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An Analysis of the Effects of 'Double Risk' of Food Insecurity in South Sudan

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Abstract

This study sets out to investigate the effect of the 'double risk' of food insecurity as manifested through coping with livelihood strains and food expenditure during a protracted humanitarian crisis in South Sudan. We used Generalized Linear Mixed Modelling for determining possible predictors of the joint outcome of adopting or not adopting a coping strategy, on one hand, and share of total household budget expenditure on food, on the other. We found out that agriculture-based livelihood sustaining endowments and certain household characteristics were significant factors of this 'double risk'. The technique was also found to exert sufficient rigour for generating an index that may be used for determining household resilience to food insecurity risk in protracted humanitarian crisis.

Keywords: *Coping strategy; Joint modelling; Generalized linear mixed model; Fixed effects; Random effects*

Abbreviations: AU: African Union; CSI: Coping Strategies Index; FAO: Food and Agricultural Organization of the United Nations; FSMS: Food Security Monitoring Survey; GLM: Generalized Linear Model; GLMM: Generalized Linear Mixed Model; NEPAD: New Partnership for Africa's Development; UNECA: United Nations Economic Commission for Africa; UNHCR: United Nations High Commissioner for Refugees; UNICEF: United Nations Children's Fund; USDA: United States Department of Agriculture; WFP: World Food Programme

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Introduction

The Relationship between Food Insecurity Coping and Food Expenditure: Coping with food insecurity experiences and increased share of total household budget spent on food tend to lower household resilience to food insecurity risks. Conceptually, certain household attributes and means of livelihood tend to influence the likelihood of the two outcomes of food in/security. High household food expenditure compromises acquisition of other equally important essentials for sustaining livelihood such as health, education and economic productivity [1].

High expenditure on food leads to adoption of coping strategies, some of which could have undesirable socioeconomic impact. A survey by the United States Department of Agriculture [2] determined that households with pregnant women, infants or children younger than 5 years old tend to spend more on food. This means such households are rendered more vulnerable when food prices shoot up and their food insecurity can be threatened, leading to morbidity and fatalities. Lokosang., *et al*. [3] observes that severe food insecurity forces households to become so desperate as to resort to adopting extreme or even unthinkable forms of survival or coping strategies. Chambers [4] posits that difficulty in coping with livelihood stresses, which of course includes food insecurity, is an outcome of vulnerability.

In this regard, it is important to understand the seriousness and the magnitude of the determinants of the joint outcome and how they impact on the status of food security. Such knowledge could help in developing appropriate policy for preventive action against adverse effects such as lack of adequate investment in agriculture, animal production, fisheries and aquaculture. Where the effect is quite pronounced, it might prompt policy makers and food security intervention developers to decide where and when to take action.

The Food and Agricultural Organisation of the United Nations (FAO) [5] cautions that major causes of food insecurity are likely to "persist for some time", forcing households to adopt short-term coping strategies and thus rendering livelihoods unsustainable. In Snel and Staring [6], coping strategies are referred to as "all the strategically selected acts that individuals and households in a poor socioeconomic position use to restrict their expenses or earn some extra income, to enable them pay for the basic life necessities (food, clothing, shelter, security and health) and not fall too far below their society's level of welfare".

Share of total household expenditure on food is one of the measures of food in/security defined under the four dimensions of food security, namely; availability, access, stability and utilization. Food expenditure obviously fits into the *access* component of food security. FAO officially catalogues this indicator as "*Share (%) of food consumption expenditure in total consumption expenditure*" in its list of indicators. It defines the indicator as "the monetary value of acquired food, purchased and non-purchased, including non-alcoholic and alcoholic beverages as well as food expenses away from home consumption in bars, restaurants, food courts, work canteens, street vendors, etc." The numerator excludes non-consumption expenditure, such as direct taxes, subscriptions and insurance premiums [7]. A study of food consumption expenditure comparing Uganda, Vietnam and Peru concludes that rural households in Uganda use a larger share of their household budget for food consumption [8].

Significance of the Study: Conceptually an increase in food consumption expenditure is not only a risk factor that entrenches resource-poor populations in poverty, and a vicious cycle of food insecurity-related vulnerability, but also forces households in this category to adopt some form of coping strategy. Conversely, when households are barely coping with lack of food, it induces propensity to spend on food. This implies that there is a reciprocal effect between the two variables (coping strategy and food consumption expenditure).

It is further worth noting that both co-indicators of structural food insecurity have dire implications on perpetual asset poverty. The more a population adopts coping strategies, the more they keep spending a lion share of their incomes on food, and the more they are drenched into more asset poverty. Maxwell [9] determines that the indicator '*food share of household budget*' has positive correlation (0.195) with the coping strategy index (CSI), which means that an increase in expenditure on food pushes a household to cope to some extent. This is consistent with a test of association we carried out in exploratory analysis of this study using logistic regression with log- link function and the Wald Chi-square test of hypothesis. We found that adoption of coping strategy associated very highly with increase in share of food expenditure

The reader might wonder as to whether food consumption expenditure applies invariably for rural population as it does for urban population! The concern could arise from the assumption that often times a substantial proportion of rural populations do not purchase food from markets, but rather produce their own food. The answer to such concern rests on two important considerations. First, although the variable "*residential setting*", or whether an interviewed household was rural or urban, was not in the survey questionnaire.

The sample data contain households or clusters located in urban centres such as Malakal, Wau and Maridi; thus mostly depended on market purchase of food. Second, it is a known fact that South Sudan emerged from a protracted civil war with wide ranging displacement of citizens. This post-conflict status of the country, worsened by a raging armed conflict during data collection, must have rendered the larger proportion of the population to be unable to produce their own food.

The study is aimed at exploring a joint model in the analysis. Most importantly, the aim was to assess the determinants of the joint risk posed by food insecurity, which could have entrenched the vulnerable and chronically food insecure populations to getting hopelessly exposed to a vicious cycle of asset poverty, as well as exposure to associated risks of food insecurity shocks.

Extensive literature search found out that joint modelling techniques had not been explored before investigating the determinants of mutually reinforcing outcomes of food insecurity risk. The technique featured in biological science research, medicine and health such as in Gardiner [10], Charlson., *et al.* [11], Zhou and Welsh [12], Verbeke and Davidian [13], Verbeke., *et al*. [14], Verbeke and Molenberghs [15] and Plackett [16]. Gardiner [10] observes that outcomes with different attributes (often continuous and categorical) do occur jointly in different settings. He models two outcomes of joint healthcare utilisation, namely; length of stay and cost and how an adverse effect affects the joint outcome. Thus, the study seeks to answer two related questions: i) do enhancers of livelihoods in structural poverty and food insecurity settings determine the combined risk of entrenchment in coping with and spending highly on food? ii) Is joint modelling of the two outcomes a potentially good tool to be relied on in analysis of this nature?

Sample and Data: Data used in the study was obtained from the Food Security Monitoring Survey [17] which was conducted in August 2014 at the peak of the conflict which raged from end of 2013 and still continuing during the submission of this article. Data were collected in all ten states of South Sudan and 145 clusters as determined during the national census of 2008. In a sample size of 3,692 households, 5.3 per cent were internally displaced as a result of the conflict. The stratified two-stage sample selection method was used based on the sampling frame of census enumeration areas and cartographic data.

The prime purpose of the FSMS was to provide essential and baseline information for monitoring the food insecurity situation in South Sudan during the armed conflict, in order that informed decisions were made for mitigating the situation. The United Nations and other humanitarian organisations were mandated to intervene for the nearly two million people displaced across the country. The survey was conducted with participation of World Food Programme (WFP), Food and Agricultural Organisation (FAO), UNICEF, UNHCR, the South Sudan National Bureau of Statistics and relevant government line ministries [17].

By April 2014 the food insecurity situation in South Sudan had reached its extreme low due to widespread displacement and reduced resilience [17]. As shown in Figure 1, food consumption levels were unacceptably high in 2014, with poor food consumption ranging from 2 to 25 *per cent* in Upper Nile State (UNS); the epicentre of the conflict-related crisis. In fact, according to the report 41 *per cent* of the households in South Sudan had inadequate food based on a seven-day recall period, while 12 *per cent* of the households had '*poor*' food consumption. In general, it was evident that the conflict worsened food consumption levels. In July 2013 11 *per cent* of the household were classified to have '*poor*' consumption. It then increased to 12 *per cent*, which could be due to the conflict.

The study outcome variables were a dichotomised *coping strategy index* (CSI) and ratio of *household expenditure on food*, which is a scale variable. The coping strategies index was first established by Maxwell [18] for "distinguishing and measuring short-term food insecurity at the household level", but also for monitoring food emergencies, early warning and the impact of interventions [19].

The proportion (ratio or percentage) of household expenditure on food is a good indicator of poverty as well as potential food insecurity vulnerability and risk. The measure is obtained by asking questions on the amount of money spent on a range of food and non-food items and services in past 30 days (31 items in total). The total consumption expenditure is then calculated and the percentage of amount spent on food is obtained. This indicator is thus by far straight forward.

The four livelihood-based effects asked during the survey were *crop cultivation* in preceding farming season, ownership of *livestock, fishing* by any household member and *main source of income*. Apart from *main source of income*, which had four levels, all the other effects had two levels. In consideration of arguments by FAO [5] that "Gender and age are two powerful determinants of the impact of protracted crises on individuals", three covariates *gender of household head, age of household* head and size of household, were also included in the explanatory variables.

Methods: Often when data are clustered with different attributes observed on the same sampling unit, mixed outcomes may occur. Gardiner [10] observes that such mixed outcomes can be in the form of continuous, count and categorical types (multinomial, ordered categorical or binary). Food security outcomes can take all these forms. Monetary measures of consumption expenditure and income often take the form of continuous variables, while asset or index-based measures from household characteristics are largely ordered categorical or binary. Nutritional status is often based on the continuous anthropometric measures of weight, height, age, arm circumference and z-scores. In this case, observed factors or events (random or fixed) may impact both outcomes. Multivariate or joint modelling is commonly applied in studies of repeated measures, longitudinal and spatial data. However, we examine the data with joint responses, given the nature of the study attributes.

Subsequently, spending more of the household income on food (measured as a continuous outcome Y_1) leads to adopting of a coping strategy (a binary outcome Y_2) during food scarcity. In order to establish the inter-dependence of the two outcomes a test of correlation was carried out before proceeding with joint modelling. Seven predictor (or explanatory) variables X_{ij}, where, $i = 1,\ldots,7$, $j = 1,\ldots K$ and K = number of levels, were included in the Generalized Logistic Regression Model for the binary response variable '*coping with food security emergency*'. These were: a) three demographic variables (*age of household head, gender of household head and household size*); b) history of livelihoods activity prior to the crisis (*crop cultivation, livestock keeping and fishing*); and c) *main source of income* (during protracted food insecurity crisis). Mathematically, the response/outcome variable is given as

$$Y_j = \begin{cases} 0 \text{ if household did not adopt any coping strategy} \\ 1 \text{ if household adopted some coping strategy} \end{cases}$$

The rationale for selection of only a few variables is two-fold. First, each of these variables is seen to affect how households coped with food insecurity in during the crisis that hit South Sudan. Secondly, the sample survey where the data came from included a few variables, as it was a repeated monitoring survey [17]. The survey concentrated on collecting data on variables for computing key food security and nutrition indicators, namely; coping strategies index, food consumption score, dietary diversity index and per cent share of total expenditure spent on food.

Table 1 shows the percentages of predictor (explanatory) variables included as possible predictors of coping with food security.

Variable Description (X_{ij})	**Category (J)**	***n***	***Per cent***
Gender of the household head (x_{1j})	Male	2683	72.7
	Female	1009	27.3
Age of the household head (x_{2j})	1 = (< 17 yrs)	42	1.1
	2 = (18-60 yrs)	3549	96.1
	3 = (> 60 yrs)	101	2.7
Size of household (x_3)	Scale	-	-
Cultivated crops past 3 months (x_{4j})	Yes	2990	81.0
	No	702	19.0
Owned livestock past 3 months (x_{5j})	Yes	3576	96.9
	No	116	3.1

Engaged in fishing past 3 months (x_{6j})	Yes	421	11.8
	No	3271	88.2
Main source of income (x_{7j})	Sale of agricultural crops	1074	29.1
	Sale of livestock products	811	22.0
	Employment/labour	798	21.6
	Petty trading	774	21.0
	Other	235	6.4

Table 1: *Predictor variables included in the analysis.*

The six variables were selected based on a sound rationale. *Gender of household head* is important on the basis that a household headed by a female or male might fare differently in situations of food crises. This argument could hold true particularly when employment is the major source of income.

From theory *age of household* head would have considerable correlation with how a household coped. The older a person gets, the better his or her adoption of coping with livelihood strains. The *size of household* (or number of individuals in a household) conceptually has a bearing on some form of coping such as meal rationing. In situations of emergencies, households with more members (especially adult ones) could tend to employ more of its members to fetch food. Conceptually households with more members could translate to more than one source of income or bigger food rations from food aid. However, care needs to be taken in interpreting *household size* as an indicator, as some respondents might tend to overstate the number of their members in order to receive bigger food rations.

The imperative of having *cultivated crops*, especially food crops in the past farming season could be a favourable factor to households during food crisis, although some might have lost or left behind everything when forced to flee their original habitats. *Owning livestock* prior to or during crisis might buffer households against facing food shortage. However, this might not have been the case, as experience in previous spells showed that South Sudanese pastoralist communities in the mid-1990s were hit hard during crisis of droughts and armed conflict. The survey asked whether any of the household members *engaged in fishing* in the last three months prior to the survey. For fishing communities along the River Nile and other main rivers in South Sudan (e.g., Jur River, Sobat River, Lol River, etc.), this variable is an important determinant of livelihood status. The *main source of income* to a household obviously plays a key role in coping with food emergencies. Households dependent on sale *of food crops* could tend to cope better than those depending on other sources of income.

A challenging aspect of the analyses is the presence of exogenous factors affecting these dual outcome variables. Hence, we need to specify a joint model for Y given the exogenous factors z. Each outcome was modelled separately using an appropriate generalized linear model by structuring the mean $E(Y_k|z_k)$ and variance $Var(Y_k|z_k)$, where $k=1,2$. The covariates z_1, z_2 do not necessarily need to be the same, although in practice some overlaps do occur. To simplify interpretation and identification, some variables may be excluded from a model for one outcome, which are included in a model for another outcome. An alternative approach to joint modelling is Copula Regression that has received some attention [20].

Linking the two outcomes is done through a shared random effect ζ in $E(Y_k|z,\zeta)$ or by structuring the covariance matrix *Var* (Y|z) to ensure potential correlations are included in the model. As our interest is centred on the influence of food expenditure percentage Y_1 on coping strategy Y_2, gives the joint distribution

$$\int (Y_1, Y_2|z) = f(Y_1|z)\, f(Y_2|Y_1, z) \qquad (1)$$

Where $f(.|.)$ is a conditional distribution? Thus Y_1 is endogenous in a second term model. The approach for modelling the data was to use SAS GLIMMIX procedure [21], for modelling the two responses conditional on random effects.

Data analysis proceeded in two stages. In the first stage, each outcome was analysed separately based on the univariate logistic regression model (GLM) fitting the selected explanatory variables. In the second stage both outcomes were analysed jointly using GLIMMIX. This procedure was used to take care of random cluster variations as the data came from randomly selected clusters of households. In the first stage the estimates of the model parameters were obtained by maximum likelihood. For formulation of the maximum likelihood of a model with continuous or Gaussian distribution and for a binary response, see McCullagh and Nelder [22], Collet [23] and McCulloch and Searle [24].

In modelling two responses, suppose that the outcome variable are Y_1 = *Food expenditure* – a continuous outcome, and Y_2 = *Coping* – a binary outcome. The two events are somehow correlated. High household food expenditure and being compelled to cope with risk of food insecurity increase vulnerability and at the same time reduce resilience during food insecurity crises. Putting it differently, when a household is obliged to adopt a coping strategy it is equally forced to spend more of its income or savings on food. Coping with food insecurity crisis is like a co-morbidity impacting on high expenditure on food and thus increases vulnerability and adversely lowers resilience to food insecurity and livelihood shocks. Therefore, one adverse event Y_1 occurs jointly with another adverse event Y_2.

If interest is centred on the effect of household food expenditure Y_1 as well as on coping with food insecurity, a joint distribution might be worth considering such that $f(Y_1, Y_2|z) = f(Y_1|z)\,f(Y_2|Y_1, z)$, where the generic notation $f(.|.)$ denotes a conditional distribution. This makes Y_1 to be potentially endogenous in a model of the second term.

Consequently, a generalized linear model $g_k(Y_{ik}|z_i) = z_{ik}\hat{}'\beta_k$, where *i* is a household, *k = 1,2* and g_k is a link function for the outcome k, is then fitted to the data. The joint model may be fitted with the different covariates from the data. The models for the two equations are in the form

$$Y_{i1}^* = z_{i1}\hat{}\ \beta_1 + \varepsilon_{i1} \text{ and } Y_{i2}^* = z_{i2}\hat{}'\beta_2 + \varepsilon_{i2} \qquad (2)$$

where $Y_{i1} = [Y_{i1}^* > 0]$ are the observable indicators, The covariates $z_i = (z_{i1}, z_{i2})$ are exogenous, which means $\varepsilon_i = (\varepsilon_{i1}, \varepsilon_{i2}) \sim N(0, \Sigma)$, where

$$\Sigma = \begin{bmatrix} 1 & \rho_{12}\sigma_2 \\ \rho_{12}\sigma_2 & \sigma_2^2 \end{bmatrix} \qquad (3)$$

This model assumes $\Sigma = diag(1, \sigma_2^2)$ which is the same as assuming the two responses separately, with exception of degrees of freedom. The covariance, expectations and variance of the parameter estimates are respectively

$$Cov(Y_{i1}, Y_{i2}|z_i) = \rho_{12}\,\sigma_2\,\Phi(z_{i1}'\beta_1) \qquad (4)$$

$$E(Y_{i1}|z_i) = \Phi(z_{i1}'\beta_1) \qquad (5)$$

$$Var(Y_{i1}|z_i) = \Phi(z_{i1}'\beta_1)\,(1-\Phi(z_{i1}'\beta_1)), \qquad (6)$$

Where Φ and Φ denote the density and cumulative distribution of the standard normal distribution. The procedure then structures the variance matrix of $Y_i = (Y_{i1}, Y_{i2})$ as

$$Var(Y_i|z_i) = A_i^{(1/2)} R_i A_i^{(1/2)} \qquad (7)$$

Where R_i is a user specified 2×2 covariance structure and A_i is the diagonal matrix of the variance of (Y_{i1}, Y_{i2}). The error matrix of Equation derives estimates for σ_2 and ρ_{12} based on the residual pseudo-likelihood. Further discussion of the GLMMs can be found in Littel., *et al*. [25], Breslow and Clayton [26] and Wolfinger and O'Connell [27], who derive extensions of the generalized linear models (GLMs) to the GLMM.

Results and Discussion

Before starting analysis using joint modelling, it was necessary to establish the correlation between the two response variables. Both Kendall’s *tau* and Spearman’s *rho* tests of correlations showed significant (p-value > 0.005 at the 0.01 significance level, two-tailed test) correlations between share of *food consumption expenditure* (a scale variable) and *coping strategy index* (also a scale variable). Since interest was to determine whether or not the variable *share of food expenditure* and *coping* were correlated, both variables needed to be measured on scale. Coping strategy index was initially scale variable as it was generated based on weights.

With a positive correlation of 0.152 (Pearson’s *rho*), the result is consistent with that of Maxwell., *et al*. [9]. This finding provided motivation to proceed with exploring joint modelling of the two correlated outcomes (share of food expenditure and adopting a coping strategy).

The univariate logistic regression model was fitted to the data with the first response variable *share of food expenditure* using Generalized Linear Model Procedure with a logit link function. From the analysis shown in Table 2, all the seven fixed effects except *gender* of household head were determined to have significant contributions to the model. Specifically, a household whose head was aged between 18 to 60 (the economically active group), had above average members, cultivated crops and owned livestock in the previous farming season, engaged in fishing and earned income from sale of livestock products and petty trade, showed significant associations with increase in food expenditure. Table 2 also shows that gender of household head and main source of income from farming and employment did not have significant association with increase in consumption expenditure. This clearly meant that both female- or male-headed households did not differ significantly in relation to increase in consumption expenditure. Similarly, there was insufficient statistical evidence suggesting that whether a household earned income from sale of agricultural harvest or not (or from some form of employment) it would still fare equally in terms of spending on food.

Parameter*	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	4.3777	0.0488	8052.96	< 0.0001
Gender: male	0.0113	0.0115	0.96	0.3280
Age: < 17	0.0692	0.0604	1.31	0.2524
Age: 18-60	0.0821	0.0335	6.01	0.0142
Household Size	-0.0097	0.002	23.29	< 0.0001
Cultivated crops: yes	0.0351	0.0135	6.71	0.0096
Owned livestock: yes	-0.1829	0.0249	54.18	< 0.0001
Engaged in fishing: yes	0.0515	0.0154	11.16	0.0008
Income Source: Agriculture	0.0196	0.0241	0.66	0.4166
Livestock products	0.123	0.0242	25.85	< 0.0001
Employment	0.0365	0.0246	2.2	0.1383
Petty trade	0.0625	0.0244	6.54	0.0105

** Values corresponding to reference categories are set to zero and are not shown.*

Table 2: *Maximum likelihood parameter estimates from the expenditure model.*

Overall, the result resonated with expectations as regards increased spending on food, especially for a population in humanitarian crises. In practice, however, this finding does not tell much, since, for instance, a household can sell its harvest to earn income, which could be spent on buying food when food prices are high. Yet, the results still showed generalised high poverty levels, where earnings and usual agriculture-based sources of livelihood could not offset demands for or improve access to adequate food. The results generally manifested entrenched food insecurity threat. With generalized high poverty levels, expenditure on food tended to prevail. This finding give reason to propose that it is worthwhile examining a model with the other co-response.

We continued to fit a GLMM model for the data with '*coping*' as a response variable, but this time allowing for random effects due to clusters. The reference category of the response was set at 0 (i.e., household did not adopt coping strategy). Note that results of Table 3 with significant effects showed negative estimates of coefficients for all seven fixed effects. This means that the odds of the reference levels associated better with the probability of adopting a coping strategy. Table 3 shows four of the seven effects included in the model to be significantly associated with adoption of coping strategy. These are *age of household head, crop cultivation, livestock ownership* and *main source of income*. The model determined gender, household size and fishing to have no significance difference in adopting a coping strategy.

Parameter*	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	1.9795	0.5810	149	3.41	0.0008
Gender: male	-0.03245	0.08983	3441	-0.36	0.7180
Age: < 17	-1.2668	0.4535	3441	-2.79	0.0052
Age: 18-60	-0.5517	0.2472	3441	-2.23	0.0257
Household Size	0.01399	0.01600	3441	0.87	0.3821
Cultivated crops: yes	-0.2117	0.1102	3441	-1.92	0.0547
Owned livestock: yes	-1.0553	0.4954	3441	-2.13	0.0332
Engaged in fishing: yes	-0.07913	0.1392	3441	-0.57	0.5699
Income Source: Agriculture	-0.4852	0.1832	3441	-2.65	0.0081
Livestock Products	-0.05759	0.1895	3441	-0.30	0.7612
Employment	-0.3686	0.1871	3441	-1.97	0.0490
Petty Trade	-0.1538	0.1873	3441	-0.82	0.4114

** Values corresponding to reference categories are set to zero and are not shown.*

Table 3: *Estimates of effect parameters from the 'coping' model.*

Note the negative coefficients of estimates of the fixed effects, which were interpreted as in earlier models. In general, there was statistical evidence that a household headed by a person aged above 60 years, did not cultivate crops, had not owned livestock and did not depend on income from a source other than employment, significantly associated with adoption of a coping strategy for its livelihood. Meanwhile, there was no sufficient statistical evidence to suggest that gender of household head, household size, fishing and main income from sale of livestock products and petty trade associated with coping.

Note also that in terms of significance of the fixed effects, results of the '*coping*' model did not differ considerably with those of the '*expenditure*' model. However, there were also some differences. Most of this model estimates in Table 1 are positive whereas almost all the significant effects in the '*coping*' model [Table 3]. The two procedures modelled two separate outcomes.

The foregoing results of fitting the two outcome variables separately [Table 2 and 3], give a sense that a household with certain attributes, such as being headed by an older person, having a larger household size, could risks being food insecure as a result of resorting to adopting a coping strategy and at the same time tending to spend more on food than other livelihood essentials. Both types of food insecurity risks seem to be associative from the point of view of common factors (age and size of household size). It would, therefore, be of interest to explore how the possible association could be if modelled jointly. This motivated the idea of fitting a joint model, in order to see whether a joint distribution of the two outcome variables have significant association with some or all of the fixed effects. It is also to be recalled that the two outcome variables were determined to be correlated.

We fitted a GLMM for both responses jointly and with the explanatory variables and latent random effect, which accounts for the association between coping and expenditure. This means that we fitted the model with random cluster intercept, i.e., a variance matrix blocked by *cluster*. The model is fitted using the maximum likelihood with adaptive Gauss-Hermite quadrature, given that it restricts the models for estimating parameters and also fulfils conditional independence assumptions and the processing of data by subject [28]. The choice enables linearization of the non-linear random effects (i.e., the *cluster* variable).

As shown in Table 4, the joint model was by far improved. It showed all seven effects as highly significant as opposed to the univariate models. That is, all fixed effects had associations with the joint outcome of '*food expenditure*' and '*coping*'. Unlike in previous models, fishing was significant after fitting the Joint Model.

Effect	Num DF*	Den DF*	F Value	*Pr* > F
Intercept	2	6998	770.17	< 0.0001
Gender	2	6998	0.96	0.3824
Age	4	6998	3.96	0.0033
Household size	2	6998	14.08	< 0.0001
Cultivated crops	2	6998	5.46	0.0043
Owned livestock	2	6998	19.47	< 0.0001
Engaged in fishing	2	6998	5.42	0.0044
Main source of income	8	6998	8.97	< 0.0001

** Numerator and denominator degrees of freedom; Pr is short for 'probability'.*

Table 4: *Type III tests of the explanatory variables from the Joint Model.*

The joint model also generated the estimates of the explanatory variables coefficients [Table 5]. Gender of household head stayed non-significant for both outcomes, as in the univariate models. The joint model determined fishing to be significant in the normal response. There were also other changes in the joint model results that showed significant relationships between some fixed effects and either of the food insecurity outcomes. An example is main source of income from employment and from petty trade, which became significant after they were shown as non-significant in the separate models. A significant probability indicates that there is sufficient statistical evidence to suggest that the corresponding variable influences both household coping and increased expenditure on food.

The coefficient estimates from the '*coping*' distribution in the joint model were close to those of the univariate '*coping*' model, and it was also dominated by negative signs, meaning that the odds of association with coping strategies were worse for the reference levels. These reference categories were age of household head of above 60 years, household size of above seven persons, household that did not cultivate crops in the previous season, and household that did not depend on agriculture for income and food, and did not earn salaries and wages. These findings are not far from expectation.

For the expenditure responses using log-link function, ownership of livestock showed significant relationship. The result showed that a household headed by a person aged 18 to 60 years, had the size of four to six members, cultivated crops, owned livestock and mainly earned income from sale of livestock and petty trade, had significant associations with increase in food expenditure. Consistent with South Sudanese realities, households normally sell cattle as a form of extreme coping strategy. This finding led us to further investigate as to whether keeping livestock is associated with extreme coping strategies, where selling cattle is a last resort. Separate analysis based on descriptive and non-parametric tests confirm that there is non-significant association between livestock keeping and adoption of severe coping strategy. In fact, only 0.6 *per cent* of households which kept cattle reported they adopted extreme coping strategies.

As noted above, some values that were significant in either of the bivariate independent models no longer seemed significant in the joint model. Although these differences did not cause major changes in significance values as to upset the test results, the disparities could arouse some concerns. Meanwhile, the factor *gender of household* head remained non-significant in all the three models; even experimental ones with results not shown. For this reason, we extended the joint analysis with a view of removing such variables from the analysis.

Effect*		Distribution	Estimate	Standard Error	DF	*t* Value	*Pr* > |t|
Intercept		Binary	1.9188	0.5996	6998	3.20	0.0014
		Normal	80.2495	3.6664	6998	21.89	<.0001
Gender: male		Binary	-0.03716	0.09081	6998	-0.41	0.6824
		Normal	1.1331	0.8573	6998	1.32	0.1863
Age: <18		Binary	1.2990	0.4573	6998	-2.84	0.0045
		Normal	5.0093	4.3001	6998	1.16	0.2441
18-60		Binary	-0.5843	0.2496	6998	-2.34	0.0192
		Normal	5.9723	2.3113	6998	2.58	0.0098
Household size		Binary	0.01301	0.01619	6998	0.80	0.4214
		Normal	-0.7763	0.1484	6998	-5.23	<.0001
Crops cultivation: yes		Binary	-0.2406	0.1115	6998	-2.16	0.0310
		Normal	2.4171	0.9834	6998	2.46	0.0140
Owned livestock: yes		Binary	-0.9075	0.5163	6998	-1.76	0.0789
		Normal	-13.6979	2.2145	6998	-6.19	<.0001
Fishing: yes		Binary	-0.1207	0.1413	6998	-0.85	0.3931
		Normal	3.7548	1.1910	6998	3.15	0.0016
Main source of income	Agriculture	Binary	-0.4685	0.1856	6998	-2.52	0.0116
		Normal	1.3368	1.7019	6998	0.79	0.4322
	Livestock	Binary	-0.09925	0.1922	6998	-0.52	0.6056
		Normal	8.7699	1.7426	6998	5.03	<.0001
	Employment	Binary	-0.3716	0.1897	6998	-1.96	0.0501
		Normal	2.9137	1.7426	6998	1.67	0.0946
	Petty trade	Binary	-0.1629	0.1899	6998	-0.86	0.3911
		Normal	4.7002	1.7420	6998	2.70	0.0070

** Reference categories are not shown.*

Table 5: *Estimates of the explanatory variable coefficients under the Joint Model.*

In inspecting the covariance parameter estimates of the joint model [Table 6], we found the estimate of the variance of the random effect cluster intercept to be 1.6543 with a corresponding standard error estimate of 0.2704. This indicates that there could be significant within-cluster variation in the intercepts, which was accounted for in the inference.

Covariance Parameter	Subject	Estimate	Standard Error
Intercept	Cluster Number	1.6543	0.2704
Residual		502.35	12.1140

Table 6: *Covariance Parameter Estimates.*

The joint model was then re-fitted for modelling correlations directly such that instead of a shared G-side random effects, an R-side covariance structure was used to model the correlations of a marginal model. The latter models covariation on the data scale. Specification of the standard variance component (*vc*) in the new model causes different clusters (pools of villages in one geographical location) to be independent, while single clusters followed this model. The *vc* structure was such that for each effect a distinct variance component was assigned, which is also known as a G-side covariance structure. This enables the R-side variance structure to only add the effects of over dispersion. The *vc* covariance structure is of the form

$$\begin{bmatrix} \sigma_B^2 & 0 & 0 \\ 0 & \sigma_B^2 & 0 \\ 0 & 0 & \sigma_B^2 \end{bmatrix}$$

With this specification of the covariance structure, some changes in the estimates of the joint model occurred [Table 7]. The most notable change was the removal of the variable *gender of household head* from the analysis. The fixed effect fishing even became highly significant.

Effect	Num DF	Den DF	F Value	*Pr* > F
Intercept	2	148	1565.24	<.0001
Age of household head	4	170	3.34	0.0117
Size of household	2	6999	24.36	<.0001
Cultivated crops	2	264	7.01	0.0011
Owned livestock	2	6	46.73	0.0002
Engaged in fishing	2	171	11.14	<.0001
Main source of income	8	873	17.15	<.0001

**After removal of gender of household head.*

Table 7: *Type III tests of effects of selected factors with unstructured covariance structure under the joint model*.*

An interesting observation [Table 8] is that no fixed effect had significant p-values in both co-responses in the joint model that includes G-side and R-side correlation. Meanwhile, in the model with only G-side correlations, three variables (with values shown in boxes) were significant in both responses. It is also interesting to note that both models showed very highly significant relationships (p-value < 0.05) between five fixed effects *(household size, crop cultivation, fishing and livestock ownership and income from sale of livestock products and petty trade)* and the response higher food expenditure. This means households with these attributes risked being food insecure due to their high spending on food.

		Joint Model with G-side Correlations only			Joint Model (G-Side and R-side Correlations)		
Effect	**Dist***	**DF**	***t* Value**	***Pr* > |t|**	**DF**	**t Value**	***Pr* > |t|**
Intercept	Binary	7000	3.18	0.0015	148	0.37	0.7108
	Normal	7000	21.93	< 0.0001	148	31.62	< 0.0001
Age: < 18	Binary	7000	-2.84	0.0045	166	-0.20	0.8407
	Normal	7000	1.36	0.1731	166	1.62	0.1064
Age: 18-60	Binary	7000	-2.33	0.0199	166	0.19	0.8457
	Normal	7000	2.80	0.0051	166	3.63	0.0004
Household size	Binary	7000	0.77	0.4388	6999	0.15	0.8804
	Normal	7000	-5.15	< 0.0001	6999	-6.98	< 0.0001
Crops cultivation	Binary	7000	-2.18	0.0295	264	-0.05	0.9568
	Normal	7000	2.53	0.0114	264	3.74	0.0002
Owned livestock	Binary	7000	-1.77	0.0760	6	-0.35	0.7363
	Normal	7000	-6.27	< 0.0001	6	-9.66	< 0.0001
Fishing	Binary	7000	-0.87	0.3842	171	0.04	0.9666
	Normal	7000	3.20	0.0014	171	4.72	< 0.0001
Income: agricul.	Binary	7000	-2.57	0.0101	873	-0.23	0.8172
	Normal	7000	1.27	0.2032	873	1.29	0.1981
Livestock	Binary	7000	-0.54	0.5926	873	0.07	0.9423
	Normal	7000	5.49	< 0.0001	873	7.74	< 0.0001
Employment	Binary	7000	-2.00	0.0451	873	-0.21	0.8307
	Normal	7000	2.10	0.0361	873	2.40	0.0167
Petty trade	Binary	7000	-0.88	0.3815	873	-0.11	0.9164
	Normal	7000	3.11	0.0019	873	3.89	0.0001

** Distribution of the response variable.*

Table 8: *Solution for fixed effects of the joint model with covariance structure.*

It is to be noted that the degrees of freedom multiplied as a result of fitting a joint model. This is mainly because each of the fitted effects were taken to have interacted with a latent variable considered in the analysis representing a joint distribution of the two joint outcome variables.

The foregoing finding led to selection of the model with R-side covariance structure only to the data and generating linear predictors and residuals. This was of course done after removing the variable *gender of household* head. Figure 1 shows a plot of the residuals against clusters. Clearly most of the errors of the model were clustered around 0, which showed good amount of prediction of the joint response variable (‘*response*’). The linear predictor could, therefore, be used as an index for determining the likelihood of food insecurity risk represented in the joint outcomes of food consumption expenditure and incidence of coping with food insecurity strains.

Finally, it is worth examining whether or not the above results provided the answers to the study questions outlined in Section 2 above. On the one dimension, the Joint Model succeeded to establish that most of the fixed effects prevalent in rural livelihood showed statistically significant association with the joint outcomes of food insecurity risk. On the other dimension, as shown by the model inspection analysis the results showed the Joint Model could be a fairly good tool for measuring the risk posed by a joint outcome characterised with a mixed response. However, given known limitations of survey data, caution needs to be exercised in interpreting these results. Further application of the method to more controlled studies might be necessary to establish its efficiency.

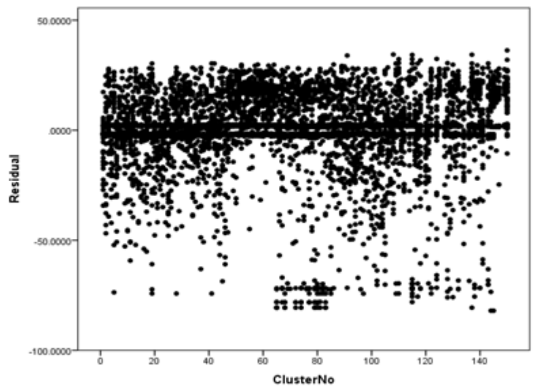

Figure 1: *Plot of residuals from the Joint Model.*

Conclusion

Analysis examined seven explanatory variables which were included in a three-step modelling approach that ended with a joint model for exploring their relationship with both household coping during food insecurity and expenditure on food. This was in order to establish how indicators of a typical agro-pastoralist economy determined the likelihood of food insecurity risk, as characterised by the joint outcomes of coping with shortage of and spending on food. In all three models explored, one of the seven assumed factors, gender of household head, persistently showed non-significant relationship with adoption of coping strategy and/or increased household expenditure on food. There were noticeable disparities in the significance of the relationships of the different levels of fixed effects and either response. There were also some noticeable inconsistencies in the way explanatory variables showed significant relationships with either outcome of food insecurity (increase in the share of expenditure on food and coping strategy experiences). This could be due to the generalized vulnerability and poverty where coping with food insecurity and livelihood strains was rampant, or was the order of the day, in many of the communities. It could also be due to misperceptions or confusion by respondents during interview in their understanding of what stood for a coping strategy.

The three-stage analysis also determined that three of the main variables investigated had significant relationships with the joint food insecurity outcomes, i.e., adoption of coping strategy and increased food consumption expenditure. These variables are crop cultivation (*p*-values = 0.001), engagement in fishing (*p*-value = 0.011) and main source of income being sale of livestock (*p*-value < 0.0001), employment (*p*-value = 0.04) and petty trade (*p-value* = 0.002), age of household head (*p*-value = 0.005) and size of household (*p*-value < 0.0001). A reasonable interpretation of this finding could be that the presence of these factors of livelihood provided adequate statistical grounds for predicting the probability of households employing both outcomes spontaneously. In other words, if conditions stayed the same, there was risk of the population becoming vulnerable to food insecurity.

Of special importance was the finding that the joint model effectively modified the results of the separate or univariate modelling of the outcomes studied. The joint model specifically caused values of hypothesis tests that had non-significant or low-significant probabilities to become highly significant. A case in point was crop cultivation (*p*-value = 0.001) and fisheries *(p*-value = 0.011), both for the normal distribution variable. This is particularly true for the normally distributed latent variable.

These findings were consistent with those of Gardiner [10]. An attempt to improve the model further by adding R-side random effects did not result in removing any of the fitted effects from the analysis. A fitted model with the variable gender of household head was re-fitted to the data, which led to generating predicted probabilities. These predicted probabilities were plotted using a scatter plot [Figure 1] to check for goodness-of-fit of the model.

Literature review led to the conclusion that joint modelling might not have been used before in analysing food security outcomes, especially those explored. Extensive literature review showed that the method had mainly been used in longitudinal health and medical studies, as well as in survival analysis. The study unsealed three important findings. First, coping strategies and food expenditure in chronic food insecure situations combined as a function of agriculture-based livelihoods and household characteristics. Second, the methods demonstrated that crop farming, fishing and income from sale of livestock combining with age of household head and household size as predictors of either or both food security outcomes in a population experiencing protracted livelihood crisis. Three, based on earlier works by Filmer and Pritchett [29], Moser and Felton [30] and Lokosang., *et al.* [31] who established that household assets tended to provide good basis for generating an index of socioeconomic status and food security of a household, the joint modelling might have the capability of generating an index for determining household resilience to food insecurity risks, especially in settings characterised by structural food insecurity. Once efficiency of the method was established (see Figure 1), predicted values of the joint response variable could be taken for the index that predicted the probability of food insecurity as exemplified by how a particular cluster of households coped with food insecurity uncertainty and increased expenditure on food.

The main issue with the results of analysis shown above is that the outputs of the Joint Model may not be easily grasped considering its somewhat complex theoretical construction. This could hold true for the concept of the latent variable of the joint model. Gardiner [10] drew attention to this aspect and proposed the use of the Copula-based regression as described in Kolev and Paiva [20]. Considering the noted limitations and known shortcomings of data from large sample surveys, it is recommended that the method (joint modelling of data with mixed outcomes) be explored further with data from a controlled study to establish its efficiency.

References

1. African Union Commission, WFP, NEPAD, UNECA. "The Cost of Hunger in Africa Study: A Regional Look at the Price of child undernutrition in Africa". Rome (2013):
2. United States Department of Agriculture. "Food Expenditure Analysis. In: Review of WIC Food Packages: Interim Report. Washington, D.C". *National Academy of Sciences, Engineering & Medicine* (2016): 325-332.
3. Lokosang L., *et al*. "The Effect of Weakened Resilience on Food Insecurity in Protracted Crisis: The Case of South Sudan". *Agriculture & Food Security* 5.2 (2016):1-8.
4. Chambers R. "Vulnerability, Coping and Policy". *IDS Bulletin* 37.4 (2006): 33–40.
5. FAO. The State of Food Insecurity in the World (SOFI). Meeting the 2015 international hunger targets: taking stock of uneven progress. Rome (2015):
6. Snel E and Staring R. "Poverty, migration, and coping strategies: An introduction". European Journal of Anthropology 38 (2001): 7–22.
7. Sibrián R., *et al.* "Measuring Hunger at Subnational Levels from National Surveys Using the FAO Approach: Manual". *Working Paper Series* (2008):
8. Maltsoglou I. "Household Expenditure on Food of Animal Origin: A Comparison of Uganda, Vietnam and Peru". *Pro-Poor Livestock Policy Initiative* (2007):
9. Maxwell DG., *et al.* "The Coping Strategy Index: a tool for rapidly measuring food security and the impact of food aid programmes in emergencies". *International Workshop on Food Security in Complex Emergencies: building policy frameworks to address longer-term programming challenges* (2003):
10. Gardiner JC. "Joint Modelling of Mixed Outcomes in Health Service Research". *SAS Global Forum* 435 (2013):
11. Charlson ME., et al. "A new method of classifying prognostic comorbidity in longitudinal studies: development and validation". *Journal of Chronic Diseases* 40.5 (1987): 373-383.
12. Zhou XH and Welsh AH. "Estimating the Retransformed Mean in a Heteroscedastic Two-Part Model". *Journal of Statistical Planning and Inference* 136.3 (2006): 860–881.
13. Verbeke G and Davidian M. "Joint models for longitudinal data:Introduction and overview. In: Longitudinal Data Analysis". *A handbook of modern statistical methods* (2008):

14. Verbeke G., *et al.* "The analysis of multivariate longitudinal data: A review". *Statistical Methods in Medical Research* 23.1 (2014): 42-59.
15. Verbeke G and Molenberghs G. "Linear Mixed Models for Longitudinal Data". *Springer* (2000):
16. Plackett R. "A class of bivariate distributions". *Journal of the American Statistical Association* 60.310 (1965): 516–522.
17. World Food Programme. "South Sudan Food Security Monitoring". *VAM Food Security Analysis* (2014):
18. Maxwell DG. "Measuring Food Insecurity: The frequency and severity of coping strategies". *International Food Policy Research Institute* 8 (1995):
19. Maxwell D and Caldwell R. "The Coping Strategies Index: Field Methods Manual (2nd Edition)". *Food Access* (2008):
20. Kolev N and Paiva D. "Copula-based regression models: A survey". *Journal of Statistical Planning and Inference* 139.11 (2009): 3847–3856.
21. IBM Corporation. IBM SPSS Amos 23.0.0 (Build 1607)". *Amos Development Corporation* (2015):
22. McCullagh P and Nelder JA. "Generalized Linear Models, 2nd Edition". *Chapman and Hall* (1989):
23. Collett D. "Modelling Binary Data. 2nd ed. Boca Raton". *Chapman and Hall* (2003):
24. Marvin HJ Gruber and Searle SR. "Generalized Linear Mixed Models". *Wiley* (2001):
25. Littell CR., *et al*. "SAS for Mixed Models, Second Edition". *SAS Institute Inc* (2006):
26. Breslow NE and Clayton DG. "Approximation Inference in Generalized Linear Mixed Models". *Journal of the American Statistical Association* 8.421 (1993): 9-25:
27. Wolfinger R and O'Connell M. "Generalized Linear Mixed Models: A Pseudo-Likelihood Approach". *Journal of Statistical Computation and Simulation* 84.3 (1993): 233–243.
28. Lange K. "Numerical Analysis for Statisticians". *Springer* (1999):
29. Filmer D and Pritchett L. Estimating wealth effects without expenditure data – or tears: an application of educational enrolment in states of India". *Demography* 38.1 (2001): 115–132.
30. Moser C and Felton A. "The construction of an asset index measuring asset accumulation in Ecuador". *Global Economy and Development* (2007):
31. Lokosang L., *et al.* "Indexing household resilience to food insecurity shocks: The case of South Sudan". *Agrekon* 53.2 (2014): 137-159.

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