Participation in non-farm work and vulnerability to food poverty of households in northern Ghana

Zereyesus Y.A.[1], Embaye, W. T.[1], Tsiboe, F, and Amanor-Boadu, V.[1]

[1]Agricultural Economics Department, Kansas State University

[2] Department of Agricultural Economics and Agribusiness, University of Arkansas

Contact Author: yacobaz@ksu.edu

Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, MA, July 31- Aug. 2

Participation in non-farm work and vulnerability to food poverty of households in northern Ghana

Abstract

Using a 2012 survey data from northern Ghana, this study seeks to establish the impact of participation in off-farm work on the vulnerability of resource poor households to food poverty. Vulnerability to food poverty is assessed based on expected future food expenditure. The potential endogeneity problem associated with participation in off-farm work by households is taken care of using novel instrumental variable approach. Analysis of 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 also included in the model as control variables. Results show that participation in off-farm work significantly increased the future expected food consumption and thereby alleviating the vulnerability of households to food poverty. Results also confirmed that food poverty and vulnerability to food poverty are not independent from each other. Off-farm work plays a crucial role in providing the means to overcome the risk of food poverty in these resource poor households. Policy tools should be designed taking into account the vulnerability of these households to food poverty, bearing in mind the significance of their food budget shares and the uncertainties surrounding food production and consumption by these households.

Key words*: vulnerability, food poverty, instrumental variable, northern Ghana, FGLS*

Introduction

The Ghanaian economy has achieved sustained growth averaging about 5% annually since 2001 (World Bank, 2014). In terms of poverty and food security, Ghana had met its Millennium Development Goal's (MDG) target of halving the proportion of hungry people in 2002 and is scheduled to achieve its MDG's 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 ones 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 et al. 2014). This is problematic because agriculture is the primary source of livelihood for about 46% of households in the country (GSS, 2012), accounting for about 26% of the GDP between 2010 to 2012 (SRID-MOFA, 2013).

The low decline in poverty and food insecurity in the north may be largely reflected in 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 already a high vulnerability to poverty in northern Ghana, of which climate variability is one of the causes (Acheampong et al., 2014). It is indicated that farm characteristics such as low income from rain fed agriculture, inadequate information, lack of knowhow, lack of access to sufficient and improved farm implement and supplies, storage facilities for water and produce, and other infrastructure expose farmers in northern Ghana to become more susceptible to such climate variability (Acheampong et al., 2014). It's also these farming households who are very vulnerable to macroeconomic shocks such as rapid food price spikes and exchange rate fluctuations.

Farming, the main source of livelihood for many of the resource poor households, is inherently risky that 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-, has been shown to provide a better assessment of food poverty under uncertainty (Pritchett, Suryahadi and Sumarto, 2000). Kurosaki (2002) observed that farming households in Pakistan employ various coping mechanisms against any risk of poverty incidence, and noted that households who have better risk coping mechanism were less vulnerable relative to households with less risk coping mechanism. Kurosaki (2002) also found that households without risk coping mechanisms experience large reductions in consumption, remained landless, and exposed 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 to the impact of off-farm work on poverty and food security in developing countries has been well documented (Ruben, 2001; Ersado, 2006; Babatunde and Qaim, 2010; Awoniyi and Kabir, 2011; Owusu, V., & Abdulai, 2009; Hoang et al., 2014; Imai et al., 2015). Research shows that off-farm income could provide self-insurance against shocks that may happen to the households, overcome farm credit constraint and enhance farm investment, absorb labor surplus, and ultimately move households out of poverty through increased total income (Barrett et al., 2001; Emran and Hou, 2013; Ferreira and Lanjouw, 2001; Hoang et al., 2014; Oseni and Winters, 2009; Owusu and Abdu, 2009; Reardon et al., 2001; Ruben, 2001).

Much of the empirical evidence focused on the relationship between off-farm income and poverty in general. On the other hand, research assessing the relationship between off-farm income and vulnerability to food poverty has been limited. In the study area, it is observed that 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 off-farm income on these farm households' expected food consumption.

The study aims to achieve two distinct but related objectives. First, the study examines the effect of household's participation in off-farm work, represented by a binary variable, and 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 off-farm work participation and the food consumption expenditure. The IV estimation is done in three steps. Assuming that we have a set of valid instruments, the parameters of interest are estimated by first fitting a binary response model (e.g. probit) of off-farm work participation on the instruments followed by computing the fitted probabilities of off-farm work participation and then using these fitted probabilities as instruments in the regression model (Adams et al. 2009). Second, the study tests whether the food poverty and 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. The study argues that resource poor households are prone to the exposure of food poverty because resource poor households spend the largest proportion of their expenditure on food. Research shows that poverty and vulnerability to poverty may not be directly related to each other (e.g. Novignon et al., 2012). However, when it comes to food poverty, there is some evidence that households under food poverty are more likely to be vulnerable to food poverty than households under non-food poverty. Ozughalu (2014) for example found that households under food poverty were more vulnerable to food poverty as compared to non-food poor in Nigeria. Using the instrumented off-farm work participation described above (Adams et al. 2009), a Feasible Generalized Least Squares (FGLS) method is employed to analyze determinants of expected future food expenditure. Results show that participation in off-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 not independent from each other.

The rest of the study is organized as follows: The next section on methodology develops the theoretical model and details the methods used to construct the variables of interest. This is followed by the discussion of the data used for the analysis. The results section presents the descriptive statistics of the main variables and the main empirical results of the estimation. The conclusion and recommendation section wraps up the study by highlighting the main findings and pointing to specific recommendations for action.

Methodology

Endogeneity of Off-farm work participation and food consumption expenditure

It is often recommended to use instruments to overcome the possible endogeneity while estimating the impact of off-farm income on the livelihood of households (e.g. Babatunde and Qaim, 2010). One of the sources of endogeneity could be the presence of measurement error during the recall of the extent of off-farm income the households earned while working outside the farm. The other possible source of endogeneity is the possible simultaneity between the off-farm income and households livelihoods, in that both of these variables may influence each other at the same time. The endogeneity issue due to recall error is minimal in the current study because it will be highly unlikely that households would be unable to correctly remember whether or not they would be engaged in off-farm work. However, the endogeneity problem associated with simultaneity is dealt with by means of instrumental variable method. Following similar application in other instances (e.g. Babatunde and Qaim, 2010; Ruben, 2001), the study uses household assets (ownership of motor bike and cell-phones), locality (capturing differences in infrastructure and the possible supply of off-farm work), household head's education and spouses' education as instruments for household's participation in off-farm work. The IV estimation is implemented following three steps. Given a set of instruments, the first step involves fitting a binary response model (probit) of off-farm work participation (y) on the instruments (Z). The second stage follows by regressing y on $\hat{y}$ and other household characteristics (M). The fitted values of off-farm work from the second stage regression will then be used in the FGLS regression which will be developed in the next section. A similar approach was used by Adams et al. (2009) using three-stage estimation procedure, in which case their third stage involves running an OLS regression using the fitted values from the second stage as described above as explanatory variables. The current study differs in this third stage such that the estimation procedure follows an FGLS technique to correct possible heteroscedasticity of the error terms in the food expenditure regression model (more on this in the theoretical model development section). As Adams et al. (2009) described it, this three-stage approach is different from the "pseudo-IV" approach of running an OLS regression by skipping the second-stage, in which case consistency is not guaranteed unless the first stage is correctly specified and the standard errors need to be adjusted.

Before implementing the above procedure, the potential endogeneity of participation of households in off-farm work and their per capita food expenditure is tested using a Linear Regression with Endogenous Treatment Effects (LRET) Model. Suppose that $Cov(M_h, e) = 0$ for all other observable household characteristics, but $Cov(f_h, e) \neq 0$ for household's off-farm participation. In this case, there will be an *endogenous dummy variable model* (Heckman, 1978). The LRET model, based on endogeneity of a dummy variable notion, first introduced in the modern literature by Heckman (1978), 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. See Maddala (1983) for the derivation of the maximum likelihood estimators for the LRET used in this study, and some empirical reviews. The LRET model developed is composed of a treatment assignment equation (Equation *(1a)*) and an outcome equation (Equation *(1b)*) as follows:

$$off\text{-}farm_h = \begin{cases} 1\,, & if\ \gamma\ \ \boldsymbol{Z}_h + \varepsilon_\gamma > 0 \\ 0\,, & if\ \gamma\ \ \boldsymbol{Z}_h + \varepsilon_\gamma \leq 0 \end{cases}, \qquad (1a)$$

$$f_h = \mu_0 + \mu_1 off\text{-}farm_h + \mu_2 \boldsymbol{M}_h + \varepsilon_\mu, \qquad (1b)$$

The *off-farm* variable takes on the value of one if either the primary/secondary man or a woman household h engages in off-farm work and zero otherwise. Participation in off-farm work is indicated by participation in off-farm economic activities such as small business, self-employment, buy-and-sell and wage or salary employment. The vector $\boldsymbol{Z}_h$ contains variables used as instruments for households' off-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 finite covariance matrix. The main variable of interest for the diagnosis of the endogeneity of off-farm work participation is the estimated correlation between the estimated error components of the regression models 1a and 1b (i.e. the hazard ratio) as will be reported in the estimation results section. The next section will be dedicated to the development of the theoretical models relating off-farm work and the vulnerability of households to food poverty.

Theoretical model

The dynamics of poverty may be influenced by natural phenomenon such as weather; production events, such as yield; market events, such as prices; and human events, such as health. Poverty is a dynamic and persistent phenomenon and so while some households remain in poverty, others can move in and out of it. As Dercan and Krishnan (2000) showed, 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 continuous state of vulnerability to poverty. As Ligon and Schechter (2003) argued, risks or any other sources of uncertainty are equally important to poverty while attempting to reduce poverty.

In a panel of 3,311 households in rural Sichuan China, Mcculloch (2003) found poverty and vulnerability to chronic poverty rates of 9% and 20%, respectively. Likewise, using panel data in rural Kenya, Christiaensen and Subbarao (2005) assessed household vulnerability to poverty and found that households faced on average about 40% chance of being poor in the future. They also discovered that farm households located in arid area with higher variability in rain fall were more vulnerable compared to households located in non-arid areas. Christiaensen and Boisvert (2000) also found that households in Mali located in areas with more shocks expected higher probability of being vulnerable to poverty. Azam and Imai (2009) studied poverty and vulnerability levels in Bangladesh in 2005 and found that many households above the poverty line were also vulnerable to poverty.

Although it is preferable to use panel data collected over long years, theoretical and statistical advances have made it possible to assess vulnerability studies based on cross sectional data (Chaudhuri, Jalan and Suryahadi, 2002). A common approach used to assess vulnerability to food poverty when applying cross-sectional data is to model vulnerability as expected poverty (Chaudhuri, Jalan and Suryahadi, 2002). The probability that household h becomes food poor at time $t+i$ is given by:

$$V_{ht} = prob(\ln f_{h,t+1} < \ln P) \tag{2}$$

Where 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 $t+i$, and P indicates food poverty line of household h, expressed in its natural log.

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:

$$\ln f_h = \alpha X_h + \varepsilon_h \qquad (3)$$

Where X_h is a vector of household's participation in off-farm work and other observable household characteristics (i.e., $\hat{y}$ and 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 of equation (3), the vulnerability to food poverty is estimated as:

$$\hat{V}_{h,t} = prob\left(\ln f_{h,t+i} < \ln P \mid X_{h,t}\right) = \Phi\left(\ln P - \hat{\alpha}\hat{\sigma}X_{h,t}\right) \qquad (4)$$

Where $\hat{V}_{h,t}$ is the estimated vulnerability to food poverty, which is the probability of the individual household's food consumption conditional on the household's participation in off-farm work and other characteristics falling below a given food poverty line. The Φ in equation (4) defines the cumulative density of standard normal distribution and $\hat{\sigma}$ is estimated standard error from equation (3).

While using cross-sectional data for analysis, the assumption of constant variance may not be achieved leading to inefficient estimates (Chaudhuri, Jalan and Suryahadi, 2002). Heteroscedasticity (i.e. the assumption of no constant variance) may be addressed by relating the variance of the consumption function as a linear function of household characteristics as shown in equation (5) below.

$$\sigma^2_{\varepsilon,h} = \beta X_h + \theta_h \qquad (5)$$

Recall from the endogeneity test section that the off-farm work participation may be related with the household's food expenditure. If farm work participation is endogenous, its instrumented value will be used in the subsequent equations. Amemiya's (1977) three-stage Feasible Generalized Least Square (FGLS) approach is then employed to overcome any inherent heteroscedasticity problem. To apply the FGLS approach, first estimate equation (3) using Ordinary Least Squares (OLS) and then using the error term from Equation (3), estimate the following Equation (6) using OLS method:

$$\hat{\sigma}^2_{OLS,h} = \hat{\beta}X_h + \hat{\theta}_h \tag{6}$$

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

The predicted values from equation (6) are used to transform Equation (5) as follows:

$$\frac{\sigma^2_{\varepsilon,h}}{\hat{\beta}x_h} = \beta\left(\frac{x_h}{\hat{\beta}x_h}\right) + \frac{\theta_h}{\hat{\beta}x_h} \tag{7}$$

Equation (7) is estimated using an OLS regression and gives the $\hat{\beta}_{FGLS}$ 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. Then, using the $\hat{\beta}_{FGLS}$, the standard error and the transformed Equation (3) are given by Equations (8) and (9), respectively, as follows:

$$\hat{\sigma}_{\varepsilon,h} = \sqrt{X_h\hat{\beta}_{FGLS}} \tag{8}$$

$$\frac{\ln f_h}{\hat{\sigma}_{\varepsilon,h}} = \alpha\left[\frac{X_h}{\hat{\sigma}_{\varepsilon,h}}\right] + \frac{\varepsilon_h}{\hat{\sigma}_{\varepsilon,h}} \tag{9}$$

Equation (9) is obtained by dividing Equation (3) by the standard error described in Equation (8). The estimated coefficient α is then asymptotically consistent and efficient.

Applying the forgoing to the research problem, and using α_{FGLS} and β_{FGLS}, we estimate the expected log food consumption and its variance by equations (10) and (11), respectively.

$$E\left[\left(\frac{\ln \hat{f}_h}{X_h}\right)\right] = \hat{\alpha} X_h \tag{10}$$

$$Var\left[\left(\frac{\ln \hat{f}_h}{X_h}\right)\right] = \hat{\sigma}_h^{\,2} \quad = \hat{\beta} X_h \tag{11}$$

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

$$\hat{V}_h = prob\left(nf_{h,t+1} < \ln P \mid X_h\right) = \Phi\left[\frac{\ln P - X_h \hat{\alpha}_{FGLS}}{\sqrt{X_h \hat{\beta}_{FGLS}}}\right] \tag{12}$$

For the current study, a vulnerability to poverty threshold of 0.5 will be used (Chaudhuri et al. 2002, Pritchett et al. 2000, Zhang 2008, and Novignon et al. 2012). A household with a 50% or more probability of falling into food poverty in the future (i.e. the next period) is considered vulnerable to food poverty. It is also shown in the literature that using 0.5 as a threshold provides a more improved prediction (Zhang 2008).

Methods

Expenditure aggregates

To develop the total household expenditure, the households' expenditures on different items were organized into their respective categories, annualized, and aggregated. The daily per capita expenditure was obtained by dividing the aggregated household expenditure by the adult equivalent in the household (household size) and then by 365 days. To deal with inflation and facilitate international comparison of the expenditure indicators, the estimates were converted from the local currency into 2010 US dollars (constant prices).

The per capita food expenditure is obtained by dividing the food expenditure per household to the number of AE in the household. In order to avoid bias in the results of the analysis, extreme values of this variable (the lower and upper 1.5%) are excluded and used the 97% of the available data.

Household hunger in the study area

The household hunger scale measures the level of hunger experienced by households in food insecure areas using a number of recall quantities asked to the 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, the household is assumed to have 'little to no hunger' condition. An indicator score of 2 to 3 illustrates 'moderate hunger', while 4 to 6 indicates 'severe hunger' condition in the household.

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 prevalence index, the poverty gap index, and the squared poverty gap index. The poverty prevalence index measures the proportion of households identified as poor or falling below an established poverty line. The poverty gap index, often referred to as the depth of poverty, 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 et al. 1984). Similarly, the study estimates the corresponding food poverty indices as follows:

$$H_\alpha = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{P - E_i}{P}\right]^\alpha \qquad (13)$$

Where H_α is the food poverty index of interest, and α with a value of 0, 1, or 2 represents the incidence, depth, and severity measures, respectively. The variable P is the food poverty line and E_i is the daily per capita food expenditure for each household, i. The above formula is taken to equal to zero if the daily per capita food expenditure for each household, i, is greater than or equal to the food poverty line. Because interpretation of poverty severity measure is not straight forward, the study will present the results of the other two poverty measures only.

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 of the following form:

$$\ln f_h = \delta_1 + \delta_2 C_h \quad (14)$$

Where F_h and C_h measure the value of daily food consumption per AE and daily caloric consumption per AE for household *h*, respectively. From equation *(13)*, the food poverty line P (i.e. the expenditure required to acquire the Recommended Daily Allowance (RDA) calories) is estimated as:

$$P = e^{\hat{\delta}_1 + RDA\hat{\delta}_2} \quad (15)$$

Where $\hat{\delta}_1$and $\hat{\delta}_2$ are estimates of δ_1 and δ_1, respectively, from equation *(14)*. The energy requirements (kcl/day) for a developing country profile, demography and anthropometry, presented in UNHCR et. al. (2004) are used to compute the AE for each household as the product of the households' total daily calorie consumption divided by the sum of the energy requirements for each household member. The Recommended Daily Allowance (*RDA*) is taken to equal 2900 calories per adult per day following the practice adopted by the latest round of Ghana's Statistical Service (GSS) survey (GSS, 2014). The fundamental assumption of equation *(14)* is that all households have a common basket of food which varies according to the household tastes and preferences and income. It also assumes that all households face identical market prices.

Developing 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' livelihoods. For example, the assumption in *equation (14)* that all households have a common basket of food which 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 at the entire study region. In order to satisfy the forgoing assumptions in *equation (14)*, the averages of food poverty lines for each district are estimated and used development of food poverty headcounts. During estimations, probability weights are used to adjust the district level effect in term of size and composition. The use of regional poverty lines has been used in the past and produced superior results (Ozughalu, 2014). The average food poverty line for the study area is 2.8 in 2010 USD Constant Prices.

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 against the Millennium Development Goals of the United Nations (2000). However, its performance has been mixed across regions (Osei-Assibey and Grey, 2013). For example, the three northernmost regions were all found to be lagging 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 used for the study comes 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, excluding the areas falling in Volta Region. The primary objective of the survey was to provide estimates of baseline indicators for USAID's Feed the Future initiative for the region covered by the survey. Among the indicators are children's and women's anthropometry, which estimates their health statuses, and women's dietary diversity measurements. There were 4410 households and nearly 25,000 individuals included in the population-based survey. The data covered demographic and socio-economic characteristics as well as educational information of the parents. Only 2,243 households had all the relevant variables needed for addressing the research problem in this research. Probability weights are used to make estimated results representative of the population in study area.

Results

Descriptive results

Expenditures on food and non-food aggregates

The average daily per capita total expenditure is $4.10 (Table 1). The expenditure sub-aggregates are 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 stationaries 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, and etc. The allocation of the daily per capita total expenditure on the seven different consumption categories are as follows: food ($2.53); education ($0.04); health ($0.08); non-food (0.91); rent (0.20); utility (0.09); and durables ($0.24). This implies that food accounted for 63 cents of each dollar of average daily per capita expenditure. Of the remaining 37 cents, non-food accounted for 21 cents, with both durables and house rent accounting for 11 cents and education, health, and utility altogether accounting for 5 cents.

Table 1 about here.

For these households, because food expenditure holds a significant proportion of their income expenditure, any factor that affects their income will proportionally affect their expenditure ability on food. The observed higher proportion of expenditure spent on food is fairly consistent across the different groups aggregated by expenditure deciles (Figure 1). Applying Engel's theory, it may be 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 proportional decline does not start until the 6th expenditure decile. In fact, the trend of the proportion of income spent on food increases at first as one moves from the lower expenditure decile up until the 5th expenditure decile and then gradually decreases from the 6th decile onwards. The exact opposite happens to the trend of the expenditure proportion on the aggregate expenditure on everything else other than food (Figure 1)

Figure 1 about here.

Statistical comparisons of the food expenditure as a proportion of their total expenditure by expenditure, by decile, is done to understand the allocation behavior of households, particularly on food. It is observed that the expenditure share on food for the upper 10th percentile is only significantly different 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 food poverty in particular and to poverty in general. 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.

Food poverty and household hunger

The prevalence of food poverty in the study area stands at 54.7% at the household level. The overall prevalence rate of households with moderate to severe hunger in the study area, as indicated by a score ≥ 2 on the household hunger scale measurement, is 36%.

Even though hunger and food poverty do not refer to the same concept in that food poverty is a result of cumulative effect of the household's deprivation situation overtime while hunger (especially extreme cases of hunger) could be a temporary one, 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 household's food poverty and the experience of hunger (Table 2). A cross tabulation analysis of food poverty and hunger statuses shows that, a total of 57.5% of the households are identified as food poor, but have not experienced moderate to severe hunger. Only 28% 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 (42.6%) have experienced food poverty and has fallen into moderate to extreme hunger at the same time. It's highly likely that a household that is identified as food poor will experience some form of hunger situation.

Table 2 about here.

Descriptive statistics of the variables used in the vulnerability model

Table 3 presents descriptive statistics of the variables used for the analysis. The daily average per capita expenditure on food is 3.26 (measured in 2010 USD constant prices) with a standard deviation of 4.46 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 down side risk to food shortages. More than six in ten of the households have a source of off-farm income. The average age of the head of the household is around 45 years and it ranges from 18 to 100 years. The average number of education years attained by a primary respondent and the secondary respondents are little more than 2 years and 0.88 years, respectively. The cumulative years of education years per household also shows that an average household has a total of 44.5 years of schooling, ranging from none to as high as 106 years of schooling. This high value of standard deviation (101.61) for the cumulative education also shows the huge disparity in educational level within the households. The average plot of land allocated to crops is 0.74 acres with a standard deviation of 1.42 acres. The average per unit yield return is estimated to be around 22.6 GHC per acre. Access to credit indicates the availability of mostly credit in the form of cash that is seen as a means of easing liquidity constraints for the households. Almost 40% of the households have access to credit. A majority of the households (81%) own their house. Access to private toilet is considered to provide 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. More than 1 quarter of the households have access to private toilet. A similar proportion of the households have indicated that they have access to electricity as well. The ownership of large durable goods is also an indication of relative standard of living. For example the ownership of refrigerator by the household allows the household to safely store perishable food items and other valuable items for longer periods of time. Only 6% of the households do have refrigerator. Slightly less than a quarter (23%) of the households has access to potable water. 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.

Table 3 about here.

Estimation results

Endogeneity test and results

The results of the first stage probit regression of the LRET model for the participation of households in off-farm work showed that the ownership of motor bike, ownership of mobile phone, household head's education, spouse's education, and locality significantly ($p< 0.01$) influence households' participation in off-farm work (Table 4) . The model statistics for the probit model indicated a pseudo R-squared of 8.42 % and the model predicts household off-farm work with 67.50% accuracy. Pairwise correlation analysis with Bonferroni's adjustment of instruments with off-farm work showed that all the instruments are significantly correlated with off-farm work. The estimated correlation (ρ) between the error terms in the first stage and second stage models is significant ($p< 0.05$) indicating that participation in off-farm work is indeed endogenous. For consistency purposes, the discussion of results in the following sections will be based on estimations using the instrumented values of the off-farm work variable.

Vulnerability to Food Poverty

The prevalence of vulnerability to food poverty by household's participation in off-farm work and other distributional characteristics of the household are presented in Table 4. The overall prevalence of vulnerability to food poverty in the study area is 61%. The table shows that the prevalence of food poverty for households participating in off-farm work is less (49.8%) compared to households not participating in off-farm work (88.9%), a difference that is significant at less than 5% alpha level. The regional prevalence to food poverty vulnerability shows that the Upper West and Upper East regions have the highest prevalence compared to the other two regions; the difference with both regions being statistically significant only in comparison to the Northern region. It is also the case that rural households are significantly more vulnerable (66.8%) compared to urban households (37.2%) at less than 5% alpha level. In terms of the expenditure deciles, as would be expected, the vulnerability figures are higher at the lower end of the expenditure deciles. However, it is evident from the results that even the higher expenditure deciles are still prone to food poverty with the lower 4 deciles having more than the overall average vulnerability rate. Pair wise comparison tests between the expenditure deciles shows that in 73% of the comparisons, the differences in vulnerability are statistically different from each other at the 5% significance level. It turns out that the strength of significance increases as one move from the lower deciles to the higher deciles (i.e. the difference between the bottom decile and second lowest decile is less stronger than the difference between the bottom decile and the third lowest decile and so on).

Table 5 about here.

Finally, Pearson's chi-squared independence test reveals that both the status of food poverty and vulnerability to food poverty are not independent from each other (Table 5). The chi squared independence test shows that food poverty and food vulnerability are in fact positively related and the relationship is statistically significant at less than 5% level.

Table 6 about here.

Determinants of vulnerability to food poverty

The result from the regression models (IV and OLS models) developed to estimate the expected future consumption of food is presented in Table 7. As might be expected, the OLS results may be inconsistent due to the endogeneity effect of the off-farm work variable. To get an intuitive assessment of this effect, if participation in off-farm work leads to higher food consumption expenditure and this effect feeds back to higher likelihood of participating in off-farm work, then the OLS estimates may overestimate the actual marginal values. For the off-farm work variable, the empirical results show that the OLS estimate (0.410) is higher than the IV estimate (0.362) which confirms the *apriori* expectation. The participation in off-farm work was significantly and positively associated with the future mean consumption expenditure on food. Holding other variables constant, households that have a source of off-farm income have significantly higher expected mean consumption on food. This result provides further evidence to previous research that shows positive association of participation in off-farm work and household expenditure. Owusu and Abdulai (2009) have drawn a similar conlcusion from a study conducted in northern Ghana by showing that participation in off-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) showed that off-farm work improved caloric consumption in Burkina Faso and Honduras, respectively. Ersado (2006) also found a positive association between off-farm income diversification and consumption expenditure in Zimbabwe. Using farm survey data from Nigeria, Babatunde and Qaim (2010) also showed that off-farm income had a positive net effect on caloric intake, dietary quality, and micronutrient supply. Using a structural econometric model, they showed that off-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 off-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. In a study conducted in Vietnam and India, Imai et al. (2015), examined impact of off-farm income on households' income and consumption and found that, off-farm income consistently increased consumption per capita, which in turn reduced poverty and vulnerability in both countries. Households engaged in off-farm income activities in the southwest zone of Nigeria also experienced increased household income, had less poverty, and higher welfare (Awoniyi and Salman, 2011). Ruben (2001) also examined the role of off-farm income on poverty using national income and expenditure survey data in rural Honduras, and found that off-farm activities improved food security, and helped farmers to purchase external inputs.

Employment in the non-agricultural sector is believed to increase 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 (e.g. Abdulai and Delgado, 1999; Matshe and Young, 2004). Off-farm work in the non-agricultural sector also complements farm productivity, in that it increases the household's capacity to purchase farm inputs, both fixed and variable inputs, thereby improving its labor productivity and ultimately yield and income (Ruben, 2001, Cover, 2003). A similar study conducted in Colombia by Deininger and Olinto (2001) has shown no adverse effect between farm and off-farm income as farming households engaged in off-farm work as a means of diversifying their income.

The following control variables are significantly and positively correlated with the expected daily per capita expenditure on food: years of schooling for the household head, and years of schooling for the spouse of the household head, area of land allotted to key crops (maize, rice, and soybean), access to credit, access to toilet, access to electricity, availability of fridge in the household, urban locality, and access to potable water. For example, households whose heads and the spouses have higher years of schooling have higher future mean consumption on food. This result further supports previous results that show households headed by employed and educated men are less vulnerable to shocks than other households groups (Ligon and Schechter, 2003).

Households' characteristics that suggest relatively better standard of living (e.g. access to electricity, toilet, and ownership of fridge) have significantly higher future mean daily per capita expenditure on food. Variables that were 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 household's land productivity. The higher the proportion of dependents in the household, the lower is the mean future daily per capita expenditure on food. This is an indication that households with high proportion of dependents are vulnerable to future food poverty. This result is in line with previous studies that confirmed that households with more number of children were found as more food vulnerable than households with less number of children (Christiaensen and Boisvert, 2000). The results on the cumulative household's years of education and the household's land productivity appear to be counter intuitive, although the coefficient of the household's land productivity is almost zero. Other variables such as age of household's head, minimum age of a child, and ownership of house were not significantly associated with the dependent variable.

Table 7 about here.

Conclusion and Recommendations

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

Farmers in northern Ghana are heavily dependent on agricultural (Zereyesus et al, 2014). With farm characteristics such as low income from rain fed agriculture, inadequate information, lack of knowhow, lack of access to sufficient and improved farm implement and supplies, and 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.

It is believed that non-agricultural sector could play a significant role in reducing households' poverty and food insecurity (Barrett et al., 2001; Emran and Hou, 2013; Ferreira and Lanjouw, 2001; Hoang et al., 2014; Oseni and Winters, 2009; Owusu and Abdu, 2009; Reardon et al., 2001; Ruben, 2001). Employment in the non-agricultural sector is also believed to equip households with better coping strategies in times of shocks as a result of increased average household income and consumption and reduced household budget constraints (e.g. Abdulai and Delgado, 1999; Matshe and Young, 2004).

While empirical support to the impact of off-farm work on poverty and food security in developing countries abound, research assessing the relationship between off-farm income and vulnerability to food poverty has been very limited. Resource poor households allocate a sizable proportion of their expenditure on food consumption. For example, in our study area, the households spend on average 63% of their expenditure on food consumption and almost 40% of households have experienced a moderate to severe form of household hunger, which is 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 off-farm income on these farm households' expected food consumption.

The objectives of the study are in twofold: First, we aim to examine the impact of household's participation in off-farm work on the extent of vulnerability to food poverty in the study area. An instrumental variable is used to overcome the endogeneity problem associated with off-farm work participation and the food consumption expenditure, applying three stage regression estimation approach (Adams et al. 2009). Second, we want to investigate the association between vulnerability to food poverty and the overall prevalence of food poverty in the study area. The study argues that food poor households are more vulnerable to food poverty because they spend the largest proportion of their expenditure on food and they are the most vulnerable to economic and non-economic shocks. Participation in off-farm work is indeed endogenous in the model. Therefore, using the instrumented off-farm work participation, a Feasible Generalized Least Squares (FGLS) method is employed to analyze determinants of expected future food expenditure. Results show that participation in off-farm work significantly increased the future expected food consumption and thereby reduces the vulnerability to food poverty. It is also confirmed that that food poverty and vulnerability to food poverty are related to each other. While designing policies, it is important to recognize the crucial role that off-farm income plays in providing the means of overcoming the risk of food poverty that these resource poor households face.

References

Abdulai, A., & Delgado, C. L. (1999). Determinants of nonfarm earnings of farm-based husbands and wives in northern Ghana. *American Journal of Agricultural Economics, 81*(1), 117-130.

Acheampong, E. N., Ozor, N., & Owusu, E. S. (2014). Vulnerability assessment of northern Ghana to climate variability. *Climatic Change, 126*(1-2), 31-44.

Adams, R., Almeida, H., & Ferreira, D. (2009). Understanding the relationship between founder–CEOs and firm performance. *Journal of Empirical Finance, 16*(1), 136-150.

Amemiya, T. (1977). The maximum likelihood and the nonlinear three-stage least squares estimator in the general nonlinear simultaneous equation model. *Econometrica: Journal of the Econometric Society*, 955-968.

Awoniyi, O. A., & Salman, K. K. (2011). Off-farm income diversification and welfare status of rural households in south west zone of Nigeria. Paper presented at the *A Conference Organized by IFPRI in Conjunction with the AV, UNECA and FARA in 1st–3rd Nov in Addis Ababa, Ethiopia.*

Azam, M. S., & Imai, K. S. (2009). Vulnerability and poverty in Bangladesh. *Chronic Poverty Research Centre Working Paper,* (141).

Babatunde, R. O., & Qaim, M. (2010). Impact of off-farm income on food security and nutrition in Nigeria. *Food Policy, 35*(4), 303-311.

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food policy*, *26*(4), 315-331.

Chaudhuri, S., Jalan, J., & Suryahadi, A. (2002). Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia.

Christiaensen, L. J., & Boisvert, R. N. (2000). *On measuring household food vulnerability: Case evidence from northern Mali*, Department of Agricultural, Resource, and Managerial Economics, Cornell University.

Christiaensen, L. J., & Subbarao, K. (2005). Towards an understanding of household vulnerability in rural Kenya. *Journal of African Economies, 14*(4), 520-558.

Deininger, K., & Olinto, P. (2001). Rural nonfarm employment and income diversification in Colombia. *World Development, 29*(3), 455-465.

Dercon, S., & Krishnan, P. (2000). Vulnerability, seasonality and poverty in Ethiopia. *The Journal of Development Studies*, *36*(6), 25-53.

Emran, M. S., & Hou, Z. (2013). Access to markets and rural poverty: Evidence from household consumption in china. *Review of Economics and Statistics, 95*(2), 682-697.

Ersado, L. (2006). *Income diversification in Zimbabwe: Welfare implications from urban and rural areas* World Bank Publications.

FAO (2014) The State of Food Insecurity in the World 2014. Strengthening the enabling environment for food security and nutrition. Food and Agriculture Organization of the United Nation, FAO, Rome, Italy

Ferreira, F. H., & Lanjouw, P. (2001). Rural nonfarm activities and poverty in the Brazilian northeast. *World Development, 29*(3), 509-528.

Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica: Journal of the Econometric Society,* 761-766.

GSS (2012) 2010 Population and Housing Census Summary Results of Final Report. Accra,Ghana.

Heckman, J. (1979). Sample Selection Bias as a Specification Error, Econometrica, 47 (1). *161*, 153.

Hoang, T. X., Pham, C. S., & Ulubasoglu, M. A. (2014). Off-farm activity, household expenditure, and poverty reduction in rural Vietnam: 2002–2008. *World Development, 64*, 554-568.

Imai, K. S., Gaiha, R., & Thapa, G. (2015). Does off-farm sector employment reduce rural poverty and vulnerability? Evidence from Vietnam and India. *Journal of Asian Economics, 36*, 47-61.

Kurosaki, T. (2002). Consumption vulnerability and dynamic poverty in the North-West Frontier province, Pakistan. *Institute of Economic Research*.

Lanjouw, P. (1998). Ecuador's rural nonfarm sector as a route out of poverty. *World Bank Policy Research Working Paper,* (1904).

Ligon, E., & Schechter, L. (2003). Measuring vulnerability. *The Economic Journal, 113*(486), C95-C102.

Matshe, I., & Young, T. (2004). Off-farm labor allocation decisions in small-scale rural households in Zimbabwe. *Agricultural Economics, 30*(3), 175-186.

Madalla, G. S. (1983). Limited-dependent and qualitative data in econometrics.

McCulloch, N., & Calandrino, M. (2003). Vulnerability and chronic poverty in rural Sichuan. *World Development, 31*(3), 611-628.

Novignon, J., Nonvignon, J., Mussa, R., & Chiwaula, L. S. (2012). Health and vulnerability to poverty in ghana: Evidence from the Ghana living standards survey round 5. *Health Economics Review, 2*, 11-1991-2-11. doi:10.1186/2191-1991-2-11

Oseni, G., & Winters, P. (2009). Rural nonfarm activities and agricultural crop production in Nigeria. *Agricultural Economics, 40*(2), 189-201.

Osei-Assibey, E. and S.K. Grey. (2013). Millennium Development Goals in Ghana. 2010 Population and Housing Census Report, Ghana Statistical Service.24.

Owusu, V., & Abdulai, A. (2009). Nonfarm employment and poverty reduction in rural Ghana: A propensity-score matching analysis. Paper presented at the *International Association of*

Agricultural Economists Conference, Beijing, China. Retrieved from *Http://purl.umn.Edu/51363* on November 2015

Ozughalu, U. M. (2014). Relationship between household food poverty and vulnerability to food poverty: Evidence from Nigeria. *Social Indicators Research*, 1-21.

Pritchett, L., Suryahadi, A., & Sumarto, S. (2000). *Quantifying vulnerability to poverty: A proposed measure, applied to Indonesia*, World Bank Publications.

Reardon, T., Berdegué, J., & Escobar, G. (2001). Rural nonfarm employment and incomes in Latin America: Overview and policy implications. *World Development*, *29*(3), 395-409.

Ruben, R. (2001). Nonfarm employment and poverty alleviation of rural farm households in Honduras. *World Development*, *29*(3), 549-560.

SRID-MOFA (2013) Agriculture in Ghana: Facts and figures (2012). Accra,Ghana

USDA (2012) USDA National Nutrient Database for Standard Reference Release 27. In: United States Department of Agriculture Agricultural Research Service. http://ndb.nal.usda.gov/ndb/.

World Bank, 2012. Retrieved from http://data.worldbank.org/country/ghana on October 14, 2015

World Bank, 2013. Retrieved from http://data.worldbank.org/country/ghana on October 14, 2015

World Bank, 2014. Retrieved from http://data.worldbank.org/country/ghana on October 14, 2015

Zereyesus YA, Ross KL, Amanor-Boadu V, Dalton TJ (2014) Baseline Feed the Future Indicators for Northern Ghana 2012. Manhattan, KS.

Zhang Y, Wan G (2008) Can we predict vulnerability to poverty. In World Institute for Development Economics Research Paper No 2008/82.

Table 1. Average Daily Per Capita Expenditure By Consumption Category in Constant 2010 Prices (US$)

Consumption Category	Average Expenditure (USD)	Standard Error	95% Confidence Interval	
			Lower	Upper
Food	2.53	0.07	2.39	2.67
Education	0.04	0.00	0.03	0.05
Health	0.08	0.00	0.07	0.09
Non-food	0.91	0.07	0.78	1.04
Rent	0.20	0.01	0.19	0.22
Utility	0.09	0.01	0.08	0.10
Durables	0.24	0.02	0.20	0.28
Total	4.10	0.12	3.87	4.33

Fig 1. Expenditure Shares by Consumption Category by Expenditure Deciles

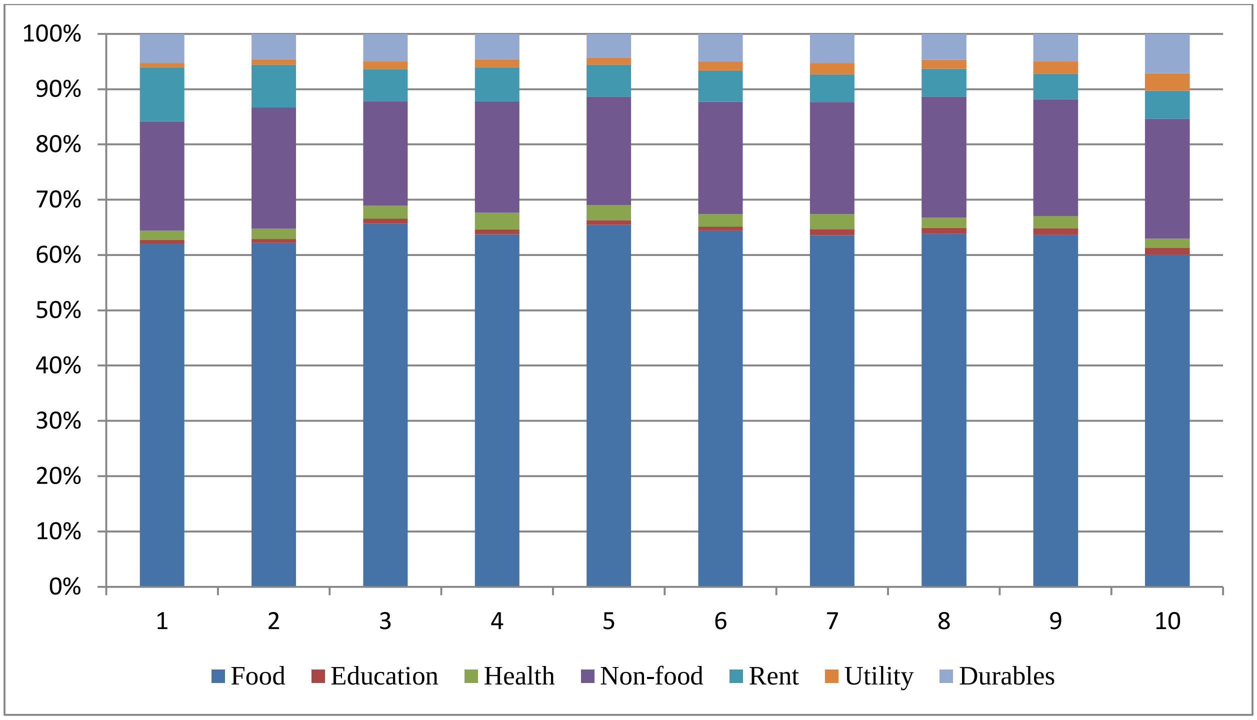

Table 2. The food poor and the hungry (percent).

	Little to No household hunger	Moderate to severe household hunger	Total
Non-Poor	72.04	27.96	100.00
Poor	57.45	42.55	100.00
Total	64.05	35.95	100.00
Pearson Chi2 (1): 82.9288			
Probability: 0.000			

Table 3. Summary statistics of the principal variables used in the study (N=2243)

Variable	Description	Mean	Std. Dev.
Off-farm work	1= Household has off-farm income source; 0=otherwise	0.64	0.48
Food expenditure	Daily per capita food expenditure (2010 USD Constant Prices)	3.26	4.46
Age of head	Age of household head	44.85	15.31
Minimum age children	Minimum age of child in the household	3.55	3.50
Primary respondent education	Years of schooling of primary respondent	2.35	5.42
Secondary respondent education	Years of schooling of secondary respondent	0.90	3.38
Household cumulative education	Cumulative Years of schooling of the members of the household	44.53	101.61
Land area	Land area (hectare)	0.74	1.42
Credit	1= Household has access to credit; 0=otherwise	0.38	0.49
House owned	1= Household owns house; 0=otherwise	0.81	0.39
Toilet	1= Household owns private toilet; 0=otherwise	0.27	0.44
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	0.27	0.45
Refrigerator	1= Household owns refrigerator; 0=otherwise	0.06	0.23
Locality	1= Household located in urban; 0=otherwise	0.22	0.42
Water	1= Household has access to potable water; 0=otherwise	0.23	0.42
Dependents	Proportion of dependents in the household	0.47	0.15
Land productivity	Per unit land productivity (GHC/acre)	22.60	363.94

Table 4. First stage probit regression and the endogeneity test results from the LRET Model

Instrument	Coef. (Robust Std. Err.)
Household owns motor vehicle	0.301
	(5.57)***
Household owns mobile phone	0.216
	(3.85)***
Head schooling	0.038
	(6.54)***
Spouse schooling	0.033
	(3.26)***
locality	0.651
	(8.55)***
Constant	-0.126
	(3.30)***
ρ	-0.562
	(6.73)***
Sigma	0.321
	(12.11)***
N	2,295

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 off-farm income and other household's distribution characteristics with off-farm income instrumented

	Mean Vulnerability (percent)	Std. Err.
Overall	60.5	0.1
Household has Off-farm income		
No	88.9	0.1
Yes	49.8	1.2
Region		
Brong Ahafo	66.6	3.1
Northern	54.6	0.1
Upper East	73.9	2.3
Upper West	76.1	2.5
Locality		
Rural	66.8	0.1
Urban	37.2	2.2
Total Expenditure Deciles		
1	85.3	0.1
2	69.5	1.7
3	68.8	1.8
4	66.8	2.2
5	60.4	2.3
6	57.6	2.5
7	51.3	2.6
8	51.1	3.0
9	42.8	3.3
10	38.6	5.0

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

	Non-vulnerable	Vulnerable	Total
Non-Poor	56.14	43.86	100.0
Poor	28.94	71.06	100.0
Total	39.50	60.50	100.0
Pearson Chi2 (1): 165.0188			
Probability: 000			

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

	OLS estimates	IV estimates
Off-farm work	0.410	0.362
	(6.63)***	(5.30)***
Age of head	-0.002	-0.001
	(0.95)	(0.79)
Minimum age children	-0.007	-0.004
	(0.83)	(0.45)
Household schooling	-0.001	-0.001
	(2.12)**	(2.50)**
Land area	0.035	0.041
	(2.41)**	(2.39)**
Credit	0.161	0.125
	(2.74)***	(2.05)**
House owned	-0.051	-0.079
	(0.69)	(1.08)
Toilet	0.396	0.364
	(5.36)***	(4.81)***
Electricity	0.470	0.453
	(5.77)***	(5.39)***
Refrigerator	0.834	0.892
	(7.83)***	(8.42)***
Water	0.404	0.432
	(3.28)***	(3.48)***
Dependents	-0.122	-0.070
	(0.84)	(0.47)
Land productivity	-0.000	-0.000
	(6.94)***	(5.12)***
R^2	0.33	0.32
N	2,243	2,243

Significance levels: *p<0.1 ** p<0.05, ***p<0.0.

Appendix: Supplemental materials

Notes A1: Technical notes on food quantity standardization to kilocalories

Data on households' consumption for eleven categories of food items were collected by the population-based survey. These included: (1) Fruits, (2) Vegetables, (3) Roots/Tubers/Plantains, (4) Nuts/Pulses, (5) Cereals/Cereal Products, (6) Fish/Animal Products, (7) Sugars/Fats/Oils, (8) Milk /Milk Products, (9) Beverages, (10) Spices/Miscellaneous, and (11) Cooked Foods from Vendors.

A four-step procedure was used in converting all food units to kilograms.

Step 1: Local food units conversion to kilos or liters

This step involved converting local food units for the respective food items to kilos or liters, using conversion factors available in the literature and information inherent in the collected data. This was done as follows:

i. For all the food categories, kilograms (liters) was used when the stated unit of measurement was recorded as kilogram (liters). Kilograms (liters) in other metric prefixes (gram, pound, gallon, and etc.) , were converted to kilograms (liters) using the appropriate conversion factor;

ii. Vegetables, Fruits, and Roots/Tubers/Plantains were converted to kilograms using average fruit weights retrieved from USDA (2014) when the local food units was recorded as “PIECE”, "BULB", "BALL", or "TUBER". These average fruit weights are presented in Table A2.

iii. For Nuts/Pulses, and Cereals/Cereal Products, unit conversion were based on “*Olonka*” conversion factors retrieved from Nagai (2008), where the stated unit of measurement was either "AMERICAN TIN, "CUP", "MARGARINE TIN", "OLONKA BOWL". *“Olonka”* is the standard of measure for many foods used in local markets in Ghana. It consists of empty margarine tin cans or plastic containers, and they vary by size depending on price and the product being sold. See Table A3 for the conversion factors.

iv. For food items which did not have any known conversion factors (Beverages, Spices /Miscellaneous and Cooked Foods from Vendors) were stated in value terms to be later converted into calories in the last step.

v. Unit of measurement for Fish/ Animal Products, Sugars/Fats /Oils, and Milk/Milk Products where mostly exclusively stated in kilograms of liters, hence no conversion was required.

Step 2: Converting liters to kilograms

Food densities retrieved from Charrondiere et al. (2012) were utilized in converting food quantities in liters to kilograms.

Step 3: Converting kilograms to kilocalories

The estimated kilogram of each food item were converted to kilocalories using food composition table retrieved from Stadlmayr et al. (2012).

Step 4: Estimating kilocalories for food items which did not have any known conversion factors

To estimate caloric consumption from food items which did not have any known conversion factors (Beverages, Spices/Miscellaneous and Cooked Foods from Vendors), we first estimated the average unit cost of caloric consumption for food items for which the caloric intake and value of consumption were available in the collected data. The value of consumption of the food items which did not have any known conversion factors were then divided by the estimated average unit cost of caloric consumption to get an estimate of total caloric intake from these food items.

Table A1: Average fruit weights from USDA National Nutrient Database

NDB No.	Description	Weight (g)
9004	Apples, raw, without skin	149
9038	Avocados, raw, California	136
9040	Bananas, raw	101
18064	Bread, wheat	28.35
11109	Cabbage, raw	714
11124	Carrots, raw	50
11900	Corn, sweet, white, raw	73
11900	Corn, sweet, white, raw	73
11205	Cucumber, with peel, raw	301
1123	Egg, whole, raw, fresh	38
11209	Eggplant, raw	548
9139	Guavas, common, raw	55
9176	Mangos, raw	336
11987	Mushrooms, oyster, raw	15
12104	Nuts, coconut meat, raw	397
12104	Nuts, coconut meat, raw	397
11278	Okra, raw	95
11282	Onions, raw	70
9205	Oranges, raw, with peel	159
9226	Papayas, raw	157
11962	Peppers, hot chile, sun-dried	0.5
9266	Pineapple, raw, all varieties	905
9277	Plantains, raw	179
11422	Pumpkin, raw	771
11507	Sweet potato, raw, unprepared	130
11518	Taro, raw 26	104
11529	Tomatoes, red, ripe, raw, year round average	62
9326	Watermelon, raw	122

Source: USDA (2014)

Table A2: Olonka conversion from Nagai, T. (2008)

Container	Circumference (cm)	Height (cm)	Volume (cm^3)	Olonka equivalence
Olonka	51.0000	17.2000	3560.0000	1.0000
Margarine tin	28.0000	10.2000	636.0000	0.1787
Conversion				
	kg/Olonka		kg/rubber cup	
Commodity	Flat to cup	Heaped up	Flat to cup	Heaped up
Cowpea	2.2291	2.5094	-	-
Gari	1.7174	1.9782	-	-
Groundnut	1.9803	2.2426	-	-
Maize	2.3043	2.5344	-	-
Millet	2.355	2.6504	-	-
Onion	1.6037	3.1123	-	-
Pepper	0.6193	0.8642	-	-
Sorghum	2.3666	2.6878	-	-
Soybean	2.2377	2.5039	-	-
Tom Brown	1.4406	1.7080	-	-
maize dough	-		3.2998	6.8033

Source: Nagai (2008)