage timely credit repayment. The use of mobile phone is associated with about 14.5 percent higher likelihood of collective marketing participation. Mobile phones promote effective communication among group members (Fischer and Qaim, 2012). Apart from its role in searching for potential buyers, updated market information related to paddy prices is transmitted via mobile phones and also used to facilitate interactions and negotiations with

Table 4. FIML estimates of endogenous switching regression model for group membership and impact on farm net revenue

Variable	Selection		Members		Non-members	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	−3.634***	0.594	7.447***	0.970	4.511***	0.492
Age	0.027***	0.008	−0.021 **	0.008	−0.001	0.007
Education	0.021	0.021	−0.016	0.023	−0.000	0.018
Gender	0.118	0.314	0.231	0.318	0.591 **	0.260
Mobile phone	0.756***	0.167	−0.003	0.211	−0.047	0.171
Radio set	0.342**	0.172	0.138	0.196	−0.109	0.145
Farm size (log)	0.012	0.142	0.461***	0.157	0.502***	0.102
Access to credit	0.744***	0.167	0.823***	0.241	0.292 *	0.171
Distance to market(log)	0.509***	0.168	−0.542***	0.201	−0.205	0.128
Bicycle	−0.421**	0.204	−0.000	0.215	0.418 **	0.181
Road status	0.628***	0.206	−0.470 *	0.267	−0.105	0.156
Tolon	0.330	0.280	−0.134	0.324	0.539 **	0.225
Sagnarigu	1.981***	0.420	−0.486	0.381	0.001	0.699
Kumbungu	−0.315	0.229	0.900***	0.303	0.920***	0.203
Savelugu Nanton	−0.525*	0.282	0.567	0.409	0.703***	0.202
Market perception	0.575***	0.169				
Residual (Credit)	−0.245	1.285				
$\ln\sigma_1$			0.185 (0.087)**			
$\rho_{\mu 1}$			−0.697 (0.342)**			
$\ln\sigma_2$					0.381 (0.052)	
$\rho_{\mu 2}$					−0.283 (0.249)	
Log likelihood: −794.95						
LR test of independent equations.: $\chi^2(1)$: 40.91***						
Observations	447		188		259	

Note(s): The dependent variable is the log of farm net revenue; *, **, *** represent significance at 10, 5, and 1 percent levels, respectively

Table 5.
FIML estimates of endogenous switching regression model for collective marketing and impact on farm net revenue

Variable	Selection		Participants		Non-participants	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	−1.867***	0.601	7.732***	1.446	4.951***	0.409
Age	−0.010	0.007	−0.003	0.012	−0.007	0.005
Education	−0.002	0.026	0.014	0.034	−0.011	0.016
Gender	0.134	0.358	0.085	0.563	0.503**	0.221
Mobile phone	0.582**	0.252	0.158	0.422	−0.127	0.147
Radio set	0.292*	0.171	−0.556 *	0.322	0.052	0.130
Farm size (log)	−0.086	0.151	0.712***	0.223	0.469***	0.096
Access to credit	0.085	0.163	0.465*	0.272	0.806***	0.129
Distance to market(log)	−0.167	0.160	−0.503	0.310	−0.185*	0.110
Bicycle	−0.126	0.196	0.138	0.344	0.143	0.150
Road status	0.492 **	0.250	−0.140	0.397	−0.143	0.144
Tolon	0.141	0.318	0.177	0.554	0.334 *	0.197
Sagnarigu	−0.072	0.323	1.051*	0.601	−0.006	0.226
Kumbungu	0.704**	0.304	0.627	0.527	0.774***	0.212
Savelugu Nanton	0.149	0.299	0.480	0.589	0.665***	0.188
Market perception	0.479 **	0.192				
Residual (credit)	0.904	1.235				
$\ln\sigma_1$			0.365 (0.171)**			
$\rho_{\mu 1}$			−1.251 (0.425)***			
$\ln\sigma_2$					0.073 (0.040)*	
$\rho_{\mu 2}$					−0.158 (0.254)	
Log likelihood: −790.10						
LR test of independent equations.: $\chi^2(1)$: 16.32***						
Observations	447		89		358	

Note(s): The dependent variable is the log of farm net revenue; *, **, *** represent significance at 10, 5, and 1 percent levels, respectively

buyers over terms of sale. Also, group members who own mobile phones are easily notified via phone communication to mobilize paddy rice at community collection centers for pickup by buyers. Similarly, given group membership, farmers who own radio sets are 6.4 percent more likely to participate in collective marketing. Using radio sets could facilitate receipt of market information on prices of inputs and output.

Distance to markets, ownership of bicycle and road status also tend to influence collective marketing participation decisions. Specifically, an additional percentage increase in distance to market results in 2.1 percent more likelihood of collective marketing participation. This suggests that farmers who live further away from the market are more likely to participate in collective marketing. Farmers who own bicycles have 2.9 percent lower probabilities of participating in collective marketing. This is plausible, because farmers who own bicycles can easily transport their paddy to market centers, where they are likely to receive higher prices. Availability of adequate road infrastructure is also crucial in rural input and output markets. It is hypothesized that good-quality roads facilitate transport of produce from communities to market centers, as well as movement of produce buyers from district and regional capitals into rice growing communities at the harvest period. We find that farmers who reside and farm around communities with motorable roads have 10.4 percent higher probability of participating in collective marketing. Communities with motorable roads are accessible to paddy aggregators and produce buying companies who normally travel from the regional capitals of northern and southern Ghana to the rice-growing communities during harvest for paddy mobilization. It is argued that communities with non-motorable roads discourage buyers from traveling to these areas to purchase produce, because they are likely to incur relatively higher proportional transaction costs.

6.2 Impact of group membership on farm net revenues

Table 4 presents the results for the determinants of group membership decisions and their impacts on farm net revenues. As stated previously, the FIML method is used to simultaneously estimate the group membership (selection) and farm net revenue (outcome) equations while controlling for farmers' observed and unobserved attributes. We identified the ESR model by including in the selection equation a variable representing farmer's perceptions on rice market demand as an instrument, which strongly influences a farmer's decision to join a farmer group, but not directly on farm net revenue. The instrumental variable test confirms the validity of the instrument (see Table A2 in online Appendix). As shown in Table 4, the results reveal negative correlation coefficients (ρ) but only significantly different from zero for the correlation between group membership (1) and farm net revenue (8a). This finding indicates that selection bias caused by observed and unobserved attributes occurred in farmers' decisions to join farmer groups. It also implies that farmers who decide to be group members earn significantly higher farm net revenues than those farmers who would have been randomly assigned to group membership. This justifies the appropriateness of using the ESR approach in the estimations. The negative ρ in both the member and non-member specifications implies positive selection bias, which suggests that farmers with above-average farm net revenues have higher probabilities of joining farmer groups.

The parameter estimates of the factors influencing farmers' decisions to join farmer groups would not be discussed due to space limitation, but are available on request. However, we first discuss the factors influencing farm net revenues, conditional on group membership decisions. Age exerts a negative impact on farm net revenues of both members and non-members, but significantly different from zero for group members. This suggests that relatively younger farmers earn higher farm net revenues from rice production and marketing. Farm size exhibits a positive and significant impact on farm net revenue for both group members and non-members. In particular, an additional percentage increase in farm size results in 0.46 and 0.50 percent increase in farm net revenues for members and non-members, respectively, thus demonstrating scale effects in rice production and marketing. Access to credit positively impacts on farm net revenues received by both group members and non-members, suggesting that farmers who are credit-constrained tend to earn significantly higher farm net revenues from rice production and marketing. Distance to market also plays significant role in farm net revenue generation. In particular, an additional percentage increase in distance to market reduces net revenue by 0.54 and 0.20 percent for members and non-members, respectively.

6.3 Impact of collective marketing participation on farm net revenues

The results of factors influencing collective marketing participation and their impacts on farm net revenues are reported in Table 5. Like the group membership model, we identified the collective marketing model, using a variable that represents farmers' perceptions on rice market demand as an instrument, which significantly influences farmers' decisions to participate in collective marketing, but not directly on farm net revenues. The instrumental variable test results, reported in Table A2 in the online Appendix, confirm that the instrument is valid. In Table 5, the results show that the estimated correlation coefficient (ρ) is significant for the collective marketing participation specification, suggesting the presence of selection bias.

Again, the parameter estimates of the factors influencing farmers' decisions to participate in collective marketing would not be discussed due to space limitation, but are available on request. With regard to the factors influencing smallholder rice farmers' net revenues, conditional on collective marketing participation, farm size exerts positive and significant impact on net revenues for both collective marketing participants and non-participants. Specifically, participants and non-participants, respectively, experience 0.71 and 0.46 percent significant gains in farm net revenues for any additional percentage increase in farm size. In addition, we find that collective marketing participating and non-participating farmers who are not credit-constrained received higher farm net revenues from rice production and marketing. As argued earlier, relatively higher farm net revenues could ensure timely and reliable credit repayment. The coefficient of distance to markets, which is considered to influence proportional transaction costs, is found to be negative, but significantly different from zero for non-participant specification. This suggests that conditional on collective marketing participation, farmers who failed to participate in collective marketing, but marketed and sold their paddy individually, experienced about 0.18 percent significant reduction in farm net revenues for any additional percentage increase in distance to market centers.

6.4 Average treatment effects of group membership and collective marketing

The results of the ATT of group membership and collective marketing on farm net revenues are presented in Tables 6 and 7. Table 6 reveals about 81.21 percent farm net revenue gain by farmers, conditional on group membership relative to non-members. To gain further insights into the impact of group membership on farm net revenues received by farmers, we disaggregated farm net revenues based on whether group members participated in collective marketing or marketed and sold their paddy individually. Table 6 reveals that group members experienced 79.52 percent farm net revenues gain from collective marketing relative to non-members, while group members who marketed and sold their paddy

Variable	Group membership Members	Nonmembers	ATT	*t*-value
Mean outcome (farm net revenue)	329.84 (23.41)	182.01 (9.11)	147.82	8.671***
Farm net revenue disaggregated by collective marketing				
Collective marketing	387.81 (47.57)	216.03 (20.57)	171.78	5.061***
Individual marketing	307.68 (26.64)	169.01 (9.66)	138.67	7.041***
Farm net revenue disaggregated by farm size				
Near landless (≤0.5 ha)	149.82 (18.43)	83.80 (6.87)	66.02	4.576***
Small (0.6–1.5 ha)	295.60 (21.70)	171.08 (9.05)	124.52	7.750***
Medium and large(>1.5 ha)	644.49 (79.62)	329.99 (22.70)	314.50	4.794***

Note(s): ATT: average treatment effect on the treated, the dependent variable is the log of farm net revenue. Computation of ATT is based on the antilog of the predictions, *** means significant at 1 percent level

Table 6. Impact of farmer group membership on farm net revenue

Variable	Participants	Non-participants	ATT	*t*-value
Mean outcome (farm net revenue)	435.55 (37.71)	268.49 (18.92)	167.06	5.871***
Farm net revenue stratification by farm size				
Near landless (≤0.5 ha)	189.96 (29.69)	116.00 (13.14)	73.96	2.636**
Small (0.6–1.5 ha)	409.60 (32.59)	276.33 (21.21)	133.27	4.977***
Medium and large(>1.5 ha)	829.71 (123.16)	442.77 (46.61)	386.94	3.594***

Note(s): ATT: average treatment effect on the treated, the dependent variable is the log of farm net revenue. Computation of ATT is based on the antilog of the predictions. **, *** means significant at 5 and 1 percent levels, respectively

Table 7. Impact of collective marketing on farm net revenue

individually gained 82.04 percent farm net revenues than non-members. This finding is consistent with the results by Ma and Abduali (2017) and Mishra *et al.* (2018b) and reinforces the significance of group membership on smallholder farm performance. It also shows that group members, regardless of the mode of marketing, significantly benefit from improved farm performance. Further, we examine ATT of group membership on farm net revenues base on farm size to examine the differential impacts on farm net revenues. Interestingly, farm net revenue significantly increases by about 78.78, 72.78 and 95.30 percent for nearly landless, small and medium and large farm sizes, respectively, conditional on group membership. This indicates that group membership tends to increase the farm net revenues of all farm size categories, although the magnitude of the increase is highest with medium- and large-scale farmers. This finding is in line with the notion of scale economies, where the average fixed costs of group members decline with larger farm sizes, resulting in higher farm net revenues.

Table 7 reports the ATT results of collective marketing participation. The results show that collective marketing participation has a positive and statistically significant impact on farm net revenues. Specifically, rice farmers who participated in collective marketing experienced 62.22 percent significant gain in farm net revenues relative to non-participants. The disaggregated results based on farm size reveal that nearly landless, small and medium and large farm size category of farmers earned 63.75, 48.22 and 87.39 percent farm net revenues, respectively. This shows that farmers with larger farm sizes tend to benefit more from collective marketing as compared to farmers with smaller farm sizes. Similar findings have been revealed from the studies by Fischer and Qaim (2012) and Zylberberg (2013), which generally suggest that smallholder farmers with group membership and participating in collective marketing benefit from improved farm performance than farmers who produce and market their paddy individually.

7. Conclusions and policy implications

This paper has investigated the factors influencing farmers' decisions to join farmer groups and to participate in collective marketing, as well as their impacts on farm net revenues. We used recent survey data of 447 smallholder rice farmers from five districts in northern Ghana. The data reveal that farmers who were members of farmer groups and participated in collective marketing obtained higher prices for their output and also incurred lower input costs. Farmers' decisions on group membership and participation in collective marketing are shown to be jointly made, indicating that most farmers with group membership also participate in collective marketing. The empirical results support the notion that farmer group membership and collective market participation decisions in smallholder agriculture essentially enhance farm performance through improvement in farm net revenues. Farmer group members regardless of their mode of marketing significantly benefit from improved farm performance. Group membership and collective marketing decisions are positively and significantly influenced by mobile phone ownership and road status. That is, farmers who own mobile phones are more likely to join farmer groups and participate in collective marketing. However, farmers who faced financial constraints were found to be less likely to have group membership and to participate in collective marketing.

The findings from this study show that government and donor support for the formation of farmer groups during implementation of agriculture and value chain interventions should as well incorporate strategies to facilitate collective marketing. Both new and existing farmer groups could be trained on demand-driven capacity-building modules such as group dynamics, business development, as well as technical capacity development. Capacity-building on group dynamics would enable farmer groups become more cohesive and thus encourage active member participation in group activities, including collective marketing. The important role of access to credit revealed by the study advocates for the need to incorporate credit schemes into agriculture and value chain development programs, as well as facilitates effective linkages between smallholder farmers and readily available financial institutions. Moreover, government investment in road infrastructure could facilitate easy access to rice growing communities by buyers and also ease produce movement to market centers.

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Appendix

Online appendix is available for this article.

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