Disaggregated impacts of off-farm work participation on household vulnerability to food poverty in Ghana

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Abstract
This study examines disaggregated impacts of participation in off-farm employment on household vulnerability to food poverty in Ghana. We use household-level data collected from smallholder farmers in Ghana. This study employs the multinomial endogenous switching regression model to account for selection bias due to both observed and unobserved heterogeneity. Our results indicate that participation in off-farm employment activities, such as petty trading, significantly decreases household vulnerability to food poverty. Our findings further show that households that do participate in arts and crafts as an off-farm activity are more vulnerable to food poverty had they not participated. This paper provides useful policy insights to enable smallholders involved in off-farm work activities to improve food consumption expenditure and reduce their risk of food poverty.

Keywords Arts and crafts · Disaggregated effects · Multinomial endogenous switching regression model · Off-farm work · Petty trading

1 Introduction
While vulnerability to food insecurity has been dynamic, covering various world regions (Bogale 2012; Zereyesus et al. 2017), farm families in sub-Saharan Africa (SSA) continue to exhibit high levels of food insecurity and poverty. More importantly, these challenges persist despite meaningful macroeconomic strides the region has achieved in recent years. Amid the stable economic growth among SSA countries, most farm families are poor and food insecure (Rodrik 2018). The ongoing Coronavirus Disease 2019 (COVID-19) pandemic is expected to erode almost all the progress to reduce poverty and food insecurity that the region has achieved over the years. The World Bank (2020) estimates that compared to 2019, between 40 and 60 million people will fall into extreme poverty (under $1.9/day) in 2020, all resulting from COVID-19.
For Ghana, especially Northern Ghana, the majority of the poor rely on the rural economy for their livelihoods (GSS 2018). About 43.94% of Ghana’s population lives in rural areas and is mostly involved in rain-reliant sustenance form of farming (GSS 2018). This suggests that most households’ vulnerability to food insecurity in Ghana is partly influenced by external factors like rainfall trends, land-use changes, climate change, population size, poor rural investment, and world markets (Asfaw et al. 2015; Bogale 2012). Enhancing productivity is essential to achieving pro-poor growth through agriculture (Klasen and Reimers 2017). Additionally, poor rural households rely on a range of non-farm economic activities as part of their livelihood strategies. Thus, diversification of livelihoods by members of farm households augments and provides alternatives from agricultural production-alternatives that are critical pathways to reducing poverty and food insecurity (OECD 2007). Reddy and Reddy (2013) reiterates that one of the critical tools for improving rural earnings and livelihoods is the diversification of rural engagements to related agricultural and non-agricultural activities. These assertions have been backed by several empirical studies (Babatunde and Qaim 2010; Owusu et al. 2011; Rahman and Mishra 2020; Zereyesus et al. 2017).

Meanwhile, whereas there is a burgeoning literature measuring the impacts of off-farm work participation on farm welfare outcomes, most studies do not disaggregate the outcomes of interest. They instead report findings on an aggregate basis. But disaggregation of outcome variables from which causal effects are measured may help unearth some critical insights which facilitate a better understanding of the outcomes and impacts of research outputs (Zereyesus et al. 2017). For example, a significant percentage of the studies that argue for non-agricultural activities emphasizes the connection between the general aggregate non-farm work and poverty and, to a lesser extent, household vulnerability to food poverty. But these analyses are on an aggregate basis. Following Davis et al. (2014), disaggregating the impacts more realistically represents the applicability of research outputs and provides a better understanding of the impacts across a given outcome of interest. Studies by Pritchett et al. (2000) and Haughton and Khandker (2009) suggest that assessing vulnerability to food poverty is a progressive indicator rather than a passive mode of poverty and offers an improved and superior appraisal of food poverty under uncertainty. Also, Imai et al. (2015) examine whether rural non-farm work affects poverty and vulnerability in Vietnam and India. They find that the log per capita food consumption expenditure significantly increases because of rural non-farm work in Vietnam and India. Moreover, Imai et al. (2015) find that access to rural non-farm work significantly lowers vulnerability in the two nations.

Similarly, Zereyesus et al. (2017) examine the effect of participation in off-farm employment on resource-poor households’ vulnerability to food poverty in Northern Ghana. They find that engagement in off-farm employment remarkably increases the looked-forward-to, hereafter, consumption, thereby reducing households’ vulnerability to food poverty. Zereyesus et al. (2017) further report that current and projected food poverty (i.e., the risk to food poverty) are inseparable. As mentioned, none of these studies disaggregates the effects of off-farm employment participation on the outcomes of interest – household vulnerability to food poverty. Moving forward, this paper attempts to fill this void by offering a micro-perspective analysis of the disaggregated impacts of off-farm employment activities on household vulnerability to food poverty. Specifically, this paper explores the determinants of farm households’ vulnerability to food poverty and participation in off-farm activities in Ghana. This study also determines disaggregated impacts of off-farm employment participation on per capita food consumption expenditure and household vulnerability to food poverty in Ghana.
Our paper makes several contributions to the literature. First, the study is the first to determine what affects smallholder farm households’ vulnerability to food poverty in Northern Ghana by employing the Vulnerability as Expected Poverty (VEP) concept (Chaudhuri et al. 2002). This is important because VEP remains a useful and paramount measure, especially for developing countries like Ghana, where panel data is not readily available (Gallardo 2018). Therefore, there is no doubt that our results based on this useful approach could provide policymakers with helpful policy insights involving off-farm work and food poverty among poor rural farmers in Ghana and similar world’s developing countries. Second, most studies look at the aggregated off-farm work engagement effects on welfare outcomes without exploring how the various activities that go into the off-farm work affect welfare (e.g., Babatunde and Qaim 2010; Owusu et al. 2011; Rahman and Mishra 2020). Such could potentially bias empirical results through potential aggregation errors (Davis et al. 2014). Third, we explore the factors that determine household participation in several off-farm engagements rather than aggregated off-farm work, which is more insightful for policy relevance. Finally, we utilize the multinomial endogenous switching regression model to account for potential selection bias from observed and unobserved confounders. This is both theoretically and empirically important as it allows us to estimate more credible disaggregated impacts of off-farm employment activities on household vulnerability to food poverty.

The rest of the paper is organized as follows. Section 2 outlines the conceptual framework and estimation technique used, while Sect. 3 presents the data and the variables employed. Section 4 presents empirical results, while Sect. 5 concludes with some policy implications.

2 Conceptual framework and estimation technique

2.1 Conceptual framework

In this section, we model how the household heads’ decision to participate (or not) in various off-farm work activities impact their vulnerability to food poverty. Farmers engage in numerous off-farm work engagements in the study area (i.e., Northern Ghana). These include carpentry, mechanic, as an electrician, are engaged in food processing, milling, hawking, and roadside restaurants (typically referred to as “chopbars”) among others. This suggests that the list of off-farm activities that farmers in Ghana is long and exhausting all of them may be challenging due to lack of data. Therefore, we considered the next plausible and key off-farm activity the smallholder and farmers reported to have participated in, after their main farming activity. We specifically broadly categorized them into two: (i) petty trading and, (ii) arts and crafts because of the diversity of these activities. We considered petty trading as trading agricultural goods and services (e.g., rice, maize cobs, horticultural products, and dairy products), imported consumer goods (e.g., second-hand clothes) in small quantities. We define arts and crafts as basketry, leatherwork, weaving, and carvings made in small quantities for sale. Here, it is assumed that the household $i$ is risk-neutral and maximizes the projected utility $U_{ij}$, gained from selecting $j$, where

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1 We thank one anonymous reviewer for bringing out this idea.
\( j = 0, 1, ..., M, M \) denotes the total number of off-farm work choices. The utility function is linear and additive and is specified as

\[
U_{ij} = X_i\gamma_j + \mu_{ij}
\]

where \( X \) is a vector of independent variables; \( \gamma \) is a vector of coefficients to be estimated; \( \mu \) is the error term assumed to follow a Gaussian distribution with mean zero and constant variance. We hypothesize that individuals would select a choice if the expected utility gained by choosing \((j)\) is greater than that derived from choosing a different option \((k)\), that is, \(U_{ij} > U_{ik}\).

As the expected utility is unseen, we denote it with a latent indicator \( D^*_i \). This can be modeled as a function of observable household attributes and an idiosyncratic random part \( \epsilon_{ij} \). The inherent indicator model can then be stated as

\[
D^*_i = Z_i\varphi_j + \epsilon_{ij}
\]

where \( \varphi_j \) is a vector of parameters to be computed; \( Z \) are socio-economic and household attributes. For the engagement choice, let \( D_i \) be the individual’s observed selection of off-farm work. Then

\[
D_i = \begin{cases} 
1 & \text{if } D_{i1} > \max_{k \neq 1} D_{ik} \\
\vdots & \vdots \\
M & \text{if } D_{iM} > \max_{k \neq M} D_{ik}
\end{cases}
\]

where \( D_i \) is a dummy variable representing that the household \( i \) will participate in a specific off-farm work activity if it offers a higher expected outcome than the alternative off-farm work activity, and zero otherwise. The off-farm work activities considered here include petty trading \( j_1 \) and arts and crafts \( j_2 \). Detailed in Eq. (2), the fundamental presupposition is that the seen parameter \( Z \) is not associated with the random part \( \epsilon \), that is \( E(\epsilon|Z) = 0 \).

Following Dubin and McFadden (1984), in the first-stage estimation, the likelihood of partaking in off-farm employment can be expressed using a typical multinomial logit model

\[
P_{ij} = \frac{\exp(Z_i\varphi_j)}{\sum_{k=1}^{M} \exp(Z_i\varphi_k)}
\]

where \( P_{ij} \) denotes the likelihood that a household \( i \) selects choice \( j \), \( Z_i \) denotes household \( i \)'s attributes and \( \varphi_j \) is the vector of variables related to the alternative \( j \).

In as much as people self-select their engagement or non-engagement in off-farm work activities, if not accounted for, selectivity bias could result in biased and conflicting parameter estimates. Specifically, unobserved characteristics may influence the selection of choices of people and effects on the results. Selection bias arises if the unobserved elements in the error terms from the choice equation and the after-effect equation are related; that is, there is an association between the two error components (i.e., \( \text{corr}(\mu, \epsilon) = p \)).

Usual regression methods like ordinary least squares result in conflicting estimates amid selectivity bias (Becerril and Abdulai 2010). Notwithstanding their limitations, approaches such as the Heckman selection models, instrumental variable, propensity score matching approaches, and endogenous switching regression (ESR) models have been employed to address selectivity bias issues in cross-sectional data (Ding and Abdulai 2020). The shortcomings of PSM include, among others, only accounting for the observable confounders
(Abdulai and Huffman 2015; Di Falco et al. 2011). The Heckman treatment effect model is estimated in two steps. The model generates heteroskedastic residuals that may not be used to obtain consistent standard errors without adjustments (Lokshin and Sajaia 2004). While the ESR model accounts for selection bias by aggregating the unobservable heterogeneity, this heterogeneity actually varies across individuals (Cornelissen et al. 2016).

The ESR model was proposed by Lee (1978) and Maddala (1983) mostly to address selection bias and, therefore, endogeneity by taking into account the observable and unobservable factors. The standard ESR model comprises two regimes for participants and non-participants. But in an instance with a minimum of three regimes, a multinomial endogenous switching regression becomes more appropriate.

Following Ng’ombe et al. (2017), Lu et al. (2021), and Ding and Abdulai (2020), we use the multinomial endogenous switching regression (MESR) model to determine the effect of different off-farm work activities on farm households’ vulnerability to food poverty. Given the selection of the two off-farm employment activities and one non-participation position, the after-effect estimation model for likely individual regime \( j \) is

\[
\begin{align*}
E(Y_{ij}|D_j = 0) &= X_i\gamma_0 + \mu_{i0} \\
E(Y_{ij}|D_j = 1) &= X_i\gamma_1 + \mu_{i1} \\
&\vdots \\
E(Y_{ij}|D_j = j) &= X_i\gamma_j + \mu_{ij}
\end{align*}
\]

(5)

where \( Y_{ij} \) is the after-effect of an individual \( i \) in regime \( j \) \((j = 0, 1, 2)\); \( X_i \) is a vector of individual attributes; \( D_j = 1 \) if the individual engages in the respective off-farm activity, equals 0, otherwise; \( \gamma \) is a vector of variables to be computed; \( \mu \) is the unseen stochastic disturbance term, which satisfies \( E(\mu_{ij}|X_i,Z_i) = 0 \) and \( \text{Var}(\mu_{ij}|X_i,Z_i) = \sigma_j^2 \). It is important to underscore the fact that \( X \) and \( Z \) could imbricate since the two indicate vectors of individual attributes. Therefore, identifying the model necessitates that, at the minimum, one variable in \( Z \) does not show up in \( X \).

We follow the framework by Dubin and McFadden (1984) and Bourguignon et al. (2007) to cater for plausible bias that emanates from the association of the error terms \( \mu \) and \( \epsilon \) in Eqs. (1) and (5). Assuming a normal linear specification \( \mu_{ij} = \sigma_j \sum j\rho_j \epsilon_j + \omega_{ij} \), the after-effect models can be stated as

\[
\begin{align*}
Y_{i0} &= X_i\gamma_{i0} + \sigma_0 \alpha_0 + \omega_{i0} \text{ if } D_j = 0 \\
Y_{i1} &= X_i\gamma_{i1} + \sigma_1 \alpha_1 + \omega_{i1} \text{ if } D_j = 1 \\
Y_{i2} &= X_i\gamma_{i2} + \sigma_2 \alpha_2 + \omega_{i2} \text{ if } D_j = 2
\end{align*}
\]

(6)

where \( \omega_{ij} \) is the residual term which is equal-sided to \( \epsilon_{ij} \) due to the independence of irrelevant alternatives assumption; \( \sigma_j \) indicates the covariance between \( \mu \) and \( \epsilon \); \( \alpha_j \) is the bias correction coefficient that can be derived from the computed probabilities in Eq. (3), which is stated as \( \alpha_{ij} = \rho_j m(P_{ij}) + \sum \rho_j m(P_{ij}) \frac{P_{ij}}{P_{ij-1}} \). Here, \( P_{ij} \) is the likelihood that household \( i \) selects choice \( j \) as in Eq. (3). Also, \( \rho_j \) is the correlation coefficient between \( \mu_j \) and \( \epsilon_j \); \( m(P_{ij}) \) is the conditional expectation, which is employed to address choosiness influences with \( m(P_{ij}) = \int J(v - \log P_{ij})g(v)dv \), where \( J(\cdot) \) is the transposed change for the Gaussian distribution function, and \( g(\cdot) \) is the unconditional density for the log-Weibull distribution, \( v = \epsilon_{ij} + \log P_{ij} \).

The first step encompasses a multinomial logit regression in estimating the likelihood of partaking and the estimate \( \varphi \) in Eq. (2). These possibilities are subsequently
employed in the after-effect equations (i.e., Eq. (6)). A limitation to this two-stage method, as detailed by Bourguignon et al. (2007), is heteroskedasticity that biases the standard errors. Besides, some unobserved factors may be considered by household heads in engaging in the various off-farm activities. This needs to be accounted for because they may affect both the decision to engage in such activities and also how vulnerable they may be to food poverty. This scenario may be problematic when it comes to identifying the actual variation in vulnerability to food poverty from off-farm activity participation as the actual impacts may be confounded (Huntington-Klein 2022). As such, econometric estimates of the impacts of participation in off-farm activities would be biased and inconsistent. Therefore, we augment the outcome equation by various household variables, to address potential unobserved heterogeneity in the second-stage estimation. These unobserved variables may include market distance and market information among others so long they would be exogenous. Therefore, for model identification, we used market distance and market information as instruments. These variables were chosen following the approach of Kubitza and Krishna (2020) whereby plausible and suitable instruments are the variables that jointly influence the participation decision, but not the outcome variable from participation. This falsification test is plausible and has garnered wide use in most causal inference research (e.g., Asfaw et al. 2012; Di Falco et al. 2011; Kiwanuka-Lubinda et al. 2021; Lu et al. 2021).

The multinomial endogenous switching regression model specifications for participants and non-participants are specified in Eqs. (7) and (8), respectively. The after-effect equations for the actual and counterfactual scenarios are detailed in Eqs. (7a) and (7b) for participants. In contrast, the equivalent conditions for non-participants appear in Eqs. (8a) and (8b). The expected after-effect from Eqs. (7) and (8) are used to derive unbiased estimates of the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU). The ATTs are calculated as the disparity among Eqs. (7a) and (7b). This would be the expected change in participants’ outcome of two off-farm work activities if they possessed similar attributes as non-participants. In a similar way, the ATUs are calculated as the disparity among Eqs. (8b) and (8a). This would indicate the expected change in the after-effect of non-participants if they possessed similar attributes as participants. A simplification of the computations of the treatment effects are presented in Table 1. The existence of sources of heterogeneity is represented by the base heterogeneity (BH) while a transitional heterogeneity (TH) will capture the total average effect. The specifications are presented as

| Table 1 Treatment and heterogeneity effect for multinomial endogenous switching regression |
|-----------------------------------------------|---------------|---------------|
| Samples                                      | Decision      | Treatment effect |
| Participation                                 | Non-participation |
| $E(Y_{11}|D_i = 1)$                            | $E(Y_{00}|D_i = 1)$ | $ATT^1$       |
| $E(Y_{21}|D_i = 2)$                            | $E(Y_{01}|D_i = 2)$ | $ATT^2$       |
| Non-participants                              | $E(Y_{10}|D_i = 0)$ | $ATT^1$       |
| $E(Y_{20}|D_i = 0)$                            | $E(Y_{00}|D_i = 0)$ | $ATT^2$       |
| Heterogeneity effect                          | $BH_{10}$     | $TH^1$        |
|                                              | $BH_{20}$     | $TH^2$        |
2.2 Measuring vulnerability

Poverty is an "inadmissible human denial in terms of economic prospect, education, health, and nutrition, as well as the absence of enablement and safety" (World Bank 2001). Poverty manifests itself as resource inadequacy—poor returns and consumptions, poor accomplishments in schooling and well-being, vulnerability to adverse shocks such as sickness, violence or in stability and deprivation of source of sustenance, and frailty in the political, social, and economic life of one’s habitation (World Bank 2001). Households vulnerable to poverty can be described as those who have the probability or ex-ante risk that will, if presently non-poor, fall below the poverty line or remain in poverty if presently poor (Chaudhuri et al. 2002). Measuring vulnerability using cross-sectional data was pioneered by Chaudhuri et al. (2002). According to Chaudhuri et al. (2002), the VEP is one of the most appropriate approaches for measuring vulnerability to poverty, especially when cross-sectional data are used, as in our case. The probability that a farm household \( h \) will be poor at a time \( t+i \) is

\[
V_{h,t} = \Pr(\ln C_{h,t+i} < \ln P)
\]

where \( V_{h,t} \) is the vulnerability to poverty of farm household \( h \) at a time \( t \), and \( C_{h,t+i} \) is food consumption of farm household \( h \) at a time \( t+i \). \( P \) indicates the poverty line of farm household \( h \) and \( \ln \) is the natural log.

A farm household’s food consumption expenditure is arrived at by considering several observable and unobservable household characteristics. The expression for household food consumption expenditure, with the assumption that the relationship is linear, and the determining factors can be specified as

\[
\ln C_{h} = \delta X_{ih} + \epsilon_{h}
\]

where \( X_{ih} \) is a vector of the farm household’s partaking in off-farm employment activities and other observable household characteristics, \( \delta \) is a vector of variables of concern, and \( \epsilon \) is the error term to capture a household’s idiosyncratic attributes assumed to follow a Gaussian distribution with mean zero and constant variance. After employing the coefficient estimates from Eq. (10), the estimation of the vulnerability to poverty is expressed as

\[
\hat{V}_{h,t} = \Pr(\ln C_{h,t+i} < \ln P | X_{h,t}) = \Phi(\ln P - \hat{\delta} \sigma_{X_{h,t}})
\]
where $\hat{V}_{ht}$ is the estimated risk to poverty, or the likelihood of a farm household’s consumption, depending on the individual’s partaking in off-farm employment activities and other attributes, falling beneath a specific poverty line. The $\Phi$ in Eq. (11) is the cumulative distribution function of the Gaussian distribution and $\hat{\sigma}$ is the estimated standard error from Eq. (10).

At the conceptual level, Chaudhuri et al. (2002) expression of vulnerability is very general in several ways. Firstly, it allows for the possibility of complicated interactions between the multiple cross-sectional determinants of a household’s level of vulnerability. Secondly, due to the fact that a household’s vulnerability is defined in terms of its future consumption prospects conditional on its current characteristics, both observed and unobserved, the possibility of poverty traps and other non-linear poverty dynamics is implicitly built in. Lastly, the possible contribution of aggregate shocks and unexpected structural changes in the macro-economy to vulnerability at the household level is also incorporated through inclusion of the time-varying parameters.

Chaudhuri et al. (2002) suggest that in cross-sectional data settings, the assumed constant variance might be violated, hence resulting in estimates that are not efficient. They posit that heteroskedasticity might be catered for by relating the deviation of the food consumption function linearly to the individual attributes and this is indicated as

$$\sigma^2_{\epsilon,h} = \gamma X_h + \eta_h$$

(12)

Since off-farm employment participation may be endogenous, there is a need to correct endogeneity using a suitable instrument. Using the instrumented off-farm employment participation variables, a standard Amemiya (1977) three-stage Feasible Generalized Least Square (FGLS) procedure is subsequently adopted to address potential implicit heteroskedasticity. To implement the FGLS procedure, one needs to initially estimate Eq. (10) using ordinary least squares (OLS) and subsequently use the residuals from Eq. (2) to estimate Eq. (6) using OLS as illustrated below

$$\hat{\sigma}^2_{OLS,h} = \hat{\gamma}X_h - \hat{n}_h$$

(13)

where $\hat{n}_h$ is the stochastic error term. The predicted values from Eq. (6) are employed in transforming Eq. (5) as follows:

$$\hat{\sigma}^2_{t,h} = \gamma \left\{ \frac{X_h}{\hat{\gamma}X_h} \right\} + \frac{\eta_h}{\hat{\gamma}X_h}$$

(14)

Equation (14) is computed using an OLS and yields $\hat{\gamma}_{FGLS}$, which is an asymptotically efficient FGLS estimate. The $\hat{\gamma}_{FGLS}$ is an efficient estimate of the idiosyncratic deviation $\sigma^2_{\epsilon,h}$ component of consumption. Using $\hat{\gamma}_{FGLS}$, the standard error, and the transformed Eq. (10), Eqs. (15) and (16) are derived as follows:

$$\hat{\sigma}_{t,h} = \sqrt{X_h\hat{\gamma}_{FGLS}}$$

(15)

$$\ln \frac{C_h}{\hat{\sigma}_{t,h}} = \delta \left[ \frac{X_h}{\hat{\sigma}_{t,h}} \right] + \frac{\varepsilon_h}{\hat{\sigma}_{t,h}}$$

(16)

Equation (16) is derived by dividing Eq. (9) by the standard error obtained in Eq. (15). The estimate $\hat{\delta}$ is an asymptotically reliable and efficient coefficient due to the fact that the
structure of heteroskedasticity is estimated from OLS instead of assuming it. Employing $\delta_{\text{FGLS}}$ and $\gamma_{\text{FGLS}}$, the estimation of the expected log of food consumption and its variance indicated by Eqs. (17) and (18), respectively,

$$E\left\{ \left[ \ln C_{h} \over X_{h} \right] \right\} = \hat{\delta}X_{h} \quad \text{and}$$

$$E\left\{ \left[ \ln \hat{C}_{h} \over X_{h} \right] \right\} = \hat{\sigma}^{2} = \hat{\gamma}X_{h}$$

Finally, we assume that the log of food consumption follows a Gaussian distribution, and the vulnerability to poverty is estimated as

$$\hat{V}_{h,t} = \text{prob}(nC_{h,t+i} < \ln P|X_{h,t}) = \Phi \left\{ \frac{\ln P - \hat{\delta}_{\text{FGLS}}X_{h}}{\sqrt{\hat{\gamma}_{\text{FGLS}}X_{h}}} \right\}. \quad (19)$$

Following, Dey (2018) we use a vulnerability poverty threshold of 0.5 for it is more appropriate. Thus, farm households with a 50% or more likelihood of falling into poverty in the future are well-thought-out as vulnerable to poverty.

3 Data

This study utilizes farm household survey data. The data were collected in Northern Ghana from October 2018 to December 2018. The sampled farm households were from the Northern, Upper East, and Upper West Regions of Northern Ghana. The sample comprises 900 farm households with 300 from each sub-region. In terms of sampling, we used a multi-stage sampling technique to choose the selected farm households. The initial step involved selecting districts from the regions based on their rice production levels in the selected regions of Northern Ghana. The second stage involved a simple random selection of farm households from the district’s different communities based on their size and rice production levels. The data collected included rice production variables and the farm households’ main characteristics in the study area. While the data were collected in 2018, the questions in the questionnaire about off-farm participation focused on the 12 months preceding the survey period. We believe this was helpful as it would allow us to collect more accurate data since the period was closer to the survey period.

Table 2 presents summary statistics of the pooled sample used in the study. The mean food consumption expenditure per household member is GHS 7.50.\(^2\) Regarding the treatments: 54% did not participate in any off-farm work while 23% and 24% participated in petty trading and arts and crafts. The respondents’ mean age was 43 years, with the majority (92%) being males. The mean number of years of schooling of the household head was 3, while 51 percent of them had a family member that had migrated to the South for “greener pastures” or better life’s opportunities. It is also worth noting that 50 percent of household heads had a family member who had a fever during the production period. We expect this to have had affected such farm households’ productivity. The average distance

\(^2\) US Dollars (USD) to Ghanaian Cedis (GHS) exchange rate for December 31, 2018. 1USD: 4.9GHS.
| Variable                        | Definitions                                                                 | Mean  | Standard Deviation |
|--------------------------------|-----------------------------------------------------------------------------|-------|--------------------|
| **Outcome**                    |                                                                             |       |                    |
| Food consumption expenditure per capita | Total food consumption per household member in GHS                          | 7.50  | 7.18               |
| **Treatments**                 |                                                                             |       |                    |
| Non-participants of off-farm work | 1 if household head does not participate in off-farm work, 0 otherwise      | 0.54  | 0.50               |
| Petty trading                  | 1 if household head participates in petty trading, 0 otherwise               | 0.23  | 0.42               |
| Arts and crafts                | 1 if household head participates in arts and crafts, 0 otherwise             | 0.24  | 0.42               |
| **Independent variables**      |                                                                             |       |                    |
| Age                            | Age of household head in years                                              | 42.45 | 9.82               |
| Gender                         | 1 if household head is a male, 0 otherwise                                  | 0.92  | 0.27               |
| Marital status                 | 1 if married, 0 otherwise                                                   | 0.89  | 0.31               |
| Household size                 | Number of household members                                                 | 9.67  | 4.27               |
| Years of schooling             | Years of formal education of the household head                            | 3.02  | 4.50               |
| Migration                      | 1 if a household member has migrated down South; 0 otherwise                 | 0.51  | 0.50               |
| Fever                          | 1 if a household member had a fever last year, 0 otherwise                  | 0.50  | 0.50               |
| Credit access                  | 1 if the household head had access to credit, 0 otherwise                   | 0.07  | 0.25               |
| Extension access               | 1 if the household head had access to extension service, 0 otherwise        | 0.39  | 0.49               |
| Farm size                      | Total farm size in hectares                                                | 0.65  | 0.59               |
| Bicycle                        | 1 if household head possesses bicycle, 0 otherwise                          | 0.82  | 0.38               |
| Cattle                         | 1 if household head possesses cattle, 0 otherwise                           | 0.23  | 0.42               |
| Goats                          | 1 if household head possesses goats, 0 otherwise                            | 0.69  | 0.46               |
| Sheep                          | 1 if household head possesses sheep, 0 otherwise                            | 0.51  | 0.50               |
| Guinea fowl                    | 1 if household head possesses Guinea fowl, 0 otherwise                      | 0.46  | 0.50               |
| Chicken                        | 1 if household head possesses chicken, 0 otherwise                          | 0.95  | 0.21               |
| Donkey                         | 1 if household head possesses donkey, 0 otherwise                           | 0.07  | 0.26               |
| Market distance                | Distance from farm to market in km                                          | 4.07  | 2.05               |
| Market information             | 1 if the household head had access to market information, 0 otherwise       | 0.72  | 0.45               |
from their farms to the nearest market was 4.07 km. Additionally, the majority (72%) of the household heads had access to market information. Table 3 presents summary statistics for the different off-farm work activities that farm households participated in.

4 Results and discussion

4.1 Determinants of vulnerability to food poverty

The generalized least squares regression results in which the log of per capita food consumption expenditure and variance of food consumption are outcome variables are shown in Table 4. The $F$-statistics for both models is significant ($P < 0.05$). This indicates sufficient evidence that there is a connection between household food consumption expenditure and the deviation from the food consumption expenditure and the explanatory variables selected. We find that age of the household head negatively and significantly influenced the food consumption expenditure of households. This implies that older household heads tend to spend less on food. This is consistent with the findings by García and Grande (2010), who found that increase in age has a negative effect on food consumption expenditure.

Once food poverty and vulnerability thresholds were established, we disaggregated them into various food poverty and vulnerability categories, as shown in Table 5. Following Pritchett et al. (2000), households were initially categorized into low vulnerability ($V_i < 0.5$) and high vulnerability ($V_i > 0.5$) groups. Subsequently, households were also classified into two groups: food non-poor ($Exp > Z$) and food poor, ($Exp < Z$) where $Exp$ is the food consumption expenditure per capita, and $Z$ is the poverty line. We did this by adopting the international poverty line of $1.9/day as the separating line. The international poverty line was chosen due to the absence of a national and regional poverty line in Ghana. The converted local rate of the Ghanaian Cedi to US dollar rate as at 2018 is indicated under Table 2. Descriptively, we found that 325 (36.11%) of the sampled households are food poor and concurrently at high risk of food poverty. This implies that these individuals are more likely to continue to be food poor in the future.

On the contrary, 341 (37.89%) of the sampled households belonged to transitory food poverty. That is, they are currently food poor but have a low vulnerability. In other words, these households can break out of food poverty in the near future. Besides, we found that 112 (12.44%) of the sampled individuals are food non-poor but highly vulnerable to being food poor. This means that 112 households are more plausible to be food poor in the near future. Additionally, it implies that 122 (13.56%) of the households have a stable state of food poverty as they are food non-poor and at the same time not at risk.

The headcount ratio for the sample is 0.74. This suggests that a higher percentage of them are food poor even though consumption is not shared across household members. It also reflects the high poverty and food insecurity in Northern Ghana (GSS 2020), attributed to the higher rate of subsistence farming. It is noteworthy to suggest that subsistence farmers rely on climate-sensitive factors and are subject to a lower urbanization rate (Zereyesus et al. 2014). Moreover, as Table 5 shows, the Pearson chi-square value between vulnerability and food poverty was positive but not statistically significant. This implies that there is less evidence suggesting a significant relationship between the sampled households’ vulnerability and food poverty. This contradicts Zereyesus et al. (2017) ’s findings, which indicate that existing food poverty and prospect food poverty are not independent of each other in Northern Ghana.
Table 3  Summary statistics by participation in diverse off-farm works

| Variable                      | Non-participants | Petty trading | Mean Diff | Non-participants | Arts and Crafts | Mean Diff |
|-------------------------------|------------------|--------------|-----------|------------------|-----------------|-----------|
| Food consumption expenditure per capita | 7.91 (7.70)      | 7.00 (6.51)  | -0.91 (0.59) | 7.91 (7.70)      | 7.09 (6.53)     | -0.83 (0.59) |
| Age of household head         | 42.25 (9.59)     | 43.61 (9.92) | 1.36 (0.81)  | 42.25 (9.59)     | 41.77 (10.17)   | -0.48 (0.80) |
| Gender of household head      | 0.91 (0.29)      | 0.92 (0.27)  | 0.01 (0.02)  | 0.91 (0.29)      | 0.95 (0.21)     | 0.05* (0.02) |
| Marital status of household head | 0.91 (0.29)    | 0.87 (0.33)  | -0.04 (0.02) | 0.91 (0.29)      | 0.87 (0.33)     | -0.04 (0.03) |
| Household size                | 9.46 (4.23)      | 9.99 (4.32)  | 0.52 (0.35)  | 9.46 (4.23)      | 9.83 (4.31)     | 0.37 (0.35)  |
| Years of schooling of household head | 2.57 (3.98)  | 3.88 (5.06)  | 1.31** (0.37) | 2.57 (3.98)      | 3.17 (4.89)     | 0.60 (0.37)  |
| Migration                     | 0.48 (0.50)      | 0.61 (0.48)  | 0.12** (0.04) | 0.48 (0.50)      | 0.50 (0.50)     | 0.01 (0.04)  |
| Fever                         | 0.50 (0.50)      | 0.63 (0.48)  | 0.13** (0.04) | 0.50 (0.50)      | 0.38 (0.49)     | -0.12** (0.04) |
| Credit access                 | 0.06 (0.25)      | 0.07 (0.25)  | 0.00 (0.02)  | 0.06 (0.25)      | 0.07 (0.25)     | 0.00 (0.02)  |
| Extension access              | 0.48 (0.50)      | 0.31 (0.46)  | -0.17*** (0.03) | 0.48 (0.50)    | 0.25 (0.43)     | -0.23*** (0.04) |
| Farm size                     | 0.77 (0.56)      | 0.49 (0.55)  | -0.27*** (0.05) | 0.77 (0.56)    | 0.56 (0.63)     | -0.20*** (0.05) |
| Bicycle                       | 0.90 (0.29)      | 0.75 (0.43)  | -0.15*** (0.03) | 0.90 (0.29)    | 0.72 (0.45)     | -0.18*** (0.03) |
| Cattle                        | 0.20 (0.40)      | 0.27 (0.45)  | 0.07* (0.03) | 0.20 (0.40)      | 0.25 (0.43)     | 0.04 (0.03)  |
| Goats                         | 0.60 (0.49)      | 0.78 (0.41)  | 0.19*** (0.03) | 0.60 (0.49)    | 0.80 (0.40)     | 0.20*** (0.04) |
| Sheep                         | 0.58 (0.49)      | 0.49 (0.50)  | -0.09* (0.04) | 0.58 (0.49)     | 0.38 (0.48)     | -0.20*** (0.04) |
| Guinea fowl                   | 0.45 (0.50)      | 0.48 (0.50)  | 0.03 (0.04)  | 0.45 (0.50)      | 0.46 (0.50)     | 0.01 (0.04)  |
| Chicken                       | 0.95 (0.23)      | 0.96 (0.20)  | 0.01 (0.01)  | 0.95 (0.23)      | 0.97 (0.18)     | 0.02 (0.01)  |
| Donkey                        | 0.08 (0.26)      | 0.08 (0.27)  | 0.00 (0.02)  | 0.08 (0.26)      | 0.05 (0.22)     | -0.02 (0.02) |
| Market distance               | 4.59 (2.12)      | 3.39 (1.58)  | -1.20*** (0.16) | 4.59 (2.12)    | 3.56 (1.99)     | -1.02*** (0.16) |
| Market information            | 0.91 (0.28)      | 0.51 (0.50)  | -0.40*** (0.03) | 0.91 (0.28)    | 0.50 (0.50)     | -0.40*** (0.03) |

***, **, and * indicate statistical significance at 1%, 5%, and 10% level.
4.2 Determinants of participation in off-farm work activities

The marginal effects from the multinomial logit model in which the dependent variable is participation in different off-farm work engagements are presented in Table 6. The null hypothesis that all regression coefficients are jointly equal to zero is rejected \( \chi^2(38) = 270.77; \ P < 0.0000 \), indicating that the multinomial logit model had strong explanatory power and fitted the data reasonably well. Nguyen-Van et al. (2017) stated that marginal effects present a good picture and meaning regarding individual probability models’ effects. We find that the marginal effects vary across the various off-farm work activities considered.

The estimates in Table 6 demonstrate that participation in diverse off-farm employment activities is significantly driven by several factors. In general, we find that household size, age, years of schooling, cattle ownership, goats, and donkeys negatively influence non-participation of a farm household in off-farm work. The statistical significance of the coefficients of household size and marital status implies that larger household size and household heads being married affect a household’s participation in off-farm engagements. This is plausible because increased household size may be associated with

### Table 4  Estimates of expected log food consumption expenditure and variance (\( N = 900 \))

|                        | Coefficient | Robust Std. Error | Coefficient | Robust Std. Error |
|------------------------|-------------|-------------------|-------------|-------------------|
| Log Age                | -0.557***   | 0.131             | 0.741***    | 0.138             |
| Gender                 | 0.007       | 0.136             | -0.245*     | 0.142             |
| Marital status         | -0.033      | 0.124             | -0.330**    | 0.136             |
| Log Household size     | -0.066      | 0.099             | -0.198*     | 0.109             |
| Log Years of schooling | 0.017       | 0.030             | 0.010       | 0.033             |
| Migration              | -0.012      | 0.069             | 0.091       | 0.076             |
| Fever                  | 0.095       | 0.062             | -0.172**    | 0.067             |
| Credit access          | -0.148      | 0.120             | -0.121      | 0.109             |
| Extension access       | 0.033       | 0.070             | -0.060      | 0.076             |
| Log Farm size          | -0.063      | 0.129             | 0.134       | 0.131             |
| Bicycle                | -0.049      | 0.084             | 0.036       | 0.089             |
| Cattle                 | 0.004       | 0.080             | -0.041      | 0.083             |
| Goats                  | 0.102       | 0.071             | -0.113      | 0.080             |
| Sheep                  | 0.021       | 0.068             | 0.036       | 0.074             |
| Guinea fowl            | -0.020      | 0.066             | 0.093       | 0.073             |
| Chicken                | -0.092      | 0.153             | 0.134       | 0.156             |
| Donkey                 | 0.210       | 0.134             | 0.037       | 0.149             |
| Constant               | 3.871***    | 0.612             | -1.084      | 0.659             |
| F (17, 882)            | 1.68        | 3.76              |             |                   |
| Prob>F                 | 0.042       | 0.000             |             |                   |
| R-squared              | 0.030       | 0.071             |             |                   |
| Root MSE               | 0.923       | 1.018             |             |                   |

***, **, and * indicate statistical significance at 1%, 5%, and 10% level
more obligations such as increased household consumption expenditure, which would require household heads to engage in off-farm income-generating activities to raise more income to meet these responsibilities. Ownership of livestock (cattle, goats, and donkeys) negatively influences non-participation in off-farm work. This could be because livestock requires more attention for care and feeding to ensure that they have the food and water. This may result in household members devoting most of their time to rearing animals, thereby trading off off-farm work (Shumetie and Mamo 2019). Moreover, such a scenario is most likely if the livestock is associated with more income-generating opportunities than alternative off-farm work participation, everything else held constant.

We find that smallholders’ participation in petty trading is significantly and positively influenced by their age, years of schooling, and livestock ownership (cattle, goats, sheep, and donkeys). Older household heads are less likely to participate in petty trading. This contradicts the findings of Imai et al. (2015). Imai et al. (2015) suggest that older farm household heads would be more energized to participate in petty trading, increasing their likelihood of engaging in extra off-farm work. An increase in the years of schooling of household heads increases their likelihood of engaging in petty trading even though participants in this off-farm work generally have lower schooling years. This is consistent with Vasco and Tamayo (2017) findings and Owusu et al. (2011), who observe similar findings in Ecuador and Ghana, respectively. On the contrary, our results show that farm size negatively influences smallholders’ likelihood to participate in petty trading. This corroborates with the findings of Imai et al. (2015).

Participation in arts and crafts by smallholders is influenced negatively by migration, fever, and marital status. Household heads who battled fever in the previous year have a reduced propensity to engage in arts and crafts as an off-farm work activity. Married household heads are less likely to participate in arts and crafts. This finding is consistent with the findings of Lopez-Acevedo et al. (2021). As pertains to most developing countries, married farmers, especially the women are responsible for many domestic and homemade chores (Mulungu and Mudege 2020), thus reducing their likelihood to engage in off-farm work. On the other hand, livestock ownership (cattle and goats) positively and significantly influences smallholders’ likelihood to participate in arts and crafts.

The last rows in Table 6 indicate falsification tests required for the selection of instrumental variables. Following Di Falco et al. (2011), these instruments’ acceptability was established by conducting a simple falsification test that a suitable selection instrument would affect the treatment variable but would not affect the outcome variable. Our results show that the selected instruments (i.e., market distance and market information) can be considered valid since the joint Wald test of their effects on off-farm work participation is significant in the first stage of the multinomial endogenous switching regression.
However, they do not influence the outcome variables \( F = 1.04 \) \( (p > 0.05) \). This suggests that the selected instrumental variables were not only appropriate but also strong.

### 4.3 Impact of participation in off-farm employment activities on food consumption expenditure per capita

Table 7 presents results from the second stage of the multinomial endogenous switching regression model. Food consumption expenditure per capita is the outcome variable for respective regimes of participation in diverse off-farm work activities. It can be observed that the age of household heads and credit access among non-participants of off-farm work activity negatively and significantly affect household food consumption expenditure. Older non-participants of off-farm work spend less on food consumption. This may be due to a lower overall income and a reduction in food required as individuals grow older. Similarly, smallholders’ lack of credit access may limit individual capacity to increase their food consumption expenditure. This is in line with the findings of
Ding and Abdulai (2020). Ding and Abdulai (2020) found that microcredit access leads to increased household per capita food consumption expenditure in China’s Sichuan Province. Goats as an asset of non-participants of off-farm work positively and significantly affect household food consumption expenditure per capita. Assets can be used as tools by households to boost their food consumption expenditure. However, none of the explanatory variables for petty trading and arts and crafts participants significantly affect food consumption expenditure per capita. The variable Mills 3 is the selectivity correction term of the specification for non-participants of off-farm work. We find that it positively and significantly affects household food consumption expenditure per capita. This result suggests that there is significant positive sample selection bias in the decision of household heads that decide to participate in arts and crafts as off-farm work. Stated differently, there is a positive correlation between the decision to participate in arts and crafts as off-farm work activities and the per capita food consumption expenditure among smallholders.

4.4 Impact of participation in off-farm work activities on household vulnerability to food poverty

The second-stage multinomial endogenous switching regression model results for the effect of participation in off-farm activities on household risk to food poverty are presented in Table 8. It can be observed that age, gender, marital status, household size, credit access, bicycle, and chicken ownership of non-participants of off-farm work positively and significantly affect household vulnerability to food poverty. On the contrary, years of schooling, livestock (goats, sheep, and donkeys) ownership of non-participants of off-farm activities negatively affect household vulnerability to food poverty. The Mills 3 selectivity correction term of the specification for non-participants of off-farm work is negative and statistically significant. This finding suggests strong evidence of sample selection bias in household heads’ decision to participate in arts and crafts as off-farm work. The result implies a negative correlation between farmers’ decision to participate in arts and crafts activities and household vulnerability to food poverty. Contrarily, we find no significant sample selectivity bias in deciding not to participate in off-farm work or choose to participate in petty trading.

Age, marital status, household size, and credit access of participants in petty trading positively and significantly influence household vulnerability to food poverty. Older household heads are likely to be unemployed or have low incomes, which would increase the risk of households being food poor. This corroborates with the findings of Zereyesus et al. (2017). Petty trading participants with large households are more at risk of food poverty. This corroborates with Imai et al. (2015)’s findings, who found similar results in Vietnam and India. However, finding the effect of access to credit of petty trading participants on households’ risk to food poverty is counter-intuitive.

On the other hand, years of schooling, sheep and donkey ownership among petty trading participants reduce a household’s vulnerability to food poverty. Years of schooling of the household head reduces the risk of households falling into food poverty. Educated household heads may be empowered to minimize the vulnerability of households to food poverty. This is consistent with the findings of Zereyesus et al. (2017). Household livestock (sheep and donkeys), which are an asset, reduce farmers’ risk of food poverty. This is also
consistent with Zereyesus et al. (2017)’s findings, who indicated that household asset ownership helps to minimize their vulnerability to poverty in Northern Ghana.

Our results further indicate that the estimates of variables age, gender, marital status, household size, years of schooling, credit access, and bicycle ownership under the arts and craft category are positive and statistically significant at influencing household’s vulnerability to food poverty. On the other hand, years of schooling, access to extension services, and livestock (goats and donkeys) ownership negatively and significantly affect the household’s vulnerability to food poverty. Extension access is essential because it provides information such as market information, making farmers more informed, enabling them to find ways to reduce their risk to food poverty. Livestock owned by households may be used to minimize household’s vulnerability to food poverty in times of distress through income-generating when they are sold or through other products like meat, milk, and/or leasing them on other farms for draught labor (Ng’ombe et al. 2017).

Table 7  Multinomial endogenous switching model estimates for the effect of off-farm work participation on food consumption expenditure per capita

| Variable                  | Non-participants | Petty trading | Arts and Crafts |
|---------------------------|------------------|---------------|-----------------|
| Log Age                   | -0.647** (0.229) | -0.629 (0.498) | -0.717 (0.495)  |
| Gender                    | 0.230 (0.216)    | -0.301 (0.372) | -0.306 (0.539)  |
| Marital status            | -0.075 (0.174)   | -0.274 (0.308) | 0.122 (0.298)   |
| Log Household size        | 0.007 (0.177)    | -0.161 (0.247) | -0.204 (0.249)  |
| Log Years of schooling    | 0.037 (0.060)    | -0.037 (0.108) | -0.000 (0.102)  |
| Migration                 | -0.167 (0.130)   | 0.084 (0.260)  | 0.149 (0.251)   |
| Fever                     | -0.056 (0.160)   | 0.149 (0.428)  | 0.156 (0.375)   |
| Credit access             | -0.357* (0.188)  | -0.262 (0.302) | 0.176 (0.311)   |
| Extension access          | 0.042 (0.117)    | 0.020 (0.198)  | -0.077 (0.203)  |
| Log Farm size             | 0.232 (0.288)    | -0.056 (0.734) | -0.133 (0.651)  |
| Bicycle                   | -0.036 (0.165)   | -0.112 (0.210) | -0.013 (0.214)  |
| Cattle                    | -0.131 (0.146)   | 0.094 (0.193)  | 0.175 (0.196)   |
| Goats                     | 0.242* (0.127)   | -0.030 (0.224) | 0.105 (0.211)   |
| Sheep                     | -0.074 (0.122)   | -0.215 (0.299) | 0.281 (0.270)   |
| Guinea fowl               | -0.052 (0.102)   | 0.033 (0.139)  | -0.045 (0.165)  |
| Chicken                   | -0.004 (0.246)   | -0.038 (0.476) | -0.038 (0.594)  |
| Donkey                    | 0.033 (0.257)    | 0.713 (0.443)  | 0.132 (0.390)   |
| Mills 1                   | 0.689 (0.534)    | 0.023 (1.083)  | -0.579 (1.005)  |
| Mills 2                   | -0.244 (1.198)   | -0.455 (0.588) | 0.556 (1.969)   |
| Mills 3                   | 2.168* (1.257)   | 0.118 (1.894)  | -0.562 (0.564)  |
| Constant                  | 5.042*** (1.009) | 6.329* (3.321) | 6.091*** (1.626) |

Standard errors are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level; Mills 1 indicates the selectivity correction term for non-participation in off-farm work only; Mills 2 indicates the selectivity correction term for participation in Petty Trading only, and Mills 3 indicates the selectivity correction term for participation in Arts and Crafts only.
4.5 Treatment and heterogeneity impacts for the multinomial endogenous switching model

Table 9 summarizes the average treatment effects of participation in off-farm activities on households’ risk to food poverty under actual and counterfactual conditions. As observed in the last column, there is a significant change in terms of participants in off-farm employment activities. The impact on a household’s vulnerability to food poverty indicates that participation in petty trading has a statistically significant impact on households’ vulnerability to food poverty. It is interesting, especially that petty trading’s positive effects are the highest among participants and non-participants. This might be for the reason that household heads, in one way or the other, participate in off-farm employment to reduce their vulnerability to food poverty. All of the base heterogeneity impacts are positive for participation and non-participation, implying that heterogeneity does not lead to less vulnerability to food poverty than non-participants. This indicates the existence of source differences among participants and non-participants in terms of household vulnerability to food poverty. The transitional heterogeneity for arts and crafts off-farm employment is negative and statistically significant. The implication is that household heads who did...
participate in arts and crafts would be more at risk of food poverty if they had not partaken in this off-farm employment.

### Table 9  Treatment and heterogeneity impact from the multinomial endogenous switching model

|                              | Participation | Non-participation | Treatment effect | Changes (%) |
|------------------------------|---------------|-------------------|-----------------|-------------|
| **Vulnerability to food poverty** |               |                   |                 |             |
| Participants Petty Trading   | 1.329 (0.044) | 1.250 (0.029)     | 0.079*** (0.021) | 6.32        |
| Arts and Crafts              | 1.358 (0.053) | 1.334 (0.035)     | 0.024 (0.025)   | 1.80        |
| Non-participants Petty Trading | 1.274 (0.028) | 1.250 (0.029)     | 0.023** (0.005) | 1.84        |
| Arts and Crafts              | 1.331 (0.031) | 1.334 (0.035)     | -0.003 (0.007)  | -0.22       |
| Heterogeneity effects        | 1.331 (0.031) | 1.358 (0.053)     | -0.028 (0.027)  |             |
|                              | 1.274 (0.028) | 1.329 (0.044)     | -0.055** (0.021)|             |

Standard errors are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level.

### 5 Conclusion

This study examined the disaggregated impacts of off-farm employment participation on households’ vulnerability to food poverty in Ghana, using farm household-level data. We employed the multinomial endogenous switching regression model to address selectivity bias and to explore heterogeneous effects of off-farm employment on non-participants and two groups of participants in off-farm employment activities. The off-farm employment engagements were categorized as petty trading and arts and crafts.

Our econometric results showed that various factors do influence household participation in off-farm employment. The sample’s headcount ratio is 0.74, indicating that a higher percentage of them are food poor even though consumption is not equally shared across household members. We consistently found significant self-selection in participation in arts and crafts, suggesting that using the multinomial endogenous switching regression (MESR) model was an appropriate estimation strategy. Given the significant effect of participation in petty trading at reducing farm household vulnerability to food poverty, policymakers should identify viable options for these activities in the study area. Besides, farm household access to various financial resources or instruments (e.g., livestock) are possible policy alternatives to promote participation in various off-farm work activities (Owusu et al. 2011; Zereyesus et al. 2017) such as petty trading. Since education encourages household participation in petty trading, stakeholders should promote farm households’ education through informal education. More importantly, governments can diversify extension services provided to farmers to include capacity building of both business and managerial skills to help farm households participate in off-farm activities more successfully.

This study has important limitations worth reporting. First, we did not quantify the returns from off-farm work activities in monetary terms as well as potential impacts on household vulnerability to food poverty. Second, due to data limitations, this study broadly considered petty trading and, arts and crafts as the main off-farm opportunities for farmers. Nonetheless, smallholder farmers in Ghana and other developing countries engage in multiple off-farm activities that may include carpentry, mechanic, electronics, food processing, milling, hawking, and roadside restaurants or “chop bars”, among others. Thus, to improve the results of this study, a potentially important gap for future research is examining the...
impacts of these activities (both as singles and combinations) on vulnerability to food poverty and household welfare. Third, this study does not consider other household members’ participation in off-farm work other than the household head. Considering returns from off-farm employment participation by all household members and using richer panel datasets to explore this subject further is an exciting opportunity for future research.

Data availability The data employed in this paper are accessible on request from the corresponding author but not made public as a result of privacy considerations.

Declarations

Declaration of competing interest None declared.

References

Abdulai, A., Huffman, W.: The adoption and impact of soil and water conservation technology: an endogenous switching regression application. Land Econ. 90(1), 26–43 (2015). https://doi.org/10.3368/le.90.1.26

Amemiya, T.: The maximum likelihood and the nonlinear three-stage least squares estimator in the general nonlinear simultaneous equation model. Econometrica 45(4), 955–968 (1977). https://doi.org/10.2307/1912684

Asfaw, S., Kassie, M., Simtowe, F., Lipper, L.: Poverty reduction effects of agricultural technology adoption: a micro-evidence from rural Tanzania. J. Dev. Stud. 48(9), 1288–1305 (2012). https://doi.org/10.1080/00220388.2012.671475

Asfaw, S., McCarthy, N., Paolantonio, A., Cavatassi, R., Amare, M., Lipper, L.: Livelihood Diversification and Vulnerability to Poverty in Rural Malawi. In: FAO (2015)

Babatunde, R.O., Quim, M.: Impact of off-farm income on food security and nutrition in Nigeria. Food Policy 35(4), 303–311 (2010). https://doi.org/10.1016/j.foodpol.2010.01.006

Becerril, J., Abdulai, A.: The impact of improved maize varieties on poverty in Mexico: a propensity score-matching approach. World Dev. 38(7), 1024–1035 (2010). https://doi.org/10.1016/j.worlddev.2009.11.017

Bogale, A.: Vulnerability of smallholder rural households to food insecurity in Eastern Ethiopia. Food Security 4(4), 581–591 (2012). https://doi.org/10.1007/s12571-012-0208-x

Bourguignon, F., Fournier, M., Gurgand, M.: Selection bias corrections based on the multinomial logit model: monte carlo comparisons. J. Econ. Surveys 21(1), 174–205 (2007). https://doi.org/10.1111/j.1467-6419.2007.00503.x

Chaudhuri, S., Jalan, J., Suryahadi, A.: Assessing Household Vulnerability to Poverty from Cross-sectional Data: A Methodology and Estimates from Indonesia. (2002). http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?db=pubmed&cmd=Retrieve&dopt=AbstractPlus&list_uids=608680748683160254related:vpYxyuweFQJ. Accessed 24 Apr 2021

Cornelissen, T., Dustmann, C., Raute, A., Schönberg, U.: From LATE to MTE: alternative methods for the evaluation of policy interventions. Labour Econ. 41, 47–60 (2016). https://doi.org/10.1016/J.LABECO.2016.06.004

Davis, K.F., D’Odorico, P., Rulli, M.C.: Moderating diets to feed the future. Earth’s Future 2(10), 559–565 (2014). https://doi.org/10.1002/2014ef000254

Dey, S.: The role of employment diversification in reducing vulnerability to poverty among marginal and small-holder agricultural households in India. Margin 12(1), 88–112 (2018). https://doi.org/10.1177/0973801017740661

Di Falco, S., Veronesi, M., Yesuf, M.: Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. Am. J. Agr. Econ. 93(3), 825–842 (2011). https://doi.org/10.1093/ajae/aar006

Ding, Z., Abdulai, A.: An analysis of the factors influencing choice of microcredit sources and impact of participation on household income. J. Int. Dev. 32(4), 505–525 (2020). https://doi.org/10.1002/jid.3466
Disaggregated impacts of off-farm work participation on…

Dubin, J.A., McFadden, D.L.: An econometric analysis of residential electric appliance holdings and consumption. Econometrica 52(2), 345–345 (1984). https://doi.org/10.2307/1911493

Gallardo, M.: Identifying vulnerability to poverty: a critical survey. J. Econ. Surveys 32(4), 1074–1105 (2018). https://doi.org/10.1111/joes.12216

García, T., Grande, I.: Determinants of food expenditure patterns among older consumers. The Spanish case. Appetite 54(1), 62–70 (2010). https://doi.org/10.1016/j.appet.2009.09.007

GSS.: Ghana Living Standards Survey (GLSS7): Poverty trends in Ghana; 2005–2017 (2018). https://www.statsghana.gov.gh/gssmain/fileUpload/pressrelease/GLSS7%20MAIN%20REPORT_FINAL.pdf. Accessed 2 Apr 2021

GSS.: Multidimensional Poverty-Ghana (2020)

Haughton, J., Khandker, S. R.: Hanbook on Poverty and Inequality. The International Bank for Reconstruction and Development/The World Bank (2009)

Huntington-Klein, N.: The Effect: An Introduction to Research Design and Causality. CRC Press (2022)

Imai, K.S., Gaiha, R., Thapa, G.: Does non-farm sector employment reduce rural poverty and vulnerability? Evidence from Vietnam and India. J. Asian Econ. 36, 47–61 (2015). https://doi.org/10.1016/j.asieco.2015.01.001

Kiwanuka-Lubinda, R.N., Ng’ombe, J.N., Machethe, C.: Impacts of interlocked contractual arrangements on dairy farmers’ welfare in Zambia: a robust Bayesian instrumental variable analysis. Agrekon 60(1), 10–30 (2021). https://doi.org/10.1080/03031853.2021.1875854

Klasen, S., Reimers, M.: Looking at pro-poor growth from an agricultural perspective. World Dev. 90, 147–168 (2017). https://doi.org/10.1016/j.worlddev.2016.09.003

Kubitza, C., Krishna, V. V.: Instrumental variables and the claim of causality: Evidence from impact studies in maize systems. In (Vol. 26, pp. 100383–100383): Elsevier B.V (2020)

Lee, L.-F.: Unionism and wage rates: a simultaneous equations model with qualitative and limited dependent variables. Int. Econ. Rev. 19(2), 415–433 (1978)

Lokshin, M., Sajaia, Z.: Maximum likelihood estimation of endogenous switching regression models. Stand. Genomic Sci. 4(3), 282–289 (2004). https://doi.org/10.1177/1536867X040040306

Lopez-Acevedo, G., Devoto, F., Morales, M., Rodriguez, J. R.: Trends and Determinants of Female Labor Force Participation in Morocco: An Initial Exploratory Analysis. In: World Bank Group (2021)

Loy, C., Addai, K.N., Ng’ombe, J.N.: Does the use of multiple agricultural technologies affect household welfare? Evidence from Northern Ghana. Agrekon 60(4), 370–387 (2021). https://doi.org/10.1080/03031853.2021.1992290

Maddala, G. S.: Limited-dependent and qualitative variables in econometrics. Cambridge University Press (1983). https://doi.org/10.1017/cbo9780511810176

Mulungu, K., Mudege, N.N.: Effect of group and leader attributes on men and women farmers’ participation in group activities in Zambia. Fem. Econ. 26(4), 178–204 (2020). https://doi.org/10.1080/13545701.2020.1791926

Ng’ombe, J.N., Kalinda, T.H., Tembo, G.: Does adoption of conservation farming practices result in increased crop revenue? Evidence from Zambia. Agrekon 56(2), 205–221 (2017). https://doi.org/10.1080/03031853.2017.1312467

Nguyen-Van, P., Poiraud, C., To-The, N.: Modeling farmers’ decisions on tea varieties in Vietnam: a multinomial logit analysis. Agric. Econ. (United Kingdom) 48(3), 291–299 (2017). https://doi.org/10.1111/agec.12334

OECD.: Promoting Diversified Livelihoods. In Promoting Pro-poor Growth: 664 Policy guidance for Donors (pp. 1–29). OECD (2007)

Owusu, V., Abdullai, A., Abdul-Rahaman, S.: Non-farm work and food security among farm households in Northern Ghana. Food Policy 36(2011), 108–118 (2011). https://doi.org/10.1016/j.foodpol.2010.09.002

Pritchett, L., Suryahadi, A., Sumarto, S.: Quantifying Vulnerability to Poverty : A Proposed Measure , Applied to Indonesia (2000)

Rahman, A., Mishra, S.: Does non-farm income affect food security? Evidence from India. J. Dev. Stud. 56(6), 1190–1209 (2020). https://doi.org/10.1080/00220388.2019.1640871

Reddy, E.L., Reddy, D.R.: A study on resource use efficiency of input factors with reference to farm size in paddy cultivation in nellore district. IOSR J. Humanit Soc. Sci. 17(1), 48–55 (2013). https://doi.org/10.9790/0837-1714855

Rodrik, D.: An African growth miracle? J. Afr. Econ. 27(1), 10–27 (2018). https://doi.org/10.1093/jae/ejw027

Shumetie, A., Mamo, K.: Effect of cropland and livestock ownership on child labour in eastern Ethiopia: empirical examination of the Wealth Paradox. Int. J. Child Care Educ. Policy 13(1), 1–15 (2019). https://doi.org/10.1186/s40723-019-0061-x
Vasco, C., Tamayo, G.N.: Determinants of non-farm employment and non-farm earnings in Ecuador: Cristian Vasco and Grace Natalie Tamayo. CEPAL Rev. 2017(121), 53–67 (2017). https://doi.org/10.18356/80b76a5e-en

World Bank.: Attacking poverty (0195211294) (2001)

World Bank.: Poverty and shared prosperity 2020: Reversals of fortune. International Bank for Reconstruction and Development / World Bank Group (2020). https://doi.org/10.1596/978-1-4648-1602-4

Zereyesus, Y.A., Embaye, W.T., Tsiboe, F., Amanor-Boadu, V.: Implications of non-farm work to vulnerability to food poverty-recent evidence from Northern Ghana. World Dev. 91, 113–124 (2017). https://doi.org/10.1016/j.worlddev.2016.10.015

Zereyesus, Y. A., Ross, K. L., Amanor-Boadu, V., Dalton, T. J.: Baseline Feed the Future Indicators for Northern Ghana 2012 Monitoring, Evaluation and Technical Support Services (METSS) (2014)

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