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Household resilience to food insecurity: evidence from Tanzania and Uganda

Abstract

Resilience has become one of the keywords in the recent scholarly and policy debates on food security. However, household resilience to food insecurity is unobservable. Therefore, the two key issues in empirical research are (i) estimating a proxy index of household resilience on the basis of observable variables and (ii) assessing whether this index is a good indicator of the construct it intends to measure, i.e. household resilience. This paper contributes to this literature providing evidence based on two case studies: Tanzania and Uganda.

Specifically, the paper: (i) proposes a method to estimate a resilience index and analyses what are the most important components of household resilience, (ii) tests whether the household resilience index is a good predictor of future food security status and food security recovery capacity after a shock, and (iii) explores how idiosyncratic and covariate shocks affects resilience and household food security.

The analysis shows that: (i) in both countries adaptive capacity is the most important dimension contributing to household resilience, (ii) the resilience index positively influences future household food security status, decreases the probability of suffering a food security loss should a shock occur and speeds up the recovery after the loss occurrence, and (iii) shocks do not seem to have any statistically significant impact, though this likely reflects the poor quality of data on idiosyncratic and systemic shocks.

Keywords: Resilience, food security, structural equation model, panel data.

JEL classification: D10, Q18, I32, O55

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1. Introduction

Empirical evidence shows that natural, economic and political risks are on the rise with significant impacts on poverty and food security. Because of global warming the frequency and intensity of floods and tornados are increasing in tropical areas (Westra *et al*., 2013; Webster *et al*., 2005). Climate change is expected to significantly lower the production of rice, wheat and maize over the next decades (WB, 2011; IPCC, 2013) and this will likely result in an increase of the number of undernourished and malnourished (Wheeler & Von Braun, 2013; Lloyd *et al*., 2011).

Since the 2007-08 commodity price crisis, food prices have been three times more volatile and their level is on average higher than before the crisis, causing a significant increase in poverty and food insecurity (FAO, 2011). The 2008-09 global recession added some 100 million more undernourished (FAO, 2009) and, despite significant progress, the current stock of undernourished worldwide is still as high as 790 million people (FAO, 2015).

Some 1.5 billion people live in conflict areas (WB, 2011) and by end of 2014 some 59.5 million individuals, of which some 19.5 million refugees, were forcibly displaced worldwide as a result of persecution, conflict, generalized violence, or human rights violations: the highest recorded level in the post-World War II era (UNHCR, 2015).

In short, natural, economic and political risks currently faced by households, farms, firms, economies, and even whole countries are more frequent and severe than before (Zseleczky & Yosef, 2014). This is probably the reason for resilience became one of the keywords of the recent policy and scholarly debates.[1]

By and large, resilience can be defined as the capacity of a system to withstand risks. Originally born in the general theory of systems, it has been later used in different fields such as ecology, engineering, psychology and epidemiology (Holling, 1996; Gunderson *et al*., 1997). Over the last decade it has been used also in social sciences and, specifically, in the analysis of complex systems such as socio-ecological systems.[2] More recently, some international organizations (FAO, 2012; EU Commission, 2012) proposed to use resilience to analyze food and nutrition security.

Despite the importance of the resilience concept, its use in the development field is relatively new and there is no consensus yet on how it should be measured (Barrett & Constas, 2014).[3]

[1] For example, the World Bank (2012) Social Protection and Labour Strategy was called "*Resilience, Equity, Opportunity*", the Davos World Economic Forum 2013 focused on "*Resilient Dynamism*" and the last IFPRI 2020 Conference, held in Addis Ababa in 2014, focused on "*Building Resilience for Food and Nutrition Security*".

[2] Socio-ecological systems are systems in which the ecological and socio-economic components are closely integrated (Gunderson & Holling, 2002).This is precisely the case of agro-food systems in developing countries, where many communities and social groups gain their livelihoods using renewable natural resources through activities such as farming, agro-forestry, and fishing.

[3] Vaitla et al. (2012, p. 5) observed that "academics and practitioners have yet to achieve a consensus on how to measure resilience", while Frankenberger et al. (2012, p. 26) noted that "the dynamic process of building resilience makes it inherently difficult to measure". The FAO-WFP-IFAD Technical Working Group on Resilience Measurement (TWG-RM,

The issue is related to the fact that resilience to food insecurity is unobservable ex ante. Therefore, the two key issues in empirical research and program implementation are (i) how to estimate a proxy index of household resilience on the basis of observable variables and (ii) assess whether this index is a good indicator of the construct it intends to measure, i.e. household resilience. This paper contributes to this literature providing evidence based on two case studies, Tanzania and Uganda.

In doing this, the paper uses one of the most promising approaches to quantitatively assess household resilience, the so-called FAO's Resilience Index Measurement Analysis (FAO, 2016). This approach uses latent variable models to estimate the resilience capacity of a given household as a function of a series of household observable characteristics.

Specifically, the paper: (i) proposes a method to estimate a resilience index and analyses what are the most important components of household resilience, (ii) tests whether the household resilience index is a good predictor of future food security status and food security recovery capacity after a shock, and (iii) explores how idiosyncratic and covariate shocks affects household food security.

The paper is structured accordingly. Section 2 defines the concept of resilience and highlights the analytical framework for its measurement. Section 3 describes the data and the econometric strategy used to estimate the resilience capacity index. Section 4 analyses the different dimensions contributing to household resilience in Tanzania and Uganda. Section 5 tests how the resilience index influences future household food security attainments in the two countries. Section 6 assesses the role of idiosyncratic and covariate shocks on food security and their relationship with household resilience. Section 7 summarizes the most important findings, discussing also some policy implications.

2. An introduction to resilience measurement framework

Resilience is a multi-faceted phenomenon. Scholars, research centers, organizations and agencies have developed their own definitions and methods to measure it. Alinovi *et al*. (2008: 300) define resilience as "the capacity of a household to keep a certain level of wellbeing (e.g. food security), notwithstanding shocks and stresses, and reorganize while undergoing change so as to still retain essentially the same function, structure, identity". More recently, the Technical Working Group on Resilience Measurement (TWGRM, 2013: 6) defines resilience as "the capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences".

These definitions imply that: (i) resilience is an outcome-based concept, being the outcome a measure of poverty, food security (as in this paper) or any other indicator of well-being; (ii) unlike similar concepts (e.g. vulnerability), resilience emphasizes long-lasting effects on the

2013) reports most of the approaches that have been recently proposed to measure resilience, including those of FAO, DFID, USAID, EC, and WFP.

outcome variable at hand; and resilience explicitly requires "agency", that is the agent's capacity to absorb, adapt and transform livelihood strategies to offset the (anticipated or actual) negative impacts of shock.

Therefore, any modeling/measurement effort should be able to capture these features, which implies the following:

- resilience has to be benchmarked to an outcome: the dependent variable measuring how resilient the agent (being it an individual, a household, a community, etc.) is in facing a shock must be a measure of his status with reference to a given output level normatively established (e.g. poverty line, minimum food caloric intake, etc.);
- resilience is a genuinely dynamic concept: it involves the complex process of preparing and responding to shocks. Furthermore, it is defined with reference to the "long-lasting" consequences of a given shock. This implies that the analytical framework cannot be static and an appropriate time frame must be defined;
- the analytical framework must be able to capture all possible pathways to ensure resilience: these pathways may be very different across agents even if they live in the same area. As a result, the analytical framework must be able to capture the causal relationship linking risks and outcomes (risk chain) and account for agents' heterogeneity in gaining a livelihood.

Measuring resilience requires dealing with the issue of choosing a proper spatial and temporal scale for the analysis (and the implications thereof).

The spatial scale of analysis depends on the study objectives and is relevant to define the indicator to be used for measuring resilience. In many cases the household is the most suitable entry point for the analysis of resilience.[4] In the specific case of food, a suitable indicator of wellbeing is household food consumption at different points in time or the change in food consumption between two points in time.[5]

However, adopting a household perspective does not mean disregarding the importance of the relationships between the households and the broader system they belong to (e.g. the community, the district, etc.). Rather, this means acknowledging that systems comprise hierarchies, each level of which involves a different temporal and spatial scale (Gunderson and Holling, 2002). Therefore, considering different levels of analysis – say food security at community level or district level or even at higher hierarchical level (province or state) - implies that the dependent variable indicator may be different. For instance, in analysing the food security at country level, a suitable indicator is the percapita caloric availability computed

[4] In fact, the household is the unit within which the most important decisions to manage risks, both ex-ante and ex-post, including the ones affecting food security, are made: e.g., what income-generating activities to engage in, what strategies to implement to manage and cope with risks, how to allocate food and non-food consumption among household members, etc.

[5] However, there is no reason whatsoever to restrict the analysis of resilience to this indicator: any wellbeing indicator at household level can be used, e.g. nutritional or health status indicators will work as well (cf. Hoddinott & Kinsey, 2002).

from the country food balance sheets, while if the analysis is a household level suitable indicators are the food caloric intake, the dietary diversity, the food consumption score, etc.[6]

This also means acknowledging that the broader system contributes to determine the household performances in terms of food security, including its resilience to food insecurity. Operationally, this implies that the characteristics of the broader system the household belongs to should be explicitly accounted for in the analytical framework and in the model.

The time frame relevant for the analysis also depends on the analytical objectives at hand. Specifically, it depends on the scale at which the analysis is carried out and on the livelihood strategies adopted by a given household, which in turn define both the risk landscape it lives in and the options available to manage risks. Generally speaking, the longer the time period covered by the analysis the better for assessing the household ability to recover after a shock occurred.

The issue of how short should be the minimum time frame for a meaningful analysis depends on the household livelihood strategy. Indeed, the strategies implemented by pastoralists or farmers are completely different from the ones of rickshaw paddlers or urban wage earners in terms of speed of income generating and asset building as well as in terms of time pattern (e.g. seasonal or not seasonal). Operationally, this means that the model should explicitly control for heterogeneity in livelihood strategies and that the time frame should be long enough to give the household a chance for recovering: more often than not, this means considering an analytical time frame spanning at least a few years.

In short, the spatial and temporal scales are very important because they define: (i) the system to be analysed (a household, a community, the whole population of a country), (ii) the variable measuring the status of the system (i.e. a well-being indicator), and (iii) the variables that influence the system status. Therefore, a very general analytical structure can be thought of as a relationship between a dependent variable, Y, indicating the system status, and some independent variables, X_i, (i = 1, …, n) that have an impact on this status:

$$Y = f\left(X_1, X_2, \ldots, X_n\right). \tag{1}$$

Our assumption is that there are some characteristics (household or context specific) that make a given household more resilient than others to the same shock. Hence, it is crucial to identify what are the attributes of this resilience "capacity":

$$Y = f\left[R\left(X_1, X_2, \ldots, X_m\right), X_{m+1}, X_{m+2}, \ldots, X_n\right], \tag{2}$$

[6] Consequently, the analytical model needs to be modified to account for these changes in the dependent variable. For instance, the higher the level of analysis the more important covariant shocks (at the proper scale) rather than idiosyncratic shocks. Usually, this also translates into a longer time frame for the analysis.

where variables 1 to m are resilience correlates, which in turn impact the status Y (e.g. food security), while variables $m + 1$ to n are other variables that impact Y, though they do not influence household resilience, R.

The analytical challenge is how to measure such a "capacity", R, and how to estimate the relation (2), that links resilience as well as other determinants to the outcome status. This is the overall objective of this paper.

3. Data and methods

3.1. Data

This paper uses two panel datasets from the World Bank's Living Standard Measurement Studies Integrated Survey on Agriculture (LSMS-ISA) both covering three rounds: the Tanzania National Panel Survey (TZNPS: 2008-09, 2010-11 and 2012-13) and the Uganda National Household Survey (UNHS: 2009-10, 2010-11 and 2011-12). These datasets are nationally representative and represent a unique opportunity to study and compare household resilience across diverse contexts. In fact, in each LSMS-ISA country a multi-purpose household questionnaire is administered to all sampled households. Furthermore, agricultural households are provided with an additional module that collects detailed agricultural information.

Table 1 shows household food security performance over time in the two countries using two different food security indicators, percapita food expenditure and household dietary diversity. More than 50 percent of households experienced a loss in both food expenditure and dietary diversity between time t and t+1 in the two countries.[7] Among the households who suffered a loss in food expenditure between time t and time t+1, 71 percent were able to recover the loss between time t+1 and t+2 in Uganda while only the 60 percent did so in Tanzania. The share of households suffering a loss in dietary diversity between t and t+1 and recovering between t+1 and t+2 is respectively 58 percent in Tanzania and 50 percent in Uganda.

Table 1. Food security patterns among Tanzanian and Ugandan households

	Tanzania		Uganda	
	Frequency	Percent	Frequency	Percent
Total households	2,866		2,015	
Suffering a loss in food expenditure between time t and t+1	1,440	50.24	1,341	66.55
Recovering the loss in food expenditure between time $t+1$ and t+2	869	60.35	957	71.36
Suffering a loss in dietary diversity between time t and t+1	1,483	51.74	1,417	70.32

[7] In the following analysis only significant changes in households' food security status are considered, establishing a 5 percent change as a lower bound to food security fluctuations. Therefore, we define a food security loss between time t and t+1 only if the household food security indicator in time t+1 is less than its value in time t minus 5 percent. Consistently, we consider that a household recovers the loss suffered between time 1 and t+1 if its food security indicator in time t+2 is greater or equal than its value in time t minus 5 percent.

Recovering the loss in dietary diversity intake between time *t+1* and *t*+2	856	58.33	712	50.25

In order to explore how idiosyncratic and covariate shocks affects resilience, two additional datasets were used, taking advantage of the LSMS–ISA geographic reference of each households that makes possible the data matching. A climatic dataset (Arslan *et al.,* 2016) including geo-referenced environmental variables (e.g. aridity index, night-light time, climatic data, etc.) was used to describe local conditions and to build natural shock variables by using the long-term coefficient of rainfall variation.[8] A second dataset, which provides long-term (1997-2014) and current (2015) data on conflict episodes for African countries (Carlsen et al., 2010),[9] was used to build a conflict intensity index (Bozzoli *et al*., 2011) by aggregating events in a given year and discounting them by their distances from where the household lives.

3.2. Methods

Resilience is a multi-faceted concept that is not directly observable. Consequently it has to be measured through a proxy. This paper adopts the FAO's Resilience Index Measurement Analysis model (RIMA) (Alinovi *et a*l., 2008 and 2010; FAO, 2016) that quantitatively assesses household resilience through latent variable modeling.

The RIMA approach is based on a two-stage procedure (Figure 1). In the first step, factor analysis (FA) is used to identify the attributes – called "pillars" in the RIMA jargon – that contribute to household resilience, starting from observed variables.[10] These attributes are: Access to Basic Services (ABS), Assets (AST), Social Safety Net (SSN) and Adaptive Capacity (AC). The summary statistics of the observed variables used for estimating the pillars are shown in the Annex. In the second step, a Multiple Indicators Multiple Causes (MIMIC) model is estimated. Specifically, a system of equations is constructed, specifying the relationships between an unobservable latent variable (resilience), a set of outcome indicators (food security indicators), and a set of attributes (pillars).

[8] The coefficient of rainfall variation is equal to the ratio between the rainfall standard deviation and the average rainfall computed over a period of thirty years (1983-2012). It should be emphasized that the coefficient of variation captures both positive and negative deviations from the long-term trend. As such, it does not perfectly capture the role played by negative shocks (droughts), which are of interested in this study. This may have implications for the significance of the empirical analysis (see Section 6).

[9] For each conflict episode, the dataset reports the date of the event, the type of the event, the actors involved, geographical information on where the event happened (reporting the exact location through its latitude and longitude), number of fatalities and the source of information.

[10] The Annex reports the list of observed variables, and their summary statistics, used to estimate the attributes. The factors considered for each attribute are only the ones able to explain at least 95 percent of the variable variance.

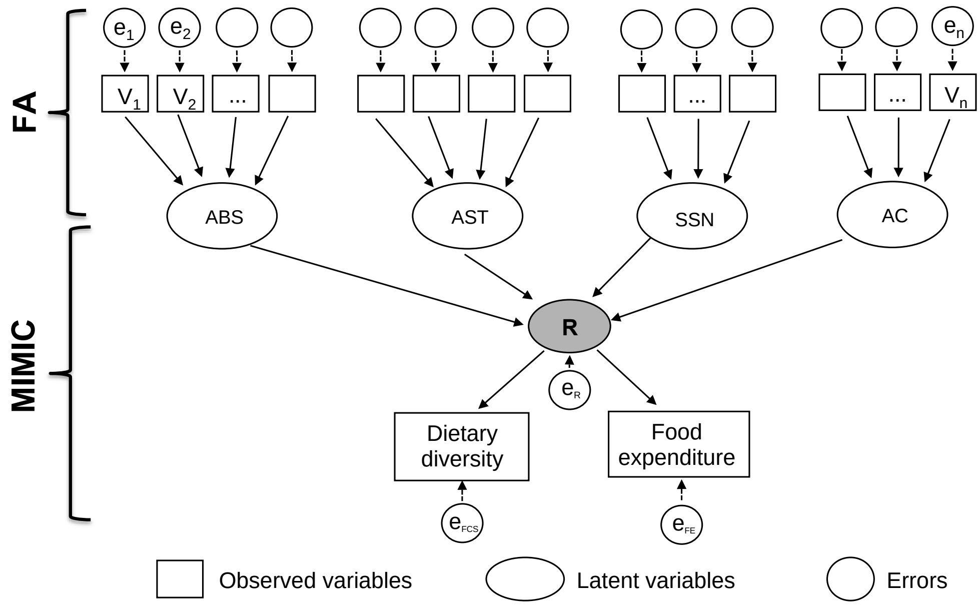

Figure 1. Resilience index estimation strategy

The MIMIC model is made by two components, namely the measurement equation (3), reflecting that the observed indicators of food security are imperfect indicators of resilience capacity, and the structural equation (4), which correlates the estimated attributes to resilience capacity:

$$\begin{bmatrix} Food\ expenditure \\ Dietary\ diversity \end{bmatrix} = [\Lambda_1, \Lambda_2] \times [RCI] + [\varepsilon_2, \varepsilon_3] \tag{3}$$

$$[RCI] = [\beta_1, \beta_2] \times \begin{bmatrix} ABS \\ AST \\ SSN \\ AC \end{bmatrix} + [\varepsilon_1]\,. \tag{4}$$

The estimated resilience capacity index (*RCI*) is not anchored to any scale of measurement. Therefore, a scale has been defined setting equal to 1 the coefficient of food expenditure loading (Λ_1), meaning that one standard deviation increase in *RCI* implies an increase of 1 standard deviation in food expenditure. This defines also the unit of measure of the other outcome indicator (Λ_2) and for the variance of the two food security indicators:

$$Food\ expenditure = \Lambda_1 RCI + \varepsilon_2 \tag{5}$$

$$Dietary\ diversity = \Lambda_2 RCI + \varepsilon_3\,. \tag{6}$$

4. Correlates of resilience

The MIMIC model provides two outputs: an estimate of the resilience capacity index (*RCI*) and the resilience structure matrix (*RSM*), which describes how different attributes correlate with resilience (Table 2).

Table 2. MIMIC results

	(1) Tanzania	(2) Uganda
ABS	0.2741***	0.0646***
	(0.0117)	(0.0123)
AST	0.0713***	0.0055
	(0.0111)	(0.0121)
SSN	0.1365***	0.1035***
	(0.0110)	(0.0122)
AC	0.3235***	0.320***
	(0.1166)	(0.0143)
Food expenditure	0.8447***	0.9915***
	(0.0107)	(0.0271)
Dietary diversity	0.6777***	0.5185***
	(0.0100)	(0.0170)
Chi2	13.38	12.84
P value	0.0039	0.0050
RMSEA	0.020	0.023
Pr RMSEA	1.000	1.000
CFI	0.998	0.996
TLI	0.994	0.989
Observations	8,598	6,045

Standard errors in parentheses: *** p<0.01

All attributes are statistically significant, except "Assets" in Uganda. "Adaptive capacity" is the attribute strongest correlated to resilience in both countries (Figure 2), while "Access to basic services" is very important only in Tanzania. "Social safety nets" also contributes significantly in both countries.

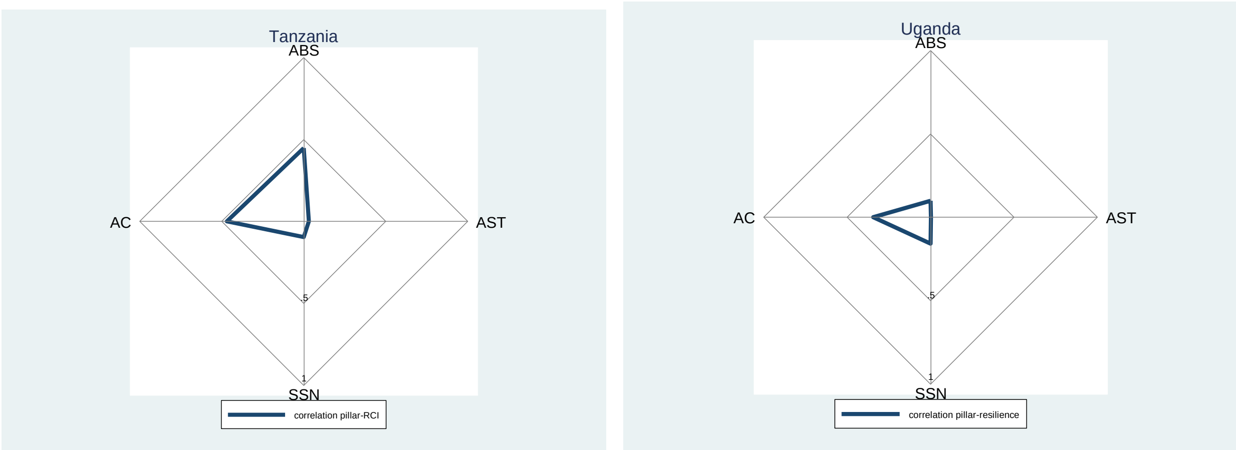

Figure 2. Attributes correlation to resilience

Figures from 2 to 4 and Table 3 analyze what are the most relevant variables per attribute in each country. In the case of "Access to basic services", the distance to school and to market are relevant variables in Uganda, while infrastructure is the most relevant variable in Tanzania. In terms of "Assets", the agricultural index and Tropical Livestock Units (TLU) play the most relevant roles. Education and the share of income earners to total household members are the most relevant variables for "Adaptive capacity". Private transfers is the most important variable for "Social safety nets".

Figure 1. Variables' relevance in ABS

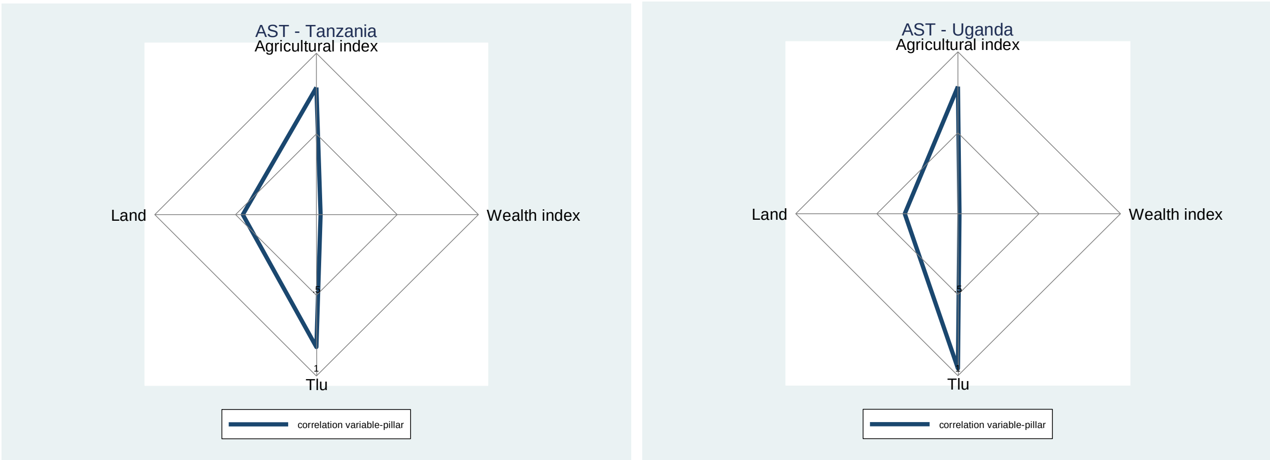

Figure 4. Variables' relevance in AST

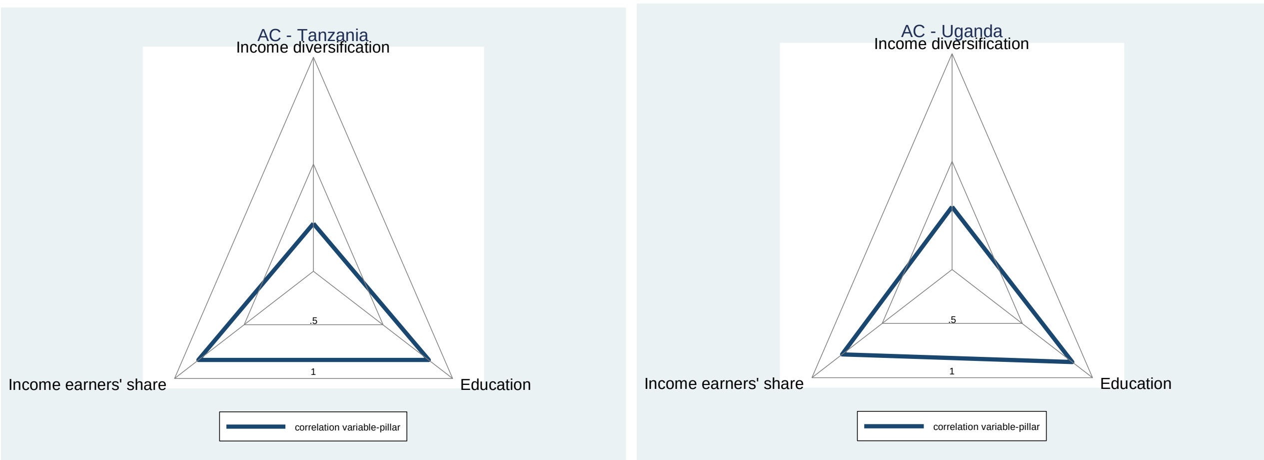

Figure 5. Variables' relevance in AC

Table 3. Variables' relevance in SSN

	Tanzania	**Uganda**
Correlation	SSN	
Private transfers	0.983	0.915
Public or other transfers	0235	0.463

5. Household resilience and food security

The relationship between resilience and food security is expected to be positive, specifically: a higher RCI in time *t* should be associated to (a) a lower loss occur between *t* and *t*+1 and (b), as a result of a shock, a higher RCI in time *t* should be associated to a faster recovery between time *t*+1 and *t*+2.

We use as indicators of food security an index capturing the quantitative dimension food security, i.e. percapita food expenditure, as well as a proxy for diet quality, i.e. the Shannon dietary diversity.[11] In order to compare the resilience levels across different periods, the resilience capacity index has been standardized through a Min-Max scaling transformation.[12]

To explore the relationship between resilience and food security a probit model is estimated, where the probability of suffering a loss in food security outcome (food expenditure or dietary diversity)[13] between time t and t+1 depends on the resilience capacity index (RCI) and a vector of household characteristics **X** in time t:

$$Prob\left(loss\ in\ FS_{t,t+1}\right) = \Phi(RCI_{h,t}, \mathbf{X}_{h,t})\ . \tag{7}$$

Furthermore, the probability of recovering between time t+1 and t+2 can be assessed using again a probit model as in eq. (7) applied to the sub-sample of households who suffered a loss between t and t+1. Tables 4 and 5 show the results of the probit model of suffering a reduction in percapita food expenditure and dietary diversity, respectively, for Tanzania and Uganda.

Table 4. Probit regression on the likelihood of suffering a food expenditure loss between t and t+1 and recovering from the loss between t+1 and t+2

	Tanzania		**Uganda**	
	(1) Loss btw t and t+1	(2) Recovery btw t+1 and t+2	(3) Loss btw t and t+1	(4) Recovery btw t+1 and t+2
RCI	**-0.0389***** (0.00690)	0.00366 (0.00504)	**-0.856***** (0.150)	**0.0227***** (0.004)
Percapita food expenditure (log)	2.348*** (0.164)	-1.185*** (0.117)	16.86*** (2.842)	-0.857*** (0.0665)
Female HH head	0.154** (0.0640)	-0.0554 (0.0852)	-0.0351 (0.071)	-0.0487 (0.089)
Age of HH head	0.000274 (0.00180)	-0.00248 (0.00239)	0.0012 (0.0022)	-0.0067** (0.00287)
HH size	0.0890*** (0.0260)	-0.0419 (0.0375)	0.0434 (0.0320)	0.0338 (0.0398)
Squared HH size	-0.00176 (0.00165)	0.000853 (0.00248)	-0.000999 (0.00217)	-0.00156 (0.00270)

[11] The percapita food expenditure is the monetary value, in US dollars, of monthly percapita food consumption (including food purchase, the value of food produced and self-consumed, and the value of food received as gift). The Shannon dietary diversity index is computed by considering the shares of the consumed calories by group of food (cereals, roots, vegetables, fruits, meat, legumes, dairy, fats and other), specifically:

$$Dietary\ diversity = -\sum_{i=1}^{n} p_i * lnp_i$$

where p_i is the share of consumed calories of the *i*-th food group.

[12] The Min-Max scaling is based on the following formula: $RCI_h^* = \frac{(RCI_h - RCI_{min})}{(RCI_{max} - RCI_{min})} * 100$, where *h* represents the *h*-th household.

[13] Alternative outcome variables – food caloric intake, food consumption score (Pangaribowo *et al.*, 2013) – have been used to test the robustness of the estimates. The general pattern does not change, though results are less statistically significant. Results are available upon request.

Rural	0.346***	-0.282***	0.348***	-0.304***
	(0.0705)	(0.0959)	(0.086)	(0.106)
Constant	-5.680***	3.344***	-1.114***	1.201***
	(0.310)	(0.478)	(0.240)	(0.310)
Observations	2,866	1,440	2,015	1,341
Log-Likelihood	-1551.561	-855.002	-1100.709	-679.7411
Pseudo-R^2	0.219	0.115	0.142	0.153
Pearson Chi2	2854.13	1447.74	2020.53	2221.08
Prob > Chi2	0.386	0.219	0.393	0.000

All explanatory variables are at time *t* except (log) percapita food expenditure in models (2) and (4), which are at time *t+1*. Regional dummies are included as control: 26 dummies in models (1) and (2) and 4 dummies in models (3) and (4). Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Probit regression on the likelihood of suffering a dietary diversity loss between t and t+1 and recovering from the loss between t+1 and t+2

	Tanzania		**Uganda**	
	(1) Loss btw *t* and *t*+1	(2) Recovery btw *t*+1 and *t*+2	(3) Loss btw *t* and *t*+1	(4) Recovery btw *t*+1 and *t*+2
RCI	**-0.0272*****	**0.0108*** **	**-0.0052*** *	**0.0138*** **
	(0.00344)	(0.00413)	(0.00253)	(0.0027)
Dietary diversity	3.031***	-2.466***	2.096***	-1.940***
	(0.144)	(0.172)	(0.125)	(0.118)
Female HH head	0.0330	0.0468	0.177**	-0.157*
	(0.0628)	(0.0880)	(0.0761)	(0.0832)
Age of HH head	-0.000445	0.00208	0.00144	0.00043
	(0.00175)	(0.00248)	(0.0023)	(0.0026)
HH size	0.000291	-0.0202	-0.119***	0.0582
	(0.0183)	(0.0375)	(0.0342)	(0.0426)
Squared HH size	-0.000306	0.00202	0.0049**	-0.00132
	(0.000902)	(0.00250)	(0.0022)	(0.00298)
Rural	0.231***	-0.175*	0.107	0.0103
	(0.0698)	(0.0967)	(0.0924)	(0.101)
Constant	-3.565***	2.478***	-1.937***	1.249***
	(0.283)	(0.476)	(0.250)	(0.306)
Observations	2,866	1,483	2,015	1,417
Log-Likelihood	-1584.558	-842.139	-966.809	-805.850
Pseudo-R^2	0.201	0.163	0.2110	0.179
Pearson Chi2	2819.64	1559.22	2018.33	1654.08
Prob > Chi2	0.567	0.023	0.406	0.000

All explanatory variables are at time *t* except dietary diversity in models (2) and (4), which are at time *t+1*. Regional dummies are included as control: 26 dummies in models (1) and (2) and 4 dummies in models (3) and (4). Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

As expected, the *RCI* in time *t* negatively affects the probability of suffering a loss between time *t* and *t*+1 in both countries irrespective of the adopted food security indicator. Vice versa, the

RCI positively affects the probability of recovering between time t+1 and t+2 in the case of Uganda for both indicators, while in the case of Tanzania this is true for percapita food expenditure, being not statistically significant, although positive, for dietary diversity. Significantly, being a rural household increases the probability of a food loss between t and t+1, and reduces the probability of a recovery between t+1 and t+2.

6. The role of idiosyncratic and covariate shocks

Despite constant country-specific characteristics, household- and context-specific events such as idiosyncratic and covariate shocks may influence household resilience capacity and eventually food security outcomes. In order to explore the role of these variable, shocks are included in model (7) as follows:

$$Prob\big(loss\ in\ FS_{t,t+1}\big) = \Phi(RCI_{h,t}, \mathbf{X}_{h,t}, \boldsymbol{S}_{h,t}, RCI_{h,t}\boldsymbol{S}_{h,t}) \quad (8)$$

where **S** is a vector of covariate or idiosyncratic shocks. Furthermore, interaction terms between the *RCI* and the shock covariate variables are included in the model aiming to capture the marginal effect of the *RCI* on food security as the shock intensity increases.

Table 6 presents the results on the role of self-reported shocks on percapita food expenditure and dietary diversity, respectively. The predictive capacity of *RCI* does not change when self-reported shock variables are included in the probit model (7) but self-reported shocks are generally not statistically significant irrespective of the adopted food security indicator. This probably depends on the low quality of the self-reported information.[14]

Table 6. Probit models of the role of idiosyncratic shocks in explaining the likelihood of suffering a loss in food consumption and dietary diversity

	Tanzania		Uganda	
	(1) Loss btw t and t+1 in food expenditure percapita	(2) Loss btw t and t+1 in dietary diversity	(3) Loss btw t and t+1 in food expenditure percapita	(4) Loss btw t and t+1 in dietary diversity
RCI	**-0.0392*****	**-0.0272*****	**-0.755*****	**-0.00570****
	(0.00697)	(0.00346)	(0.154)	(0.00256)
Drought/flood	0.0815	-0.00310	0.0778	-0.234***
	(0.0682)	(0.0680)	(0.0707)	(0.0747)
Crop pest and disease	0.0411	0.0104	-0.0894	-0.193
	(0.0720)	(0.0717)	(0.150)	(0.153)
Fall in price of crops	0.0569	0.00481		
	(0.0762)	(0.0758)		
High cost of inputs	-0.0613	-0.114	-0.388**	-0.0771

[14] LSMS-ISA questionnaires include information about the major shocks self-reported by the respondent. In Tanzania LSMS-ISA, section R "*Recent shocks to household welfare*" asks the household whether it has been negatively affected by a list of shocks over the past 5 years. Furthermore, for the three most significant shocks, additional information are collected: reduction of income/assets caused by the shocks, dispersion of the shocks and year of occurrence. The Uganda LSMS-ISA section 16 "*Shocks and coping strategies*" collects information of the shocks occurred during the last 12 months; the length of the shock; the reduction in income, assets, food production and food purchase due to the shock; and the strategies adopted to cope with the shock.

	(0.0773)	(0.0763)	(0.189)	(0.195)
Rise price of food	-0.0378	0.0180	0.196***	0.273***
	(0.0622)	(0.0612)	(0.0700)	(0.0744)
Livestock shock	-0.101	-0.0128		
	(0.0689)	(0.0684)		
Business failure	0.0375	-0.0410		
	(0.165)	(0.162)		
Loss of employment	-0.0490	0.154	0.177*	-0.0806
	(0.121)	(0.121)	(0.0960)	(0.0978)
Water shortage	0.0499	0.0371		
	(0.0613)	(0.0611)		
Illness	0.139	-0.0655		
	(0.0919)	(0.0894)		
Death of HH members	-0.0391	-0.0183		
	(0.0763)	(0.0759)		
Death others	0.0357	0.0356		
	(0.0574)	(0.0568)		
Break household	-0.0265	-0.109		
	(0.125)	(0.122)		
Jail	0.222	-0.0126		
	(0.339)	(0.310)		
Robbery	-0.0768	-0.0812	-0.0882	0.0483
	(0.0901)	(0.0878)	(0.113)	(0.119)
Dwelling demage	-0.165	-0.0783		
	(0.246)	(0.243)		
Conflict			0.0466	-0.379
			(0.267)	(0.282)
Fire	0.318	0.0748	-0.101	0.0869
	(0.205)	(0.197)	(0.298)	(0.355)
Other	0.134	0.0795		
	(0.150)	(0.148)		
Percapita food expenditure (log)	2.367***		14.96***	
	(0.165)		(2.914)	
Dietary diversity		3.038***		2.189***
		(0.144)		(0.130)
Female HH head	0.162**	0.0425	-0.0491	0.172**
	(0.0650)	(0.0637)	(0.0717)	(0.0768)
Age of HH head	-2.07e-05	-0.000383	0.00110	0.00192
	(0.00183)	(0.00178)	(0.00222)	(0.00235)
HH size	0.0890***	-0.000194	0.0416	-0.124***
	(0.0251)	(0.0187)	(0.0322)	(0.0347)
Squared HH size	-0.00173	-0.000267	-0.000957	0.00524**
	(0.00153)	(0.000919)	(0.00218)	(0.00227)
Rural	0.344***	0.254***	0.343***	0.161*
	(0.0740)	(0.0733)	(0.0884)	(0.0949)
Constant	-5.699***	-3.606***	-1.324***	-2.062***
	(0.315)	(0.290)	(0.249)	(0.262)
Observations	2,866	2,866	2,015	2,015
Log-Likelihood	-1544.912	-1580.590	-1091.282	-954.120
Pseudo-R^2	0.222	0.203	0.150	0.221
Pearson Chi2	2857.81	2802.07	2034.58	1966.49
Prob > Chi2	0.282	0.565	0.268	0.676

Regional dummies are included in all models.
Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

The role of exogenously estimated and covariate shocks – an index of violence intensity and the rainfall coefficient of variation (see section 3.1) is presented in Tables 7 and 8, respectively for percapita food expenditure and household dietary diversity.

Unfortunately, the statistical significance of shocks does not improve much, probably because of the crude modelling of these shocks.[15] But introducing shocks improves the estimates of other variables, while some other variables confirm the role they played in eq. (7). In fact, RCI remains negative and statistically significant, in both countries and for both indicators, when it is evaluated at the men value of violence index and rainfall variation. Also being a rural household increases the probability of suffering a food loss between t and t+1. Furthermore, belonging to a female-headed household increases the likelihood of the loss. The role of household size merges more clearly: the larger the household size the less likely the reduction of the dietary diversity at household level, while the likelihood of reduction in terms of food expenditure is confirmed only for Tanzania, being not statistically significant for Uganda. For both food security indicators the squared household size variable has a sign opposite to the household size that indicates that the impacts of the latter decreases with the household size.

[15] In particular, it seems counterintuitive that the coefficient of variation of rainfall is negatively correlated with a loos in food security attainments. But is is probably due to the fact that this parameter captures both positive and negative deviations from the trend. Furthermore, this value is not really a shock, but a figure that reflects only the long-term natural riskiness of a given areas: as such it is only a poor proxy for natural shocks.

Table 7. Probit models of the role of covariate shocks in explaining on the likelihood of suffering a food expenditure loss between t and t+1

	Tanzania						Uganda	
	(1) Loss btw *t* and *t*+1	dy/dx of model (1)	(2) Loss btw *t* and *t*+1	dy/dx of model (2)	(3) Loss btw *t* and *t*+1	dy/dx Of model (3)	(4) Loss btw *t* and *t*+1	dy/dx Of model (4)
RCI	**-0.042*** **	**-0.012*** **	**-0.056*** **	**-0.012*** **	**-0.857*** **	**-0.264*** **	**-0.873*** **	**-0.265*** **
	(0.007)		(0.011)		(0.151)		(0.152)	
Conflict intensity index	-0.063	-0.019	-0.233	-0.023	0.000859	0.0002	0.00288	0.0005
	(0.059)		(0.242)		(0.00512)		(0.0137)	
Rainfall CV	-2.254**	**-0.681** **	-5.468**	-0.525**	0.266	0.082	-2.801	0.0118
	(1.098)		(2.206)		(1.545)		(3.624)	
RCI * Conflict intensity index			0.0021				-5.72e-05	
			(0.003)				(0.000209)	
RCI * Rainfall CV			0.0544*				0.0695	
			(0.032)				(0.0743)	
Percapita food expenditure (log)	2.458***		2.474***		16.87***		16.87***	
	(0.180)		(0.180)		(2.858)		(2.867)	
Female HH head	0.176**		0.176**		-0.0353		-0.0351	
	(0.0692)		(0.0692)		(0.0712)		(0.0713)	
Age of HH head	0.0010		0.0010		0.00106		0.000929	
	(0.0019)		(0.0019)		(0.00221)		(0.00221)	
HH size	0.099***		0.10***		0.0434		0.0424	
	(0.0294)		(0.029)		(0.0321)		(0.0323)	
Squared HH size	-0.002		-0.0023		-0.00102		-0.000966	
	(0.0018)		(0.0018)		(0.00218)		(0.00218)	
Rural	0.316***		0.310***		0.359***		0.362***	
	(0.0759)		(0.0764)		(0.0923)		(0.0925)	
Constant	-4.771***		-4.006***		-1.180***		-0.492	
	(0.629)		(0.759)		(0.410)		(0.839)	
Observations	2,486		2,486		2,015		2,015	
Log-Likelihood	-1328.671		-1326.850		-1100.653		-1100.211	
Pseudo-R^2	0.228		0.230		0.142		0.143	
Pearson Chi2	2489.24		2473.66		2019.73		2020.10	
Prob > Chi2	0.290		0.359		0.3859		0.371	

Regional dummies are included as control; specifically 26 in columns (1) and (2) and 4 in columns (3) and (4).
*** p<0.01, ** p<0.05, * p<0.1

Marginal effect of RCI is calculated at the average value of violence index and rainfall variation. Marginal effect of violence intensity is calculated at the average value of RCI.
Marginal effect of rainfall variation is calculated at the average value of RCI. Delta-method is employed for standard errors of marginal effects.
The number of observations in Tanzania is reduced due tot the presence of missing information on the conflict intensity index.

Table 8. Probit models of the role of covariate shocks in explaining on the likelihood of suffering a dietary diversity loss between t and t+1

	Tanzania				Uganda			
	(1)		(2)		(3)		(4)	
	Loss btw *t* and *t*+1	Dy/dx of model (1)	Loss btw *t* and *t*+1	Dy/dx of model (2)	Loss btw *t* and *t*+1	Dy/dx of model (3)	Loss btw *t* and *t*+1	Dy/dx of model (4)
RCI	**-0.024*** **	**-0.0076*** **	**-0.031*** **	**-0.0075*** **	**-0.0056** **	**-0.0015** **	**-0.008**	**-0.0015** **
	(0.0037)		(0.0079)		(0.0025)		(0.0169)	
Conflict intensity index	0.0046	0.0014	0.193	0.013	0.0095*	**0.0025***	0.00843	0.002
	(0.058)		(0.223)		(0.0053)		(0.017)	
Rainfall CV	0.654	0.2042	-1.214	0.181	-2.352	-0.6305	-2.944	-0.609
	(1.064)		(2.046)		(1.610)		(3.761)	
RCI * Conflict intensity index			-0.0024				1.21e-05	
			(0.0027)				(0.00025)	
RCI * Rainfall CV			0.0312				0.0131	
			(0.0293)				(0.0753)	
Dietary diversity	2.982***		2.987***		2.112***		2.110***	
	(0.154)		(0.155)		(0.127)		(0.127)	
Female HH head	0.0216		0.0238		0.177**		0.178**	
	(0.0674)		(0.067)		(0.0763)		(0.0766)	
Age of HH head	-0.0003		-0.00042		0.00161		0.00159	
	(0.001)		(0.00188)		(0.00233)		(0.00233)	
HH size	0.0019		0.00194		-0.121***		-0.121***	
	(0.0192)		(0.0192)		(0.0344)		(0.0344)	
Squared HH size	-0.0003		-0.0003		0.00501**		0.00501**	
	(0.0009)		(0.0008)		(0.00226)		(0.00226)	
Rural	0.232***		0.238***		0.138		0.139	
	(0.075)		(0.0755)		(0.0989)		(0.0992)	
Constant	-3.995***		-3.610***		-1.454***		-1.319	
	(0.605)		(0.722)		(0.425)		(0.865)	
Observations	2,486		2,486		2,015		2,015	
Log-Likelihood	-1371.986		-1371.107		-964.985		-964.964	
Pseudo-R^2	0.202		0.203		0.212		0.212	
Pearson Chi2	2434.81		2429.11		2028.22		2027.30	
Prob > Chi2	0.587		0.608		0.336		0.329	

Regional dummies are included as control; specifically 26 in columns (1) and (2) and 4 in columns (3) and (4).
*** p<0.01, ** p<0.05, * p<0.1
Marginal effect of RCI is calculated at the average value of violence index and rainfall variation. Marginal effect of violence intensity is calculated at the average value of RCI.

Marginal effect of rainfall variation is calculated at the average value of RCI. Delta-method is employed for standard errors of marginal effects.
The number of observations in Tanzania is reduced due tot the presence of missing information on the conflict intensity index.

7. Conclusions

This paper proposes a measure of resilience capacity at household level and provides empirical evidence on how the estimated resilience index contributes to understand food security attainments in Tanzania and Uganda. The main results of the analysis are the following:

a) adaptive capacity is the most relevant attribute contributing to household resilience, and education and the percentage of income earners at household level are the most relevant component of adaptive capacity in both countries;
b) the resilience index positively influences future household food security outcomes (proxied by percapita food expenditure and the Shannon dietary diversity index): it decreases the probability of suffering a future food security loss and speeds up the recovery after the loss occurrence, and
c) the resilience index keeps playing the same role in both countries and for both food security indicators even when idiosyncratic and covariate shocks are considered;
d) however, shocks do not prove to be statistically significant, but this is probably the result of poor data.

Besides the specific results highlighted above, the resilience measuring approach proposed in this paper can be used to guide policy interventions. First, it helps in identifying the most relevant characteristics that contribute to build resilience capacity at household level. For instance, in Tanzania and Uganda education clearly results to be the most useful tool to increase household resilience. Second, the proposed approach can be used to reduce the multi-dimensionality of the resilience capacity into an index suitable for targeting purposes. In doing this, the least resilience households can be identified and specific interventions to increase their own resilience capacity can be implemented thus reducing the household vulnerability to food insecurity.

The results of this paper are encouraging in operationalizing the concept of resilience as a policy objective. However, the way to fully operationalize this concept is still long and further evidence needs to be provided before using it. For instance, a better understanding of the role of idiosyncratic and covariate shocks is needed. Moreover, this paper did not analyze the different mechanisms through which the household resilience capacity affects household food security. In other words, the empirical tests presented in this paper confirm the existence of a positive association between the RCI and household food security without investigating conduit mechanism to food security attainments.

Additional avenues for further research are largely conditional upon the availability of good data. For instance, the analysis should be extended to other African countries, surveyed by the LSMS-ISA project to ensure the comparability of the datasets. An expanded sample of countries can provide more robust evidence, confirming or confuting the results presented here.

Furthermore, using longer time series of household surveys, as soon as they will be available, may prove useful in deepen the analysis especially on the role of shocks and stressors, andthe relationships between household resilience capacity and shocks on food security attainments.

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Annex - Summary statistics of the variables used in the estimates (pooled samples, 3 rounds)

		Uganda				Tanzania			
Variable	**Note**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Food expenditure (US dollars) percapita	Monetary value, expressed in US dollars, of percapita monthly food consumption, including bought, auto-produced, received for free (as gifts or part of a conditional project) and stored food.	14.053	17.511	0	190.358	20.116	12.377	0.43	90.029
(log) Food expenditure		2.183	1.081	0	5.254	2.816	0.631	0	4.5
Shannon dietary diversity	The index combines the calories consumed by 9 food groups (cereals, roots, vegetables, fruits, meat, legumes, dairy, fats and other) and their relative abundance. The dietary diversity index is given by: Ψ=1-∑_(i=1)^n p_i * ln(p_i) where p_i expresses is the share of consumed calories of group i in a sample of n food groups (cereals, roots, vegetables, fruits, meat, legumes, dairy, fats and other). A bigger value of the index means greater dietary diversity.	1.144	0.452	0	1.993	1.292	0.335	0	2.084
ABS									
Infrastructural index	Principal component index with dummies for having home; cement roof; brick walls; non-dirty floor; run water; toilet; electricity.	-0.105	0.937	-0.898	4.567	0.203	0.304	-0.038	1.024
Distanced to school	The distance is expressed in KM	22.793	14.457	0	90	0.515	1.801	0	33.333
Distance to market	The distance is expressed in KM	35.766	35.216	0	300	0.419	2.334	0	100
AST									
Agricultural index	The index is created through factor analysis. A list of variable is assuming value 1 or 0 is used, depending on whether or not a household has specific agricultural tools as plow, barrow, etc.	0.016	0.768	-0.858	18.427	-0.102	0.95	-0.733	14
Wealth index	The index is created through factor analysis. A list of variable is assuming value 1 or 0 is used, depending on whether or not a household has specific non-productive assets, as television, radio, lamp, etc.	0.04	1.263	-1.726	11.269	0.075	0.639	-0.923	2.297
Land owned	Hectares of owned land percapita.	1.44	5.458	0	330.264	1.296	2.04	0	34.803
Tropical Livestock Unit (TLU)	TLU standardizes different types of livestock into a single unit of measurement. The conversion factor adopted is: 1 camel; 0.7 cattle; 0.55 donkeys/mules/horses; 0.1 sheep/goats; 0.01 chickens.	1.318	8.323	0	575.26	1.366	4.248	0	66.4
AC									
Income diversification	Principal component index with dummies for income from (1) agriculture and fishing wages; (2) non-agriculture wages; (3) farming production; (4) livestock and fishing production; (5) non-agriculture business; (6) transfers and (7) other income sources.	0.28	0.376	-0.593	1.385	0.17	0.421	-0.463	1.299
Average education	Numbers of average years of education among HH members	4.715	3.665	0	17	5.202	3.349	0	17
Income earners' share	Number of active HH members (>15 and <64 years old) over HH size	0.484	0.251	0	1	0.526	0.237	0	1
SSN									
Private transfers (US dollars)	Received private transfers monthly percapita in US dollars.	1.525	5.815	0	123.607	0.728	1.466	0	12.157
Other transfers (US dollars)	Received non-private transfers monthly percapita in US dollars.	0.39	2.656	0	49.333	0.028	0.284	0	20.055

HH control characteristics									
Female HH head	dummy=1 if yes	0.314	0.464	0	1	0.247	0.431	0	1
Age of HH head	Numeric	47.683	14.943	0	100	48.23	15.224	17	107
HH size	Numeric	5.539	2.847	1	23	5.579	3.008	1	55
Squared HH size	Numeric	38.784	40.381	1	529	40.179	68.261	1	3025
HH engaged in agriculture	dummy=1 if yes	0.839	0.367	0	1	0.766	0.423	0	1
Shocks									
Drought / Floods	dummy=1 if yes	0.367	0.482	0	1	0.224	0.417	0	1
Crop pest and disease	dummy=1 if yes	0.034	0.18	0	1	0.168	0.374	0	1
Fall in price of crops	dummy=1 if yes	0.028	0.165	0	1	0.178	0.383	0	1
High cost of inputs	dummy=1 if yes					0.182	0.386	0	1
Livestock shock	dummy=1 if yes					0.156	0.363	0	1
Rise price of food	dummy=1 if yes	0.317	0.466	0	1	0.522	0.5	0	1
Business failure	dummy=1 if yes					0.041	0.199	0	1
Loss of employment	dummy=1 if yes	0.107	0.309	0	1	0.02	0.14	0	1
Water shortage	dummy=1 if yes					0.254	0.435	0	1
Illness	dummy=1 if yes					0.074	0.262	0	1
Death HH members	dummy=1 if yes					0.11	0.313	0	1
Deaths others	dummy=1 if yes					0.324	0.468	0	1
Break household	dummy=1 if yes					0.046	0.21	0	1
Jail	dummy=1 if yes					0.005	0.071	0	1
Fire	dummy=1 if yes	0.01	0.101	0	1	0.016	0.126	0	1
Robbery	dummy=1 if yes	0.051	0.22	0	1	0.076	0.265	0	1
Dwelling demage	dummy=1 if yes					0.008	0.087	0	1
Conflict	dummy=1 if yes	0.017	0.13	0	1				
Other	dummy=1 if yes					0.04	0.195	0	1
Rainfall variation	The ratio of the SD of Dec-Jun rainfall 1983-2012 over the Average of Dec-Jun rainfall 1983-2012.	0.229	0.027	0.17	0.311	0.245	0.082	0.125	0.536
Conflict intensity index	Information about the exact geographic location of each event (yj) (from ACLED dataset) and the household (i) in that year are needed. Then the square of the distance (d) in degrees between the household and each of the events is estimated. The index is given as Conf = Σ (j=1.....J) e−α(d(yj ,i)), where α is a distance-discount factor. The index therefore captures the number of ''geographically discounted'' events for each individual. As in Bozzoli *et al.*, α = 10.	6.962	15.17	0	74.701	1.809	4.538	0	27.64
Obs.		6,045				8,598			