https://doi.org/10.59277/AERD.2025.1.09

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DETERMINANTS OF FOOD POVERTY: A QUANTILE REGRESSION APPROACH

ABSTRACT

This paper examines the incidence, depth and severity of food poverty and profiles the food poor in a developing country context. It also examines the drivers of food poverty in Uganda. Based on data obtained from Uganda National Household Survey 2016/2017 and 2019/2020, this study employed the Foster-Greer-Thorbecke (FGT) index for poverty measurement. The results show that food poverty increased from 36.6% in 2016/2017 to 40.6% in 2019/2020. A quantile regression analysis was used to assess the influence of different factors at different points in the distribution of food. This points to the need for targeted interventions for food poverty and general poverty reduction in Uganda and other developing countries.

Key words: food consumption, food poverty, FGT, quantile regression.

JEL Classification: I3, I32, R2

1. INTRODUCTION

Agenda 2030 and Sustainable Development Goals (SDGs) aim to promote sustainable development globally, ensuring no one is left behind. SDG 2 specifically targets ending hunger, achieving food security, improving nutrition, and promoting sustainable agriculture. However, many households in developing nations, including Uganda, are facing deprivation. The Uganda National Household Survey (UNHS) 2019/2020 reported that 20.3% of Uganda's population lived below the poverty line, while 42% faced multidimensional poverty (Uganda Bureau of Statistics, 2022). The purpose of this study is to profile the food poor in Uganda and to examine the drivers of food poverty. Existing studies have focused on food security, but research on food poverty remains scanty. A comprehensive food poverty profile is essential for effective policy design, as food expenditure constitutes a major share of household income. As Bidani and Ravallion (1993) highlighted, poverty profiles guide interventions, and this study aims to enhance policy discourse on reducing food poverty. While ordinary least squares (OLS) regression is commonly used to assess household welfare, it captures only average effects. Quantile regression provides a more detailed analysis, identifying differential impacts across welfare distribution. This study sheds lights into food poverty in Uganda and its drivers.

2. STATE OF KNOWLEDGE

Food poverty is a critical development challenge that attracts attention due to its implications for health, education, and overall household welfare. A number of studies have examined the measurement and drivers of food poverty (Greer & Thorbecke, 1986; Kendall, Olson & Frongillo, 1995; Swindale & Bilinsky, 2006; Vilar-Compte *et al*., 2017; Barrett, 2010). Galli *et al*. (2019) and Bradshaw (2007) showed that food poverty is often a consequence of natural disasters, low food production, food wastage, unemployment, political distortions, and geographical disparities. In a cross-national study, Allee *et al*. (2021) found that per capita cereal production, per hectare cereal yield, governance metrics, and logistics influence access to food. Fyles & Madramootoo (2016) noted that some of the drivers of food poverty are high population growth rates, a rise in biofuel production, climate change, inflation, and changing consumption patterns. Misselhorn (2005) observed that in Southern Africa, inadequate access to food was a consequence of poverty, environmental factors, conflict, and community-specific moderating factors such as management of common property resources and access to public goods. In developed countries, changes in social safety nets are associated with an increase in food poverty. In the United Kingdom, for instance, Cooper, Purcell & Jackson (2014) showed that the 2013 cuts in the social security system drove many vulnerable and poor families into food poverty. In Uganda, the major drivers of food poverty are often idiosyncratic and covariate shocks such as drought, floods, storms, pests, and diseases, which result in the loss of agricultural output (Nakalembe, 2018).

The preceding strand of literature shows that the drivers and effects of food poverty are well documented; however, there is limited literature on the incidence of food poverty. For instance, Smith *et al*. (2018) estimated the geographic distribution of factors contributing to household food poverty in the UK and noted that while there was a recognition of household food poverty as a policy issue, no routine measurement was undertaken. Similarly, Loopstra & Tarasuk (2015) showed that the use of food bank data as a measure of food poverty in Canada is not accurate and instead suggested that food poverty measurement and interventions should be based on representative household data. The absence of consistent measurement of food poverty hampers proper planning and targeting of those most in need.

In a developing country such as Uganda, where poverty is prevalent (Abegaz, 2018), a profile of food poverty has not been given adequate attention. Food poverty has been routinely lumped under income poverty measures since the 1990s, as reported in Appleton (2003). In contrast, other developing countries such as Nigeria, Kenya, Indonesia, and Ghana have comprehensive food poverty profiles that can be used to design interventions. Greer & Thorbecke (1986) used the first Kenyan Integrated Rural Survey to estimate the extent and distribution of food poverty among Kenyan small farmers. Their analysis showed that there was significant variation in food poverty based on region of residence, household size, size of landholding, farming patterns, type of employment, and characteristics of the household head. According to the Kenya National Bureau of Statistics (Kenya National Bureau of Statistics 2023), 28% of households, or 3.5 million households, were food poor in Kenya in 2021. The data also showed that there was substantial variation in food poverty incidence across counties, with the lowest food poverty found in Nairobi in 14.8% of its population. On the other hand, food poverty incidence levels were found to be higher, affecting more than half of the population in four out of the 47 counties.

Based on the Ghana Household Budget Survey, Kyemere & Thorbecke (1986) constructed a food poverty profile for Ghana, and their results showed that food poverty was prevalent in rural areas near the Sahel, in female-headed households, households headed by self-employed persons, and households with many illiterate persons. The Ghana food poverty profile showed that different people are affected differently and should be targeted to improve the welfare of the poor. In the case of Nigeria, Ozughalu & Ogwumike (2015) used the Nigeria Living Standard Survey and produced a food poverty profile based on the Food Energy Intake approach and the Foster-Greer-Thorbecke (FGT) index. Their study showed that food poverty was widespread in Nigeria and that there is a need for public intervention to increase access to food. In a study of American Indians and Alaska Natives, Jernigan *et al*. (2017) used data from the Current Population Survey Food Security Supplement and found that between 2000 and 2010, 25% of American Indians and Alaska Natives were persistently food poor and were twice as likely to be food poor compared to their white counterparts. The study showed the need for targeted public policy to promote access to healthy foods among ethnic minority populations.

The preceding analysis shows that food poverty is a matter of concern in many countries. However, there is limited research on the incidence of food poverty. Furthermore, the drivers of food poverty are assumed to have the same average effects, yet they are mostly idiosyncratic. This limited research affects targeting of the most affected households and hence impedes on the likelihood of achieving SDG 2. Therefore, there is a need for regular profiling of food poverty and analysis of the determinants of food consumption expenditure based on robust econometric methods such as quantile regressions.

3. MATERIAL AND METHOD

Poverty measurement and profile depend on the measurement of welfare which is commonly based on consumption expenditure or income as discussed in

Ravallion (1998). In the case of Uganda, Uganda Bureau of Statistics (UBOS) measures household food welfare in terms of expenditure on consumption per adult equivalent (CPAE) to meet the daily dietary requirements. The daily energy requirement is the amount of food energy needed for a healthy body to perform normal physical activity based on the joint United Nations University (UNU), Food and Agriculture Organization (FAO) and World Health Organization (WHO) (2004) methodology. The consumption expenditure is based on market and non-market food consumption adjusted for inflation, regional differences, household composition and size. Formally, CPAE for a household at any time is computed as:

$$CPAE_{it} = \frac{1}{n_{it}^{*}} \sum_{i=1}^{K} q_{jit} p_{jt} \tag{1}$$

Where q_{jit} is the quantity of food item/commodity j consumed by a household over period t, p_{jt} is the inflation-adjusted price of the commodity j and n_i^* is the equivalent number of adults in the household as defined in FAO/WHO/UNU (2004). Once household welfare is measured by the $CPAE_{it}$, a poverty line is set to determine the poverty rate. The poverty line is the minimum CPAE and any household that falls below is deemed to be poor. There are several methods that can be used to set poverty lines to measure poverty and food poverty in particular. The methods include the Direct Calorie Intake (DCI) method, Food Energy Intake method, Cost of Basic Needs approach, and Arbitrary-Choice-of-Index (ACI) method as discussed in Ravallion (1998, 2008, 2010) and Asra and Santos-Francisco (2001).

The Uganda Bureau of Statistics uses the Cost of Basic Needs approach to arrive at both the food poverty line and the income poverty line as discussed in Appleton (2001) and UBOS (2021). Since Uganda's food poverty line (absolute poverty line) meets the monotonicity, transfer, and focus axioms[1] (Sen, 1976), the food poverty rate can be measured. Specifically, if real food CPAE is below the poverty line, then the household is food poor. In the 2016/2017 and 2019/2020 UNHS data, the food poverty line was Uganda Shillings (UGX) 30,611 (about USD 15.1) per month (in 2009/2010 prices).

Whereas there are ways of computing poverty rates, the commonly used method is the FGT 1984 index since it satisfies the monotonicity, transfer, and focus axioms and it is additively decomposable for population subgroups. The ability to decompose a poverty measure for subgroups is relevant to this paper's objective of profiling the food poor. Consequently, in computing food poverty

[1] The axiom of monotonicity and transfer implies that a decrease in consumption of a household that is below the poverty line must increase the poverty rate and transferring consumption from a poor to a richer household should increase the poverty rate, all else constant. On the other hand, the focus axiom ensures the poverty measurement is based on consumptions of the poor households only.

rates, gap (depth) and severity, the FGT index (Foster *et al*., 1984) was applied as follows:

$$FGT(\alpha) = \frac{1}{n}\sum_{i=1}^{p}\left(\frac{z - y_i}{z}\right)^{\alpha} \tag{2}$$

From equation (2), y_i denotes the food CPAE of food poor household i, while n, p and z denote the total population, the food poor population and the food poverty line, respectively. The parameter α is the food poverty aversion parameter. When α is equal to zero, equation (2) becomes the food poverty headcount ratio:

$$FGT(0) = \frac{1}{n}\sum_{i=1}^{p}\left(\frac{z - y_i}{z}\right)^{0} = \frac{p}{n} \tag{3}$$

When α is equal to 1, the index is the food poverty gap (depth), which measures the average gap between the food poverty line and household food CPAE, and it is estimated as:

$$FGT(1) = \frac{1}{n}\sum_{i=1}^{p}\left(\frac{z - y_i}{z}\right) \tag{4}$$

The severity of food poverty is estimated with α equal to 2 to give higher consideration to those who are very far away from the poverty line, and the index is defined as:

$$FGT(2) = \frac{1}{n}\sum_{i=1}^{p} I\left(\frac{z - y_i}{z}\right)^{2} \tag{5}$$

Equation (3) is applied to measure the food poverty headcount index, which measures the share of a population living under the food poverty line. Equation (4) is used to estimate the Poverty Gap Index to capture the average food consumption expenditure deficit of the food poor relative to the food poverty line, that is, the depth of food poverty. Furthermore, the Poverty Severity Index [Equation (3)] is computed, which is the Squared Food Poverty Gap Index, to place greater emphasis on the populations that are further away from the food poverty line. In all estimations, sample weights are included to avoid biased estimates. The sample weights ensured that the total population and subgroup population were equal to the official estimated population at the time of the surveys. The Araar & Duclos (2007) Distributive Analysis Stata Package was used to test for statistical significance of differences in food poverty rate before and during coronavirus disease 2019 (COVID-19) lockdown periods.

In the analysis of food poverty, it is crucial to examine the factors that influence household food consumption expenditure. From a micro-economic perspective, one can model household food consumption decisions as a minimisation of expenditure subjective to household utility. That is:

$$\begin{aligned} &\underset{q_j \geq 0}{Min} \quad \sum_{j=1}^{K} p_{it} q_{jit} \\ &s.t \quad \bar{U} = U\left(q, G, L\right) \end{aligned} \tag{6}$$

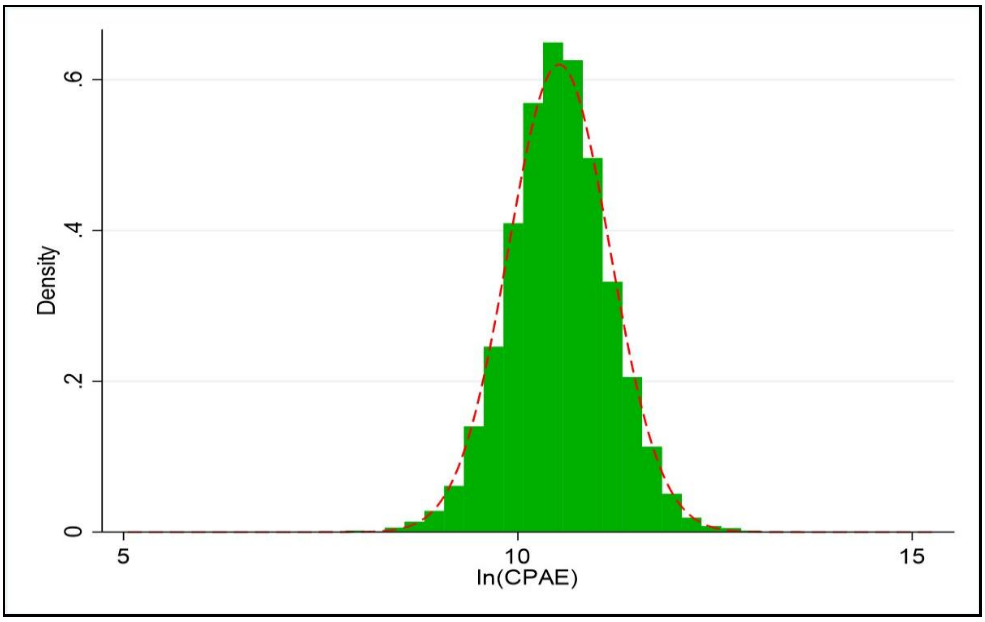
Where q is a vector of food items, G is a vector of all other goods, and L is leisure. Let q^* *(p,U)* be vector of the Hicksian (compensated) demand function of food items, that solves the household cost minimisation problem in equation (6). By duality of cost minimisation and utility maximization, the Hicksian demand function q^* *(p,U)* is equal to the observed Marshallian demand function q^* *(p,M)*, where M is the household's income. The observed food CPAE defined by:

$$p.q^*\left(p,U\right) = p.q^*\left(p,M\right) \tag{7}$$

The CPAE depends on the price of food items, household income and factors that influence household utility/ consumption decisions. Therefore, we can estimate the effect of the observable factors on food poverty by considering how the factors influence CPAE.

Several studies such as Glewwe (1991), Mukherjee and Benson (2003), Datt & Jolliffe (2005), and Litchfield & McGregor (2008) applied the Ordinary Least Squares (OLS) method to examine the determinants of household welfare. Most of the studies involved fitting the natural logarithm of per capita consumption on a number of explanatory variables. The OLS method minimises the sum of residuals squared to estimate the vector of parameters to measure the average change in the dependent variable associated with a change in explanatory variables. One weak assumption of the OLS method is that the associations between explanatory variables and dependent variables are the same at all levels of the dependent variable. In the presence of skewed distribution, outliers, and multimodal data, the conditional mean obtained from OLS fails to fully explain the variation of dependent variable at different points of its distribution.

The idea of Quantile Regression was introduced by Koenker & Bassett (1978) to account for differences in parameters at different points in the distribution of a variable. In our data, the distribution of the CPAE and its logarithms is not normally distributed as illustrated in Figure 1. Consequently, OLS parameter estimates are likely to be sensitive to outliers in the distribution of the natural logarithms of CPAE.



Source: Author's computation based on UNHS 2019/2020 data.
Figure 1. Empirical Distribution of log of CPAE.

To account for the lack of common parameters at different points in the distribution of the dependent variable (CPAE), we applied quantile regression. If we let *Yi* denote the natural logarithms of food CPAE, then a stochastic relationship *Yi* and explanatory variables can be stated as:

$$Y_i = X_i{}'\beta + \varepsilon_i \tag{8}$$

Angrist & Pischke (2008) noted that for discrete random variables and for variables with less well-behaved densities, with probability distribution function F(Y)=Pr(Y<y) the τ^{th} quantile can be defined as:

$$Q_\tau\left(y_i \mid X_i\right) = X_i{}'\beta_\tau = \inf\left(y : F_Y(y_i \mid X_i) \ \geq \tau\right) \ , \ \forall \ 0 < \tau < 1 \tag{9}$$

In contrast with OLS regression which minimises the sum of squared residuals, quantile regressions minimise a quantile of weighted sum of the positive and negative residual terms defined as:

$$Min \sum_{y_i > \hat{\beta}'X} \tau \left| y_i - \hat{\beta}'X_i \right| + \sum_{y_i < \hat{\beta}'X} \left(1-\tau\right) \left| y_i - \hat{\beta}'X_i \right| \tag{10}$$

In equation (10), τ is the quantile level and when $\tau = 0.5$, the model becomes a median regression. For clarity, we note that quantile regression puts weights on distances between the values predicted by the regression line and the observed values and then minimises the weighted distances. Therefore, it is not a regression on each quantile. It allows parameters to vary according to the distribution of the dependent variable. The coefficients are not sensitive to outliers of the dependent variable as it would have been under OLS. Furthermore, the quantile estimator is more robust even when errors are not normally distributed (Buchinsky, 1998; Cameron and Trivedi, 2005). Therefore, quantile regression appears appropriate for this study to detect differences in the upper and lower tails of the distribution of the dependent variable.

In the estimations, the vector of explanatory variables used include: characteristics of household heads such as age, gender, marital status, education level and main source of income. Other explanatory variables include household size, location of residence (rural/urban), ownership of non-agricultural enterprises and financial decision-making power in the household. The choice of the explanatory variables is based on the literature such as Glewwe (1991), Biyase & Zwane (2018), and Eigbiremolen *et al*. (2018). For instance, Allee *et al*. (2020) showed that **income levels and sources** is a fundamental determinant of food expenditure. Different income sources, such as agricultural and non-agricultural earnings, may have heterogeneous effects across the distribution of food CPAE (Allee *et al*., 2020). Education influences food consumption through its impact on income, nutritional awareness, and food choices. Higher educational attainment is associated with greater dietary diversity, particularly in upper quantiles of food CPAE (Günther & Leonov, 2012). Larger households often experience lower food consumption per capita due to resource constraints, though economies of scale may mitigate the negative effects at higher quantiles (Koenker & Hallock, 2001). Urban and rural households face distinct food prices and access to markets, leading to differential impacts across quantiles (Hoddinott & Haddad, 1995). Similarly, age may reflect lifecycle effects on food consumption, while gender dynamics influence household spending priorities, with female-headed households often prioritising food expenditure (Ogunniyi *et al*., 2021).

The data used in this study came from the 2016/2017 and the 2019/2020 Uganda National Household Surveys (UNHS) of UBOS. The choice of data was based on the fact that they contained measures of welfare and food poverty lines, and indeed the same poverty line facilitate comparison over time. Each dataset is large, with over 10,000 observations obtained through stratified random sampling with sample weights to ensure that estimates are representative of the population and subgroups. For each data set, data collection was spread over a period of 12 months to account for seasonality and to ensure comparability across survey waves. Part of the 2019/2020 data set was collected during the COVID-19 pandemic. This provided a unique opportunity to profile food poverty during shocks.

For the purpose of this study, we used data on **household demographics** (household size, age, household head gender and education levels), sources of income, food expenditure (adjusted to per adult equivalent measures to ensure comparability across households), and **regional and location variables** to control for regional price differences and food accessibility. Statistical software, STATA, was used to merge relevant sections of the data sets based on household identifiers. A minimum of 11,970 observations from 2019/2020 were used in the quantile regression. These were households with a balanced number of explanatory variables. Some households were dropped from the regressions due to missing observations on some variables but this didn't affect the robustness of the findings.

To profile the food poor, food poverty was computed based on inflation and location-adjusted food poverty lines. The FGT class of poverty indicators were computed, including the headcount ratio, the poverty gap (depth) and poverty severity (Foster *et al*., 1984). This was performed for geographical location, demographic and socio-economic characteristics of households to profile the food poor in Uganda. Quantile regression analysis was conducted to examine how socio-economic factors influenced food consumption expenditure in different quantiles. The results are presented in the following section.

4. RESULTS AND DISCUSSION

In line with the objective of tracking changes in food poverty since the adoption of the SDGs, our analysis started with the 2016/2017 UNHS data, and the results are displayed in Table 1. It shows that the headcount food poverty incidence in Uganda was 36.7% in 2016/2017, with food poverty gap (depth) of 10.2% and severity index of 4.2%. The food poverty headcount rate was higher than the income poverty rate (21.4%). In absolute terms, the number of food-poor people was about 13.72 million, which far exceeded the number of income-poor (8.3 million). This indicates that food poverty is a dire problem in Uganda, relative to income poverty. Considering urban and rural areas as subgroups, in 2016/2017, food poverty was higher in rural areas (39.9%) than in urban areas (26.3%). The food poverty gap (depth) and food poverty severity indices were in rural areas and the contribution of the rural population to food poverty was 82.3%. This indicates that rural households, which largely depend on subsistence agriculture, were not producing enough output to meet dietary needs and also lacked income to purchase food items.

Table 1

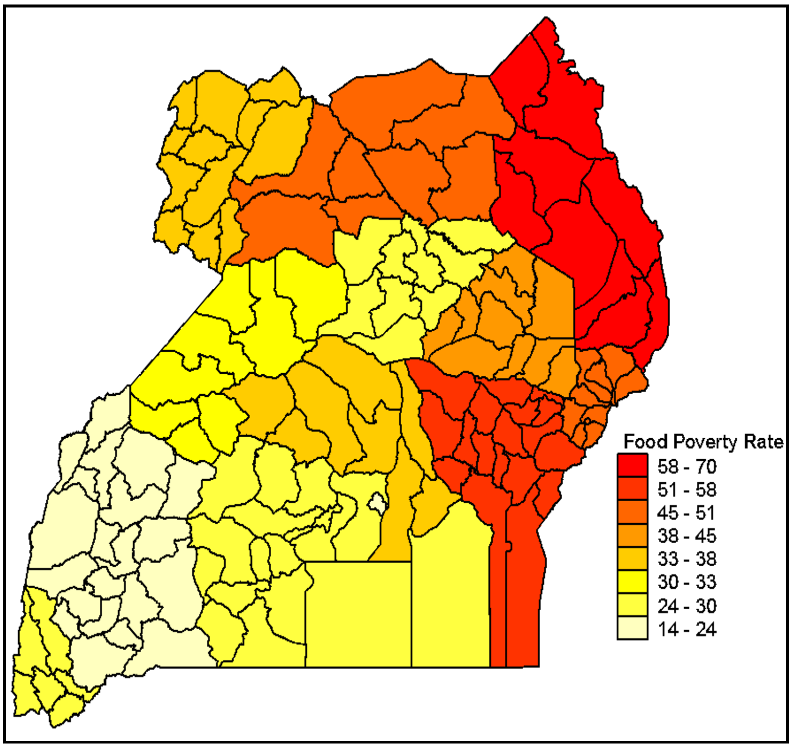
2016/2017 Food Poverty Headcount, Depth, and Severity in Uganda by Location

	Mean food CPAE	**P_0 Headcount**	**P_1 Gap**	**P_2 Severity**	**Contribution to food poverty (%)**
Uganda	51,019	36.6	10.3	4.2	100%
Urban	61,374	26.3	7.0	2.7	17%
Rural	46,042	39.9	11.4	4.7	83%
Regions					
Buganda	49,886	30.3	8.5	3.5	22.7%
Eastern	34,608	51.1	14.6	6.0	36.6%
Northern	39,244	42.7	12.6	5.4	24.3%
Western	52,719	23.5	6.0	2.3	16.4%
Sub regions					
Kampala	65,851	20.2	5.2	2.0	2.3%
Buganda South	50,132	30.0	8.4	3.4	10.4%
Buganda North	43,334	34.6	10.0	4.2	10.0%
Busoga	34,283	52.2	15.3	6.4	14.7%
Bukedi	33,619	57.7	17.8	7.5	8.6%
Elgon	34,753	48.4	13.3	5.3	6.8%
Teso	36,103	44.9	11.4	4.2	6.5%
Karamoja	28,140	69.6	24.1	11.1	5.4%
Lango	46,300	29.5	8.2	3.2	4.8%
Acholi	35,069	51.2	17.7	8.4	6.1%
West Nile	40,198	38.1	9.1	3.2	8.1%
Bunyoro	45,544	33.1	9.3	3.6	5.5%
Tooro	49,788	24.3	5.7	2.1	5.0%
Ankole	62,414	14.5	3.7	1.4	3.2%
Kigezi	49,149	26.0	6.5	2.6	2.7%

Source: Authors' computation based on UNHS 2016/2017 data.

Regionally and sub-regionally, the highest incidence of food poverty in Uganda in 2016/2017 was in the northern and eastern regions with Karamoja, Bukedi, Busoga, Acholi and Teso subregions registering headcount ratios that were higher than the national average (36.6%). The worst affected subregion was Karamoja, which had a food poverty rate of 69.6%, followed by Bukedi (57.7%) and Busoga (52.2%). The mean food CPAE (UGX 28,140≈USD13.8) in Karamoja subregion was lower than the food poverty line of UGX 30,611 (USD15.1) per month. This indicates that food poverty in Karamoja was possibly so bad due to the harsh semi-arid climate that does not support food crop production. Furthermore, the poverty index and the severity of food poverty was also highest in the northern and eastern regions and the subregions of Karamoja, Bukedi, Busoga, Acholi, and Teso. On the other hand, the incidence, depth, and severity of food poverty was moderate in Buganda and the western region. Ankole, Kampala and Tooro subregions have relatively low headcount, depth, and severity indices in comparison to other sub regions. However, due to the large population of Buganda and Busoga, these subregions have the highest contribution to the number of food poor people in Uganda. Figure 2 provides the spatial distribution of the incidence of food poverty in Uganda in 2016/2017. It is apparent that while it would be easiest to reduce food poverty in Buganda and western regions, it would take a concerted effort to do so in the northern and eastern regions. It is obvious that reducing food poverty is a precondition for reducing overall poverty in Uganda.

The preceding analysis shows that by the time the SDGs were adopted, many Ugandans were facing food poverty, with the eastern and northern regions having very high incidence, depth and severity indices. It is plausible that over time, government, development partners and households could have implemented some interventions under the 2016 National Coordination Framework for the Implementation of the SDGs, to reduce food poverty and achieve SDG1. The outcome of such interventions would be reflected in changes in food poverty over time and across geographical locations. This is examined by estimating the food poverty incidence, depth, and severity based on UNHS 2019/2020, which was collected five years after the adoption of the SDGs. Table 2 shows that there was an increase in the incidence of food poverty to 40.6% from 36.7% (Table 1).



Source: Authors' computations based on the UNHS 2016/2017 dataset.
Figure 2. Spatial Pattern of Incidence of Food Poverty in Uganda in 2016/2017.

The food poverty depth and severity also increased in 2019/2020. In absolute terms, the number of food poor people increased to 16.7 million, from 13.72 million. Rural residents had a higher food poverty rate (43.4%), compared to their urban counterparts (33.3%). The depth and severity of poverty also increased in both rural and urban areas.

Considering the four regions of Uganda, in 2019/2020, the incidence of food poverty was higher in the northern (54%) and eastern regions (49%) than in the western (30.8%) and central (31.7%) regions. The same pattern is exhibited in the depth and severity of food poverty. This implies that between 2016/2017 and 2019/2020, food poverty worsened in all four regions of Uganda.

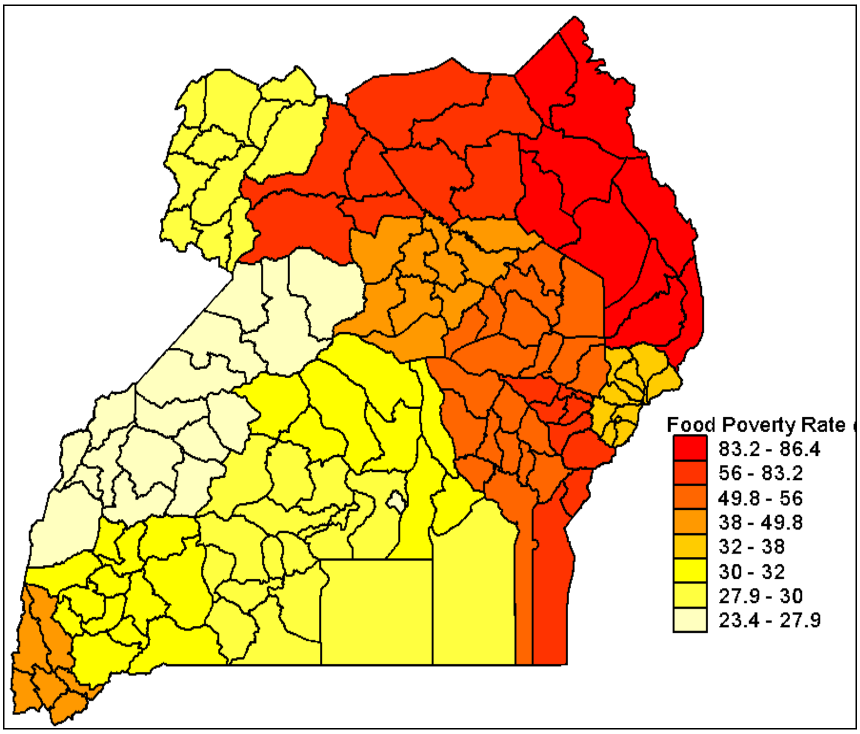
Table 2

Food Poverty Headcount, Depth, and Severity in Uganda by Location in 2019/2020

	Mean food CPAE	**P_0 Headcount**	**P_1 Gap**	**P_2 Severity**	**Contribution to food poverty (%)**
Uganda	41,492	40.6	12.5	5.5	100
Urban	47,682	33.0	9.6	4.1	22
Rural	39,247	43.4	13.5	5.9	78
Regions					
Buganda	46,922	31.7	8.7	3.4	22.7
Eastern	37,608	49.2	14.8	6.3	36.6
Northern	34,915	54.0	20.1	10.0	24.3
Western	44,871	30.8	8.2	3.2	16.4
Sub regions					
Kampala	58,578	23.5	5.8	2.4	2.4
Buganda South	47,923	29.9	7.5	2.7	9.7
Buganda North	41,193	37.1	11.2	4.7	9.7
Busoga	37,039	49.7	15.2	6.6	11.9
Bukedi	32,495	57.8	19.0	8.3	8.4
Elgon	48,197	33.5	8.7	3.4	4.2
Teso	34,181	53.6	15.1	6.2	7.0
Karamoja	19,195	86.4	44.2	27.0	6.0
Lango	35,295	49.8	14.9	6.1	7.2
Acholi	23,624	83.2	34.2	17.1	8.8
West Nile	46,673	29.1	7.5	2.9	5.5
Bunyoro	48,484	25.3	5.8	2.1	3.9
Tooro	43,718	27.9	6.5	2.3	5.0
Ankole	46,818	31.1	8.7	3.6	6.1
Kigezi	37,122	44.3	14.2	6.2	4.2

Source: Authors' computations based on the UNHS 2019/2020 dataset.

In terms of subregions, almost all subregions experienced an increase in the incidence, depth and severity of food poverty in 2019/2020. The only subregions that showed a fall in food poverty were Elgon and West Nile. The worst affected subregions were Karamoja, Acholi, Bukedi and Teso, with the food poverty headcount ranging from 53.6% to 86.4%. Even the subregions that had low food poverty rates in 2016/2017 experienced significant increases in 2019/2020. For instance, the Ankole subregion, which had the lowest food poverty rate of 14.5% in 2016/2017 had a food poverty rate of 31.1% in 2019/2020. Other subregions with significant increases in food poverty were Lango, Kampala, Buganda North and Kigezi. Figure 3 provides a spatial profile of food poverty in Uganda in 2019/2020.



Source: Authors'computations based on UNHS 2019/2020 data.
Figure 3. The Spatial Pattern of Food Poverty Incidence in Uganda in 2019/2020.

A comparative analysis of both the results in Table 1 and Table 2 and the spatial patterns in Figure 2 and Figure 3, showed that on average, the food poverty incidence is increasing in most subregions and nationally. The depth and severity of food poverty in Uganda is also on the rise. Consequently, the likelihood of achieving SDG 1 and ensuring a healthy population is being jeopardized through inadequate food energy intake. Therefore, it is important to profile the food poor by their demographic and socio-economic characteristics.

Table 3 profiles food poverty by gender, age and marital status of household heads. Food poverty is higher in female-headed households than in male-headed. This is consistent with the income poverty rate in Uganda, which is higher in female-headed households (UBOS, 2021). This is possibly related to inequitable land rights, limited physical ability to produce agricultural products, and low income of female household heads. Meinzen-Dick *et al*. (2019) showed that women's land rights, bargaining power and decision-making have an impact on consumption in Uganda. Therefore, there is need to integrate gender equity in the fight against food poverty and poverty in general.

Table 3

2019/2020 Food poverty profile by characteristics of household heads

	Mean food CPAE	**P_0 Headcount**	**P_1 Gap**	**P_2 Severity**	**Contribution to food poverty (%)**
Uganda	41,492	40.6	12.51	5.47	100
Gender					
Male	41,650	40.0	11.93	5.06	71
Female	41,090	42.2	13.96	6.51	29
Age of Household Head					
Less than 18 years	71,957	19.7	9.15	6.50	0.03
19–24 years	48,374	29.7	8.22	3.45	3.0
25–30 years	45,944	36.5	10.83	4.69	10.1
31–40 years	40,268	44.2	14.34	6.46	30.5
41–59 years	39,659	42.0	12.90	5.61	41.3
60+	43,163	36.7	10.65	4.49	15.1
Marital Status of Household Head					
Married(monogamous)	40,936	41.0	12.16	5.12	65.0
Married (polygamous)	37,038	47.0	16.52	8.14	15.9
Divorced/ separated	45,431	34.8	10.53	4.57	7.5
Widow/ widower	42,053	38.6	12.35	5.51	10.4
Never married	67,518	22.0	5.97	2.52	1.2

Source: Authors' computations based on UNHS 2019/2020 data.

The household head age influences household welfare and decision-making as discussed in Kyereme and Thorbecke (1987), and Rose and Charlton (2002). Table 3 shows that food poverty incidence in Uganda is more pronounced in households headed by a person in the 31–50 age bracket, yet this is one of the most productive periods in a person's lifecycle. It is plausible that these households have limited resources or high household sizes. The lower food poverty rate in households headed by persons below 18 can be explained by bequeaths (Anyanwu, 2014), support from charity organisations, and the physical ability of young adolescents to work for basic survival. It is also plausible that the higher food poverty in households headed by an older person (60+) is due to a decrease in income and physical ability to produce for domestic consumption in old age.

Considering the marital status of household heads, the incidence, depth and severity of food poverty is highest among those in polygamous households (47%), followed by households headed by monogamously married persons. This is possibly explained by the inadequate resources to feed many people relative to single-person households (never married). In a similar study on Nigeria, Anyanwu (2014) found that marital status has a significant influence on poverty and by extension, on food poverty.

The estimates in Table 4 show that household size, education attainment and source of livelihood in household heads influence the incidence, depth and severity of food poverty in Uganda. The incidence and depth of food poverty was particularly more pronounced in households with five persons or more. This is plausible since food consumption per capita tends to fall with household size. The finding is similar to Ozughalu & Ogwumike (2015) and Greer & Thorbecke (1986) who noted that the incidence of food poverty is slightly lower in households with more than 15 people in comparison with households of 5–10 people. This indicates that the severity of food poverty appears to increase with household size. Therefore, a reduction in food poverty requires that household sizes be maintained at levels that do not adversely affect welfare. Policy measures on reproductive health and education are critical.

Educational attainment of household heads influences livelihoods, household consumption decisions and welfare.

Table 4 shows that the incidence of food poverty is highest among households headed by those without any formal education, followed by those who have some elementary education. It is lowest among households headed by those who completed a university degree and above. This finding is similar to the incidence of income poverty reported in UBOS (2021); Anyanwu (2014) and Ozughalu & Ogwumike (2015).

Table 4

Food Poverty Profile by household size, education and source of livelihood

	Food CPAE	**Head Count**	**Gap**	**Severity**	**Contribution to Food Poverty (%)**
Uganda	41,492	40.6	12.51	5.47	100
Household Size					
1-2 persons	68,058	16.9	4.89	2.17	3.0
3-4 persons	46,207	31.7	8.91	3.66	17.9
5-10 persons	37,441	45.5	14.31	6.36	72.7
11-15 persons	34,197	53.2	16.39	6.89	6.1
16+ Persons	40,450	38.3	15.13	6.54	0.4
Highest Education Level					
Never attended school	34,726	53.6	19.55	9.73	21.0
Some Primary	38,844	44.3	13.46	5.70	40.7
Completed P.7 Only	38,915	39.1	12.04	5.09	13.5
Post-Primary Vocational	44,099	41.7	9.89	3.03	1.0
Some Secondary	42,981	38.8	10.70	4.31	9.8
Completed Secondary	48,221	29.2	7.72	3.23	7.7
Completed Diploma	49,322	27.9	7.62	3.16	5.1
Degree and above	68,643	15.8	3.79	1.56	1.3

Table 4 (continued)

Main Source of Livelihood					
Crop farming(small scale)	37,493	46.0	13.74	5.78	49.6
Livestock(small scale)	45,855	28.4	9.31	4.07	1.2
Commercial farming	42,882	34.7	10.76	4.62	7.7
Wage employment	44,654	39.1	11.96	5.30	18.1
Non-agricultural enterprise	44,153	36.4	11.64	5.38	16.6
Property income	56,606	22.2	8.19	3.74	0.6
Pension and social security	60,128	8.0	2.78	1.64	0.1
Senior citizen grant	32,448	64.0	27.97	15.46	0.5
Domestic remittances	44,955	37.8	11.82	5.18	3.8
International remittances	63,261	13.8	4.00	1.89	0.1
NGO food aid	53,207	11.0	5.06	2.33	0.01
Other sources	43,286	35.6	13.52	7.26	1.7
COVID-19					
Before COVID-19	41,295	41.5	12.98	5.75	N/A
During COVID-19	41,692	39.8	12.02	5.18	N/A

Source: Authors' computations based on UNHS 2019/2020 data.

The availability of food for consumption is largely determined by the ability of the household head to produce food items (subsistence) and/or income to buy food from the market. Table 4 shows that the highest incidence of food poverty (64%) is among those in households whose heads depend on the Senior Citizens' Grant, a social protection grant given to persons aged 80 and above. The grant is UGX 25,000 per month (approximately USD 6.6 in nominal terms) and is not sufficient to meet household monthly consumption expenditure. Households that depend on small-scale agriculture as source of livelihood have the second highest incidence of food poverty, with a rate of 46%. Since most farmers in Uganda are engaged in smallholder crop agriculture, people in such households make up 49.6% of the food poor (8.6 million). On the other hand, small-scale livestock farmers have a relatively lower food poverty rate of 28.4%. This indicates differences in productivity and value of outputs between crop and livestock farming, that is to say, on average, small-scale livestock farming appears to be more beneficial than small-scale crop farming.

Other sources of livelihood with pronounced food poverty incidence are wage employment (39.1%), non-agricultural enterprise (36.4%) and domestic remittances (37.8%). A high food poverty rate among wage earners indicates that wages are not sufficient to sustain household consumption needs. On the other hand, food poverty is lowest among those whose household depends on pension (8%)[2], international remittances (13.8%) and NGO food aid (11%). The depth and severity of food poverty consistently vary across different sources of livelihood in Uganda.

[2] This category of households represents formally employed Government workers who are guaranteed a monthly remittance equivalent to 25% of their previous wage.

Since livelihoods influence consumption, it is critical to profile food poverty during episodes of shocks. Part of 2019/2020 UNHS data was collected before the onset of the COVID-19 pandemic and its associated lockdown that affected livelihoods, while another part was collected during the pandemic.

Table 5 shows that before the COVID-19 pandemic the food poverty rate was 41.5%, but declined to 39.8% during the pandemic, yet the difference is not statistically significant (p=0.3245).

In terms of sources of livelihood, households that depend on property income experienced a statistically significant decrease in food poverty during the COVID period, indicating that those who depend on property income are relatively secure compared to all other income sources. Although the increases were not statistically significant, there was an increase in food poverty in households that depend on commercial farming, pension/social security, senior citizens grants and NGO food aid. This was probably due to disruptions in resource flows which occurred across many sectors in the pandemic lockdown period.

Table 5

Food poverty (percentage) by source of livelihood pre- and during COVID-19

Main source of livelihood	Pre COVID-19	During COVID-19)	Difference
Crop farming (small scale)	46.68	45.22	-1.46
Livestock farming (small scale)	29.38	26.75	-2.63
Commercial farming	31.63	38.25	6.62
Wage employment	41.77	36.77	-5.00*
Non-agricultural enterprise	37.04	35.87	-1.17
Property income	35.35	13.11	-22.24**
Pension & social security	7.32	9.80	2.49
Senior citizen grant	59.60	66.76	7.16
Domestic remittances	45.24	31.50	-13.74*
International remittances	21.57	6.81	-14.76
NGO food aid	0.00	11.01	11.01
All	41.5	39.8	-1.7

Notes: *, ** implies that the differences are statistically significant at 10% and 5%, respectively
Source: Authors' computations based on UNHS 2019/2020 data.

From the preceding descriptive results, it might appear that the food CPAE for every household could be affected by geographical and socio-economic factors in the same way. This may not necessarily be the case as discussed in equations (6) through (9). The results in Table 6 show that the parameter estimates from OLS are different from the bootstrapped quantile regression. In the analyses, the dependent variable is the natural logarithm of food CPAE and the determinants of food CPAE are socio-economic and demographic variables. The goodness of fit for quantile regression in each of the five CPAE quantiles was assessed using $\beta(\tau)$, which is analogous to pseudo-R-squared, and the Wald's test as recommended by Koenker

& Machado (1999). The values of *β(τ)* in the 20th, 40th, 50th, 60th, and 80th quantiles indicate that the quantile regression model fits the data well. It is noted that a measure of goodness of fit increased as the quintile measure is increasing. Wald's test indicates that the coefficients are different across the quantiles with a p-value of 0.000. Furthermore, the link test for model specification shows that the model is well-specified. The link test is based on the null hypothesis that the regression equation is properly specified and the squared predicted value of the dependent variable cannot explain the variation of the dependent variable. The high p-value on the coefficient of $\hat{y}_i^2$ in the quantile regression indicates that the regression models are well specified.

Table 6

Determinants of Food CPAE: OLS and Quantile Regression Results

Y= ln(CPAE)	**OLS**	**Q20**	**Q40**	**Q50**	**Q60**	**Q80**
VARIABLES	OLS	Q20	Q40	Median	Q60	Q80
Household size	-0.203***	-0.206***	-0.260***	-0.273***	-0.238***	-0.256***
	(0.011)	(0.012)	(0.008)	(0.007)	(0.007)	(0.009)
Age of HH Head	0.019***	0.040***	0.019***	0.011*	0.032***	0.029***
	(0.006)	(0.009)	(0.005)	(0.006)	(0.005)	(0.005)
Sex of HH (Female)	-0.066***	-0.065***	-0.088***	-0.083***	-0.082***	-0.052***
	(0.022)	(0.024)	(0.020)	(0.014)	(0.019)	(0.018)
Main Income Source						
Livestock farm (small)	0.142***	0.106	0.136*	0.155***	0.148***	0.210***
	(0.055)	(0.078)	(0.073)	(0.043)	(0.041)	(0.070)
Commercial Farming	0.062**	0.025	0.054*	0.052**	0.103***	0.123***
	(0.025)	(0.039)	(0.029)	(0.023)	(0.026)	(0.036)
Wage Employment	-0.070***	-0.033	-0.028	-0.038*	-0.061***	-0.051**
	(0.018)	(0.027)	(0.021)	(0.022)	(0.016)	(0.023)
Non Agric. Enterprise	0.042**	-0.010	0.035**	0.030**	0.013	0.041***
	(0.018)	(0.024)	(0.017)	(0.013)	(0.021)	(0.014)
Property Income	0.145*	0.000	0.080	0.130	0.094	0.183
	(0.080)	(0.103)	(0.097)	(0.092)	(0.076)	(0.155)
Pensions	0.334***	0.324*	0.347**	0.277***	0.251*	0.253*
	(0.124)	(0.185)	(0.161)	(0.104)	(0.130)	(0.137)
Senior Citizen Grant	-0.293***	-0.576***	-0.440***	-0.363***	-0.327***	-0.231*
	(0.073)	(0.065)	(0.146)	(0.109)	(0.105)	(0.121)
Distance to Clean Water						
3 to 5 kMs	-0.038	-0.040	-0.059	-0.039	-0.042	-0.034
	(0.032)	(0.041)	(0.037)	(0.041)	(0.028)	(0.030)
5 to 8 kms	-0.087	-0.086	-0.184*	-0.181*	-0.198	-0.095
	(0.110)	(0.309)	(0.096)	(0.098)	(0.174)	(0.124)
8 or more kms	-0.464**	-0.569*	-0.486	-0.319	-0.335	-0.688
	(0.196)	(0.334)	(0.518)	(0.368)	(0.381)	(0.432)
COVID period	-0.020	-0.001	-0.034**	-0.039***	-0.024*	-0.041***
	(0.013)	(0.011)	(0.014)	(0.010)	(0.013)	(0.013)

Table 6 (continued)

Constant	10.755***	10.039***	10.592***	10.773***	10.907***	11.184***
	(0.047)	(0.052)	(0.039)	(0.050)	(0.031)	(0.042)
Observations	11,971	11,975	11,970	11,970	11,972	11,975
R-squared/Pseudo R^2	0.167	0.096	0.109	0.117	0.114	0.127
Linktest - p-values on $\hat{y}_i^2$	0.632	0.293	0.255	0.217	0.724	0.852

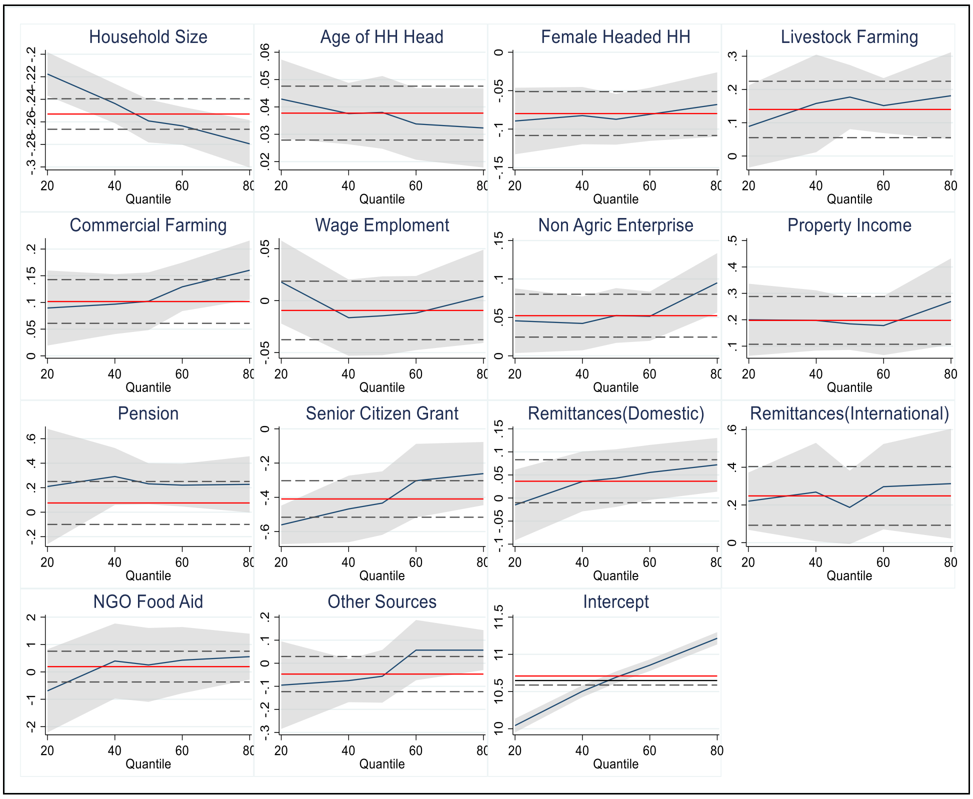
Note: Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Other control variables used are regional dummies, type of fuel used for cooking, marital status, location.
Source: Author's calculations using data from Uganda National Household Survey 2019/2020.

The results in Table 6 show that there is a negative relationship between household size and food CPAE. This reflects scarcity and it is plausible since average food consumption per person tends to decrease with the number of people, if resources are limited. Whereas the OLS regression showed that for an increase in household size by one person, food CPAE would fall by 20.3%, the quantile regression results indicated that the effect is not uniform across the distribution of food CPAE. At $\tau = 0.2$, increase in household size reduced CPAE by 20.6%, but in $\tau = 0.8$, the reduction was 25.6%, which is larger than the estimated effect based on the OLS method. This is illustrated in Figure 4 (red line is the OLS estimate while the grey line is a plot of coefficients for the quantiles with a 95% confidence interval) in the panel labeled. Considering the age of the household head, with the OLS, an increase in age by one year was associated with a 1.9 % increase in food CPAE, but the quantile regression showed variations in the coefficients along the distribution of food CPAE.

The effect of household head gender on food CPAE also differed across quantiles. Whereas the OLS estimate suggests that in comparison with male-headed households, food CPAE in female-headed households is lower by 5.26%, the quantile estimate at $\tau = 0.8$ showed that food CPAE is lower by 3.05%. Note that this interpretation is based on the fact that the authors estimated a log-linear model and therefore the coefficient for categorical variables needs to be transformed to give intuitive meanings[3].

The results in Table 6 also show that the effect of household income sources differed across food CPAE quantiles. Households that depended on livestock farming and commercial farming had higher food CPAE (by 13.65% and 9.42% respectively, from the OLS model) than those who depended on small-scale crop farming (the base category). However, the magnitude of the effects varied across the quantiles. This also applied to other sources of income such as wage income, property income, non-agricultural enterprises, wage employment, remittances and senior citizens' grant.

[3] For instance, the coefficient for female-headed households is computed as exp (-0.054)-1)*100 yields -3.05, which is a percentage difference. Generally for such categorical variables represents the percentage difference in CPAE relative to the base category.



Source: Authors' computations based on UNHS 19/2020 data.
Figure 4. Quantile coefficient plots.

Education level of household head is another factor that influences household livelihoods and food CPAE in Uganda. The results in Table 6 indicate that relative to those who have never attended any formal schooling, those who attained primary, secondary, post-secondary and university level education had higher food CPAE and the magnitude of positive effect increased with the level of education for both the OLS and quantile regression results. For instance, from the OLS results, for a household whose head completed some primary education, the CPAE was 25.86% higher than for a household whose head never attended formal education. Figure 4 indicates a significant difference between the OLS estimate of the quantile regression coefficients for education at secondary, tertiary and university levels. The quantile regression results showed that the effect is not uniform and thus provided deeper intuition about the effect of education at different levels of food CPAE.

Household consumption is often affected by disasters and epidemics such as COVID-19 that disrupt economic activities and supply chains. The regression results in Table 6 show that COVID-19 had a negative effect on food CPAE. In the OLS model, the COVID-19 period was weakly associated with a 2.07% decrease in food CPAE, but the effect was not uniform as shown by the quantile regression results. Households at $\tau = 0.8$ of the food CPAE distribution experienced a slightly higher (3.1%) reduction in food CPAE than those in the lower quantiles. The foregoing discussion shows that quantile regressions can provide insights into how the effects of poverty covariates are not constant for a given population but rather vary depending on the quantile in which they fall in the distribution.

Table 7

Robustness Check with 2016/2017 UNHS Data set

VARIABLES	**OLS**	**Q20**	**Q40**	**Q50**	**Q60**	**Q80**
Household size	-0.253***	-0.239***	-0.254***	-0.250***	-0.257***	-0.255***
	(0.007)	(0.010)	(0.006)	(0.009)	(0.012)	(0.011)
Age of Household Head	0.019***	0.009*	0.013***	0.022***	0.021***	0.029***
	(0.005)	(0.005)	(0.004)	(0.006)	(0.007)	(0.007)
Gender of household Head						
Female	0.033***	0.025	0.016	0.019	0.031*	0.041**
	(0.013)	(0.019)	(0.014)	(0.021)	(0.018)	(0.017)
Sources of Income						
Small livestock farm	0. 122***	0.142***	0.096**	0.077	0.099**	0.146**
	(0.039)	(0.047)	(0.040)	(0.048)	(0.040)	(0.069)
Commercial farming	0.159***	0.202***	0.193***	0.206***	0.155***	0.104*
	(0.036)	(0.042)	(0.057)	(0.037)	(0.039)	(0.058)
Wage Employment	-0.048***	-0.068***	-0.029	-0.016	-0.025	-0.023
	(0.015)	(0.019)	(0.018)	(0.021)	(0.023)	(0.023)
Non Agric. Enterprise	0.064***	0.063***	0.066***	0.066***	0.064***	0.060***
	(0.015)	(0.022)	(0.018)	(0.020)	(0.023)	(0.020)
Property Income	0.058	-0.051	0.077	0.036	0.089	0.059
	(0.053)	(0.086)	(0.048)	(0.061)	(0.057)	(0.081)
Pensions	0.051	0.193	0.077	0.121	0.066	0.075
	(0.076)	(0.151)	(0.106)	(0.088)	(0.087)	(0.116)
Remittances	0.001	0.005	-0.003	0.003	0.013	0.004
	(0.024)	(0.025)	(0.040)	(0.031)	(0.032)	(0.035)
Organisational Support	0.286	0.339	0.069	-0.019	0.522	0.314
	(0.239)	(0.343)	(0.390)	(0.420)	(0.388)	(0.319)
Education Level						
Some primary	0.093***	0.150***	0.093***	0.091***	0.062**	0.037*
	(0.018)	(0.028)	(0.022)	(0.018)	(0.025)	(0.023)
Completed primary	0.189***	0.240***	0.184***	0.197***	0.172***	0.133***
	(0.021)	(0.037)	(0.030)	(0.029)	(0.028)	(0.030)
Some secondary	0.238***	0.311***	0.239***	0.225***	0.196***	0.169***
	(0.021)	(0.023)	(0.024)	(0.023)	(0.031)	(0.030)
Lower secondary	0.281***	0.346***	0.257***	0.262***	0.232***	0.227***
	(0.025)	(0.034)	(0.029)	(0.027)	(0.037)	(0.026)
Higher secondary	0.306***	0.376***	0.290***	0.319***	0.262***	0.220***
	(0.035)	(0.040)	(0.050)	(0.035)	(0.053)	(0.063)

Table 7 (continued)

Diploma	0.400***	0.459***	0.385***	0.369***	0.344***	0.308***
	(0.029)	(0.038)	(0.043)	(0.039)	(0.033)	(0.066)
Degree	0.543***	0.568***	0.546***	0.546***	0.509***	0.556***
	(0.042)	(0.069)	(0.057)	(0.040)	(0.029)	(0.056)
Constant	11.158***	10.653***	11.019***	11.147***	11.333***	11.754***
	(0.071)	(0.089)	(0.089)	(0.104)	(0.108)	(0.111)
Observations	10,396	10,396	10,396	10,396	10,396	10,396
R-squared/Pseudo R^2	0.273	0.138	0.149	0.154	0.159	0.169
Linktest - p-values on $\hat{y}_i^2$	0.597	0.660	0.785	1.000	0.856	0.831
Wald's Test (p-values)	0.000	0.000	0.000	0.000	0.000	0.000

Note: Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Other control variables used are regional dummies, type of fuel used for cooking, marital status, location.
Source: Author's calculations using data from Uganda National Household Survey 2016/2017.

This finding is similar to Eyasu (2020) who found that in Ethiopia the determinants of poverty did not have uniform effect as would be predicted by OLS, but differed by quantiles. Similarly, Garza-Rodriguez (2021) used quantile regression and OLS found that the parameters on determinants of poverty in Mexico were significantly different. Furthermore, Bosco (2019) showed that in the study of poverty determinants, quantile regression yielded more reliable results than OLS regression. It is also noted that there has been no study that examined food poverty profile and determinants of food CPAE in Uganda. Therefore, this study contributes to the literature by applying a more robust method to shed light on the determinants of food poverty, as a major contributor to overall poverty in Uganda.

A robustness check analysis with data from the 2016/2017 Uganda National Household Survey is shown in Table 7. The results indicate that food CPAE is not affected along its distribution in the same way as it would be assumed under OLS. Indeed that results show that the effect of household size, household age and gender, source of livelihood and education level are not the same across quintiles of food CPAE. Therefore, quantile regressions can yield informative results in the analysis of food poverty.

5. CONCLUSIONS

The purpose of this study was to profile food poverty in Uganda and track the progress towards the attainment of SDG2 (zero hunger) which is linked to SDG 1 (End poverty in all its forms). We used the FGT poverty indices and quantile regression to analyse the incidence and drivers of food poverty in Uganda. Our results indicate that food poverty is very high in Uganda. Nationally, headcount food poverty increased from 36.6 % in 2016/2017 to 40.6% in 2019/2020. This indicates that it might be challenging for Uganda to achieve SDG 1 and SDG 2.

Spatially, food poverty is highest in Karamoja, Acholi, Lango, Bukedi and Busoga subregions, with the incidence of food poverty hitting as high as 86.4% in Karamoja subregion. The depth and severity of food poverty followed a similar pattern with food poverty incidence. However, in terms of contribution to food poverty (the number of food-poor persons), Busoga, Buganda have the highest number of food-poor persons. This indicates the need for targeted interventions to reduce food poverty rates in areas with very high rates and in areas that highly contribute to national food poverty.

In terms of socio-economic background, the incidence of food poverty in Uganda is highest in female-headed households, polygamous families and large households with over five persons. Furthermore, households that depend on small-scale crop farming and whose heads have never attended formal education have the highest food poverty rates. The COVID-19 pandemic had limited effect on food poverty in Uganda, possibly due to the use of past savings to cushion households during the shock, as well as the freed up time that could have been used to produce food during the local lockdown period.

Quantile regression results showed that the factors that affect food consumption expenditure do not have uniform coefficients as would be assumed under OLS (conditional mean). There was significant variation of the coefficients at different points of consumption expenditure distribution. This indicates the need to tailor interventions so that households that are most affected by a factor receive the most appropriate poverty-reducing interventions.

Based on the empirical evidence, it is recommended that the Government of Uganda and development partners should empower individuals and households through gainful employment, commercialisation of agriculture, increasing access to quality education (SDG 4), and reducing gender imbalance (SDG 5). Social assistance to the elderly should be increased since most recipients are food-poor and above working age.

Interventions in reproductive health aspects can help the population in planning optimal household size, which has a direct bearing on food poverty. Therefore, increasing access to safe and affordable family planning services can reduce food poverty in Uganda in the long run. Given that educational attainment of the household's heads influences food poverty, access to education beyond the primary school level and expansion of economic opportunities can enable households to acquire productive skills and facilitate the movement of food-poor people to decent jobs in industry and services.

Our empirical evidence showed that food poverty is high in female-headed households. Consequently, there is a need to design interventions to empower female-headed households, and these may include guaranteeing land rights, social protection, and other forms of affirmative action. Since food poverty can be solved through increased access to food, improved agricultural productivity and production can play a significant role in reducing food poverty in Uganda. Easing access to modern inputs, extension services and credit can enhance agricultural productivity and increase supply and access to food. Future studies could examine the extent to which government interventions in agriculture can have an impact on food poverty in Uganda. This is because every financial year, significant resources are allocated to agriculture, but the efficacy of the interventions remains murky.

6. ACKNOWLEDGEMENTS

The authors acknowledge Uganda Bureau of Statistics (UBoS) for enabling access to survey data that were used in this study.

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