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Implications of Non-Farm Work to Vulnerability to Food Poverty-Recent Evidence From Northern Ghana

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Summary. — Using survey data from northern Ghana, this study seeks to establish the impact of participation in non-farm work on the vulnerability of resource poor households to food poverty. Vulnerability to food poverty is assessed based on expected future food expenditure of households. The potential endogeneity problem associated with participation in non-farm work by households is overcome using a novel instrumental variable approach. Analysis of the determinants of expected future food expenditure is done using a standard Feasible Generalized Least Squares (FGLS) method. Demographic and socioeconomic variables, location variables, and household facilities are included in the model as control variables. Our study finds that participation in non-farm work significantly increased the future expected food consumption, thereby alleviating the vulnerability of households to food poverty. Our study also confirms that current food poverty and future food poverty, i.e., vulnerability to food poverty, are not independent from each other. Non-farm work plays a crucial role in providing the means to overcome the risk of food poverty in these resource poor households. Policies that promote off-farm income generating activities, such as small businesses and self-employment, as well as the creation and support of businesses that absorb extra labor from the farm, should be encouraged in the study region. Because households in the study region are exposed to above average levels of hunger and food poverty, the study recommends the government of Ghana and development partners to take measures that enhance the resilience of these resource poor households.

Key words — vulnerability, food poverty, instrumental variable, northern Ghana, FGLS

1. INTRODUCTION

The Ghanaian economy has achieved sustained growth, averaging about 6% annually since 2001 (World Bank, 2014). In terms of poverty and food security, Ghana met its Millennium Development Goal (MDG) of halving the proportion of hungry people in 2002 and was scheduled to achieve its MDG poverty target in 2015. Based on this remarkable achievement, the World Bank re-classified Ghana as a lower middle income country (World Bank, 2012). However, these achievements are uneven across the country. For example, the northern section of the country, especially the area above the latitude 8°N, has some unpleasant statistics. A significant proportion of the farming and rural population still experiences extreme forms of poverty and food insecurity (Zereyesus, Ross, Amanor-Boadu, & Dalton, 2014). This is problematic because agriculture is the primary source of livelihood for about 50% of households in the country (Quaye, Hall, & Luzadis, 2010), accounting for about one third of the GDP (Breisinger, Diao, & Thurlow, 2009).

The minor in poverty and food insecurity in the north may be largely reflective of the region's much higher rate of subsistence farming, which is dependent on climate sensitive factors, and much lower rate of urbanization. Migrants from northern Ghana to major urban centers in the south in pursuit of "greener pastures" have also been much less successful relative to their southern peers, owing largely to their lower levels of education and skills (World Bank, 2013).

There is a high risk of poverty in northern Ghana, and climate variability is one of the causes (Acheampong, Ozor, & Owusu, 2014). Farmers in northern Ghana are more susceptible to climate variability due to farm characteristics, such as low income from rain fed agriculture, inadequate information, lack of know-how, lack of access to sufficient and improved farm implement and supplies, storage facilities for water and produce, and other infrastructure. (Acheampong *et al.*, 2014). These farming households are also very vulnerable to macroeconomic shocks such as rapid food price spikes and exchange rate fluctuations.

Farming, the mainstay for many resource-poor households, is inherently risky; it exposes farm households to greater vulnerability to poverty. Assessing the vulnerability to food poverty, a forward-looking measure instead of a static form of poverty, provides a better assessment of food poverty under uncertainty (Pritchett, Suryahadi, & Sumarto, 2000). Kurosaki (2002) observes that farming households in Pakistan employ various coping mechanisms against any risk of poverty incidence, and he notes that households who have better risk coping mechanisms were less vulnerable relative to households with less effective risk coping mechanisms. Kurosaki (2002) also finds that households without risk coping mechanisms experience large reductions in consumption, remain landless, and expose their children to absenteeism in school.

The non-agricultural sector can play an important role in reducing households' poverty and food insecurity. The empirical support of the impact of non-farm work on poverty and food security in developing countries is well documented (Awoniyi & Salman, 2011; Babatunde & Qaim, 2010;

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Ersado, 2006; Hoang, Pham, & Ulubasoglu, 2014; Imai, Gaiha, & Thapa, 2015; Owusu, Abdulai, & Abdul-Rahman, 2011; Ruben, 2001). Research shows that non-farm income could provide self-insurance against shocks that may happen to the households, overcome farm credit constraints, enhance farm investment, absorb labor surplus, and ultimately move households out of poverty through increased total income (Barrett, Reardon, & Webb, 2001; Emran & Hou, 2013; Ferreira & Lanjouw, 2001; Hoang *et al.*, 2014; Oseni & Winters, 2009; Owusu *et al.*, 2011; Reardon, Berdegué, & Escobar, 2001; Ruben, 2001).

Much of the empirical evidence focuses on the relationship between non-farm income and poverty in general. On the other hand, research assessing the relationship between non-farm income and vulnerability to food poverty has been limited. In the study area, almost 40% of households have experienced a moderate to severe form of household hunger, an extreme case of household food insecurity (Zereyesus *et al.*, 2014). Given that food security is the primary objective of such impoverished households, it is of paramount importance to examine the impact of non-farm income on these farm households' current and future food consumption. The concept of participation in non-farm work in rural areas includes all economic activities, except agriculture, livestock, fishing, and hunting (Lanjouw & Feder, 2001). For the current study, a farming household is considered to be participating in non-farm work if a household head and/or the spouse of a household head participate in running a small business, are self-employed (i.e., weaving, sewing or textile production), or work as employees.

The study aims to achieve two distinct but related objectives. First, it examines the effect of a household's participation in non-farm work, represented by a binary variable, on the extent of vulnerability to food poverty in the study area. An instrumental variable (IV) method is used to overcome the endogeneity problem associated with non-farm work participation and food consumption expenditure. The IV estimation is done in three steps. Given a set of valid instruments, the parameters of interest are estimated by: first fitting a binary response model (e.g., probit) of non-farm work participation on the instruments, followed by computing the fitted probabilities of non-farm work participation, and then using these fitted probabilities as instruments in the regression model (Adams, Almeida, & Ferreira, 2009).

The second objective of the study tests whether current food poverty and future food poverty, i.e., vulnerability to food poverty, are independent from each other. This is done by estimating the overall prevalence of food poverty and the extent of vulnerability to food poverty in the study area. Given that food expenditure accounts for a significant proportion of the household income in northern Ghana, these households are particularly susceptible to current and future food poverty. Research shows that poverty and vulnerability to poverty may not be directly related to each other (e.g., Novignon, Nonvignon, Mussa, & Chiwaula, 2012). However, when it comes to food poverty, there is some evidence that suggests that households currently food poor are more likely to experience food poverty in the future than households that are not currently food poor. For example, Ozughalu (2014) found that households in Nigeria that were food poor at the time were also exposed to greater food poverty in the future as compared to non-food poor households. Using the instrumented non-farm work participation described above, a Feasible Generalized Least Squares (FGLS) method is employed to analyze determinants of expected future food expenditure. Results show that participation in non-farm work significantly increased the future expected food consumption of household, thereby reducing their vulnerability to food poverty. It turns out that food poverty and vulnerability to food poverty are also dependent on each other.

The rest of this study is organized in the following manner. The next section develops the conceptual framework, the endogeneity test on non-farm work participation, and the estimation strategy used. This is followed by the discussion of the data and methods used to construct the variables of interest. The results section presents the descriptive statistics of the primary variables and the main empirical results of the estimations. The summary and conclusions section wraps up the study by highlighting the main findings and pointing to specific recommendations for action.

2. CONCEPTUAL FRAMEWORK, ENDOGENEITY TEST, AND ESTIMATION STRATEGY

(a) *Conceptual framework*

The farm household is defined as an economic unit that makes production and consumption decisions (De Janvry & Sadoulet, 2016). Following the farm household model (FHM) literature, a representative household maximizes expected utility (U) from the consumption of goods, including food, (G) and leisure (l) (Chang, Huang, & Chen, 2012; Singh, Squire, & Strauss, 1986). The expected utility function is maximized subject to cash income, labor use, and total time constraints. The total time available to the household (T) is equal to its time allocated to on-farm work (L_1), non-farm work (L_2), and leisure (l). The household's total cash expenditure is constrained by total cash income, with the following full-income constraint:

$$P_G G + w_r l = w_r T + \pi + w_m L_2 + E \tag{1}$$

Here P_G, w_r, and w_m are the price of the consumed goods, household reservation wage rate, and market wage rate, respectively. The left-hand side of Eqn. (1) shows the household's total expenditure on food and the purchase of its own time (i.e., the opportunity cost of leisure). The right-hand side of Eqn. (1) consists of total time valued at the household's reservation wage rate ($w_r T$), profit from farming (π), non-farm work income ($w_m L_2$), and all other non-labor income (E), respectively. Maximizing the households' utility function with respect to L_1, L_2 and l, subject to the full-income constraint, involves taking the partial derivatives to attain the first-order conditions that maximize the household's total utility. The optimal labor allocation functions for the farm work and non-farm work are expressed by $L_1(w_m, w_r, P_G, P_y; A)$ and $L_2(w_m, w_r, P_G, P_y; A)$, respectively (e.g., Chang *et al.*, 2012; Owusu *et al.*, 2011). P_y is the price of agriculture output, and A represents household and location characteristics. The optimal allocation of labor implies that a household will supply labor to the farm where the value of the marginal product of on-farm family labor equals the competitive non-farm wage, w_m (Chang *et al.*, 2012).

Non-farm work participation is determined when the utility of participating in non-farm work exceeds that of not participating. An individual i will have a positive number of non-farm work hours if the market wage (w_m) is greater than the reservation wage (w_r) (Huffman, 1991; Owusu *et al.*, 2011). In reality, however, these utilities and wage differentials are not observable. What is observable is the decision to participate or not to participate in the non-farm sector.

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(b) *Endogeneity of non-farm work participation and food consumption expenditure*

Prior literature recommends using instruments to overcome the possible endogeneity when estimating the impact of non-farm income on the livelihood of households (e.g., Babatunde & Qaim, 2010). One source of endogeneity may be the presence of measurement error attributed to the recall of the extent of non-farm income earned by the household. The other source of endogeneity may be the simultaneity between non-farm income and the household's food poverty status; these variables may simultaneously influence each other. Endogeneity due to recall error is minimal here, because it is unlikely that household respondents will incorrectly report whether or not they participated in non-farm work. However, the endogeneity associated with simultaneity is systemic, so it is addressed by means of an instrumental variable method. Following prior literature (e.g., Babatunde & Qaim, 2010; Ruben, 2001), this study uses household assets (ownership of motor bikes and cell-phones), locality, household head's education, and spouse's education as instruments for the household's participation in non-farm work. Mobile phone ownership is expected to reflect the utilization of information to facilitate non-farm work participation. Education reflects the difference in human capital that may influence non-farm work participation (Barrett *et al.*, 2001). Locality is included as an instrument to account for differences in marketing constraints and labor market structure that are specific to a household's location.

The Instrumental Variable (IV) estimation is implemented following three steps. The first step involves fitting a binary response model (probit) of non-farm work participation (y) on the instruments ($\boldsymbol{Z}$). In the second stage, (y) is regressed on ($\hat{y}$) and other household characteristics ($\boldsymbol{M}$). The fitted values of non-farm work from the second-stage regression are then used in the FGLS regression. A similar approach was used by Adams *et al.* (2009), where their third stage involves running an OLS regression using the fitted values from the aforementioned second-stage procedure. This study differs in the third stage, because our estimation procedure uses an FGLS technique to correct possible heteroscedasticity of the error terms in the food expenditure regression model. As Adams *et al.* (2009) described, this three-stage approach is different from the "pseudo-IV" approach of running an OLS regression, which skips the second-stage. In that approach, consistency is not guaranteed unless the first stage is correctly specified, and the standard errors are adjusted.

Before implementing the above procedure, the potential endogeneity of participation of households in non-farm work and their food expenditure is tested using a Linear Regression with Endogenous Treatment (LRET) effects model. Suppose $Cov(M_h, e) = 0$ for all other observable household characteristics, and $Cov(f_h, e) \neq 0$ for the household's non-farm participation, then there is an *endogenous dummy variable model* (Heckman, 1979). The LRET model (Heckman, 1979), based on the idea of endogeneity of a dummy variable, estimates the Average Treatment Effect (ATE) and other parameters by either full maximum likelihood or a two-step consistent estimator of a linear regression model, augmented with an endogenous binary-treatment variable. The LRET model is composed of a treatment assignment equation (Eqn. (2a)) and an outcome equation (Eqn. (2b)).

$$Non\text{-}farm_h = \begin{cases} 1, & \text{if} \quad \gamma \boldsymbol{Z}_h + \varepsilon_\gamma > 0 \\ 0, & \text{if} \quad \gamma \boldsymbol{Z}_h + \varepsilon_\gamma \leqslant 0 \end{cases}, \tag{2a}$$

$$f_h = \mu_0 + \mu_1 non\text{-}farm_h + \mu_2 \boldsymbol{M}_h + \varepsilon_\mu, \tag{2b}$$

The *non-form* variable equals one if the household head and/or the spouse of the household head, *h,* engage in non-farm work, and zero otherwise. The vector, $\boldsymbol{Z}_h$, contains variables used as instruments for households' non-farm work participation. The $\boldsymbol{M}_h$ is a vector of observable household characteristics. The error terms, ε_γ and ε_μ, are assumed to have bivariate normal distribution with mean zero and a finite covariance matrix. The main variable of interest to determine the endogeneity of non-farm work participation is the correlation between the estimated error components of regression models 2a and 2b (i.e., the hazard ratio).

(c) *Estimation strategy*

The dynamics of poverty may be influenced by natural phenomena, like weather; production events, such as yield; market events, such as prices; and human events, such as health. Poverty is a dynamic and persistent phenomenon; while some households remain in poverty, others can move in and out of it. As Dercon and Krishnan (2000) show, both poverty and consumption can vary. Due to persistent shocks and risks, such as variation in weather and output, price fluctuations, and health risks, millions of people are in a continuous state of vulnerability to poverty. As Ligon and Schechter (2003) argue, risks or any other sources of uncertainty are equally important to poverty when attempting to reduce poverty.

In a panel of 3,311 households in rural Sichuan China, McCulloch and Calandrino (2003) find rates of poverty and vulnerability to chronic poverty of 9% and 20%, respectively. Using panel data in rural Kenya, Christiaensen and Subbarao (2005) assess household vulnerability to poverty and find that households face, on average, about a 40% chance of being poor in the future. They also discover that farm households located in arid areas with higher variability in rainfall are more vulnerable compared to households located in non-arid areas. Christiaensen and Boisvert (2000) also find that households in Mali located in areas with more shocks expect a higher probability of being vulnerable to poverty. Azam and Imai (2009) study poverty and vulnerability levels in Bangladesh in 2005 and find that many households above the poverty line are also vulnerable to poverty.

Theoretical and statistical advances make possible the assessment of vulnerability studies using cross sectional data (Chaudhuri, Jalan, & Suryahadi, 2002). A common approach used to assess vulnerability to food poverty when using cross-sectional data is to model vulnerability as expected poverty (Chaudhuri *et al.*, 2002). The probability that household h will be food poor at time $t + i$ is:

$$V_{h,t} = prob(\ln f_{h,t+i} < \ln P) \tag{3}$$

V_{ht} is the vulnerability to food poverty of household h at time t, and $f_{h,t+i}$ is food consumption of household h at time $t + i$. P indicates the food poverty line of household h, and ln is the natural log.

The household's food consumption expenditure is determined by a number of observable and unobservable household characteristics. The expression for household food consumption expenditure, assuming a linear relationship with its determinants, is expressed as:

$$\ln f_h = \alpha X_h + \varepsilon_h \tag{4}$$

X_h is a vector of the household's participation in non-farm work and other observable household characteristics (i.e., $\hat{y}$ and $\boldsymbol{M}$) and α is a vector of parameters of interest, and ε is the error term, related to individual idiosyncratic characteristics with mean zero and normal distribution. Using the estimated coefficients from Eqn. (4), the vulnerability to food poverty is estimated as:

$$\hat{V}_{h,t} = prob(\ln f_{h,t+i} < \ln P|X_{h,t}) = \Phi(\ln P - \hat{\alpha}\hat{\sigma}X_{h,t}) \quad (5)$$

$\hat{V}_{h,t}$ is the estimated vulnerability to food poverty, or the probability of the individual household's food consumption, conditional on the household's participation in non-farm work and other characteristics, falling below a given food poverty line. The Φ in Eqn. (5) defines the cumulative density function of standard normal distribution, and $\hat{\sigma}$ is the estimated standard error from Eqn. (4).

When using cross-sectional data for analysis, the assumption of constant variance may not hold, thus leading to inefficient estimates (Chaudhuri *et al.*, 2002). Heteroscedasticity may be addressed by relating the variance of the consumption function as a linear function of household characteristics as shown in Eqn. (6).

$$\sigma^2_{\varepsilon,h} = \beta X_h + \theta_h \quad (6)$$

The endogeneity test section explains that the non-farm work participation may be endogenous in the household's food expenditure function. If non-farm work participation is endogenous, its instrumented value will be used in the subsequent equations. Using the instrumented non-farm work participation variable, a standard Amemiya's (1977) three-stage Feasible Generalized Least Square (FGLS) approach is then used to overcome any inherent heteroscedasticity problem. To apply the FGLS approach, one must first estimate Eqn. (4) using OLS, and then, using the error term from Eqn. (4), estimate Eqn. (7) using OLS:

$$\hat{\sigma}^2_{OLS,h} = \hat{\beta}X_h + \hat{\theta}_h, \quad (7)$$

where $\hat{\theta}_h$ is a random error term.

The predicted values from Eqn. (7) are used to transform Eqn. (6) as follows:

$$\frac{\sigma^2_{t,h}}{\hat{\beta}X_h} = \beta\left\{\frac{X_h}{\hat{\beta}X_h}\right\} + \frac{\theta_h}{\hat{\beta}X_h}. \quad (8)$$

Eqn. (8) is estimated using an OLS regression and gives $\hat{\beta}_{FGLS}$, which is an asymptotically efficient FGLS estimate. This $\hat{\beta}_{FGLS}x_h$ is an efficient estimate of the idiosyncratic variance $\sigma^2_{\varepsilon,h}$ component of the food consumption. Using the $\hat{\beta}_{FGLS}$, the standard error, and the transformed Eqn. (4), Eqns. (9) and (10) are developed as follows:

$$\hat{\sigma}_{\varepsilon,h} = \sqrt{X_h\hat{\beta}_{FGLS}}, \quad (9)$$

$$\frac{\ln f_h}{\hat{\sigma}_{\varepsilon,h}} = \alpha\left[\frac{X_h}{\hat{\sigma}_{\varepsilon,h}}\right] + \frac{\varepsilon_h}{\hat{\sigma}_{\varepsilon,h}}. \quad (10)$$

Eqn. (10) is obtained by dividing Eqn. (4) by the standard error determined in Eqn. (9). The coefficient α is then an asymptotically consistent and efficient estimate.

Using α_{FGLS} and β_{FGLS}, we estimate the expected log of food consumption and its variance represented by Eqns. (11) and (12), respectively,

$$E\left\{\left[\frac{\ln \hat{f}_h}{X_h}\right]\right\} = \hat{\alpha}X_h \quad and \quad (11)$$

$$E\left\{\left[\frac{\ln \hat{f}_h}{X_h}\right]\right\} = \hat{\sigma}^2_h = \hat{\beta}X_h. \quad (12)$$

Finally, assuming the log of food consumption is normally distributed, the vulnerability to food poverty is estimated as:

$$\hat{V}_h = prob(nf_{h,t+1} < \ln P|X_h) = \Phi\left\{\frac{\ln P - \hat{\alpha}_{FGLS}X_h}{\sqrt{\hat{\beta}_{FGLS}X_h}}\right\}. \quad (13)$$

In this study, a vulnerability to poverty threshold of 0.5 is used (Chaudhuri *et al.*, 2002; Novignon *et al.*, 2012; Pritchett *et al.*, 2000; Zhang & Wan, 2008). A household with a probability of 50% or more of falling into food poverty in the future is considered vulnerable to food poverty. Zhang and Wang (2008) show that using 0.5 as a threshold provides an improved prediction.

3. DATA AND METHODS

(a) *Data*

Ghana is a country in West Africa, with an estimated population in 2012 of about 24 million. As a country, Ghana has been performing very well according to the Millennium Development Goals of the United Nations. However, its performance has been mixed across regions (Whitehead, 2006). For example, the three northernmost regions are all lagging behind the national average on poverty reduction goals. As a result of this uneven progress, the majority of development agencies, including the U.S. Agency for International Development (USAID), turned their focus on the northern part of the country.

Data for this study come from the 2012 population-based survey commissioned by USAID and conducted in the area above 8°N of Ghana, including the areas falling into the administrative regions of Brong Ahafo, Northern, Upper East, and Upper West, and excluding the areas falling in the Volta Region. The primary objective of the survey is to provide estimates of baseline indicators for USAID's Feed the Future initiative for these regions. There are 4410 households included in the population-based survey. Data on the demographic and socio-economic characteristics, as well as educational information of household members, was collected from the households. Information pertaining to non-farm work participation was collected from the head of the household and the spouse of the head of the household. The following exclusions are applied to the data set to get the final 1,749 observations used for the main model: (i) households that did not provide any response on any of the aggregate expenditure categories (35 households), (ii) households not engaged in any type of farming (349), (iii) households with expenditure per adult equivalent of zero or missing (626), (iv) households with extremely low or extremely high daily per adult equivalent expenditure (84), (v) households without educational information on the spouse of the primary respondent (849), (vi) households with missing information on yield per hectare (668), and (vii) households with missing information on availability of water or motor vehicle or mobile phone (50). Some variations of the main model use different numbers of observations depending on which variables are included in the model, as shown in the estimation of results section. Probability weights are used to make estimated results representative of the population in the study area.

(b) *Expenditure aggregates*

The empirical literature shows that consumption is smoother and less-variable than income and that consumption is not closely tied to transient income shocks (Deaton & Zaidi, 2002). Consumption aggregates in the current study are based on the observed expenditures incurred on a range of food and non-food items. To estimate the aggregate household expenditure, the individual expenditure items are organized into their respective categories, annualized, and aggregated. The daily expenditure per adult equivalent is obtained by dividing the aggregate household expenditure by 365 days and then by household size in adult equivalent.

For food expenditure, the survey uses a seven-day recall period of household's food consumption to measure its expenses on food. The daily per adult equivalent food expenditure is obtained by dividing the seven-day food expenditure per household by 7 and then by the household size in adult equivalent. To deal with inflation and facilitate international comparison of the expenditure indicators, all expenditure estimates are converted from the local currency into 2010 US dollars (constant prices).

(c) *Household hunger in the study area*

The household hunger scale (HHS) measures the level of hunger experienced by households in food insecure areas using a number of recall quantities asked of respondents. The indicator measures the quantity, not the quality, of food accessible to a household. To estimate the household hunger scale, a household member is asked a series of questions about food accessibility and the frequency of food insecure situations during a 4-week or 30-day recall period. Frequent occurrence of food insecure situations is associated with increasing severity of food insecurity or hunger within the household. Two types of indicators, a categorical HHS indicator and a median HHS, can be constructed from the HHS. When the indicator is one or less, then the household is assumed to have a 'little to no hunger' condition. An indicator score of 2 to 3 illustrates 'moderate hunger', and 4 to 6 indicates a 'severe hunger' condition in the household.

(d) *Measuring household's food poverty*

The Food and Agriculture Organization (FAO) of the United Nations defines food insecurity as: "*A situation that exists when people lack secure access to sufficient amounts of safe and nutritious food for normal growth and development and an active and healthy life. It may be caused by the unavailability of food, insufficient purchasing power, inappropriate distribution, or inadequate use of food at the household level*" (FAO, 2014, p. 50). FAO (2014) further states that food insecurity, inappropriate care and feeding practices, together with poor conditions of health and sanitation, are the primary causes of poor nutritional status in many developing areas, such as northern Ghana.

The three commonly reported aspects of consumption poverty are: the poverty headcount index, the poverty gap index, and the squared poverty gap index. The poverty headcount index measures the proportion of households identified as poor or falling below an established poverty line. The poverty gap index, often referred to as poverty depth, measures the extent to which those identified as poor fall below the poverty line; and the squared poverty gap index, also referred as poverty severity, measures the extent of inequality among the poor (Foster, Greer, & Thorbecke, 1984). This study estimates the corresponding food poverty indices as follows:

$$H_\alpha = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{P-E_i}{P}\right]^\alpha. \tag{14}$$

H_α is the food poverty index of interest, and α, with a value of 0, 1, or 2, represents the headcount, depth, and severity measures, respectively. The variable P is the food poverty line, and E_i is the daily per adult equivalent food expenditure for each household, i. Eqn. (14) is equal to zero if the daily per adult equivalent food expenditure for each household, i, is greater than or equal to the food poverty line. This study presents the results of the food poverty headcount for these data.

(e) *Food poverty line and calorie consumption*

If information on food expenditure and caloric consumption is available, it is possible to estimate a cost-of-calories function using the following equation:

$$\ln f_h = \delta_1 + \delta_2 C_h, \tag{15}$$

where f_h and C_h measure the value of daily per adult equivalent food consumption and daily per adult equivalent caloric consumption of household h, respectively. From Eqn. (14), the food poverty line, P, the expenditure required to attain the Recommended Daily Allowance (RDA) of calories, is estimated as:

$$P = e^{\hat{\delta}_1 + RDA\hat{\delta}_2}, \tag{16}$$

where $\hat{\delta}_1$ and $\hat{\delta}_2$ are estimates of δ_1 and δ_2, respectively, from Eqn. (15). Household size in terms of adult equivalence (AE) is computed by dividing the total energy requirements of the household by 2,900 kilocalories using the nutrition requirement scale of the National Academy of Sciences-National Research Council (1989).[1] The *RDA* value of 2,900 calories per adult per day is also used by the latest round of Ghana's Statistical Service survey practices (GSS, 2014). The fundamental assumption of Eqn. (15) is that all households have a common basket of food that varies according to the household tastes, preferences, and income. Eqn. (15) also assumes that all households face identical market prices.

(f) *District level food poverty lines*

There are 45 administrative districts in the study area. Districts are considered to represent some level of homogeneity in terms of the households' characteristics. The assumption in Eqn. (15) that all households have a common basket of food that varies according to the household tastes and preferences and income and that all households face identical market prices can safely be assumed at the district level rather than for the entire study region. To satisfy the foregoing assumptions in Eqn. (15), the food poverty line for each district is estimated and then averaged to develop the overall food poverty line. During the estimation, probability weights are used to adjust the district level effect in terms of size and composition. Regional poverty lines have been used in the past and produced superior results (Ozughalu, 2014). If the daily per adult equivalent food expenditure is lower than the estimated food poverty line, the household is considered to be food poor. This definition is used to estimate the food poverty headcount in the study area.

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4. DESCRIPTIVE RESULTS

(a) *Expenditures on food and non-food aggregates*

The average daily per adult equivalent aggregate expenditure is $4.00 (Table 1). The expenditure sub-aggregates include food, education, health, non-food, house rent, utility, and durables. The non-food sub-aggregate includes a broad range of items from shoes and clothes to school stationeries and transportation expenses that are not grouped under any of the other categories. The utility sub-aggregate includes expenses, such as vehicle fuels, telephone bills, etc. The allocation of the daily per adult equivalent aggregate expenditure on the seven different consumption categories is as follows: food ($2.62); education ($0.03); health ($0.10); non-food (0.80); rent (0.16); utility (0.08); and durables ($0.20). This implies that food accounted for 66 cents of each dollar of average daily per adult equivalent expenditure. Of the remaining 34 cents, non-food accounted for 20 cents, durables for 5 cents, house rent accounted for 4 cents, and the sum of education, health, and utility accounted for 5 cents.

Given that food expenditure accounts for a significant proportion of the income expenditure for these households, factors that affect their income will proportionally affect their ability to spend on food. The observed higher proportion of expenditure spent on food is consistent across the different groups, aggregated by expenditure deciles (Figure 1). Based on Engel's theory, it is expected that food share of total income declines with increasing income, if a state of food security has been achieved. However, for these households, the trend of the proportion of income spent on food initially increases as the household moves up from the lower expenditure decile until the 5th expenditure decile is reached, and then the proportion gradually decreases from the 6th decile onward. The opposite occurs in the trend of the expenditure proportion on the aggregate expenditure on everything other than food (Figure 1).

Significance tests of food expenditure as a proportion of aggregate expenditure across the expenditure deciles uses mean comparison t-tests. The expenditure share on food for the upper 10th percentile is the only one that is statistically significant and lower than the rest of expenditure deciles. This is indicative of the situation that the large majority of households in the study area are prone to poverty, in general and food poverty, in particular. In contrast, it is observed that the upper 10th percentile had expenditure on durables, as a proportion of total expenditure, significantly higher than the rest of the expenditure deciles.

Table 1. *Average Daily per capita expenditure by consumption category in 2010 constant prices (US$)*

Consumption category	Average expenditure (US$)	Standard error	95% confidence interval	
			Lower	Upper
Food	2.62	0.12	2.38	2.87
Education	0.03	0.00	0.03	0.04
Health	0.10	0.01	0.09	0.12
Non-food	0.80	0.03	0.74	0.86
Rent	0.16	0.01	0.15	0.18
Utility	0.08	0.01	0.06	0.09
Durables	0.20	0.01	0.18	0.22
Total	4.00	0.14	3.73	4.27

(b) *Variables used in the vulnerability model*

Table 2 presents descriptive statistics of the variables used for the analysis. The average daily per adult equivalent expenditure on food is 2.62 with a standard deviation of 3.87 USD. The high standard deviation around the mean is indicative of the high variability in the magnitude of expenditure among the households. This may also be associated with higher downside risk to food shortages. More than six in ten of the households have a source of non-farm income. They get their non-farm income from operating a small business; weaving, sewing or textile production; or working as employees. The average age of the household head is around 45 years, and it ranges from 18 to 100 years. The average years of education attained by the household head and the spouse of the household head are more than 2 years and 0.85 years, respectively. The cumulative years of education per household shows that an average household has a total of 44.9 years of schooling, ranging from none to as high as 90 years of schooling. The average per hectare return on yield is used as a proxy for managerial ability in the model (Hoang et al., 2014). The average per hectare return on yield is estimated to be around 396.6 USD per household per year. Access to credit in the form of cash is seen as a means of easing liquidity constraints for the households. Almost 40% of the households have access to credit.

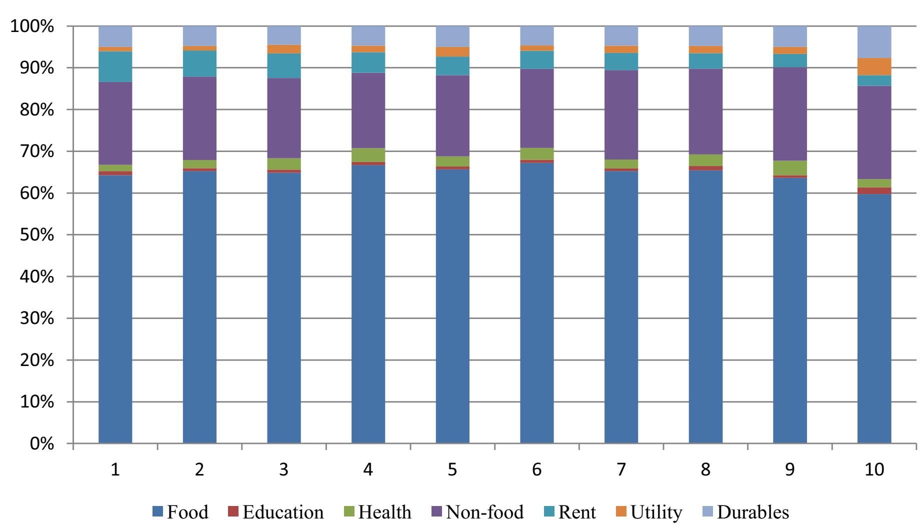

Figure 1. *Expenditure shares by consumption category and expenditure deciles.*

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A majority of the households, 82%, own their house. Access to a private toilet is considered as an added security and protection from sanitation related diseases. The productivity and other health related conditions of the household members may also have some association with such toilet facilities. A quarter of the households have access to a private toilet. A similar proportion of the households have access to electricity. The ownership of large durable goods is another indication of relative standard of living. For example, the ownership of a refrigerator allows the household to safely store perishable food items and other valuable items for longer periods of time; only 3% of the households have a refrigerator. Just over 2% of the households have access to potable water inside their homestead. Almost half of the household composition is made up of dependents who are either below the age of 15 or above the age of 70. Regional differences are included to represent the specific agricultural systems within each region. Locational distribution of the sample shows that 8%, 61%, 17%, and 14% of the households are located in Brong Ahafo, Northern, Upper East, and Upper West regions, respectively.

5. MODEL ESTIMATION RESULTS

(a) *Food poverty and household hunger*

The average food poverty line for the study area is estimated to be 2.6 USD. Using this poverty line, the prevalence of food poverty is about 55.1% at the household level. The overall prevalence of households experiencing moderate to severe hunger, as indicated by a score greater than or equal to 2 on the household hunger scale, is 37.1% (Table 3).

Food poverty is a result of the cumulative effect of the household's deprivation situation over time, while hunger, especially extreme cases of hunger, could be a temporary situation. Even though hunger and food poverty do not refer to the same concept, it is plausible to expect a certain level of dependence between food poverty and hunger. Pearson's chi squared test of independence between poverty and hunger scale of a household is rejected at the 99% significance level, implying that there exists a relationship between a household's food poverty and hunger status (Table 3). A cross tabulation analysis of food poverty and hunger statuses shows that a total of 56.21% of the households are identified as food poor, but have not experienced moderate to severe hunger. Only 29% of the households are identified as having no food poverty but have fallen into some sort of hunger. Although this number is smaller relative to the other categories, it is indicative of the fact that even the food non-poor households can experience some sort of hunger at some point. Close to half of the households, 43.8%, have experienced food poverty and have fallen into moderate to extreme hunger at the same time. It is highly likely that a household that is identified as food poor will experience some form of hunger.

(b) *Endogeneity of non-farm work*

The results of the first-stage probit regression of the LRET model for the participation of households in non-farm work showed that ownership of a motor bike, ownership of a mobile phone, household head's education, and locality have a statistically significant influence, at the 1% level, on households' participation in non-farm work (Table 4). The pseudo R-squared for the probit model is 0.05, and the model predicts household non-farm work with 65.50% accuracy. Using Bonferroni's adjustment, pairwise correlation analysis, of instruments with non-farm work shows that all the instruments are significantly correlated with non-farm work. The estimated correlation (ρ) between the error terms in the first-stage and second-stage models is statistically significant at the 5% level, indicating that participation in non-farm work is endogenous.

Table 3. *The food poor and the hungry (percent)*

	Little to no household hunger	Moderate to severe household hunger	Total
Non-poor	71.02	28.98	100.00
Poor	56.21	43.79	100.00
Total	62.87	37.13	100.00
Pearson Chi2 (1): 76.85			
Probability: 0.000			

Table 2. *Summary statistics of the principal variables used in the study (N = 1749)*

Variable	Description	Mean	Std. Dev.
Non-farm work	1 = Household has non-farm income source; 0 = otherwise	0.63	0.48
Food expenditure	Daily per adult equivalent food expenditure (2010 USD Constant Prices)	2.62	3.87
Age of head	Age of household head	45.25	16.23
Head's education	Years of schooling of household head	2.14	5.19
Spouse's education	Years of schooling of head's spouse	0.73	3.08
Household cumulative education	Cumulative years of schooling of the members of the household	7.19	12.96
Credit	1 = Household has access to credit; 0 = otherwise	0.39	0.49
House owned	1 = Household owns house; 0 = otherwise	0.82	0.38
Toilet	1 = Household owns private toilet; 0 = otherwise	0.25	0.43
Motor Bike	1 = Household owns a motor-bike; 0 = otherwise	0.36	0.48
Mobile Phone	1 = Household owns a mobile phone; 0 = otherwise	0.31	0.46
Electricity	1 = Household has electricity; 0 = otherwise	0.23	0.42
Refrigerator	1 = Household owns refrigerator; 0 = otherwise	0.03	0.18
Locality	1 = Household located in urban; 0 = otherwise	0.19	0.39
Water	1 = Household has access to potable water; 0 = otherwise	0.02	0.15
Dependents	Proportion of dependents in the household	0.44	0.20
Land productivity	Per unit land productivity (USD/ha)	396.57	337.46
Brong Ahafo region (BA)	1 = Household located in BA region; 0 = otherwise	0.08	0.25
Northern region (N)	1 = Household located in N region; 0 = otherwise	0.61	0.49
Upper East region (UE)	1 = Household located in UE region; 0 = otherwise	0.17	0.37
Upper West region(UW)	1 = Household located in UW region; 0 = otherwise	0.14	0.35

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For consistency purposes, the discussion of results in the following sections is based on estimations using the instrumented values of the non-farm work variable.

(c) *Vulnerability to food poverty*

The prevalence of vulnerability to food poverty by household's participation in non-farm work and other distributional characteristics of the household are presented in Table 5. The overall prevalence of vulnerability to food poverty in the study area is 58.6%. The table shows that the prevalence of food poverty for households participating in non-farm work (44.7%) is less than for households not participating in non-farm work (87.1%); the difference between households is significant at less than the 5% alpha level. The regional prevalence of food poverty vulnerability shows that the Upper West and Upper East regions have a higher prevalence than the other two regions. Brong Ahafo has a significantly lower vulnerability rate than the rest of the three regions. Urban households (37.3%) are significantly less vulnerable at the 5% level than rural households (63.1%).

As expected, the vulnerability figures are higher at the lower end of the expenditure deciles. However, the results show that even the higher expenditure deciles are also prone to food poverty. The lower four deciles have a higher vulnerability than the overall average vulnerability for all deciles. Pairwise comparison tests between the expenditure deciles shows that in 78% of the comparisons, the differences in vulnerability are statistically different from each other at the 5% significance level. The strength of significance increases as one moves from the lower deciles to the higher deciles; in essence, the difference between the bottom decile and second lowest decile is weaker than the difference between the bottom decile and the third lowest decile, and so on.

Pearson's chi-squared independence test reveals that the status of food poverty and vulnerability to food poverty are codependent (Table 6). The chi squared independence test shows that food poverty and vulnerability to food poverty are positively related, and the relationship is statistically significant at the 5% level.

Table 4. *First stage probit regression and the endogeneity test results from the Linear Regression Endogenous Treatment Model*

Instrument	Coef. (*t*-value)
Household owns motor vehicle	0.312 (5.35)***
Household owns mobile phone	0.158 (2.28)**
Head's schooling	0.032 (4.54)***
Spouse's schooling	0.016 (1.30)
Locality	0.551 (6.17)***
Constant	−0.097 (2.20)**
ρ	−0.625 (3.28)***
Sigma	0.217 (3.86)***
N	1,749

Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.0$.
ρ = estimated correlation between the treatment-assignment errors and the outcome errors; its significance indicates the rejection of the null hypothesis of no correlation between the treatment errors and the outcome errors.

Table 5. *Vulnerability to food poverty profile for household's non-farm income and other household's distribution characteristics with non-farm income instrumented*

	Mean vulnerability (percent)	Std. Err.
Overall	58.6	1.1
Household has non-farm income		
No	87.1	1.3
Yes	44.7	1.4
Region		
Brong Ahafo	15.9	3.2
Northern	54.5	1.4
Upper East	84.3	2.3
Upper West	81.1	2.9
Locality		
Rural	63.1	1.2
Urban	37.3	2.7
Total expenditure deciles		
1	84.5	2.5
2	70.8	3.0
3	72.1	3.0
4	62.0	3.3
5	57.4	3.6
6	48.8	3.5
7	45.8	3.8
8	41.7	3.9
9	37.9	4.2
10	25.9	5.7

Table 6. *The food poor and the food poverty vulnerable (percent)*

	Non-vulnerable	Vulnerable	Total
Non-Poor	58.5	41.5	100.0
Poor	30.3	69.7	100.0
Total	41.4	58.6	100.0
Pearson Chi2 (1): 136.7			
Probability: 0.000			

(d) *Determinants of vulnerability to food poverty*

The results from the IV and OLS regression models developed to estimate the expected future consumption of food are presented in Table 7. As discussed, the OLS results may be inconsistent due to the endogeneity effect of the non-farm work variable. If participation in non-farm work leads to higher food consumption expenditure and this effect feeds back into a higher likelihood of participating in non-farm work, then the OLS estimates may overestimate the actual marginal values. For the non-farm work variable, the empirical results show that the OLS estimate of 0.498 is higher than the IV estimate of 0.375, confirming the *a priori* expectation.

The participation in non-farm work is significantly and positively associated with the future mean consumption expenditure on food. Holding other variables constant, households that have a source of non-farm income have a significantly higher expected mean consumption on food. This result aligns with previous research that shows a positive relationship between participation in non-farm work and household expenditure. Owusu *et al.* (2011) show that participation in non-farm work by a sample of 300 farm households resulted in a positive and statistically significant effect on households' income and food security status. Both Reardon *et al.* (2001) and Ruben (2001) show that non-farm work also improved caloric consumption in Burkina Faso and Honduras, respectively. Ersado (2006) found a positive association between non-farm income diversification and consumption expenditure in Zimbabwe. Using farm survey data from Nigeria, Babatunde and Qaim (2010) also showed that non-farm income had a positive net effect on caloric intake, dietary quality, and micronutrient supply. They showed that non-farm income contributed to higher food production and farm income by easing capital constraints, leading to improved household welfare. Hoang *et al.* (2014) also showed that for every additional household member participating in non-farm work, the probability of household's poverty decreased by 7–12% and household's total expenditure increased by 14% during a two-year period. Imai *et al.* (2015) examined the impact of non-farm income on households' income and consumption in Vietnam and India, and found that, non-farm income consistently increased consumption per capita, thereby reducing poverty and vulnerability in both countries. Households engaged in non-farm income activities in the southwest zone of Nigeria also experienced increased household income, had less poverty, and higher welfare (Awoniyi & Salman, 2011). Ruben (2001) also examined the role of non-farm income on poverty using national income and expenditure survey data in rural Honduras, and found that non-farm activities improved food security, and helped farmers to purchase external inputs.

Employment in the non-agricultural sector is believed to increase the average household's income, thereby easing household's budget constraints, increasing its consumption, and equipping the household with better coping strategies in times of shocks (Abdulai & Delgado, 1999; Matshe & Young, 2004). Non-farm work in the non-agricultural sector also complements farm productivity by increasing the household's capacity to purchase farm inputs, thereby improving the household's labor productivity, yield production, and income (Clover, 2003; Ruben, 2001). In Colombia, Deininger and Olinto (2001) show no adverse effect between farm and non-farm income as farming households engaged in non-farm work as a means of diversifying their income.

Several control variables are significantly and positively correlated with the expected daily per capita expenditure on food (Table 7). These variables include years of schooling for the household head, years of schooling for the spouse of the household head, access to credit, access to toilet, access to electricity, availability of a refrigerator, average per hectare yield return, and access to potable water. For example, a household whose head and their spouse have more years of schooling has a higher future mean expenditure on food. This result agrees with previous research that show households headed by employed and educated men are less vulnerable to shocks than other household groups (Ligon & Schechter, 2003). Households' characteristics that suggest a relatively higher standard of living (e.g., access to electricity, toilet, and ownership of a refrigerator) have significantly higher future mean daily per capita expenditure on food.

Variables that are significantly and negatively correlated with the expected daily per capita expenditure on food are: cumulative household's years of education, proportion of dependents, and the regional indicators. The higher the proportion of dependents in the household, then the lower the mean future daily per adult equivalent expenditure on food. This is an indication that households with a high proportion of dependents are vulnerable to future food poverty. This result is in line with previous studies that confirm that households with more children are more food vulnerable than households with fewer children (Christiaensen & Boisvert, 2000). Compared to the Brong Ahafo region, the other three regions have significantly lower expected per adult equivalent food expenditures.

Table 7. *Regression results of expected log per capita food expenditure*

	OLS estimates (t-value)	IV estimates (t-value)
Non-farm work	0.498	0.375
	(7.60)***	(4.48)***
Age of head	0.003	0.003
	(1.39)	(1.63)
Head's schooling	0.023	0.028
	(2.95)***	(3.36)***
Spouse's schooling	0.021	0.038
	(1.62)	(2.88)***
Household's schooling	−0.001	−0.013
	(2.76)***	(3.73)***
Credit	0.226	0.167
	(3.49)***	(2.45)**
House owned	0.114	0.082
	(1.42)	(1.03)
Toilet	0.352	0.291
	(4.05)***	(3.15)***
Electricity	0.481	0.479
	(5.59)***	(5.27)***
Refrigerator	0.715	0.608
	(4.55)***	(3.57)***
Water	0.245	0.264
	(1.75)*	(1.67)*
Dependents	−0.449	−0.489
	(3.10)***	(3.22)***
Northern region	−0.284	−0.290
	(2.93)***	(3.18)***
Upper East region	−0.605	−0.691
	(4.96)***	(5.44)***
Upper West region	−0.463	−0.610
	(3.51)***	(4.33)***
Land productivity	−0.000	0.000
	(0.36)	(5.58)***
R^2	0.33	0.38
N	1,749	1,749

Significance levels: $^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.0$.

The result on the cumulative household's years of education appears to be counter intuitive. It may be rationalized that higher cumulative household education years may not mean higher per adult equivalent food expenditure, especially for households with several dependents and younger members who may not contribute to the household's total income. Other variables such as age of household head, and ownership of house are not significantly associated with per adult equivalent food expenditure.

Alternative models of the determinants of vulnerability to food poverty are also estimated. Results of these alternative models are included in Table 8. These models are based on alternative specifications of: (i) the education of household head and the spouse of the household head, and (ii) the land productivity, and regional effects of land productivity. These alternative specifications confirm the consistency of the positive and significant effect of non-farm work participation on expected food consumption expenditure. The effects of the control variables on the dependent variable are similar across these models. Model A1 shows a similar regional effect of land productivity, except for the interaction term between land productivity and the Upper East region. The main regional effects of Northern and Upper West regions are insignificant. The education variables for both the head and spouse are entered as binary variables in Model A2. In comparison to having no education, both primary and secondary education for both the head and spouse are positively and significantly related to the expected food consumption expenditure. Model A3 shows that when the land productivity variable is excluded from the analysis, the results for the remaining variables remain consistent with the main model, even though the sample size is larger here.

6. SUMMARY AND CONCLUSIONS

The Ghanaian economy has been doing well during the last 15 years (World Bank 2014) resulting in Ghana's reclassification as one of the lower middle income countries (World Bank, 2012). Despite the remarkable overall national economic growth and progress in reducing poverty and hunger, relatively less progress has been achieved in the northern part of Ghana. The prevalence of poverty and food insecurity in the north remains more than twice that of the national average, attracting attention from the government of Ghana and donor agencies.

Farmers in northern Ghana are heavily dependent on agricultural income (Zereyesus *et al.*, 2014). With farm characteristics such as low income from rain fed agriculture, inadequate information, lack of expertise, lack of access to sufficient and improved farm implements and supplies, and lack of storage facilities for water and produce, these farmers are at higher risk of poverty (Acheampong *et al.*, 2014). These farming households are also very vulnerable to macroeconomic shocks, such as rapid food price spikes and exchange rate fluctuations.

The non-agricultural sector plays a significant role in reducing households' poverty and food insecurity (Barrett *et al.*, 2001; Emran & Hou, 2013; Ferreira & Lanjouw, 2001; Hoang *et al.*, 2014; Oseni & Winters, 2009; Owusu *et al.*, 2011; Reardon *et al.*, 2001; Ruben, 2001). Employment in the non-agricultural sector also equips households with better coping strategies in times of shocks through increased average household income and consumption and reduced household budget constraints (e.g., Abdulai & Delgado, 1999; Matshe & Young, 2004).

While empirical support of the impact of non-farm work on poverty and food security in developing countries abounds, research assessing the relationship between non-farm income and vulnerability to food poverty has been very limited. Food expenditure forms a significant portion of a resource poor household's budget. In our study area, the households spend an average of 66% of their expenditure on food consumption, and almost 40% of these households have experienced a moderate to severe form of household hunger, which is an extreme case of household food insecurity (Zereyesus *et al.*, 2014). Thus, it is of paramount importance to examine the impact of non-farm income on these farm households' expected food consumption and their vulnerability to food poverty.

This study has two objectives. First, we examine the impact of a household's participation in non-farm work on the extent of vulnerability to food poverty in the study area. Applying a three-stage regression estimation approach, an instrumental variable is used to overcome the endogeneity associated with non-farm work participation and food consumption expenditure (Adams *et al.*, 2009). Second, we investigate the association between vulnerability to food poverty and the overall prevalence of food poverty in the study area. We argue that food poor households are also more vulnerable to food poverty considering the higher share of food expenditure in their budget.

Test results show that participation in non-farm work is endogenous in the model. Using the instrumented non-farm work participation values, a Feasible Generalized Least Squares (FGLS) method is employed to analyze determinants of expected future food expenditure. Results show that participation in non-farm work significantly increased the future expected food consumption of households, leading to lower vulnerability to food poverty. It is also confirmed that food poverty and vulnerability to food poverty are related to each other.

We conclude with the following policy recommendations. Policies that promote off-farm income generating activities, such as small businesses and self-employment, as well as the creation and support of businesses that absorb extra labor from the farm, should be encouraged in the study region. Increasing rural households' access to financial capital is also a viable policy option to improve availability of non-farm work (Owusu *et al.*, 2011). Our results also call for the provision and expansion of cost effective roads and marketing infrastructure (e.g., Aidoo, Mensah, & Tuffour, 2013) to help provide markets for non-farm products. Because households in the study region are exposed to above average levels of hunger and food poverty, we recommend that the government of Ghana and development partners should take immediate action to enhance the resilience of these resource poor households. Finally, we suggest that future research focuses on understanding how farm households' non-farm labor supply is affected by other policies, such as direct income payments.

Some limitations of the current study are discussed. First, this study does not estimate the exact level of non-farm labor supply or the extent of non-farm income earned. Second, this research does not take into account the participation in non-farm work by household members, other than the head and/or the spouse of the household head. Third, the study does not disaggregate effects of different non-farm income types on the expected food expenditure of households. Future studies may find it helpful to extend the current paper along these lines.

NOTES

1. See Notes A1 in the Appendix for an in-depth description of the nutrient calculations.

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APPENDIX A. SUPPLEMENTARY DATA

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.worlddev.2016.10.015.

Table 8. *IV regression results of expected log per capita food expenditure for alternative models*

	Model A1[a]	Model A2[b]	Model A3[c]
Non-farm work	0.325	0.279	0.464
	(3.87)***	(2.71)***	(6.40)***
Age of head	0.001	0.005	0.005
	(0.25)	(2.74)***	(3.49)***
Head's schooling (cont.)	0.028		0.032
	(3.54)***		(4.89)***
Head prim. schooling		0.462	
		(2.51)**	
Head sec. schooling		0.434	
		(3.72)***	
Spouse's schooling (cont.)	0.027		0.042
	(2.02)**		(4.87)***
Spouse prim. schooling		0.653	
		(3.28)***	
Spouse sec. schooling		0.710	
		(4.65)***	
Household's schooling	−0.012	−0.016	−0.015
	(3.35)***	(5.10)***	(5.38)***
Credit	0.155	0.190	0.188
	(2.28)**	(2.58)**	(3.14)***
House owned	0.094	0.056	0.040
	(1.16)	(0.57)	(0.54)
Toilet	0.292	0.321	0.265
	(3.28)***	(3.03)***	(3.36)***
Electricity	0.463	0.429	0.402
	(5.09)***	(4.39)***	(5.01)***
Refrigerator	0.670	0.813	0.694
	(4.05)***	(6.70)***	(6.27)***
Water	0.314	0.419	0.451
	(1.94)*	(3.04)***	(3.90)***
Dependents	−0.679	−0.265	−0.458
	(4.47)***	(1.47)	(3.45)***
Northern region	0.020	−0.193	−0.170
	(0.15)	(1.96)**	(2.20)**
Upper East region	−0.429	−0.574	−0.693
	(2.45)**	(4.37)***	(6.70)***
Upper West region	−0.067	−0.467	−0.504
	(0.38)	(3.41)***	(4.61)***
Land productivity	0.001		
	(6.85)***		
N * Land productivity	−0.001		
	(2.73)***		
UE * Land productivity	−0.000		
	(1.50)		
UW * Land productivity	−0.001		
	(4.65)***		
R^2	0.42	0.46	0.37
N	1,749	1,749	2,405

[a] Model A1. Uses all the explanatory variables as in the main model (Table 7), plus the interaction terms between region and land productivity variables.
[b] Model A2. Uses all the explanatory variables as in the main model (Table 7), except the land productivity variable is removed, and education variables for both head and the spouse of head are specified as categorical variables (primary or not, and secondary or not).
[c] Model A3. Uses all the explanatory variables as in the main model (Table 7), except the land productivity variable is removed.