Received: 26 November 2023 | Revised: 13 April 2024 | Accepted: 28 May 2024

DOI: 10.1002/wfp2.12076

RESEARCH ARTICLE

WFP WORLD FOOD POLICY WILEY

Can farmer organization membership improve household food security and nutrition? Evidence from Northern Ghana

Kwabena Nyarko Addai[1] | **John N. Ng'ombe**[2] | **Omphile Temoso**[3]

[1]Department of Accounting, Finance and Economics, Griffith Business School, Griffith University, Nathan, QLD, Australia

[2]Department of Agribusiness, Applied Economics and Agriscience Education, North Carolina Agricultural and Technical State University, Greensboro, NC, USA

[3]UNE Business School, University of New England, Armidale, NSW, Australia

Correspondence
Kwabena Nyarko Addai, Department of Accounting, Finance and Economics, Griffith Business School, Griffith University, Nathan QLD 4111, Australia.
Email: kwabena.addai@griffithuni.edu.au

Abstract

We examine the impact of farmer organization (FO) membership on food and nutrition security among rural rice farmers, using cross-sectional data from a household survey from Ghana. We employ an endogenous switching regression (ESR) model to account for selection bias from observed and unobserved factors. Our findings show that participation in FOs significantly increases household dietary diversity by 10.56% and reduces food insecurity by 9.7%. The residualized quantile regression model results are consistent with the ESR model across both outcome variables. Policymakers should consider promoting FO membership as a strategy to enhance food and nutrition security among smallholders in developing countries.

KEYWORDS

farmer organization, household dietary diversity score, household food insecurity access scale

1 | INTRODUCTION

Despite efforts to address hunger, food insecurity, and malnutrition, the world still faces significant challenges in achieving the goal of eradication by 2030 (FAO et al., 2022). In 2021, 828 million people, or 10.5% of the world's population, experienced hunger, an increase of 46 million people since 2020 and 150 million since the start of the COVID-19 pandemic. These statistics underscore the persistent post-pandemic inequalities both between and within nations, which have been exacerbated by unequal economic recovery trends and income losses among the most vulnerable populations. Furthermore, food supply chains continue to be disrupted by ongoing pandemic effects, conflicts, and climate-related shocks such as extreme weather events, particularly in low-income countries with limited adaptive capacity (FAO et al., 2020).

Sub-Saharan Africa (SSA) is particularly vulnerable to food insecurity because of its heavy reliance on cereal imports, rapid population growth, and stagnating agricultural productivity (Giller, 2020; van Ittersum et al., 2016). Africa now has the highest rate of undernourishment in the world, with 19% of the population affected in 2019, up from 17.6% in 2014, more than twice the global average (FAO et al., 2020). In response to these challenges, several studies have proposed solutions such as the adoption of improved agricultural technologies, climate-smart agriculture, and promotion of farmer organizations (FOs) (Addai et al., 2022; Bizikova et al., 2020; Di Marcantonio et al., 2022; Lu et al., 2021; Manda, Khonje, et al., 2020; Wossen et al., 2017). Our study aligns with these studies but focuses specifically on the impact of FOs on food security and nutrition.

This study aims to investigate whether membership in FOs improves food security and nutrition among smallholder households. Specifically, we examine whether FO membership (i.e., crop-focused cooperatives) enhances household dietary diversity scores (HDDS) and reduces the household food insecurity access scale (HFIAS) to measure dietary diversity and food insecurity, respectively, among smallholder farm households. Our data were collected from Northern Ghana, an area with over 3 million food-insecure people (WFP, 2022).

FOs, which include associations, cooperatives, producer organizations, self-help groups, and women's groups, play a crucial role in supporting the interests of their members (Bizikova et al., 2020). Membership in FOs has been shown to improve farmers' productivity, income, and wealth levels (Bizikova et al., 2020; Di Marcantonio et al., 2022; Ma et al., 2021; Ortega et al., 2019; Tsai & Luh, 2022). These organizations help smallholders access markets, credit, rural extension services, and natural resource management (Tabe-Ojong, 2022). They also help build farmers' skills in production, marketing, and leadership, and improve their psychological well-being (Gugerty et al., 2019). As such, FOs have become core elements of rural development, agricultural productivity, and anti-poverty policies in Ghana and the entire Global South (Bijman & Wijers, 2019; Tefera et al., 2017).

The United Nations Sustainable Development Goals (2015) represent a global commitment to combating hunger and improving the welfare of smallholders and the environment (Bizikova et al., 2020). While smallholder farmers play a substantial role in the global food supply, many experience food insecurity (Ricciardi et al., 2018). They are also highly vulnerable to climate change and environmental degradation, particularly in SSA (Issahaku & Abdulai, 2019).

Numerous studies (e.g., Di Marcantonio et al., 2022; Dohmwirth & Liu, 2020; Ma et al., 2021; Ortega et al., 2019; Tsai & Luh, 2022) have explored the impact of FO membership on smallholder households' welfare. Tsai and Luh (2022) studied the effects of different FOs on smallholder farmers' economic performance and found that participating in FOs only benefits farm households when the returns from social capital investment outweigh the time cost of participation. In a related study, Di Marcantonio et al. (2022) examined the impact of producer organizations (PO) on dairy farmers' self-assessed experiences of unfair trading practices and negotiation power and found mixed results. On one hand, they found that membership in POs reduces the likelihood of farmers reporting unfair trading practices. On the other hand, they found that PO membership reduces members' self-assessed negotiation power. Ma et al. (2021) also found that membership in cooperatives increases banana yield by 3% and reduces the variance and downside risk exposure by 60% and 114%, respectively. However, there is no conclusive evidence on the effect of FO membership on food and nutrition security among smallholder households especially in the Global South, which warrants further research.

Therefore, our study adds the following to the literature. First, we address a gap in knowledge regarding the impact of FOs on food and nutrition security in Ghana, which is one of the regions with the highest levels of food insecurity in the Global South. The Comprehensive Food Security and Vulnerability Analysis (CFSVA) 2020 reports that 11.7% of the population in Ghana are food insecure, indicating that at least 3.6 million people are affected by food insecurity (WFP, 2022). Of these, 1.6 million people are severely food insecure, and 2 million people are moderately food insecure. Notably, 78% of the food insecure population (2.8 million people) reside in rural areas, while 22% (0.8 million people) live in urban areas. In urban areas, 5.5% of the population experiences food insecurity, of which 3.2% experience severe food insecurity and 2.3% experience moderate food insecurity (WFP, 2022). In rural areas, 10.9% of the population experiences moderate food insecurity, while 18.2% experience the same in urban areas. The Guinea savannah and deciduous forest zones have the highest concentration of hungry people in Ghana (Lu et al., 2021). Although the Government of Ghana has made several efforts to improve the situation, few studies have assessed the contribution of FOs to food security and nutrition, particularly for marginalized, remote, and socially disadvantaged households who typically suffer from food insecurity.

Secondly, we employ an endogenous switching regression (ESR) model to account for potential selection bias issues in our analysis. This is crucial because failing to control for selection bias can lead to biased estimates (Wooldridge, 2010). Moreover, we supplement our ESR model findings with residualized quantile regression to assess the heterogeneous effects of FOs on food and nutritional security. By doing so, we can identify the effects of FO membership on both the mean and distribution of food and nutritional security, which will allow us to disentangle the impacts more informatively across outcome distributions.

The remainder of the paper is structured as follows. The data and variables used in the study are described in the next section while the econometric and estimation strategies are presented in Section 3. The findings and discussion are presented in Section 4. Section 5 has the study's conclusions and recommendations for policy.

2 | THEORETICAL FRAMEWORK

Farmer-based organizations (FOs) are organizations formed by farmers to collectively market their produce, purchase inputs, and share resources (Gezahegn et al., 2020). They exist as agricultural cooperatives, community-based associations and other institutions that focus on achieving the needs of farmers. In Ghana, examples of FOs include Kookoo Abrabopa, Organic Group, Peasant Farmers' Association of Ghana (PFAG) among others.

The FOs have the potential to impact food and nutritional security mainly through the two pathways shown in Figure 1. The first pathway is through access to better knowledge of

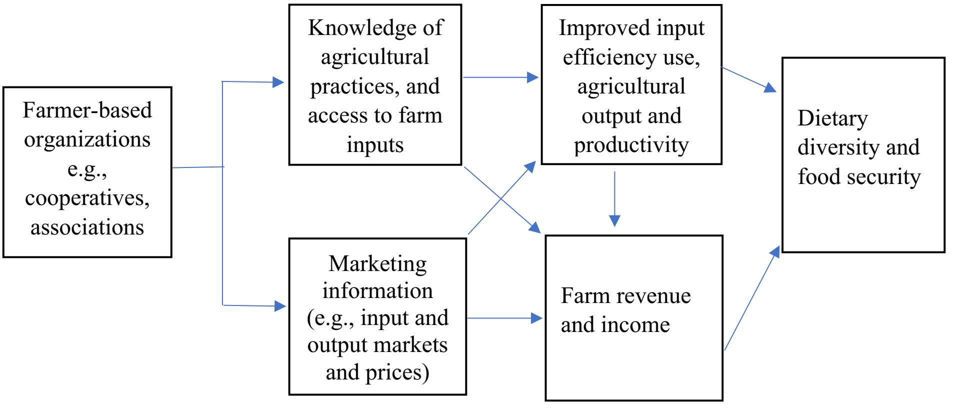

FIGURE 1 The relationship between FO membership and food and nutrition security.

agricultural practices and farm inputs, which result in increased agricultural production or output among farmers (Kumar et al., 2018; Ma, Renwick, et al., 2018; Michalek et al., 2018). González-Flores et al. (2014) suggest that access to higher input use does not necessarily imply higher farm yields. They suggest that such needs to be complemented by how different inputs are efficiently used. Importantly and not coincidentally, Ma, Renwick, et al.'s (2018) finding vindicates González-Flores et al. (2014) as the former found that cooperatives improve technical efficiency of apple farmers in China. As shown in Figure 1, increased knowledge of agricultural practices, and access to farm inputs enhance technical efficiency and then agricultural output and productivity. Increased agricultural productivity and output increase the availability of diverse nutritious foods, food self-sufficiency and food security (Baldos & Hertel, 2014).

Another way that FO membership can improve dietary diversity and food security is through access to marketing information and increasing agricultural prices. Farmer-based organizations generally provide farmers with marketing information on input and output prices, enabling them to sell their output at competitively higher prices (Ma & Abdulai, 2016; Ma, Renwick, et al., 2018). Chagwiza et al. (2016) show that farmers belonging to FOs, such as dairy cooperatives, have access to higher dairy product prices. Hoken and Su (2018) indicate that FO members face higher price margins, increasing their crop incomes. Both pathways indicate how FO can potentially improve farm performance, especially in adopting improved inputs resulting in higher crop yields (see Hoken & Su, 2018; Kumar et al., 2018; Ma & Abdulai, 2016; Ma, Renwick, et al., 2018). However, it is noteworthy to mention that while the theoretical framework in Figure 1 is used in this paper for crop-based cooperatives, it can apply to other types of FOs.

Moreover, following Wu et al. (2023), both knowledge of agricultural prices and access to marketing information can improve farm revenue and farm input efficiency, as indicated in Figure 1. As mentioned, this paper follows a similar line of inquiry but with special attention paid to the impacts of FO membership on food and nutrition security. Without a clear understanding of the impacts of farmer-based organizations, such as crop-based agricultural cooperatives, on food and nutrition security, designing effective policies and programs to support their development and growth is difficult. This is because FOs play a crucial role in smallholder agriculture, and their activities can have far-reaching implications for the food and nutrition security of their members and the broader community. However, the specific impacts of these organizations on different dimensions of food and nutrition security may vary depending on their objectives, operations, and the local contexts in which they operate (Wu et al., 2023). Without a clear understanding of how FO membership affects various aspects of food and nutrition security, such as food availability, access, utilization, and stability, it becomes challenging to identify the most effective policy interventions and support programs. Some key reasons why this understanding is essential include the following. First, different food and nutrition security dimensions may require different interventions or support mechanisms. For example, if FOs primarily impact dietary diversity and nutrient intake (utilization dimension), interventions focused on improving agricultural productivity or market access (availability and access dimensions) may be less effective.

Second, by understanding the specific impacts of FOs on food and nutrition security, policymakers can identify gaps or areas that require more attention and prioritize interventions accordingly (Manda, Alene, et al., 2020). Third, limited resources available for supporting FOs need to be allocated efficiently. Without a clear understanding of their impacts, resources may be misaligned, leading to suboptimal outcomes (Ketkar & Workiewicz, 2022). Moreover, clear knowledge of the expected impacts of FOs on food and nutrition security is essential for developing effective monitoring and evaluation frameworks to assess the success of interventions and make necessary adjustments. Therefore, by conducting rigorous research to understand the specific impacts of FO membership on different dimensions of food and nutrition security, policymakers and development organizations can design more targeted, evidence-based policies and support programs. This, in turn, can optimize the potential of FOs to contribute to improving food and nutrition security in rural communities.

3 | DATA

3.1 | Sampling and data collection

The study uses data collected from a farm household survey conducted among rice farmers in Northern Ghana between October and December 2018. The sample was selected using a multistage approach, beginning with a purposive sampling of the Northern Zone of Ghana, which includes the previous Northern, Upper East, and Upper West regions of Ghana. These regions were selected because they are among the country's most poverty-stricken and hunger-prone areas, with poverty prevalence rates of 54.8%, 70.9%, and 61.1%, respectively (GSS, 2018), and the highest prevalence rate of food insecurity among the country's 3.6 million food-insecure individuals (GSS, 2018). From each of these regions, a district was selected based on its high rice production levels: Savelugu (Northern Region), Nadowli-Kaleo (Upper West), and Kassena Nankana East (Upper East). Next, townships or societies were randomly selected from the operational zones of the Ministry of Food and Agriculture (MoFA), and rice farm households were randomly chosen from the different villages based on the number of rice farm households. The final sample consisted of 900 farm households, with 300 from each region. Data on rice production variables and farm household attributes were collected through a structured research instrument (questionnaire).

Our dataset focuses on rice farmers, as rice holds significant importance as a strategic crop in Ghana's economy. Rice cultivation serves both as a staple food and a cash crop. The demand for rice has been steadily increasing because of factors such as population growth, urbanization, and evolving consumer preferences. As Tanko et al. (2019) highlight, paddy rice production in Ghana experienced annual fluctuations between 2008 and 2020, ranging from 302,000 tons to

987,000 tons. In 2020 alone, the total rice consumption in Ghana reached approximately 1,450,000 tons, reflecting an average per capita consumption of around 45.0 kg per year (Bissah et al., 2022). These statistics emphasize the significance of rice as a key dietary component in the country and highlight the growing demand for rice-related products. Numerous factors affecting rice output and information on the research area's farm households were collected.

3.2 | Definition of variables and descriptive statistics

Like in most other low-income countries, many FOs exist in Ghana which are available for rice farmers. They include associations, cooperatives, producer organizations, self-help groups, women's groups, and others (Bizikova et al., 2020). In this study, to avoid losing focus, we streamlined FO membership as when as a household head is a member of an agricultural cooperatives or self-help groups. Therefore, we considered a household head to be an FO member provided that he/she was affiliated with no less than an agricultural cooperative or a self-help group that concentrates on the requirements of farmers. The variable definitions are reported in Table 1. Two outcome variables are used in the study: the log of Household Dietary Diversity Score (HDDS) and log of Household Food Insecurity Access Score (HFIAS).

We used the HDDS and the HFIAS to quantify household food and nutrition security. The HDDS is created depending on how many food types the household consumes over a specific period. According to the Food and Agriculture Organization (FAO) of the United Nations' suggested classification system, food items were divided into 12 groups (Kennedy et al., 2011). Cereals, tubers, and roots; legumes; vegetables; meat; eggs; fish and other seafood; fruits; milk and milk products; oils and fats; sweets; species; and condiments and beverages make up the 12 food groups. If any household member consumed a food item from a certain food group within a specific seven-day period, that food group receives an extra point on the HDDS. Consequently, the HDDS's range is 0–12. Among other things, the HDDS is preferred because it also considers the accessibility and availability of food, which are important factors of food security (WFP, 2009). The ability of the household to afford a range of foods through obtaining the many different food categories consumed over the period is therefore related to a diverse diet. Food security in the home and socioeconomic position are related to increased dietary diversity (Lu et al., 2021).

To control the complexity of food security challenges, the HFIAS was created (Coates et al., 2007). The HFIAS is a subjective quick rural assessment approach that examines respondents' impressions of household food security experiences over the preceding four weeks rather than attempting to evaluate the four variables of availability, access, utilization, and stability independently (1 month). The responses of the respondents are combined to create a rank indicator value for food insecurity that represents all four aspects of a household. The nine-food security-related questions in the HFIAS are divided into three main categories: Concern over food availability, a lack of diversity and favored foods, and the effects of food shortages are the first two (insufficient food intake and its physical consequences). The scale consists of nine occurrence questions and nine frequency-of-occurrence questions, and HFIAS score varied from 0 to 27. The lower the score, the less food insecurity (higher access) a household experienced and vice versa.

The HDDS and the HFIAS are two commonly used indicators to measure different dimensions of food security (Coates et al., 2007). We use both measures to provide a more comprehensive assessment of the food security, because they capture distinct aspects of the food security concept. Food security is a multidimensional concept that encompasses four main pillars:

TABLE 1 Variable definitions.

Variable name	Description
Outcome variables	
Household Dietary Diversity Score (HDDS)	A measure of household food access and dietary diversity. It is calculated based on the number of different food groups consumed by the household over previous 7 days (0–12)
Household Food Insecurity Access Score (HFIAS)	A measure of household food insecurity, specifically focusing on the access component of food security. It is calculated based on a set of questions that capture the household's experiences related to food insecurity. A food secure household has a score of 0, absolutely food insecure household has a score of 27
Treatment variable	
Farmer organization membership	1 if household head is a farmer organization member, 0 otherwise
Independent variables	
Gender	1 if household head is a male, 0 otherwise
Age	Age of household head in years
Years of schooling	Years of formal education of the household head
Household size	Number of household members
Marital status	1 if household head is married, 0 otherwise
Farm size	Total rice farm size in hectares
Total livestock	Total livestock units
Credit access	1 if the household head had access to credit, 0 otherwise
Off-farm income	Household head's income from non-farm activities including off-farm employment in GHS[a]
Market distance	Distance from farm to market in km
Farm distance	Distance from home to the farm in km
Asset value	Total value of assets (GHS) in a farm household
Market information	1 if the household head had access to market information, 0 otherwise
Ecological zone dummies	
Guinea savannah zone	1 if farm is in the Guinea savannah zone, 0 otherwise
Sudan savannah zone	1 if farm is in the Sudan savannah zone, 0 otherwise
Selection instrument	
A farmer's relatives in FO	1 if a farmer's relatives have an FO membership, 0 otherwise

[a]US Dollars (USD) to Ghanaian Cedis (GHS) exchange rate for December 31, 2018: 1USD: GHS 4.9.

availability, access, utilization, and stability (Coates et al., 2007). HDDS and HFIAS are linked to these pillars as follows. HDDS is primarily an indicator of the dietary diversity and quality of the household's food consumption, which is closely related to the utilization dimension of food security. A diverse diet is essential for meeting nutritional requirements and promoting good health, which is a crucial aspect of food utilization (Mataka et al., 2023). HDDS also reflects, to some extent, the accessibility dimension of food security, as a more diverse diet implies access to a variety of food groups, which is often influenced by economic access and household resources.

The HFIAS is a direct measure of the access dimension of food security, specifically focusing on households' ability to access sufficient and adequate food (Coates et al., 2007). It captures a household's experiences related to food insecurity, such as worrying about food, compromising on food quality and quantity, and experiencing hunger because of limited access to food. The HFIAS provides insights into the severity and prevalence of food insecurity within a population, which is a key aspect of the access dimension. Using the two measures to capture food and nutrition security in this study allows us to present a more comprehensive picture of the food security situation. This combined approach allows us to assess in detail the effects of FOs membership not only on the households' ability to access food but also the diversity and quality of their diets, which are essential for ensuring adequate nutrition and overall food security.

The descriptive statistics based on FO membership are presented in Table 2. Table 2 shows that members of FOs are more food secure and dietary diverse than nonmembers. Notwithstanding, one cannot establish a causal relationship between FO membership and the outcome variables as one cannot account for individual and systematic differences between members and non-members of FOs. It is observed that 65% of FO members are male, whiles 72% are non-members. On

TABLE 2 Differences in characteristics of farmers by FO membership.

			FO membership				
	Pooled sample		Members (n = 363)		Non-members (n = 537)		
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Diff (t-stats)**
Log HHS	1.81	0.25	1.85	0.21	1.75	0.01	−0.109***
Log HFIAS	2.15	1.15	2.31	1.00	1.94	1.30	−0.369***
Gender	0.68	0.46	0.65	0.48	0.72	0.45	0.072**
Age	52.45	9.81	50.96	9.70	54.55	9.61	3.588***
Years of schooling	3.02	4.50	2.93	4.32	3.14	4.74	0.211
Marital status	0.89	0.31	0.90	0.30	0.88	0.33	−0.022
Household size	6.12	2.02	6.14	2.07	6.10	1.95	−0.038
Off-farm income	178.16	271.12	191.85	302.65	158.92	218.18	−32.932*
Credit access	0.33	0.47	0.33	0.47	0.33	0.47	−0.008
Asset value	1130.13	403.34	1201.38	394.05	1029.92	395.359	−171.459***
Farm distance	3.99	2.36	4.733	2.368	2.936	1.904	−1.797***
Market information	0.72	0.45	0.87	0.34	0.52	0.50	−0.34
Market distance	4.07	2.05	4.69	2.00	3.195	1.79	−1.492***
Farm size	0.64	0.54	0.81	0.59	0.41	0.37	−0.394***
Total livestock units	45.00	44.44	43.05	44.53	47.74	44.23	4.682
Guinea Savannah zone	0.67	0.47	0.71	0.46	0.61	0.49	−0.098***
Sudan Savannah zone	0.33	0.47	0.29	0.46	0.39	0.49	0.097***
Farmer's relatives in FO	0.39	0.49	0.54	0.50	0.17	0.37	−0.371***

***Denotes significance level of 1%.
**Denotes significance level of 5%.
*Denotes significance level of 10%.

average, members of FOs are younger than non-members. The age of household heads is bound to affect FO membership, and people tend to be more conservative as they age. The average years of schooling of FO members and non-members are 2.93 and 3.14 years, respectively.

It is also observed that members and non-members averagely have the same household size. In terms of off-farm income, FO members (GHS191.85), on average, have higher off-farm income than non-members (GHS158.92). Eighty-seven percent of FO members had access to market information, and 52% for non-members. On average, FO members (4.73 km) travel long distances to the farm than non-members (2.94 km).

4 | ECONOMETRIC AND ESTIMATION STRATEGY

4.1 | The choice of farmer organization membership

The decision to join a FO is binary. Farmers decide whether to join based on a set of observable factors. Following Addai et al. (2022) and Tabe-Ojong (2022), we model membership in FO in a random utility framework. In this context, a farmer's decision, is primarily based on a comparison of the expected utilities (U_{Pi} and U_{Ni}) obtained from FO membership and non-membership, respectively. Let the difference in the expected utility be represented by UT_i^*, it follows that farmer i will join a FO if $UT_i^* = U_{Pi} - U_{Ni} > 0$. However, the utility difference UT_i^* is unobservable, but can be specified as a function of observable factors in a latent variable framework as

$$UT_i^* = \delta X_i + \upsilon_i, \text{ with } M_i = \begin{cases} 1 \text{ if } UT_i^* > 0 \\ \\ 0 \text{ otherwise} \end{cases} \tag{1}$$

where UT_i^* is a latent utility indicator of the binary decision M_i, which is equal to 1 if farmer i participates in a FO, and zero otherwise; δ represents vector of unknown parameters to be estimated; X_i denotes a vector of observable factors. Following literature (e.g., Ma & Abdulai, 2016; Manaswi et al., 2020; Nikam et al., 2019; Tabe-Ojong, 2022), X_i includes gender, age, farm size, credit access, market distance, farm distance, total livestock unit, asset value, off-farm income, years of schooling, household size, marital status, market information, zone dummies, and υ_i is the error term. A farmer's probability of joining a FO $\Pr(M_i = 1)$ can be specified as

$$\Pr(M_i = 1) = \Pr\left(UT_i^* > 0\right) = \Pr(\upsilon_i - \delta X_i) = 1 - F(\delta X_i) \tag{2}$$

where F is the cumulative distribution function for υ_i and the rest is as defined before.

Without loss of generality, we assume that the vector of our outcome variables (i.e., HDDS and HFIAS) is a linear function of independent variables X_i as well as a dummy of FO membership whereby the outcome equation can be specified as

$$Y_i = \varphi X_i + \gamma M_i + \varepsilon_i \tag{3}$$

where Y_i represents the outcome variables; X_i is a vector of explanatory variables; M_i represents membership in a FO; φ and γ are parameters to be estimated and ε_i is the error term.

Controlling for observable and unobservable characteristics that determine FO membership is necessary to get consistent and unbiased results because such characteristics may be correlated with the outcome variable. Both observable and unobservable household characteristics may be linked to membership in FOs and the outcome variables in our non-experimental data. Quasi-experimental methods like propensity score matching (PSM) and inverse-probability weighted regression adjustment (IPWRA) do account for this selection bias. However, they only take into account observable attributes and ignore unobservable elements like management aptitude, preferences, and risk. To account for both observed and unobserved factors in this context, we employ the endogenous switching regression (ESR) model (Lokshin & Sajaia, 2004). For FO members and non-members, it uses the full information maximum likelihood (FIML) approach to jointly estimate one selection equation and two outcome equations.

4.2 | Endogenous switching regression approach

The ESR technique is a one-stage procedure that first estimates the factors that influence farmers' decisions to join FOs and then moves on to factors that influence outcomes (Issahaku & Abdulai, 2019; Lokshin & Sajaia, 2004). This method accounts for selection bias brought about by observable and unobservable factors to get accurate and reliable parameter estimates. The ESR model is a powerful tool for impact estimation in situations where self-selection into treatment groups is a concern, and is widely used in fields such as economics, public policy, and social sciences (e.g., Kumar et al., 2018; Liu et al., 2021). The model is described below as having two regime equations for farmers who are members of FOs and those who are not, with the criteria function M_i dictating which regime they must contend with.

$$Regime\ 1: Y_P = \varphi_P Z_i + \varepsilon_P \text{ if } M_i = 1 \tag{4a}$$

$$Regime\ 2: Y_N = \varphi_N Z_i + \varepsilon_N \text{ if } M_i = 0 \tag{4b}$$

where Y_P and Y_N are the outcome variables (log of HDDS and log of HFIAS) for FO members (Regime 1) and non-members (Regime 2), respectively; Z_i is a vector of observable factors determining the outcome variables; φ_P and φ_N are unknown parameters to be estimated; ε_P and ε_N are error terms. Accordingly, it is assumed that the error terms in Equations (1), (4a), and (4b) have a trivariate normal distribution with a mean of zero and a non-singular covariance matrix represented as

$$cov(\varepsilon_P \varepsilon_N \upsilon_i) = \begin{bmatrix} \sigma_P^2 & \sigma_{PN} & \sigma_{P\upsilon} \\ \sigma_{PN} & \sigma_N^2 & \sigma_{N\upsilon} \\ \sigma_{P\upsilon} & \sigma_{N\upsilon} & \sigma_\upsilon^2 \end{bmatrix} \tag{5}$$

where $\sigma_P^2 =$ variance of ε_P, $\sigma_N^2 =$ variance of ε_N, $\sigma_\upsilon^2 =$ variance of υ_i, $\sigma_{PN} =$ covariance of ε_P and ε_N, $\sigma_{P\upsilon} =$ covariance of ε_P and υ, *and* $\sigma_{N\upsilon}$ is the covariance of ε_N and υ. Following Greene (2018), we assume that $\sigma_\upsilon^2 = 1$, as δ in the selection equation is estimable only up to a scale factor.

For the ESR model to be correctly identified, some variables in the regime equations may overlap with those in the selection equation but at least one variable should be in the selection equation and not in the regime equations. Such a variable to be a valid selection instrumental variable should meet three conditions which are relevance, exclusion restriction and exogeneity.

As used in Ma et al. (2021), we use a farmer's relatives' FO membership as an instrumental variable. A farmer's relatives' FO membership is relevant as it is strongly correlated with FO membership (Table A1 in Appendix). It also reasonably satisfies the exclusion restriction since it does not necessarily affect the dietary diversity and food insecurity on its own but rather through its effect on FO membership in this context (see Model 2 and Model 3 results in Table A1). Moreover, our selected IV should satisfy the exogeneity condition since it was unrelated to any other factors that affect the outcome variable, plausibly including unobserved confounders. The selection instrument's validity was assessed using the falsification test as proposed by Di Falco et al. (2011) whereby it was indicated it significantly affected FO membership but not the outcome variables among non-FO members. The falsification test results are shown in Table A1 and they show that a farmer's relatives' FO membership can be considered as a valid selection instrument: it is a statistically significant driver of a farmer's decision to join an FO (Model 1, $\chi 2 = 113.36$; $p = 0.000$) but not of the dietary diversity (Model 2, F-stat. = 1.56, p = 0.212) and food insecurity (Model 3, F-stat. = 0.62, p = 0.432) by the farm households that did not belong to a FO.

The observed systematic difference between FO members and non-members is considered by the ESR model as it has been described so far. Inverse Mills ratios for FO members and non-members are computed together with the relevant covariance components, σ_{Pv} and σ_{Nv}. To account for unobserved factors, these components are included in Equations (4a) and (4b) after estimating the selection Equation (1) as

$$Y_P = \varphi_P Z_i + \sigma_{Pv}\lambda_{Pi} + \varepsilon_P \text{ if } M_i = 1, \tag{6a}$$

$$Y_N = \varphi_N Z_i + \sigma_{Nv}\lambda_{Ni} + \varepsilon_N \text{ if } M_i = 0. \tag{6b}$$

In Equations (6a) and (6b), the inverse Mills ratios λ_{Pi} and λ_{Ni}, evaluated at δX_i, are used to account for selection bias arising from unobserved factors, which generates heteroskedastic standard errors (Greene, 2018; Wooldridge, 2010). In line with Lokshin and Sajaia (2004), a more appropriate way to estimate the ESR model is using the FIML approach, which estimates the selection and outcome equations jointly and generates correlation coefficients ρ_{Pv} or ρ_{Nv} associated with the error terms in the selection and outcome equations. The significance of coefficients ρ_{Pv} or ρ_{Nv} would confirm the presence of selection bias issues (Lokshin & Sajaia, 2011).

4.3 | Estimating the average treatment effects of farmer organization membership

The ESR model can be used to assess further the effect of FO membership on the outcome variables in addition to calculating the effects of observed factors on the outcome variables (HDDS and HFIAS) in the FO membership and non-membership regimes. Given that HDDS and HFIAS are discrete and bounded random variables, we took the natural logarithm of these variables in our analysis. This transformation was necessary to meet the assumptions of the ESR model, which assumes normally distributed errors in the outcome model specification. To determine the typical course of treatment for the treated, we compare the expected outcomes from FO members to the expected outcomes of the counterfactual situation that they are not members of FO (ATT). In particular, the anticipated outcomes of farmers who are members (observed) and farmers who are not members (counterfactual) are expressed as

$$E[Y_{Pi}|M=1] = \varphi_P Z_i + \sigma_{Pv}\lambda_{Pi}, \tag{7a}$$

$$E[Y_{Ni}|M=1] = \varphi_N Z_i + \sigma_{Nv}\lambda_{Pi}. \tag{7b}$$

Finally, the ATT associated with FO membership is computed as the difference between Equations (7a) and (7b), expressed as

$$ATT = E[Y_{Pi}|M=1] - E[Y_{Ni}|M=1] = Z_i(\varphi_P - \varphi_N) + \lambda_{Pi}(\sigma_{Pv} - \sigma_{Nv}), \tag{8}$$

$$ATU = E[Y_{Pi}|M=0] - E[Y_{Ni}|M=0] = Z_i(\varphi_P - \varphi_N) + \lambda_{Pi}(\sigma_{Pv} - \sigma_{Nv}). \tag{9}$$

4.4 | Estimating the heterogeneity effects of farmer organization membership

Since the ESR does not support quantile estimations, we estimated the quantile treatment effects (QTEs) regressions in Equation (1). This was to investigate how FO membership affects various portions of the distribution of the outcome variables and to take into account heterogeneity at various distributions of these outcomes. To accomplish this task, we followed Borgen et al. (2022b). The residualized quantile regression (RQR), proposed by Borgen et al. (2022a), is used because it fills in the gaps in the present estimates of the unconditional quantile treatment effects. This method is simple to understand, computationally quick, and is able to include high-dimensional fixed effects (Borgen et al., 2022b). The methods currently used to find unconditional QTEs for continuous treatment variables are insufficient (Borgen et al., 2022a).

Contrary to popular belief, Firpo et al.'s (2009) unconditional quantile regression model does not identify QTE, while Powell's (2020) generalized quantile regression model is not feasible with high-dimensional fixed effects, and Firpo's (2007) propensity framework only allows for binary treatment variables. In the first step of the RQR, the treatment variable is regressed against the control variables using, for instance, linear regression. The treatment variable in the quantile regression model is then employed in the second step with the residuals (Borgen et al., 2022a). According to Borgen et al. (2022a), the initial step separates the variance of the treatment variable into a residual piece that is independent of the controls and a piece that may be explained by the observed control variables. The control variables are redundant in the second phase since they remove confounding factors. Therefore, the RQR method avoids the issue that conditional quantile regression's interpretation of the treatment coefficients changes when controls are included along with the treatment variable (Borgen et al., 2022a).

5 | RESULTS AND DISCUSSIONS

5.1 | Determinants of farmer organization membership

The drivers of FO membership by household heads are presented in the second column of Tables 3 and 4. Results reveal that the age and education level of the household head have

TABLE 3 Determinants of household dietary diversity score among members and non-members of FOs.

			HDDS			
	Selection		Members		Non-members	
Variables	**Coeff**	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
Constant	−1.019**	0.402	2.061***	0.103	1.478***	0.127
Gender	−0.086	0.096	0.022	0.022	−0.004	0.032
Age	−0.015***	0.005	0.001	0.001	−0.003*	0.002
Years of schooling	−0.024**	0.011	0.008***	0.003	0.001	0.003
Marital status	−0.318**	0.143	0.035	0.035	−0.141***	0.048
Household size	0.029	0.022	−0.001	0.005	0.011	0.007
Off-farm income	0.001***	0.000	0.000	0.000	0.000**	0.000
Asset value	0.001***	0.000	−0.000**	0.000	0.000***	0.000
Credit access	0.094	0.092	−0.019	0.021	0.012	0.031
Market information	0.691***	0.123	−0.129***	0.034	0.358***	0.039
Farm distance	−0.001	0.025	0.007	0.006	−0.014	0.010
Market distance	0.122***	0.026	−0.015**	0.006	0.043***	0.010
Farm size	0.645***	0.125	−0.036	0.022	0.1755***	0.047
Total livestock units	−0.002**	0.001	0.001***	0.000	−0.000	0.000
Guinea savannah	0.299***	0.106	0.006	0.027	0.162***	0.035
A farmer's relatives in FO	0.243***	0.071				
Ln σ_P			−1.096***	0.052		
Ln σ_N					−1.354***	0.044
ρ_P			1.716***	0.182		
ρ_N					−1.509***	0.190
Wald χ^2 (14)	226.60***					
Log-likelihood	−332.777					
Observations	900		363		537	

***Denotes significance level of 1%.
**Denotes significance level of 5%.
*Denotes significance level of 10%.

statistically similar effects on FO membership. Older farmers are less likely to join FOs, potentially because of increased risk aversion and resistance to change. Similarly, more educated farmers are less inclined to join FOs, as they may already possess knowledge and resources related to farming practices. These findings align with previous studies conducted in Cameroon (Tabe-Ojong, 2022).

Marital status also plays a role, with married household heads being less likely to join FOs. The demands of married life, including off-farm income-generating activities, may limit their time availability for FO engagements. Conversely, farmers with off-farm income sources are more likely to join FOs, as additional income enhances their ability to meet membership requirements (Addai et al., 2022). Our results further reveal that the total asset value of household heads

TABLE 4 Determinants of household food insecurity access score among members and non-members of FOs.

	Selection		HFIAS			
			Members		Non-members	
Variables	Coeff	SE	Coeff	SE	Coeff	SE
Constant	−0.833*	0.428	1.188**	0.518	2.205***	0.347
Gender	−0.449***	0.102	−0.121	0.102	−0.144	0.103
Age	−0.007	0.005	0.001	0.005	−0.004	0.004
Years of schooling	0.000	0.011	−0.012	0.011	−0.012	0.010
Marital status	−0.058	0.157	0.073	0.161	0.015	0.135
Household size	−0.011	0.023	−0.012	0.022	0.023	0.020
Off-farm income	0.000**	0.000	−0.000***	0.000	−0.001***	0.000
Asset value	0.001***	0.000	−0.000***	0.000	−0.000***	0.000
Credit access	0.063	0.099	−0.166*	0.099	−0.008	0.084
Farm distance	−0.035	0.028	−0.016	0.028	0.012	0.024
Market information	−0.232*	0.138	1.771***	0.148	0.886***	0.111
Market distance	−0.003	0.026	0.027	0.027	0.079***	0.022
Farm size	0.075	0.109	0.123	0.111	0.120	0.097
Total livestock units	−0.002	0.001	0.001	0.002	−0.001*	0.001
Guinea savannah zone	0.742***	0.120	0.188	0.155	−0.365***	0.112
A farmer's relatives in FO	0.957***	0.105				
Ln σ_P			−0.086**	0.034		
Ln σ_N					−0.153***	0.037
ρ_P			−0.181	0.192		
ρ_N					0.017	0.163
Log-likelihood	−1661.129					
Wald χ^2 (14)	224.01***					
Observations	900		363		537	

***Denotes significance level of 1%.
**Denotes significance level of 5%.
*Denotes significance level of 10%.

positively influences FO membership. Higher asset values reflect greater economic and resource endowment, increasing farmers' perception of the benefits associated with FO membership (zu Selhausen, F. M., 2016). Access to market information is another significant factor driving FO membership. Market information empowers farmers to make informed decisions, leading to improved market access and stronger bargaining power (Bizikova et al., 2020).

Distance to the market also impacts FO membership, with farmers farther from the market facing higher transaction costs. FO membership provides benefits such as storage facilities and collective transportation arrangements, reducing transaction costs and motivating farmers to join. This finding is consistent with similar studies conducted in different countries (Ma, Abdulai, & Goetz, 2018). Additionally, results show that total livestock units owned by farmers have a negative effect on their decision to join FOs. Livestock, considered sacred in the study area, is primarily traded in times of crisis (Addai et al., 2022).

5.2 | Determinants of household dietary diversity score among members and non-members of FOs

Table 3 presents the determinants of HDDS among members and non-members of FO. These are ESR model estimates when the outcome variable is log of HDDS. It can be observed that the age of non-members of FO reduces the HDDS of households relative to members. This is consistent with the findings of Chegere and Stage (2020), who found the same among farmers in Tanzania.

On the other hand, FO members with more years of schooling benefit from enhanced HDDS, as education improves their knowledge of food and nutritional security (Issahaku & Abdulai, 2019). Non-members of FOs who are unmarried tend to have lower HDDS, possibly because of having fewer people to feed and therefore fewer dietary needs. The presence of off-farm income among non-members is associated with reduced HDDS, as they may allocate this income to other needs besides nutrition, contrary to findings from Koppmair et al. (2017).

The asset value of FO members is negatively related with HDDS, while non-members' asset value tends to improve HDDS. FO members may prioritize diversifying their assets for production needs rather than using them to enhance dietary diversity and nutrition. Non-members, however, may trade off their assets to improve their dietary diversity. Access to market information among FO members tends to decrease HDDS, whereas non-members benefit from improved HDDS through access to market information (Kissoly et al., 2018). This could be due to market information enabling better price awareness and availability of various food items. Similarly, members of FOs who have greater market distance experience decreased HDDS, as distant markets limit access to a variety of foodstuffs needed for dietary diversity (Kissoly et al., 2018).

Larger farm size among non-members of FOs improves HDDS, likely because larger farms facilitate diversified production activities that contribute to dietary diversity (Issahaku & Abdulai, 2019). In contrast, the total livestock units owned by FO members positively and significantly improve HDDS, as livestock can serve as income-generating assets to support dietary diversity (Manda, Alene, et al., 2020). Non-members of FOs in the Guinea Savannah agroecological zone exhibit greater improvement in HDDS compared with those in the Sudan Savannah agroecological zone. This suggests that contextual factors influence the relationship between FO membership and HDDS. The correlation coefficients ($\rho 1$) and ($\rho 2$) are significant for members and non-members of the HDDS equation, suggesting the presence of selection bias is associated with unobservable factors. The unobservable selection bias justifies the use of the ESR model in the estimations.

5.3 | Determinants of household food insecurity access score among members and non-members of FOs

Table 4 presents the drivers of HFIAS among members and non-membership of FOs. In other words, they are ESR model estimates when the outcome variable is log of HFIAS. Off-farm income negatively and significantly impacts HFIAS among members and non-members of FOs, suggesting that farmers with off-farm income have their HFIAS reduced significantly. This implies that off-farm income can help improve farm households' food and nutrition security. This result is in line with the findings of Musara and Musemwa (2020), who observed the same among farm households in Zimbabwe. The asset value of FO members and non-members reduces HFIAS, implying that household asset value improves food and nutrition security. Assets of households can be crucial to improving food security. Access to market information by members and non-members of FOs increases HFIAS, suggesting that increased market information access reduces food and nutrition security. Increased distance to markets for non-members increases HFIAS, implying a reduction in food and nutrition security. This might be because a distant market will reduce households' accessibility to food items needed to improve food and nutritional security because of increased transactions costs.

The number of livestock units owned by non-members of FOs reduces HFIAS, suggesting an improvement in household food and nutrition security with livestock ownership. This is consistent with the findings of Jodlowski et al. (2016), who indicated that livestock ownership improves food security through both direct consumption of animal products produced on farm and increased consumption expenditure. Besides, they suggested that expanded livestock ownership alters the local food economy to influence food consumption by households lacking farm animals. Relative to the Sudan Savannah agroecological zone, non-members of FOs in the Guinea Savannah agroecological zone reduce HFIAS, implying an improvement in food and nutrition security among non-members of FOs.

The correlation coefficients ($\rho 1$) and ($\rho 2$) are insignificant for members and non-members of the HFIAS equation. This is because the selection bias emanating from unobserved factors is undetectable because of low statistical power. That is to say that there is no evidence to confirm that unobservable factors influence both households' heads' decision to join FOs and HFIAS simultaneously in the study. Notwithstanding, the ESR method also accounts for selection bias from observed factors; hence its use in this study remains important.

5.4 | Average treatments effects of FO membership

Our estimates of the average treatment effects on the treated (ATT) and the average treatment effect on the untreated (ATU) are presented in Table 5. It is important to note that these estimates account for selection bias resulting from both observable and unobservable

TABLE 5 FO impacts on HDDS and HFIAS: ESR estimates.

Outcome		FO membership		Treatment effect	t-Value	Change (%)
		Members	Non-members			
HDDS	ATT	6.408(0.015)	5.796 (0.043)	0.612(0.041)	15.020***	10.56%
	ATU	11.294(0.074)	9.201(0.028)	2.092(0.092)	22.719***	22.74%
HFIAS	ATT	9.965(0.302)	11.035(0.243)	−1.069(0.386)	−2.764***	−9.70%
	ATU	8.066(0.225)	9.942 (0.248)	−1.876(0.354)	−5.297***	−18.87%

Note: The outcomes are logged to represent the dependent variables, and the ATTs are calculated based on their predictions. ATT, average treatment effects on the treated; ESR, endogenous switching regression.

***Denotes significance level of 1%.

**Denotes significance level of 5%.

*Denotes significance level of 10%.

characteristics. The ATT estimates suggest that membership in FOs improves food and nutritional security among farm households, with members gaining 10.56% more dietary diversity (i.e., HDDS) than non-members. Additionally, our estimates indicate that membership in FOs reduces food insecurity (i.e., HFIAS) by 9.7%. The ATU estimates show that non-members of FOs would experience a 22.74% increase in HDDS and an 18.89% increase in food security had they joined FOs. These results demonstrate the significant impact of FO membership on improving food and nutritional security among farm households, highlighting the potential benefits of such membership for individual farmers and rural communities.

5.5 | Heterogeneous treatment effects of FO membership

The FO membership effects on food and nutrition security estimates based on the residualized quantile treatment effect regression is presented in Table 6. The estimates indicated that the magnitude of the changes in HDDS and HFIAS differs across the quantiles of these food and nutrition security outcomes. For the HDDS, the impact of FO membership decreases from 0.1 to 0.9. Concerning the HFIAS, food and nutrition security improves from the lower quantile (0.25) to the highest quantile (0.90). This is an indication that FO impacts on HFIAS increase along the quantile.

5.6 | Robustness checks

To ensure the robustness of our treatment effect results from the ESR, we also employ the PSM and IPWRA methods for impact evaluation. This is because results from the ESR model may be sensitive to its model assumption i.e., selection of instrumental variable for its identification. Table 7 presents the estimates of the two approaches, which provide additional evidence for the positive and statistically significant impact of FO membership on HDDS and HFIAS. Specifically, the ATT estimates from the IPWRA and PSM methods for HDDS are 0.056 and 0.046, respectively, and for HFIAS are −0.132 and −0.246, respectively. It is worth noting that the estimates from the IPWRA and PSM models are generally smaller than those from the ESR, as these models are unable to fully account for unobservable characteristics in their estimations.

TABLE 6 Treatment effect of FO membership at different quantiles of HDDS and HFIAS based on residualized quantile treatment effect regression.

	HDDS		HFIAS	
Quantile	**Coefficient**	**SE**	**Coefficient**	**SE**
0.10	0.202***	0.030	0.000	0.103
0.25	0.165***	0.025	2.095***	0.125
0.50	0.000	0.023	0.170*	0.092
0.75	0.000	0.020	−0.180***	0.066
0.90	0.000	0.022	−0.153***	0.053

***Denotes significance level of 1%.
**Denotes significance level of 5%.
*Denotes significance level of 10%.

TABLE 7 Impacts on HDDS and HFIAS: PSM and IPWRA estimates for robustness check.

Outcomes	ATT (IPWRA)	ATT (PSM)
HDDS	0.056* (0.031)	0.046* (0.028)
HFIAS	−0.132* (0.075)	−0.246** (0.116)

Note: The outcomes are logged to represent the dependent variables and the ATTs are calculated based on their predictions. ATT, average treatment effects on the treated; IPWRA, inverse probability weighted regression adjustment; PSM, propensity score matching.

***Denotes significance level of 1%.

**Denotes significance level of 5%.

*Denotes significance level of 10%.

Nevertheless, the consistency of the results across all three methods provides further evidence for the significant impact of FO membership on improving food and nutritional security among farm households, highlighting the potential benefits of such membership for rural communities.

6 | CONCLUSION AND POLICY IMPLICATIONS

This study examined the impact of FO membership on food and nutrition security, measured by HDDS and HFIAS of smallholder households. We used data from a farm household survey conducted in Northern Ghana in 2018. The endogenous switching regression (ESR) model was employed in estimating the impact of FO membership to account for observable and unobservable selection bias that emanates from the non-random membership of FOs. We complemented the ESR model results with the residualized quantile regression, inverse-probability weighted regression adjustment (IPWRA) and propensity score matching (PSM).

We found that household head's age, years of schooling, married status, and the total livestock units owned negatively and significantly influence FO membership. On the other hand, farm size, market distance, off-farm income, total asset value, and access to market information positively and significantly influence FO membership. Our results suggest that on average, FO membership improves dietary diversity and reduces food insecurity in smallholder households by 10.56% and 9.7%, respectively. Also, we found that farmers that are not members of FOs would have their dietary diversity and food security significantly increase if they joined FOs.

With Northern Ghana, the region containing over 3 million food insecure people in the country, the findings have implications for policy development, especially in line with achieving the UN's Sustainable Development Goal 2 of ending hunger, achieving food security, and improving nutrition, and promoting sustainable agriculture. To the extent that FO membership promotes dietary diversity and reduces household food insecurity, efforts should be made to encourage farm household heads to join FOs. This should be enhanced by boosting the FOs' capacity as a pathway to improving food and nutrition security. One possible passageway through which FO membership promotes dietary diversity and food security is by ensuring that FOs serve as effective channels for disseminating knowledge of agricultural practices and farm inputs that result in increased agricultural production or output among farmers (Kumar et al., 2018; Ma, Renwick, et al., 2018; Michalek et al., 2018). It is well established that improved knowledge of agricultural practices and access to farm inputs are critical factors that enhance technical efficiency, leading to increased agricultural productivity and output. These improvements in turn increase the availability of diverse, nutritious foods, promote food self-sufficiency, and contribute to overall food security and FOs should be conduits for accessing such improvements.

We found that that access to marketing information boosts farmers' propensity to join FOs. Since FOs are channels through which such information can be accessed by remote farmers in rural areas (Chagwiza et al., 2016; Ma, Abdulai, & Goetz, 2018), that FOs improve dietary diversity and food security is plausible because availing marketing information to farmers enables farmers to be aware of the prevailing prices and sell their output at competitive prices, thus earning more income that they can use to buy diverse foods and improve their dietary diversity and food security. By enhancing farmers' access to market information, FOs can enable them to better participate in agricultural markets and benefit from higher returns on their investments. Policymakers and development practitioners should focus on supporting FOs as effective channels for disseminating knowledge and information to farmers to achieving food security and improving nutrition. Encouraging smallholder farmers in developing countries to join FOs could potentially provide them with greater access to resources and support, as well as a stronger voice in advocating for policies that benefit their interests. These benefits could ultimately contribute to improving their food and nutrition security, so promoting membership in such organizations should be a viable strategy for policymakers.

While our selection instrument has shown promise by passing the falsification test discussed earlier, it is important to acknowledge that it may not be flawless and could potentially violate the exogeneity or exclusion restriction in some way. Finding an ideal instrument for an empirical analysis is empirically challenging, especially that the extent to which the selected instrumental variable addresses the endogeneity problem in empirical studies is not entirely clear, as we may not have a complete understanding of the underlying generative processes (Bellemare, 2012). This indicates that our selection instrument is not perfect, and therefore, caution should be exercised when interpreting our causal effect results. However, considering that our selection instrument is intuitive and has successfully passed an important falsification test, there is no immediate need for excessive concern regarding selection bias in the estimations conducted within this study.

ACKNOWLEDGEMENTS

Open access publishing facilitated by Griffith University, as part of the Wiley - Griffith University agreement via the Council of Australian University Librarians.

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interests to declare that are relevant to the content of this article.

ORCID

Kwabena Nyarko Addai https://orcid.org/0000-0001-6757-8155
John N. Ng'ombe https://orcid.org/0000-0002-1410-1350
Omphile Temoso https://orcid.org/0000-0002-3327-0467

REFERENCES

Addai, K. N., Temso, O., & Ng'ombe, J. (2022). Participation in farmer organizations and adoption of farming technologies among rice farmers in Ghana. *International Journal of Social Economics*, *49*(4), 529–545. https://doi.org/10.1108/IJSE-06-2021-0337

Baldos, U. L. C., & Hertel, T. W. (2014). Global food security in 2050: The role of agricultural productivity and climate change. *Australian Journal of Agricultural and Resource Economics*, *58*(4), 554–570. https://doi.org/10.1111/1467-8489.12048

Bellemare, M. F. (2012). As you sow, so shall you reap: The welfare impacts of contract farming. *World Development*, *40*(7), 1418–1434. https://doi.org/10.1016/j.worlddev.2011.12.008

Bijman, J., & Wijers, G. (2019). Exploring the inclusiveness of producer cooperatives. *Current Opinion in Environmental Sustainability*, *41*, 74–79. https://doi.org/10.1016/j.cosust.2019.11.005

Bissah, M. N., Kotey, D. A., Tongoona, P., Egbadzor, K. F., Gracen, V., & Danquah, E. Y. (2022). Factors influencing rice production in the south-eastern belt of Ghana. *Heliyon*, *8*(12), e12404. https://doi.org/10.1016/j.heliyon.2022.e12404

Bizikova, L., Nkonya, E., Minah, M., Hanisch, M., Turaga, R. M. R., Speranza, C. I., Karthikeyan, M., Tang, L., Ghezzi-Kopel, K., Kelly, J., Celestin, A. C., & Timmers, B. (2020). A scoping review of the contributions of farmers' organizations to smallholder agriculture. *Nature Food*, *1*(10), 620–630. https://doi.org/10.1038/s43016-020-00164-x

Borgen, N. T., Haupt, A., & Wiborg, Ø. N. (2022a). Quantile regression estimands and models: Revisiting the motherhood wage penalty debate. *European Sociological Review*, *39*, 317–331. https://doi.org/10.1093/esr/jcac052

Borgen, N. T., Haupt, A., & Wiborg, O. (2022b). Flexible and fast estimation of quantile treatment effects: The rqr and rqrplot commands. *The Stata Journal*, *16*, 403–415.

Chagwiza, C., Muradian, R., & Ruben, R. (2016). Cooperative membership and dairy performance among smallholders in Ethiopia. *Food Policy*, *59*, 165–173. https://doi.org/10.1016/j.foodpol.2016.01.008

Chegere, M. J., & Stage, J. (2020). Agricultural production diversity, dietary diversity and nutritional status: Panel data evidence from Tanzania. *World Development*, *129*, 104856. https://doi.org/10.1016/j.worlddev.2019.104856

Coates, J., Swindale, A., & Bilinsky, P. (2007). *Household food insecurity access scale (HFIAS) for measurement of food access: Indicator guide*. Food and Nutrition Technical … (August), Version 3-Version 3. https://doi.org/10.1007/s13398-014-0173-7.2

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 825–842. https://doi.org/10.1093/ajae/aar006

Di Marcantonio, F., Havari, E., Colen, L., & Ciaian, P. (2022). Do producer organizations improve trading practices and negotiation power for dairy farms? Evidence from selected EU countries. *Agricultural Economics*, *53*(S1), 121–137. https://doi.org/10.1111/agec.12730

Dohmwirth, C., & Liu, Z. (2020). Does cooperative membership matter for women's empowerment? Evidence from South Indian dairy producers. *Journal of Development Effectiveness*, *12*(2), 133–150. https://doi.org/10.1080/19439342.2020.1758749

FAO, IFAD, UNICEF, WFP, & WHO. (2020). *The state of food security and nutrition in the world: Transforming food Systems for Affordable Healthy Diets* (978-92-5-109888-2). FAO.

FAO, IFAD, UNICEF, WFP, & WHO. (2022). *The state of food security and nutrition in the world 2022* (978-92-5-136499-4). FAO.

Firpo, S. (2007). Efficient semiparametric estimation of quantile treatment effects. *Econometrica*, *75*(1), 259–276. https://doi.org/10.1111/j.1468-0262.2007.00738.x

Firpo, S., Fortin, N., & Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, *77*(3), 953–973. https://doi.org/10.3982/ecta6822

Gezahegn, T., Van Passel, S., Berhanu, T., D'Haese, M., & Maertens, M. (2020). Structural and institutional heterogeneity among agricultural cooperatives in Ethiopia: Does it matter for Farmers' welfare? *Journal of Agricultural and Resource Economics*, *46*(2), 325–342.

Giller, K. E. (2020). The food security conundrum of sub-Saharan Africa. *Global Food Security*, *26*, 100431. https://doi.org/10.1016/j.gfs.2020.100431

González-Flores, M., Bravo-Ureta, B. E., Solís, D., & Winters, P. (2014). The impact of high value markets on smallholder productivity in the Ecuadorean sierra: A stochastic production frontier approach correcting for selectivity bias. *Food Policy*, *44*, 237–247. https://doi.org/10.1016/j.foodpol.2013.09.014

Greene, W. H. (2018). *Econometric analysis* (8th ed.). Pearson.

GSS. (2018). *Ghana living standards survey (GLSS7): Poverty trends in Ghana; 2005–2017*. Ghana Satistical Service. https://www.statsghana.gov.gh/gssmain/fileUpload/pressrelease/GLSS7%20MAIN%20REPORT_FINAL.pdf

Gugerty, M. K., Biscaye, P., & Leigh Anderson, C. (2019). Delivering development? Evidence on self-help groups as development intermediaries in South Asia and Africa. *Development and Policy Review*, *37*(1), 129–151. https://doi.org/10.1111/dpr.12381

Hoken, H., & Su, Q. (2018). Measuring the effect of agricultural cooperatives on household income: Case study of a rice-producing cooperative in China. *Agribusiness*, *34*(4), 831–846. https://doi.org/10.1002/agr.21554

Issahaku, G., & Abdulai, A. (2019). Can farm households improve food and nutrition security through adoption of climate-smart practices? Empirical evidence from Northern Ghana. *Applied Economic Perspectives and Policy*, *42*(3), 559–579. https://doi.org/10.1093/aepp/ppz002

Jodlowski, M., Winter-Nelson, A., Baylis, K., & Goldsmith, P. D. (2016). Milk in the data: Food security impacts from a livestock field experiment in Zambia. *World Development*, *77*, 99–114. https://doi.org/10.1016/j.worlddev.2015.08.009

Kennedy, G., Ballard, T., & Dop, M. C. (2011). *Guidelines for measuring household and individual dietary diversity*. Food and Agriculture Organization of the Unite Nations.

Ketkar, H., & Workiewicz, M. (2022). Power to the people: The benefits and limits of employee self-selection in organizations. *Strategic Management Journal*, *43*(5), 935–963. https://doi.org/10.1002/smj.3349

Kissoly, L., Faße, A., & Grote, U. (2018). Implications of smallholder farm production diversity for household food consumption diversity: Insights from diverse agro-ecological and market access contexts in rural Tanzania. *Horticulturae*, *4*(3), 14. https://doi.org/10.3390/horticulturae4030014

Koppmair, S., Kassie, M., & Qaim, M. (2017). Farm production, market access and dietary diversity in Malawi. *Public Health Nutrition*, *20*(2), 325–335. https://doi.org/10.1017/S1368980016002135

Kumar, A., Saroj, S., Joshi, P. K., & Takeshima, H. (2018). Does cooperative membership improve household welfare? Evidence from a panel data analysis of smallholder dairy farmers in Bihar, India. *Food Policy*, *75*, 24–36. https://doi.org/10.1016/j.foodpol.2018.01.005

Liu, M., Min, S., Ma, W., & Liu, T. (2021). The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. *Journal of Rural Studies*, *83*, 106–116. https://doi.org/10.1016/j.jrurstud.2021.02.021

Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, *4*(3), 282–289. https://doi.org/10.1177/1536867X0400400306

Lokshin, M., & Sajaia, Z. (2011). Impact of interventions on discrete outcomes: Maximum likelihood estimation of the binary choice models with binary endogenous regressors. *Stata Journal*, *11*(3), 368–385. https://doi.org/10.1177/1536867x1101100303

Lu, W., Addai, K. N., & Ng'ombe, J. N. (2021). Impact of improved rice varieties on household food security in Northern Ghana: A doubly robust analysis. *Journal of International Development*, *33*(2), 342–359. https://doi.org/10.1002/jid.3525

Ma, W., & Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, *58*, 94–102. https://doi.org/10.1016/j.foodpol.2015.12.002

Ma, W., Abdulai, A., & Goetz, R. (2018). Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. *American Journal of Agricultural Economics*, *100*(2), 502–520. https://doi.org/10.1093/ajae/aax079

Ma, W., Renwick, A., Yuan, P., & Ratna, N. (2018). Agricultural cooperative membership and technical efficiency of apple farmers in China: An analysis accounting for selectivity bias. *Food Policy*, *81*, 122–132. https://doi.org/10.1016/j.foodpol.2018.10.009

Ma, W., Zheng, H., & Yuan, P. (2021). Impacts of cooperative membership on banana yield and risk exposure: Insights from China. *Journal of Agricultural Economics*, *73*, 564–579. https://doi.org/10.1111/1477-9552.12465

Manaswi, B. H., Kumar, P., Prakash, P., Anbukkani, P., Kar, A., Jha, G. K., Rao, D. U. M., & Lenin, V. (2020). Impact of farmer producer organization on organic chilli production in Telangana, India. *Indian Journal of Traditional Knowledge*, *19*(1), 33–43.

Manda, J., Alene, A. D., Tufa, A. H., Feleke, S., Abdoulaye, T., Omoigui, L. O., & Manyong, V. M. (2020). Market participation, household food security, and income: The case of cowpea producers in northern Nigeria. *Food and Energy Security*, *9*, e211. https://doi.org/10.1002/fes3.211

Manda, J., Khonje, M. G., Alene, A. D., Tufa, A. H., Abdoulaye, T., Mutenje, M., Setimela, P., & Manyong, V. M. (2020). Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia. *Technological Forecasting and Social Change*, *158*, 120160. https://doi.org/10.1016/j.techfore.2020.120160

Mataka, T., Kaitibie, S., & Ratna, N. N. (2023). Can women's empowerment in livestock farming improve household food security? Empirical evidence from rural households in Malawi. *Agriculture & Food Security*, *12*(1), 35. https://doi.org/10.1186/s40066-023-00436-2

Michalek, J., Ciaian, P., & Pokrivcak, J. (2018). The impact of producer organizations on farm performance: The case study of large farms from Slovakia☆. *Food Policy*, *75*, 80–92. https://doi.org/10.1016/j.foodpol.2017.12.009

Musara, J. P., & Musemwa, L. (2020). Impacts of improved sorghum varieties intensification on household welfare in the mid-Zambezi Valley of Zimbabwe. *Agrekon*, *59*(2), 254–267. https://doi.org/10.1080/03031853.2020.1721306

Nikam, V., Singh, P., Ashok, A., & Kumar, S. (2019). Farmer producer organisations: Innovative institutions for upliftment of small farmers. *Indian Journal of Agricultural Sciences*, *89*(9), 1383–1392. https://doi.org/10.56093/ijas.v89i9.93451

Ortega, D. L., Bro, A. S., Clay, D. C., Lopez, M. C., Tuyisenge, E., Church, R. A., & Bizoza, A. R. (2019). Cooperative membership and coffee productivity in Rwanda's specialty coffee sector. *Food Security*, *11*(4), 967–979. https://doi.org/10.1007/s12571-019-00952-9

Powell, D. (2020). Quantile treatment effects in the presence of covariates. *Review of Economics and Statistics*, *102*(5), 994–1005. https://doi.org/10.1162/rest_a_00858

Ricciardi, V., Ramankutty, N., Mehrabi, Z., Jarvis, L., & Chookolingo, B. (2018). How much of the world's food do smallholders produce? *Global Food Security*, *17*, 64–72. https://doi.org/10.1016/J.GFS.2018.05.002

Tabe-Ojong, M. P. Jr. (2022). Do producer organisations promote environmental sustainability through organic soil investments? Evidence from Cameroon. *Journal of Development Effectiveness*, *1-23*, 453–475. https://doi.org/10.1080/19439342.2022.2130961

Tanko, M., Ismaila, S., & Sadiq, S. A. (2019). Planting for food and jobs (PFJ): A panacea for productivity and welfare of rice farmers in Northern Ghana. *Cogent Economics & Finance*, *7*(1), 1693121. https://doi.org/10.1080/23322039.2019.1693121

Tefera, D. A., Bijman, J., & Slingerland, M. A. (2017). *Agricultural co-operatives in Ethiopia: Evolution, functions and impact* (Vol. 29) (pp. 431–453). John Wiley and Sons Ltd.

Tsai, M.-H., & Luh, Y.-H. (2022). Group heterogeneity and the economic effect of farmer organisation participation: Empirical evidence from Taiwan. *Journal of Agricultural Economics*, *74*, 473–491. https://doi.org/10.1111/1477-9552.12515

van Ittersum, M. K., van Bussel, L. G., Wolf, J., Grassini, P., van Wart, J., Guilpart, N., Claessens, L., de Groot, H., Wiebe, K., Mason-D'Croz, D., Yang, H., Boogaard, H., van Oort, P. A., van Loon, M. P., Saito, K., Adimo, O., Adjei-Nsiah, S., Agali, A., Bala, A., … Cassman, K. G. (2016). Can sub-Saharan Africa feed itself? *Proceedings of the National Academy of Sciences of the United States of America*, *113*(52), 14964–14969. https://doi.org/10.1073/pnas.1610359113

WFP. (2009). *Emergency food security assessment handbook* (Second ed.). World Food Programme. www.wfp.org

WFP. (2022). *Comprhensive food security and vulnerability analysis 2020*. World Food Programme.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). The MIT Press. https://doi.org/10.2307/j.ctv5rdzwc.1

Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., Feleke, S., Olanrewaju, A., & Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, *54*, 223–233. https://doi.org/10.1016/j.jrurstud.2017.06.022

Wu, F., Guo, X., & Guo, X. (2023). The impact of cooperative membership on family farms' income: Evidence from China. *Applied Economics*, *55*(55), 6520–6537. https://doi.org/10.1080/00036846.2022.2159009

zu Selhausen, F. M. (2016). What determines women's participation in collective action? Evidence from a Western Ugandan coffee cooperative. *Feminist Economics*, *22*(1), 130–157. https://doi.org/10.1080/13545701.2015.1088960

How to cite this article: Addai, K. N., Ng'ombe, J. N., & Temoso, O. (2024). Can farmer organization membership improve household food security and nutrition? Evidence from Northern Ghana. *World Food Policy*, *10*(2), 180–202. https://doi.org/10.1002/wfp2.12076

APPENDIX A

TABLE A1 Falsification test results of selected instrument.

Variable name/model	Probit model	OLS regression of log HDDS on FMillsO nonmembers	OLS regression of log HFIAS on nonmembers
A farmer's relatives in FO	0.937***	0.194	0.346
	(0.089)	(0.155)	(0.440)
Constant	−0.625***	6.089***	6.692***
	(0.057)	(0.076)	(0.218)
Log-likelihood	−550.224		
Observations	900	537	537

***Statistically significant at 1% level.