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POVERTY IN UPPER WEST REGION OF GHANA: DETERMINANTS AND POLICY PRESCRIPTIONS

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Abstract
This study examines the factors influencing monetary and non–monetary poverty in Upper West Region of Ghana. The authors relied on primary data collected using a questionnaire from 395 households to construct a multidimensional non–monetary measure of poverty using the Multiple Correspondence Analysis (MCA) while invoking instrumental variables estimation approaches that deal with potential endogeneity eminent in poverty studies. The results reveal varying determinants of both measures of poverty. The findings indicate that, gender matters more for non–monetary poverty than monetary poverty while household size and educational level robustly influences only monetary poverty. Age weakly affects only non–monetary poverty albeit in a non–linear fashion. Access to microcredit, savings and gainful employment individually reduces household poverty while improving welfare. Job insecurity accelerates poverty irrespective of the measure while remittance and financial inclusion are exceedingly crucial for only non–monetary poverty. Although crop loss and idiosyncratic risks increase household poverty, they mean less for non–monetary poverty. In addition to finding weak impact of government social protection programmes on poverty, we also do not find any dampening effect of such programmes on household shocks. To the extent that households are exposed to spatial and idiosyncratic shocks in the face of weak protection programmes, we call for a new broad set of policies and safety nets capable of insulating households against these vagaries.

Keywords: Monetary poverty, non-monetary poverty, shocks, IV-probit, Wa

Introduction
The World Bank (1990: 26) defines poverty as "the inability to attain a minimum standard of living". Undoubtedly, to the extent that poverty is dynamic and diverse do not allow a generally accepted definition although it is largely used to denote deprivations writhed either in monetary or non–monetary terms or both. In monetary terms, poverty is concerned with inadequate income and low purchasing power to purchase basic essential consumption goods and services for survival, while non–monetary poverty is associated with low asset ownership, poor housing conditions, social and financial exclusion, poor nutrition and health, inadequate access to public services and low educational attainment among others (World Bank, 2001). Given this, poverty is increasingly seen as a multidimensional concept that goes beyond the narrowed income–based approach. Thus, combining issues around the multidimensional indicators to broadly measure and analyze poverty is gaining more attention in the literature (Alkire and Santos, 2010; Alkire and Foster 2011; Ezzrari and Verme, 2012; Guedes et al., 2012; Ningaye et al., 2011; Wang and Alkire, 2009; Jansen et al., 2015).

Despite the discovery of commercial offshore oil reserves in 2007 and the subsequent attainment of a middle income country status in 2010 on the back of impressive growth rates in the past decade, poverty is still rife in Ghana notwithstanding the decreasing rates. Cooke et al. (2016) provide detailed poverty analysis in Ghana. On the trends of poverty, between 1992 and 2013, the country's poverty level decreased by more than half, from about 57% to 24%, indicating the country's achievement of the first Millennium Development Goal (MDG) target albeit slow substantial annual reduction rate since 2006. However, the poverty incidence continues to be higher in rural areas relative to the urban areas. Evidence from the recent trends of poverty in Ghana suggests that Upper West Region is the poorest region with a poverty incidence of 71% higher than the national average of 24%.[1] The higher rates of poverty in the country have since propelled successive governments to embark on prominent social protection intervention strategies [notably the Livelihood Empowerment Against Poverty (LEAP), Fertilizer Subsidy Policy National Health Insurance Scheme (NHIS) among others]. Indeed, all these programmes are targeted at addressing the structural causes of poverty.

The prevalent nature of poverty across the globe has called for thorough examination of the determinants of poverty. Baulch and Hoddinott (2000) and Dercon and Shapiro (2007) surveyed several studies on poverty dynamics in the developing world. The burgeoning studies on the determinants of poverty have among others identified demographics, socio-economic, physical assets and access to improved public services and social protection programmes as important conduits to help explain households' poverty status and resilience to shocks. Jalan and Ravallion (1998) argue that variations in demographic factors such as large household size are positively related to chronic poverty. Alisjahbana and Yusuf (2003) also contend that higher human capital proxied by number of years of schooling lowers the probability of being chronically poor thus improving on household's capacity to withstand shocks.

Undoubtedly, despite poverty being a multifaceted concept, at the empirical front, it is largely measured along income - based and categorized into the absolute and/or relative monetary terms. This approach, however, makes the view on poverty far from reality. To the extent that social relations and the other welfare indicators are left out potentially renders monetary-based measures misleading. Sadly, majority of these studies appear to leave little room for multidimensional poverty existing which does not unearth the other crucial aspects of poverty. This study thus aims to empirically examine the factors that uniquely influence monetary and non-monetary poverty. We also assess whether the effect of government's social protection programmes on both measures of poverty differ. Beyond the direct effect of such programmes, we also aim to determine whether efforts by successive governments through spending on social protection policies help dampen or magnify the effect of household shocks on poverty.

This paper specifically aims at examining the determinants of poverty in Upper West Region of Ghana. It contributes to existing studies on poverty in many ways. As a pioneering work in Ghana and probably in Africa, this study unearths the drivers of monetary and non–monetary poverty where the latter is constructed as a Composite Welfare Index (CWI) to capture the multidimensional aspect of poverty. Secondly, it offers crucial information to extend understanding on the effect of shocks and government policies and how they interact to influence household poverty. Methodologically, we use different estimation approaches that account for potential endogeneity often prevalent in several studies on poverty notably Fields et al. (2003), Haddad and Ahmed (2003), Dartanto and Nurkholis (2013), Donkoh (2010) and Musah et al. (2016) among others.

The rest of the study is structured as follows: the next section provides a brief review of the determinants of poverty while Section 3 outlines our methodology. Section 4 presents our empirical findings and discussion with Section 5 concluding the study with key implications for policy.

Empirical Literature on the Determinants of Poverty

Indeed, reducing poverty is a global concern featuring strongly in the first Sustainable Development Goals (SDGs). Given this understanding, several attempts have been made to identify factors influencing poverty. However, most of these studies do not relate to Africa where poverty is rife (see Shirazi, 1995; Dartanto and Nurkholis, 2013; Alkire et al., 2017). Even the few studies on

[1] For detailed background to poverty in Ghana, see GSS (2014 a,b); Ibrahim and Yeboah (2014); Musah et al. (2016).

Africa are largely concentrated in Southern Africa (see for instance Oluoko–Odingo, 2009; Mukherjee and Benson, 2013; Jansen et al., 2015) where poverty levels are not as high compared to Western Africa.

Okidi and Kempaka (2002) observe that self-employed farming households in Uganda are more probable to be chronically poor. There is also evidence that household heads working in the agricultural sector are more likely to be poor owing to the low productivity and earnings (see Dercon and Krishnan 2000; Okidi and Kempaka 2002). However, Kedir and McKay's (2005) evidence suggests that households in Ethiopia with a head working as a waged employee are less likely to be poor.

Fields et al. (2003) analyze the dynamics of household per capita incomes relying on longitudinal data sets from Indonesia, South Africa, Spain and Venezuela. Evidence from their study shows that age of the household head, gender, change in the number of children, household location, employment status of the head and change in employment status of the head are significant determinants of poverty. Haddad and Ahmed (2003) examined the determinants of total, chronic, and transitory poverty in Egypt using quantile regression where varying factors were found. For instance, the number of years of schooling of adult household member reduces the forms of poverty with huge effect on chronic poverty. The value of land and livestock reduces (increases) chronic (transitory) poverty while large number of children under 15 and household size increases both total and chronic poverty. Further results show that relative to rural households, households in urban areas have a lower probability of falling into transitory poverty.

In the case of South Africa, Jansen et al. (2015) rely on the National Income Dynamics Study (NIDS) data to examine the determinants of poverty across various objective and subjective methods. To measure poverty, the authors use absolute and relative monetary approaches in addition to life satisfaction, and other subjective indicators of multidimensional poverty. Results from their multivariate analysis reveal varying drivers of poverty across the monetary and non–monetary measures. For instance, while relative to the employed, unemployed household head and increases in number of children are positively associated with poverty in all the methods, the effect of education on poverty is negative and only significant for the monetary-based approach. Similar results are also obtained for marital status suggesting that those who are married or cohabitating are less likely to be poor. Compared to females, males are associated with a significantly lower likelihood to be poor based on only the income–based measure. In addition, while increases in age heighten poverty for all the methods, there exists an inverted U–shaped nexus of age and poverty for only the monetary–based approach. Households' access to private assets, permanent employment and medical aid coverage have a significantly negative impact on the likelihood of being poor across all methods.

Using the sixth wave of the Ghana Living Standard Survey (GLSS 6), Musah et al. (2016) highlight the level of income (in)equality in the three Northern Regions of Ghana (Upper West, Upper East and Northern) using Lorenz curves where real household consumption expenditure is used as a proxy of income. Their findings show a relatively lower Gini coefficient of 0.45 for Upper West Region suggesting that households at lower income levels may have the same income levels and those with higher incomes may also have similar income levels. However, Musah et al.'s (2016) study did not examine the key factors driving poverty, and hence does not sufficiently deepen our understanding of poverty dynamics in the region.

Relying on data from the GLSS and CWIQ, Coulombe and Wodon (2007) find that, the highest probability of being poor is among heads working in agriculture while those working in the construction sector are less likely to be poor. Furthermore, the likelihood of being poor falls with the educational attainment of household heads. However, lowest rates of poverty are observed among public sector workers, followed by wage earners in the private formal sector, the self–employed in non–agricultural activities with the self–employed in agriculture having the highest level of poverty. Their analyses suggest that substantial differences in poverty incidence are driven largely by demographic characteristics, educational levels, sector of activity and employment status.

Donkoh (2010) examined the determinants of poverty in Ghana using GLSS 5 relying on probit estimations. Results from the study show that level of education, ownership of durable assets and international remittances are negatively related to poverty while dependent size and remoteness from the national capital exacerbate poverty. Ennin et al. (2011) on the other hand, employed the binomial logistic model to determine the factors which influence households' poverty status using data from three rounds of the GLSS. Their results show that larger households, uneducated household heads, and those with heads that have agriculture as their primary occupation are poorer.

Indeed, the above discussions highlight the influence of demographic and socio-economic characteristics on poverty while ignoring how household shocks impact on poverty. Dercon and Krishnan (2000) use a data set of 1,450 households in different communities in rural Ethiopia, surveyed thrice over 18 months' period and conclude that households' risks contribute to poverty fluctuations. The authors find that household consumption is affected by idiosyncratic and common shocks, including rainfall and household-specific crop failure, while households respond to seasonal incentives regarding changing labour demand and seasonality prices. Dercon and Shapiro (2007) note that the impact of shocks and risks on poverty has been relatively understudied in the literature of poverty dynamics. The less attention to household shocks in poverty is largely due to data limitation on shocks experienced by households. In the case of Chile, for instance, Contreras et al. (2004) found that health problems were associated with increased probability of falling into poverty. Dartanto and Nurkholis' (2013) study in Indonesia reveal that while households living outside Java–Bali are more exposed to negative shocks than those in Java–Bali, results from their ordered probit suggest that the impact of economic risks and health shocks on household poverty status outside Java–Bali is statistically insignificant. However, households in Java–Bali experiencing economic risks resulting from crop loss, job loss and falling prices have a tendency to be poor. Further findings reveal that health shocks proxied by the number of daily activities disrupted by health problems also explain differences in poverty. This evidence is, however, inconsistent with Jansen et al. (2015) whose study in South Africa finds that the impact of better health on monetary poverty is insignificant.

While these studies identified some factors influencing poverty, three key gaps still remain in the literature necessitating further research efforts. First, despite the growing recognition of the multidimensional nature of poverty, most of these studies measure poverty relying solely on income-based indicators. Secondly, and flowing directly from the narrow focus of much of extant literature, little is known on whether the drivers of monetary and non-monetary poverty differ. Thirdly, while key social intervention programmes may well contribute to poverty through their impact on household shocks, little is known on the role of shocks and government poverty programmes on poverty dynamics. More importantly, the nature and extent through which policy variables interact with shocks in influencing poverty is not established empirically. What we know so far on policy variables–poverty nexus is largely gleaned from public discourse with little or no empirical backing. In this study, we are able to include additional explanatory variables that have not been explored in local studies before and to the extent that Upper West region is the poorest Region in Ghana deserves far nuanced and in–depth analysis.

Methodology

Data

This study relies on primary data gleaned from households in Upper West Region of Ghana to examine the determinants of poverty. Three districts in Upper West Region (Wa West = 92.4%, Wa East = 83.8% and Nadowli–Kaleo = 68.5%) were purposively selected based on their high poverty incidence as reported in the Ghana Poverty Map report of the Ghana Statistical Service (GSS, 2015). The household population in each district based on the 2010 National Population and Housing Census was used to arrive at representative households sample size of n = 395 distributed as follows: Wa West = 140, Wa East = 131 and Nadowli–Kaleo = 124.[2] The data was collected in April, 2018.

The mixed methods approach involving the quantitative and qualitative techniques of data analysis was used. The quantitative data was collected using a household questionnaire divided into five sections: first, household demographic traits

[2] We do not show the sample size determinations but are available upon request from the authors.

namely gender of household head, age of household head, marital status, education qualification, household size and religion. Second, socio–economic characteristics such as employment status, household consumption expenditure among others. Third, shocks/risks notably crop loss, higher cost of production, lower crop prices, job loss and abrupt health problems. Fourth, government poverty reduction policies namely NHIS, LEAP and fertilizer subsidy. Fifth, multidimensional indicators involving three dimensions: education, health and living standards.

Measuring Monetary and Non-monetary/Multidimensional Poverty

In this study, poverty was measured using the consumption expenditure and multidimensional indicators. The former was used to measure the monetary poverty while the multidimensional indicators were used to construct a non-monetary measure of poverty. Indeed, poverty can be measured either in absolute or relative terms. While the former measuring in real terms of a given level of consumption basket to maintain a minimum subsistence, the latter measures living standard of an individual relative to other people's consumption expenditure. Rodriguez (2016) notes that any definition of poverty should define a given level of welfare below which a typical household is considered poor. Thus, relying on household consumption expenditure, poverty exists if a household's consumption expenditure falls below a certain economic welfare benchmark believed to comprise of a rational minimum standard of living. The Ghana Statistical Service (GSS), through its formal surveys, estimates the annual lower and upper poverty lines based on household consumption and expenditure levels. The GSS (2014b) sets nutrition-based income poverty lines which are equivalent to GH₵ 792 and GH₵ 1,314 for lower and upper poverty lines respectively. If a household falls below the lower poverty line, such a household is taken to be in extreme poverty and hence cannot satisfy their minimum nutritional needs even if they devote their entire budget to food consumption. However, those households whose annual consumption expenditure exceeds the upper poverty line are said to be non–poor and are able to consume enough food to meet their nutritional needs as well as meeting other basic non-food needs including entertainment. Conversely, households whose annual consumption expenditure fall between the lower and upper poverty lines are assumed to be poor. In this study, monetary-based poverty is defined using a binary choice of the form:

$$p_i = \begin{cases} 1 = \text{poor if consumption} < \text{GH₵}1{,}314 \\ 0 = \text{non} - \text{poor if consumption} \geq \text{GH₵}1{,}314 \end{cases} \quad (1)$$

Beyond the income/monetary poverty, the multidimensional poverty measures complement the one-dimensional approach such as income measures. Undoubtedly, several approaches have been used to construct a multidimensional non-monetary poverty (see Jansen et al., 2015). Among these approaches, the Principal Components Analysis (PCA) is increasingly used to construct an asset index to measure non-monetary poverty. However, this approach is not suitable when the indicators used are ordinal, binary, or categorical since the PCA is designed for continuous variables with the assumption that the indicators are normally distributed (Alkire et al., 2015). Thus, a more appropriate technique which this study adopts is the Multiple Correspondence Analysis (MCA). Relative to the PCA, the use of MCA and subsequent construction of the Composite Welfare Indicator (CWI) leverages on categorical variables in addition to making fewer assumptions regarding the distributions of the indicators. In the MCA analyses, each modality of the categorical variables is typically restricted to binary involving zeros and ones. Following Alkire and Santos (2010), we use three dimensions (namely education, health and living standard) and 10 indicators (namely educational achievement, nutrition, child school attendance, child mortality, improved drinking water, cooking fuel, electricity, improved sanitation, flooring and asset ownership). Measurement of the questions is constructed in the negative and deprivation is observed if a household head responds to the affirmative. For instance, *"has any household member aged 10 years or older not completed five years of schooling? Has any adult under 70 years of age or any child for whom there is nutritional information is undernourished in terms of weight for age?"* A value of 1 shows that the indicator is observed while 0 indicates otherwise.

Since the correspondence analysis is a geometric decomposition, if we use two categorical indicators,

y_l and $y_{l'}$, a simple correspondence analysis examines the linkage between the binary indicators relying on a two-way contingency table called the correspondence matrix represented by **P.** Indeed, the elements of **P** are the set of relative frequencies across the categories of the two indicators represented by $\mathbb{P}_{ll'}$ $\forall$ $l = 1, \ldots, \mathbb{L}$; $l' = 1, \ldots, \mathbb{L}'$ where $\mathbb{L}$ and $\mathbb{L}'$ respectively denotes the number of response categories of each of the two indicators. Alkire et al. (2015) note that a basic MCA algorithm analyzes the relationship relying on a Singular Value Decomposition (SVD) of the matrix of the standardized residuals **Z** where the total variance in the contingency table is called the total inertia. We estimate the total inertia and the component weights from the SVD of **Z** where the eigenvalues called principal inertias measure the variance in the contingency table.

We can extend to a general set of binary indicators where the correspondence analysis considers a multiple table of all the relationships among the pairs of variables. In this case, the indicator matrix **I** encapsulates an individual-by-categories matrix where the elements are the zeros and ones with columns for all the indicators while the rows match to the individual respondents. We perform the MCA using the STATA command *mca* which estimates the MCA on the Burt matrix constructed with our 10 indicators. Figure 1 plots the axes coordinates which give a visual bi-plot representation of the relationship across all the indicators used in this study.

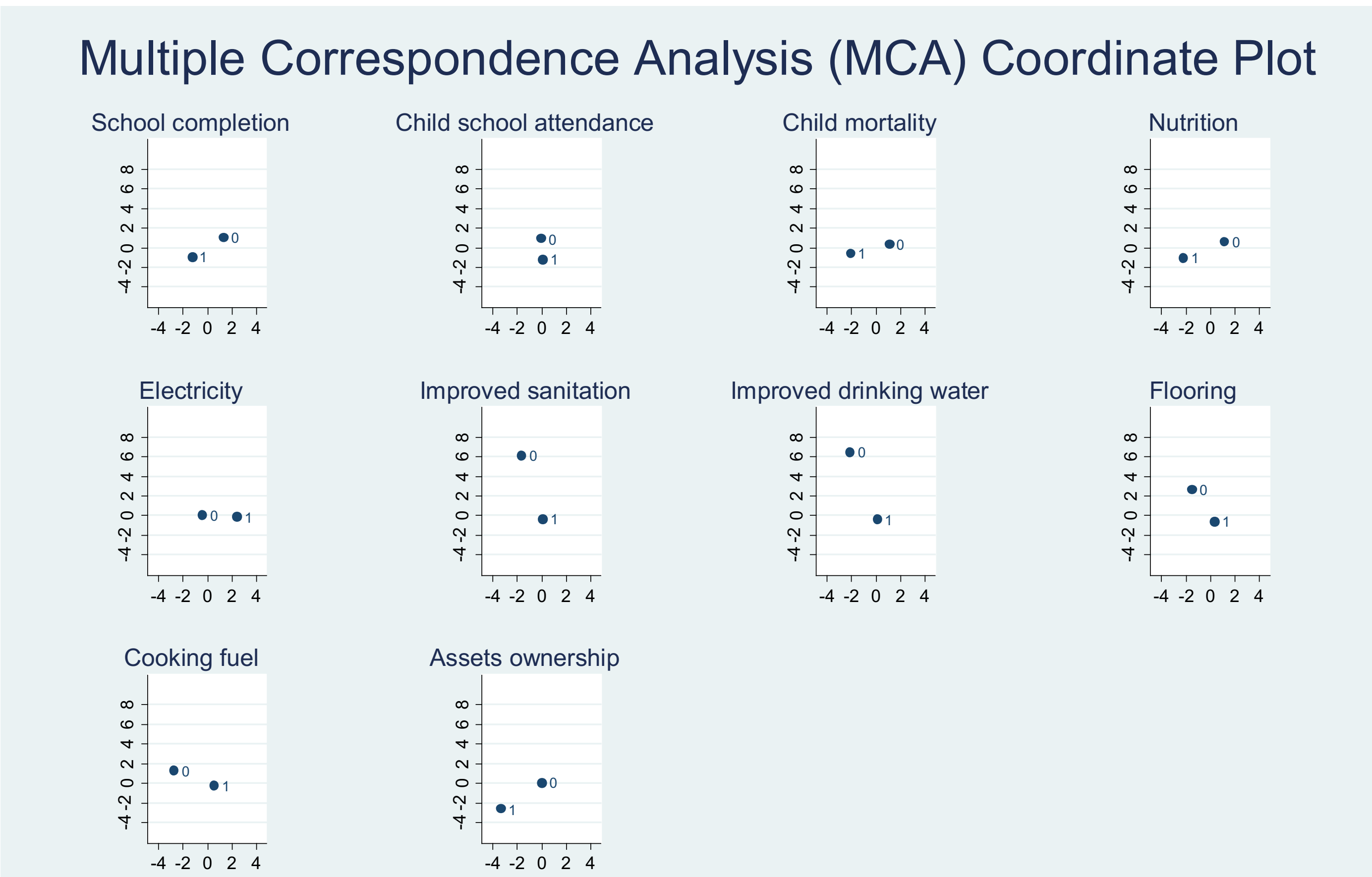

Figure 1: Multiple Correspondence Plot
Source: Authors' estimations

Table 1: Multiple Correspondence Analysis (MCA)

Dimension	Principal inertia	Percentage	Cumulative percentage
Dim 1	0.0230127	60.74	60.74
Dim 2	0.0070104	18.59	79.24
Dim 3	0.0000538	0.14	79.38
Total	0.0378882	100.00	

Notes: Burt/adjusted inertias used; number of axes = 2; Number of observations = 395

From Figure 1 and Table 1 above, the first dimension explains about 60.7% of the reported inertia while the second dimension explains about 18.5%. The first dimension is comparatively higher due to the fitting of the diagonal sub-matrices.[3] An important advantage of the MCA for poverty analysis, as noted by Asselin (2009) is that, this approach assigns more weight to indicators with fewer individuals. Thus, if few households are deprived for any given dimension, these households are allocated a greater weight and with this, the MCA gives more importance to minority population who are comparatively deprived. Indeed, the MCA leverages on what is called the reciprocal bi-additivity which argues that the composite deprivation score of a household is the simple average of the factorial weights of the deprivation categories. Based on this, we formulate the Composite Welfare Indicator (CWI) in equation (2) as:

$$CWI_i = \frac{1}{K}\sum_{k=1}^{K}\sum_{J_{k=1}}^{J_k} W_{J_k}^{k} I_{J_k}^{k}{}_i \tag{2}$$

with $W_{J_k}^{k} = \frac{s^k}{\sqrt{\lambda_i}}$

where k is the number of dimensions, k = 1,…., K=3; j is the number of modalities/indicators of each k with j = 1, …….., J_k = 10; I is the binary indicator for each j taking the value 1 if a household has indicator j and 0 otherwise; W is the weight obtained from the MCA of the factor score on the first axe normalized by the eigenvalue λ; s is the factor score; i is the household index.

Essentially, CWI aggregates the multidimensional indicator information to reflect societal poverty in a way that is consistent and robust. The weights from the MCA have both positive and negative values. However, the presence of negative values is inappropriate for measuring poverty (Ezzrari and Verme, 2012) and as such, following similar studies (see Asselin, 2002; Booysen et al., 2005; Sahn and Stifel, 2003), we add the 3.5 to each index to the values in a way that the highest negative value (–2.826453) is transformed into non-zero. Our final CWI thus has a mean of about 3.500, a standard deviation of 1.001, minimum and maximum values 0.674 and 5.003 respectively.

Empirical Strategy

Using the above poverty measures, this study aims at estimating the factors affecting monetary and non-monetary poverty. In doing this, standard estimation approaches using the Ordinary Least Squares (OLS) would involve setting up a model where poverty is a function of the independent variables as follows:

$$P(p_i = 1|Z) = \beta_1 + \beta_2 Z_i + \varepsilon_i \tag{3}$$

where p_i is the poverty status of household i obtained from equation (1); Z_i comprises the demographic, socio-economic, risk/shocks, government social protection schemes and their interaction variables while ε_i is the error term.

However, since our monetary poverty measure is binary, from equation (3) above, estimating such a model using the OLS poses two significant problems (Asteriou and Hall, 2011; Gujarati and Porter, 2009). First, non-normality

[3] For brevity, we do not present the remaining statistics for the column categories in standard normalization but are available upon request from the authors.

of ε_i is not guaranteed although it does not influence the OLS estimates. A more pronounced problem is that the variances of ε_i are not homoskedastic (Greene, 2008). A second challenge is the likelihood of the non-fulfillment of the restriction in equation (3). To the extent that dependent variable is dichotomous, a scatter plot would show only two horizontal points taking the value 1 if a household is poor and 0 otherwise. Yet, fitting an OLS would leave the monetary poverty measure unbounded by the 1s and 0s especially if outliers exist among the regressors. Thus, a more appropriate technique is the use of limited dependent variables such as a probit regression technique which estimates the likelihood that a household is either poor or non-poor by directly forecasting the dichotomous outcome given Z_i. However, given Z_i, we suspect that at least one of our regressors are correlated with ε_i leading to endogeneity problem. In this case, the standard probit model is incapable in dealing with potential endogeneity and for that matter, we construct a dichotomous dependent model with endogenous regressors using instrumental variables probit (ivprobit) estimation approach. Formally, we construct the following model:

$$p_{1i}^* = p_{2i}\delta + z_{1i}\gamma + \varepsilon_i \qquad (4)$$

$$p_{2i} = z_{1i}\Pi_1 + z_{2i}\Pi_2 + \epsilon_i \qquad (5)$$

where $i = 1, 2, \ldots\ldots, N = 395$, p_{2i} is a $1 \times m$ vector of the endogenous variables; z_{1i} is a $1 \times k_1$ vector of exogenous variables; z_{2i} is $1 \times k_2$ vector of additional instruments; δ and γ denote vectors of the structural parameters while Π_1 and Π_2 are matrices of the reduced-form parameters. We assume that, $(\varepsilon_i, \epsilon_i) \sim N(0, \Sigma)$. Indeed, the order condition for identification of the structural parameters necessitates that $k_2 \geq m$. Notice that models (4) and (5) are recursive models since p_{1i}^* is also a function of p_{2i} in equation (4) but p_{1i}^* does not appear in equation (5). In this case, p_{1i}^* is unobservable.

Our model here examines the drivers of monetary poverty given the set of the independent variables including household savings behaviour. However, we suspect that the unobservable factors influencing p_i also affect households savings. Therefore, this study treats savings behavior as endogenous while using all the respective regressors in addition to households' benefit of any other social protection intervention programme and nutrition status of adult household members as instruments in our estimations using the *ivprobit* command in STATA which employs the maximum likelihood estimator. We test the exogeneity of our instruments using the Wald test where rejection of the null hypothesis suggests that there is enough information in our sample to show the existence of endogeneity otherwise the standard probit would be appropriate.

Beyond the monetary poverty, we also examine the determinants of non-monetary poverty using the constructed CWI. However, relative to the binary monetary measure of poverty, the non-monetary multidimensional measure is continuous making the *ivprobit* estimation technique inappropriate. Since the multidimensional poverty may also suffer from the same potential endogeneity, an instrumental variable regression technique which provides an elegant way of obtaining consistent estimates in the presence of endogenous regressor(s) is employed.

Analysis and Discussion of the Empirical Findings

In this section, the empirical findings on the drivers of poverty based on the monetary and non-monetary-based measures are presented and analyzed. This begins with descriptive statistics as shown in Table 2. From Table 2, about 23% of the households were female–headed with an average age of 36 years. With regard to their marital status, 85% were married with 95% of the married household heads in monogamous marriages. It is also observed that about 54% have formal education with an average number of years of schooling of about five (5) years. Turning to spatial characteristics, majority (96.7%) of the households are in the rural areas. Average household size is with 88% of the household heads gainfully employed. Out of this, only 13% are in the formal sector. Turning to household consumption, our descriptive statistics show an annual average consumption expenditure of GH₵ 913.30 with GH₵ 285 and GH₵ 2,964 as the minimum and maximum expenditure respectively.

Table 2: Descriptive Statistics

Variables	Mean	SD	Min	Max
Demographic characteristics				
Gender of household head (1=Female; 0=Male)	0.226	0.418	0	1
Age of household head (in years)	36.175	10.246	18	70
Household size	6.096	2.296	2	15
Marital status (1=Married; 0=Others)	0.850	0.356	0	1
Type of marriage (1=Monogamous; 0=Polygamous)	0.951	0.498	0	1
Educational background (1=Formal; 0=Others)	0.539	0.499	0	1
Number of years of schooling (in years)	4.893	5.071	0	20
Religion (1=Islam; 0=Others)	0.278	0.448	0	1
Locality (1=Rural; 0=Others)	0.967	0.1786	0	1
Socio–economic characteristics				
Gainfully employed (1=yes; 0=No)	0.883	0.321	0	1
Category of employment (1=Formal; 0=Informal)	0.132	0.143	0	1
Moonlighting (1=Yes; 0=No)	0.655	0.475	0	1
Job insecurity (1=Yes; 0=No)	0.070	0.256	0	1
Remittance (1=Yes; 0=No)	0.356	0.479	0	1
Financial inclusion (1=Yes; 0=No)	0.258	0.438	0	1
Savings (1=Yes; 0=No)	0.901	0.298	0	1
Borrowing (1=Yes; 0=No)	0.640	0.480	0	1
Average household consumption expenditure (annual)	913.298	406.197	285	2,964
Livestock ownership (1=Yes; 0=No)	0.949	0.219	0	1
Access to microcredit	0.220	0.414	0	1
Shocks/risks variables				
Experience frequent shocks (1=Yes; 0=No)	0.881	0.324	0	1
Crop loss (1=Yes; 0=No)	0.668	0.471	0	1
Job loss (1=Yes; 0=No)	0.027	0.164	0	1
Lower crop prices (1=Yes; 0=No)	0.000	0.000	0	1
Increased cost of production (1=Yes; 0=No)	0.111	0.315	0	1
Illness (1=Yes; 0=No)	0.073	0.261	0	1
Idiosyncratic health shock (1=Yes; 0=No)	0.243	0.429	0	1
Average number of days lost to health shock	1.772	4.085	0	30
Improved public facilities (1=Yes; 0=No)	0.498	0.500	0	1
Government policy/social protection interventions				
Social protection programmes (1=Yes; 0=No)	0.997	0.050	0	1
Health insurance (1=Yes; 0=No)	0.924	0.265	0	1
LEAP beneficiary (1=Yes; 0=No)	0.078	0.269	0	1
Fertilizer subsidy (1=Yes; 0=No)	0.053	0.224	0	1
Benefits from any other social intervention programme (1=Yes; 0=No)	0.005	0.071	0	1

Authors' computations based on the survey data.

With regards to household experience of shocks, this survey suggests that about 88% of the households experience some form of frequent shock with crop loss being the highest (66.8%) followed by idiosyncratic health shock (24.3%) where a typical household head experiencing health shock loses an average of 1.77 days to it. Indeed, government social protection programmes, about 99.7% of the households are aware of at least one form of those interventions with about 92% accessing healthcare under the NHIS. Further evidence suggests that 7.8% and 5.3% benefit from the LEAP and fertilizer subsidy programmes respectively.

Given the aim of this study in determining the drivers of poverty in Upper West Region, for each measure of poverty, we performed three regressions. First, we examined how demographic and socio-economic characteristics influence poverty. In the second regression, we controlled for the effect of shocks and government policies on poverty in addition to demographic and socio-economic factors. In the final regression, we examined whether government interventions impact on poverty through its effects on shocks. Table 3 below presents the empirical findings.

Table 3: Determinants of Monetary and Non–monetary Poverty

Variables	Monetary			Non–monetary		
	1	2	3	4	5	6
Demographic characteristics						
Constant	–	–	–	1.9176 [0.79]	–2.1327 [–0.74]	0.6452 [0.38]
Gender of household head	0.3857** [2.25]	0.2595 [1.33]	0.2466 [1.15]	–0.1243** [–2.24]	–0.6227* [–1.92]	–0.5946** [–1.97]
Age of household head	0.0344 [0.57]	0.0498 [0.73]	0.0432 [0.57]	0.2199 [1.54]	0.1893* [1.83]	0.1678* [1.78]
Age square	–0.0003 [–0.53]	–0.0006 [–0.74]	–0.0005 [–0.59]	–0.0023 [–01.41]	–0.0022* [–1.76]	–0.0019* [–1.70]
Marital status	0.2516 [0.46]	0.3716 [0.58]	0.5578 [0.81]	–0.7833 [–0.73]	–0.5114 [–0.67]	–0.4015 [–0.57]
Type of marriage	–0.0617 [–0.20]	–0.1408 [–0.37]	–0.2568 [–0.62]	0.4212 [0.62]	0.4169 [0.85]	0.3677 [0.80]
Number of years of schooling	–0.0689** [–2.05]	–0.0816** [–2.15]	–0.0909** [–2.38]	0.0341 [0.50]	0.0200 [0.42]	0.0205 [0.46]
Household size	–0.2965*** [–2.96]	–0.3468*** [–3.02]	–0.3834*** [–3.87]	–0.0932 [–1.08]	–0.0981 [–1.53]	–0.0887 [–1.50]
Religion	–0.3633 [–1.38]	–0.3947 [–1.29]	–0.4773 [–1.57]	0.5709 [1.36]	0.4366 [1.45]	0.4131 [1.46]
Locality	0.2965*** [2.96]	0.3517*** [3.16]	0.6815** [2.02]	–0.4368* [–1.79]	–0.7141** [–2.47]	–0.3854** [–2.25]
Wa West	0.4074*** [3.01]	0.2676** [2.47]	0.3344** [2.51]	–0.2124** [–2.32]	–0.2740*** [–3.110]	–0.3013** [–2.41]
Wa East	0.1542** [2.34]	0.1861** [2.45]	0.2310*** [3.32]	–0.2011** [–2.38]	–0.2652* [–1.80]	–0.2823* [–1.79]
Socio–economic characteristics						
Gainfully employed	–0.0556** [–2.05]	–0.1018** [–2.34]	–0.3690** [–2.26]	0.5168** [2.08]	0.6547** [2.31]	0.4258** [2.36]
Category of employment	0.9611*** [3.32]	0.6815** [2.05]	0.7096** [1.99]	1.5275* [1.89]	0.7481 [1.52]	0.6944 [1.53]
Moonlighting	0.1652 [0.95]	0.2500 [1.26]	0.2617 [1.27]	0.3203 [0.81]	0.3503 [1.25]	0.3487 [1.31]
Job insecurity	1.4275* [1.80]	1.7406* [–1.83]	2.0367** [–2.20]	–1.4130* [–1.85]	–0.9808* [–1.85]	–0.9805** [–1.96]
Remittance	–0.0955 [–0.39]	–0.0316 [–0.11]	0.0411 [0.13]	1.2133** [2.11]	0.6544* [1.82]	0.6340* [1.88]
Financial inclusion	0.1644 [0.63]	0.0826 [0.28]	0.0105 [0.03]	0.4240** [2.14]	0.7840* [1.90]	0.7599** [1.97]
Savings	–0.525*** [–4.17]	–0.588*** [–2.97]	–0.8864* [–1.81]	15.7001** [2.81]	11.6399*** [3.11]	10.8679*** [3.25]
Borrowing	0.3464	0.3499	0.2105	1.8896	0.8889	0.7923

	[0.89]	[0.93]	[0.46]	[1.57]	[1.46]	[1.43]
Livestock ownership	–0.1246	–0.0617	–0.0349	–0.5962	–0.4850	–0.4656
	[–0.39]	[–0.18]	[–0.09]	[–0.82]	[–0.94]	[–0.96]
Access to microcredit	–0.4368*	–0.7150**	–0.8167***	0.4532*	0.6258**	0.6148**
	[–1.79]	[–2.39]	[–2.80]	[1.99]	[2.04]	[2.12]
Shocks/risks variables						
Crop loss		0.6559**	0.6748*		0.0132	–0.0272
		[1.89]	[1.77]		[0.02]	[–0.05]
Job loss		–0.8782	–1.0113		–0.9722	–0.9828
		[–1.09]	[–1.17]		[–1.14]	[–1.19]
Increased cost of production		–0.4880	–0.5377		–0.4689	–0.5101
		[–0.92]	[–0.94]		[–0.77]	[–0.88]
Idiosyncratic health shock		0.0272**	0.0934***		0.6452	0.6054
		[2.07]	[3.22]		[1.25]	[1.25]
Days lost to health shock		0.0205**	0.3216*		–0.0613	–0.1221
		[2.49]	[1.79]		[–1.25]	[–0.99]
Government policy/social protection interventions						
Health insurance		0.0833	0.0069		0.3790	0.3657
		[0.27]	[0.02]		[0.81]	[0.78]
LEAP beneficiary		–0.3219	–0.3814		0.0397	0.0316
		[–1.06]	[–1.21]		[0.10]	[0.08]
Fertilizer subsidy		0.0597	–4.0566		–1.0448**	–0.6031
		[0.18]	[1.43]		[–2.07]	[–0.41]
Interaction variables						
Crop loss × Fertilizer subsidy			0.2253			–0.4646
			[1.65]			[–0.30]
Job loss × LEAP			0.4322			0.0732
			[1.45]			[0.03]
High production cost × LEAP			0.3789			–0.4716
			[1.19]			[–1.38]
Health shock × NHIS			0.0335			0.0674
			[0.38]			[0.57]
Diagnostics						
Wald chi–squared	228.86	202.93	162.55			
p–value	[0.000]	[0.000]	[0.000]			
Rho	0.7052	0.6495	0.5060			
Sigma	[0.1914]	[0.3181]	[0.4486]			
Wald test of exogeneity chi–squared (*p*–value)	2.85	3.98	2.95			
	[0.031]	[0.029]	[0.035]			
Observations	395	395	395	395	395	395
F–test (*p*–value)				1.75(0.0297)	1.60(0.0270)	1.68(0.0147)
Under–identification test (Anderson canonical correlation LM statistic): chi–squared (*p*–value)				7.824 (0.0200)	9.859 (0.0072)	10.878 (0.0043)
Weak identification test (Cragg–Donald Wald *F*-statistic):				13.779	14.657	15.123
Sargan statistic (over–identification test of all instruments): (*p*–value)				3.452 (0.0632)	11.490 (0.0007)	13.519 (0.0002)

Cumby–Huizinga test of non-autocorrelation at order 1 (Chi-squared) *p*-value	1.232 (0.2213)	1.532 (0.2533)	1.13234 (0.1645)

Notes: *, ** and *** respectively denotes significance at 10, 5 and 1% levels. Values in [ ] are the z–values. The monetary and non-monetary poverty are respectively estimated using the STATA commands "*ivprobit*" and "*ivreg2*". The coefficients of the *ivprobit* are the marginal effects. The autocorrelation test is performed with the "*ivactest"* routine. Stock and Yogo (2005) weak identification test critical values: 10% maximal IV size 19.93; 15% maximal IV size 11.59; 20% maximal IV size 8.75; 25% maximal IV size 7.25.

Demographic Characteristics

Beginning with columns 1 and 4, it can be observed that relative to males, females are more likely to be poor given the positive and significant coefficient. However, for the multidimensional poverty, the coefficient of gender is negative and significant at 5% indicating that females have about 12.4% lower welfare compared to men. This evidence does not support Ningaye et al's (2011) finding that gender insignificantly influences multidimensional poverty in Cameroon. With regards to the effect of age on monetary and non-monetary poverty, our evidence suggests that higher age is associated with higher poverty although this effect is not statistically significant at conventional levels. The inclusion of the age square is not also significant revealing that age–poverty nexus does not exhibit nonlinearities. Marital status of household head is also not a significant determinant of poverty. Thus, compared to those not married, being a married household head does not contribute to both monetary and non-monetary poverty. While this holds, we decompose the forms of marriage to examine whether, relative to those in monogamous households, polygamous households are more likely to be poor. We find that the coefficient of the forms of marriage is negative for monetary and positive for non-monetary poverty albeit insignificantly.

On the impact of education on poverty, the findings show that higher level of education reduces only incidence of monetary poverty with no impact on multidimensional poverty. In particular, a 1-year increase in number of years of education of household head significantly lowers monetary poverty by 0.0689%. Indeed, a better education raises the chances of being non-poor as higher level of education delivers better opportunities for a good job and, subsequently, an enhanced income. This evidence is consistent with Donkoh (2010); and Dartanto and Nurkholis (2013). Household size also dampens poverty where households with large sizes contribute to about 0.2965% reduction in consumption poverty. A conjectural elucidation can be traced to the labour supply phenomenon consistent with the labour intensive African local economies. Given agriculture as the main economic activity, larger households imply more farm hands for own-production activities in the face of low modernization and relatively higher productivity all things being equal. To this extent, large households could positively contribute to higher subsistence and economies of scale in consumption expenditure. Indeed, there is evidence that with a fixed income, large households are forced to reduce consumption per head in order to support the additional members (see Jalan and Ravallion, 1998; Haddad and Ahmed, 2003; Dartanto and Nurkholis, 2013; Woolard and Klasen, 2005; Ennin et al., 2011; Biyase and Zwane, 2017). However, the existence of size economies in total household consumption counters the widely held conclusion that larger households are poorer. Interestingly, while both education and household size dampen poverty, the impact of household size on monetary poverty is at least 4.3 times larger than the effect of education. We, however, find no evidence of the effect of education and household size on non-monetary poverty. Further evidence suggests that relative to those living in urban areas, households in rural areas are more likely to be poor. This finding is consistent with Donkoh's (2010) and Ennin et al.'s (2011) studies in Ghana. On average, compared to rural areas, urban livelihoods are probably less risky, largely based more on wage work in addition to higher economic activities and job opportunities in both the formal and informal sectors. To the extent that returns in urban areas are potentially higher than the rural areas, households in rural areas are more likely to fall into poverty. On the district dummies, we observe that compared to households in Nadowli–Kaleo, those in Wa West and Wa East have higher likelihood of being poor. More tellingly, the probability is higher among those in Wa

West, a finding that is in synch with the evidence that poverty incidence is rife in that district.

Socio–economic Characteristics

Turning to the effect of socio-economic traits on poverty, there exists a negative relationship between poverty and employment. For instance, relative to the unemployed, having a gainful employment dampens monetary poverty (column 1) while increasing welfare (column 4). Thus, fully employed household heads have lower probability of being poor with huge impact on the non-monetary poverty. This finding is particularly consistent with Kedir and McKay (2005) whose study reveals that waged household heads in Ethiopia have higher probability of escaping poverty. Given those employed, we examine whether there are variations in this effect given the category of employment. On this score, we find that while being employed is less associated with poverty, relative to those employed in the formal sector, households working in the informal sector are more likely to be poor given the positive coefficient on monetary poverty. The coefficient of formal sector workers is also positive in the wealth index equation suggesting these category of households have enhanced welfare. This finding is attributed to the regular and sustainable flow of earnings as household heads in the formal sector are more likely to earn more on the back of predictable income flows. This notwithstanding, while the category of employment matters for poverty, its impact on monetary poverty is huge measuring 1.8 times higher than the effect on non-monetary poverty. Undoubtedly, the formal sector in Ghana promises a stable income and higher wage rates. Perhaps, wages received from working in the formal sector are at least high enough to smoothen consumption and not to dampen multidimensional poverty. Our evidence is consistent with the finding of Dartanto and Nurkholis (2013) and Kedir and McKay (2005).

Further evidence shows a positive coefficient of job insecurity on poverty although the effect is slightly significant. For the non-monetary poverty, the impact of job insecurity is negative. Thus, compared to those with secure jobs, household heads who are likely to lose their jobs in the next three months are more likely to be poor. Indeed, the higher tendencies to loose one's job spurs households' vulnerability to poverty. Savings have also proven crucial in the determination of poverty given the negative (positive) and significant effect on (non)monetary. In columns 1 and 4, relative to those who do not save, households that save for future use are less likely to be poor and so is access to microcredit. Notice that while both savings and access to credit are associated with lower poverty albeit not robust for non-monetary poverty, the impact of savings on poverty reduction is exceedingly relevant. Moonlighting, livestock ownership and borrowing are not robustly related to both measures of poverty.

Shocks/Risks Variables

In columns 2 and 5, we control for shocks/risks and key government's social protection intervention programmes. Among the economic risk variables, we observe that households experiencing crop losses are more likely to be non-poor given the positive and statistically significant coefficients on monetary poverty. However, job loss and experiencing frequent higher cost of production do not appear to significantly influence poverty although the coefficients enter with negative signs. Thus, households working in agriculture are not able to dampen agricultural risks such as the crop loss and are exposed to its vagaries thus increasing their probability of falling into poverty. In the case of abrupt cost of production, households are able to dampen their cost of production shock on poverty perhaps by diversifying their agricultural cultivations.

With regards to idiosyncratic risk involving health shock, the findings show that households experiencing disrupted health problems and higher days lost to health shock exacerbates poverty. Indeed, households experiencing frequent health shocks may be incapacitated to work or might have to allocate time and productive resources to medical care while others are compelled to sell their assets for treatment. In this regard, households are more likely to be monetarily poor. This evidence is akin to Contreras et al. (2004) and Dartanto and Nurkholis (2013).

With regards to the impact of shocks on non-monetary poverty, the findings reveal that none of the shock variables influences the wealth index measuring the multidimensional poverty although the coefficients are negatives expect crop loss and idiosyncratic health shock. We turn to how government social protection policies influence poverty.

Government Policy/Social Protection Interventions

The findings do not however indicate any significant effect of government policy intervention on poverty reduction. For instance, given the coefficients of health insurance and fertilizer subsidy beneficiaries, even if government's policies will have any impact on monetary poverty, such effect is rather an amplifying one. Nonetheless, the effect of fertilizer subsidy on multidimensional poverty is negative and significant at 5% indicating that, relative to non-beneficiaries of fertilizer subsidy, beneficiaries are more likely to be multidimensionally poor. In the case of the impact of cash transfer, relative to non-beneficiaries, LEAP beneficiaries are less likely to be poor. However, none of these effects is significant based on our sample evidence suggesting that these programmes may not be yielding the poverty–reducing effects as envisaged. Interestingly, Ibrahim and Yeboah (2014) argue that, LEAP as a direct cash transfer programme contributes significantly to supplementing households' incomes in addition to improving their well-being and livelihoods. While this sharply contrasts the findings of this study, the differences in settings and severity of household poverty may account for the differences in the level of effect. Ibrahim and Yeboah's (2014) study was based on urban households in the Ashanti Region with low poverty incidence. In this case, poverty may not be severe relative to Upper West Region where our sample comprises of 97% of households in rural areas. To the extent that, households in our sample are relatively more likely to be stuck in poverty means that, contribution of LEAP to their poverty reduction may be insignificant. While this result is unexpected, it well points to the ineffectiveness of such social protection policies in protecting the poor perhaps due to incorrect targeting.

Some Further Dynamics

In columns 1 to 3, access to microcredit, savings and being gainfully employed are negatively and significantly related to poverty at conventional levels while household heads working in the informal sector and those with job insecurity are more likely to be poor. Interestingly, gender loses its significance in the monetary poverty equation but not the non-monetary. While impact of age does not matter in monetary poverty, its effect is statistically significant suggesting that higher age of household head is associated with higher wealth index (column 5). However, the square term is negative and slightly significant at 10% suggesting a threshold effect and inverted U-shaped in particular. Taking the partial derivative of the non-monetary poverty equation with respect to age and setting the result to zero produces an inflection point of 43 years. The implication is that the wealth index is an increasing function of age, household head's welfare decreases after 43 years. Remarkably, while the inverted U-shaped relationship is in line with Jansen et al,'s (2015) study in South Africa, the authors argue that such a non-linear relationship between age and poverty only exists for monetary and non-monetary poverty. Apart from the different setting/location, the differences in the turning point may provide some clue to the varying effect of age on the different measures of poverty. While Jansen et al.'s (2015) inflection point suggests that household heads fall into income poverty after 17 years and hence unable to make ends meet, our turning point, however, indicates that household heads care more of the other multidimensional aspects of poverty and attempt to reduce same by having better education, improved health and living standards as well as acquisition of assets such as TV, telephone, car among others until they attain the age of 43. Therefore, an understanding of the settings may show that, it is less probable for at least a 17-year old household head to have lower desire for dampening multidimensional poverty. Number of years of schooling and household size significantly exert negative effects on monetary poverty with no apparent impact on the non-monetary poverty. However, marital status, type of marriage and religion do not explain household's poverty irrespective of the measure of poverty. Further results reveal that rural households and those living in Wa West and Wa East have higher proclivity to be in poverty.

We provide a qualitative analysis of poverty and its determinants relying on case studies. One household head in Wa West District retorts:

Poverty is when you don't have money to buy food and other things you want. Although I work hard to fend for my family, I still don't have much to eat, I cannot also save money even if I constrain our household consumption. If not witchcraft, what else could be determining poverty? [Male household head, 51, Wa West district]

To this household head, a key driver of poverty is a spiritual attack from enemies who are often seen to lock-up household's chances to succeed in life. Decrease in household consumption with the aim of improving income since GHS1.00 saved today is expected to increase income and consumption. However, this is not straightforward owing to the paradox of thrift in standard economic theory. As households become thriftier, savings at best remains the same if all household members increase the percentage of their income saved. To this household, the paradox of thrift is witchcraft. In his view, a typically poor household is seen to be on a jinx whose toils will never bear fruits without also seeking or responding spiritually in equal measure. While the study cannot empirically verify the veracity of this claim, given the deep-rooted traditional beliefs of the households, this view on the cause of poverty may be tenable among households in our study areas.

Beyond the spiritual undertones, one household head in Nadowli–Kaleo District has a different view on poverty. To him,

I am definitely not poor because I have three motorbikes while my next neighbour has only one. Poverty is caused by laziness and as the adage goes, "there is no food for the lazy man"

[Male household head, 43, Nadowli–Kaleo district]

Several other causes were ascribed to include unemployment, poor harvest, illness and low wages. Undoubtedly, major government social intervention programmes are designed with the aim of dampening shocks/risks that households are frequently exposed to. On this score, we examine whether those programmes have any effect on poverty via shocks. This is done by including in the poverty equation a multiplicative interactive term of dummies for shock and beneficiaries of such programmes. In columns 3 and 6, the findings do not provide evidence of any dampening effect. Specifically, we do not find that fertilizer subsidy insulates households against crop loss. Similarly, government cash grant policy – LEAP – among others is expected to help smoothen household consumption expenditure and welfare by dampening rising cost of farm production and as well cushion households during times of job loss. To this extent, it is anticipated that such a cash transfer programme could help reduce poverty through its impact on economic shocks. However, the study does not find any evidence to support the dampening role of LEAP given the insignificance of the interactive term. Similar findings of the interaction between health shock and National Health Insurances Scheme suggesting that the impact of health insurance scheme as a means of extending primary healthcare access to the poor is incapable of reducing households' exposure to idiosyncratic risk and as such its impact on poverty reduction is imaginary are observed. This holds true irrespective of the measure of poverty. Thus, the interaction variables of government policy interventions and their respective economic and idiosyncratic shocks do not statistically affect household poverty confirming our earlier finding that such government assistance weakly contributes to poverty reduction. Given our sample, it may well suggest that poverty in these areas are rife in a way that the effect of these programmes on overall poverty are infinitesimally felt.

On the interaction of social protection programmes and shocks in poverty, a female household head in Wa East opines that:

Although government makes efforts to reduce our poverty levels through social spending, such projects do not help cushion us against vulnerabilities and poverty because they are windfalls.

[Female household head, 46, Wa East District]

This assertion is largely corroborated by our empirical findings. For both the different estimation approaches, none of the risk variables and government intervention programmes have any effect on multidimensional poverty. For the monetary poverty, however, the impact of crop loss, idiosyncratic shocks maintain their positive signs and significance (column 3). Thus, once the interactive terms are controlled for, the impact of shocks on monetary poverty is more damaging. Access to microcredit and savings enhances poverty reduction. From columns 3 and 6, it is vivid that microcredit matters more for monetary poverty and so is saving for multidimensional poverty. Interestingly, relative to the financially excluded, household heads who are financially included have between 42.4% to 78.4% probability of higher welfare. In the case of monetary poverty, the impact of financial inclusion is benign. Job insecurity and being gainfully employed remain robustly related to poverty. Interestingly, while the coefficient of remittance does not significantly affect monetary poverty irrespective of the model specification, its impact on multidimensional poverty is positive and significant. This implies that, relative to those who do not receive remittance, household heads who receive remittance from a family member working in an urban area are more likely to escape non-monetary poverty. The varying effect of remittance on poverty may well suggest that recipient households use remittances – that take the form of family transfers – to tackle other multidimensional aspects of poverty and not to support their consumption expenditure. While Hall (2007) argues that remittances play a crucial role in poverty dynamics, our evidence shows that, it only matters more for multidimensional poverty.

While the category of employment only matters more in monetary poverty, the effect of differences in the category of employment on non-monetary poverty is weak. Indeed, among the socio-economic characteristics, only borrowing, livestock ownership and moonlighting do not influence both measures of poverty. For the demographic factors, while spatial characteristics and location dummies robustly matter for both measures of poverty, household size and level of education significantly explain monetary poverty relative to non-monetary poverty. Conversely, gender and age also matter more for non-monetary poverty with age–welfare link exhibiting a threshold effect consistent with the earlier finding except in this case the turning point is slightly higher (44 years).

The under–identification test is a Lagrange Multiplier (LM) test of whether the equation is identified. In other words, we examine whether the excluded instruments are "relevant", and correlates with the endogenous regressors. It tests the null hypothesis that the equation is under-identified. This study rejects the hypotheses suggesting that all our models are identified. We also examine the weak identification test which arises when the excluded instruments are correlated with our endogenous regressors albeit weakly. We assume the error terms to be independently and identically distributed hence the weak identification test as reported by "*ivreg2*" as an F version of the Cragg–Donald Wald test statistic with Stock and Yogo (2005) reporting the critical values. The null hypothesis being tested is that the estimator is weakly identified in the sense that it is subject to bias. Rejection of their null hypothesis represents the absence of a weak instruments problem. Values of our Wald test statistics reveal that rejection of the null hypotheses at 15% maximal IV size. In addition, following Staiger and Stock (1997) "rule of thumb" that the F-statistic should be at least 10 for weak identification not to be considered a problem is satisfied.

For the non-monetary poverty, the consistency of our instrumental variable regression coefficients depends on the validity of our instruments which we test using the Sargan test of over-identifying restrictions with the null hypothesis that the instruments are valid. Given the null hypothesis, the test statistics is distributed as chi-squared in the number of $L - K$ over-identifying restrictions.[4] From columns 4 to 6, the higher (low) Sargan test statistics (p–values) suggests that all our instruments are valid and hence uncorrelated with the error term. We further examine whether our error terms exhibit first order autocorrelation. The high (low) p-values (chi-squared test) do not provide evidence to reject the null hypothesis of non-autocorrelation suggesting that our errors are serially independent.

Conclusion

In this study, factors that influence monetary and non-monetary poverty were empirically examined. The impact of government social protection programmes on both measures of poverty were also investigated. The study relied on data from 395 households in the Upper West Region of Ghana to construct a multidimensional non-monetary measure of poverty using the Multiple Correspondence Analysis (MCA) and the Composite Welfare Index (CWI) while invoking instrumental variables estimation approaches that deal with potential endogeneity.

Results from the study reveal varying determinants of both measures of poverty. For instance, on the demographic factors, the gender of a household head matters more for non-monetary poverty than monetary poverty while household size and educational level robustly relate to only monetary poverty. Age weakly influences only multidimensional poverty while exhibiting some

[4] Where L and K respectively denote number of instruments and regressors.

non-linearities in the relationship. Only location dummies are significant drivers of both monetary and non-monetary poverty. On the socio-economic drivers, access to microcredit, savings and gainful employment individually reduces household poverty while improving welfare. Job insecurity accelerates poverty irrespective of the measure while remittance and financial inclusion are exceedingly crucial for only non-monetary poverty. Moonlighting, borrowing and livestock ownership do not matter in poverty dynamics. Further findings suggest insignificant effects of shocks on non-monetary with varying impact on monetary poverty as only crop loss and idiosyncratic risks increase household probability of being poor. In addition to finding weak impact of government social protection programmes, there was no finding on any dampening effect of such programmes on household shocks.

Implications for Policy

These findings reveal several implications for policy. The insignificant effect of such programmes raises important questions on their implementation. For instance, is poverty adamant because higher proportion of households have sunk deep into it or does the level of poverty mirrors exactly the percentage of poor households moving in and out of poverty or poor targeting? In all the cases, a specific policy antidote is needed to spur household income and asset accumulation aimed at improving on welfare. To the extent that households are exposed to spatial and idiosyncratic shocks in the face of weak social protection programmes may well call for a new broad set of policies and safety nets capable of insulating households against these vagaries. However, in doing this, a clear understanding of the different factors influencing poverty is needed since such policies may as well have different impact on the measures of poverty. While there is circumstantial evidence on the roll-out of the various social protection programmes albeit insignificant effects, it is imperative for policy makers to re-examine the targeting and delivery approaches in such a way that needy households are captured. For example, while LEAP as a cash transfer programme gives cash grants to households according to household size, it nonetheless offers the same amount of cash to beneficiaries irrespective of their location. Meanwhile, evidence from the patterns and trends of poverty in Ghana suggests that poverty is largely prevalent in Northern Ghana and highest in Upper West Region where this study is based. Although poor households may be identical in their inability to enjoy a certain minimum level of standard, there are potential differences in the depth of poverty and therefore, well-designed social protection policies should be agile to respond to the different severity of poverty. Perhaps what can aid in leaping a household out of poverty may have insignificant effect on another household given the relative severities.

Finally, providing livelihood opportunities and supporting the efforts in maintaining sound income generating activities may also promise to decrease overall poverty. Findings from this study provide important areas for further research. It would be interesting to examine whether poverty is largely chronic or transient in addition to identifying the different factors influencing them. Such a study has crucial implications for administrative delivery and targeting of any anti–poverty intervention programmes.

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