



Drivers and stressors of resilience to food insecurity: evidence from 35 countries

Marco d'Errico¹ · Jeanne Pinay¹ · Ellestina Jumbe¹ · Anh Hong Luu²

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Abstract

The recent COVID-19 global pandemic has revealed that despite numerous development efforts, there are still inefficiencies in maintaining the living standards of people when shocks and stressors occur. While addressing issues arising from the pandemic is dramatically urgent, this should not come at the cost of averting resources and efforts from sustainable and equal growth and prosperity goals. The importance of resilience for the humanitarian and development nexus, has probed United Nations agencies, international organizations, donors, and governments to investigate key facts and determinants of this capacity. After approximately 15 years of empirical evidence, few research questions remain unexplored and unanswered. Are there few and consistently relevant elements that determine resilience capacity? What shocks are most dramatically reducing resilience? What coping strategies are most frequently adopted in the presence of shocks? This paper attempts to respond to these questions by pooling together a unique database of 35 countries. This study combines the most recent FAO-RIMA (Resilience Index Measurement and Analysis) datasets with a large set of data from the Multiple Indicator Cluster Survey (MICS) produced by the United Nations International Children's Emergency Fund (UNICEF). The analysis covers the period between 2014 and 2020 by investigating 50,622 households. The size of the sample provides our findings with great statistical power, therefore adding external validity. Our results show that firstly, diversification of income sources, education, access to land, livestock, and agricultural inputs, are the main drivers of households' resilience capacity. Secondly, we gather evidence that the prevailing shocks are natural, health, and livelihood. Thirdly, we find that reducing the quantity and quality of food consumed, seeking an extra job, selling assets, taking credit, relying on relatives and social networks are the most adopted coping strategies. Finally, we found evidence of how mitigating strategies are adapted to the shocks: for instance, increasing working hours is adopted when a natural shock occurs while accessing credit is chosen when health shocks occur. Our results show that adequate investments in resilience are conditional to a) engaging with activities that are broadly consistent across countries and b) fine-tuning the interventions based on context specificity.

Keywords Resilience · Cross-countries analysis · Shocks · Coping strategies · RIMA · MICS · Growth

JEL Classification O12 · Q5 · I32 · C01

1 Introduction

155 million people in 55 countries were in crisis or worse in 2020, with an increase of around 20 million from 2019 (GRFC¹2021). People are looking at new challenges (like

COVID-19) and old ones as the main prevailing factors that reduce food security and limit resilience. The new challenges have an unprecedented strength and an increased transmission capacity due to the reinforced interconnectivity of food systems (FAO, 2021). The pandemic, for instance, has affected over 237 million people (as of October 2021). Resilience, considered as *the capacity that ensures shocks and stressors do not have long-term development consequences* (Constas et al., 2014a) is seen as the right lens to strengthen

✉ Marco d'Errico
marco.derrico@fao.org

¹ Food and Agricultural Organization of United Nations, Agrifood Economics Division, Rome, Italy

² Food and Agricultural Organization of United Nations, Agrifood Economics Division, Brussels, Belgium

¹ Global Report on Food Crises (<https://www.wfp.org/publications/global-report-food-crises-2021>).

households' capacity to bounce back from shocks. Resilience, in fact, is functional to both humanitarian and development interventions: supporting households during acute crisis, while promoting peaceful and robust communities, long-term and sustainable growth, all make part of poverty reduction strategies.

Stemming from naval architecture and ecology, the concept of resilience has arrived at the socio-economic literature on food systems and food security with a seminal paper in 2005 (Pingali et al., 2005). Since then, many efforts have been put in place to achieve a common understanding and an agreed metrics for resilience measurement. The literature has plenty of approaches and attempts to classify them (see for instance Gonzalez-Quintero & Avila-Foucat, 2019). Still, after approximately 15 years of activities, some research questions remain unexplored and unanswered. What is missing is a systematic measure of resilience which employs cross-countries data analysis to provide generalizable responses. This paper is a first attempt to provide answers to the following research questions: (i) Are there few and consistently relevant elements that determine actual resilience capacity (RQ1)? (ii) Are there few and consistently relevant elements that determine growth in resilience capacity (RQ2)? (iii) What are the most recurrent shocks (RQ3)? (iv) What are the most frequently adopted coping strategies (RQ4)?

This study brings together the most recent FAO-RIMA (Resilience Index Measurement and Analysis) datasets collected over the last 10 years. Furthermore, to complement the evidence provided and increase the number of countries under study and the significance of the results, we use a large set of data from the Multiple Indicator Cluster Survey (MICS) produced by the United Nations International Children's Emergency Fund (UNICEF). The MICS data covers 23 countries from various parts of the world. For each country, we employ two sets of data collected at two points in time to investigate the determinants of resilience growth or contraction over time. As the MICS focuses on issues affecting the lives of children and women, a specific RIMA analysis framework was designed to adapt with its structure. In total, this paper uses data from no less than 35 different countries and combines static and dynamic analysis. The total sample size is 50,622 households, which gives us a strong statistical power.

The remainder of the paper is as follows: we first provide an overview of the literature on resilience measurement, cross countries evidence, and shock analysis. Second, we present the data used and the methods adopted. Finally, we report and discuss the results of the analysis before concluding in the last section.

2 Literature review

2.1 Resilience measurement

Over time, the concept of resilience has been used in different fields such as engineering, ecology, psychology, epidemiology (Holling, 1996; Gunderson, 2000), and many approaches have been proposed for its measurement (Ansah et al., 2019). These methods can be grouped into different clusters like qualitative and quantitative approaches; subjective method, impact-pathways approach, participatory and non-participatory, and so on. In particular, the participatory approaches focus on both physical and social components; it considers the ability of communities to pool their abilities to build resilience collectively, by accumulating personal knowledge, skills, and resources. The Analysis of the Resilience of Communities to Disaster (ARC-D), adopted by Clark-Ginsberg et al. (2020), is an example of a tool used in this kind of approach. Another approach, called the Flood Resilience Measurement for Communities (FRMC) and formed by the Zurich Flood Resilience Alliance, has been adopted by Pettengel et al. (2020). Given that the data collection in these approaches is largely based on the facilitators' skills, it tends to overestimate the aggregated entity (i.e., the community) with little consideration of the disaggregated entities (i.e.: individuals' tastes and aspirations). To address such a shortfall, the emergence of qualitative approaches helped exploring different scales at which resilience can be studied. Studies using this approach include Mock et al. (2015), Chacowry et al. (2018). Substantial evidence indicates that this approach yields contextual information, including both enabling and disabling factors of resilience, however, one possible limitation mentioned by Mavhura et al. (2021) is that long period data are needed to track changes in resilience aspects. Next, resilience analysis can also be measured subjectively (such as in studies by Jones & Tanner, 2015; Bene et al., 2019; Jones & d'Errico, 2019) or structured around the different steps of the resilience process (e.g., Bene et al., 2017, 2020; Bene & Haque, 2022) or measured based on capital/capacities like in the approach developed by USAID/TANGO and used in Smith et al. (2015), TANGO (2018), Smith et al. (2019), and Smith and Frankenberger (2017, 2022). Unlike the above-mentioned methods, the quantitative approach uses variables collected from households. These data are consolidated in various forms such as ranks, scores, and indices to provide a reliable framework for decision-makers. Practitioners, in general, had to deal with an underlying problem: resilience

to food insecurity is unobservable ex-ante. Resilience was therefore measured using proxy indices of household resilience based on observable variables (Constas et al., 2014a, b; D'Errico et al., 2016). A notable use of such indices includes Li et al. (2016) and Yoon et al. (2016). The indices allow for tracking and comparability over time. They can be drawn from both large-scale surveys and secondary data. Within the quantitative approaches, some use static models such as Vaitla et al. (2012) and others employ dynamic models such as Cisse and Barret (2018) and Signorelli et al. (2016). Alinovi et al. (2008) and Alinovi et al. (2010), were among the first to use resilience into the food insecurity topic; they have also incorporated both ex-ante and ex-post management decisions by measuring resilience index as a latent variable (unobserved) and adopting a two-stage factor analysis based on observable variables. One further elaboration is the RIMA methodology developed by the Food and Agriculture Organization of the United Nations (FAO, 2016; D'Errico et al., 2018a).

2.2 Cross-countries evidence

While the literature on resilience measurement has significantly increased over the last 15 years, and notwithstanding a great interest in understanding the main drivers of resilience, there is a significant gap in terms of cross-country comparisons. Some studies, such as Adolf et al. (2020), try to identify critical drivers of tropical forest resilience regarding recovery rate from previous disturbances. Kwan and Walsh (2017) investigate the main drivers of resilience for old people through disaster management. With the recent onset of the Covid-19 pandemic, which has greatly disturbed the food system, Béné (2020ab) suggests, in his review on resilience and impact of shocks, that assets, savings, and access to income insurance are critical aspects to building household and community resilience. He also indicates that this proposal, accompanied by diversification of income sources and access to essential services, can ensure a well-balanced functioning system.

A review of frameworks of indicators for resilience measurement published by the Overseas Development Institute in 2015 identified 17 separate indicator frameworks (see Schipper & Langston, 2015). The effort to draw comparisons across settings and/or aggregate finding across studies requires way more harmonization. The absence of such a framework limits our ability to draw conclusions about the effect of a resilience strategic approach. Consequently, drawing high-level inferences for policy makers and donors will be hindered by the lack of empirical convergence and consistent findings. This paper is a first attempt to fill this important gap.

2.3 Shocks and coping strategies

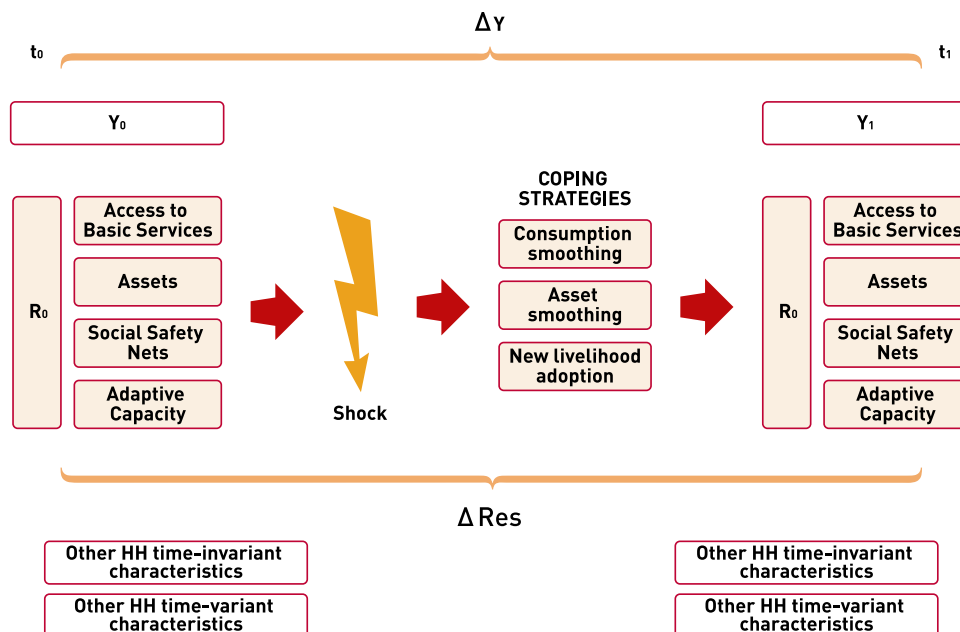
One of the key questions that this paper seeks to respond, is if there exist consistent “shock-specific” response mechanisms. A reaction to a shock can either imply asset depletion or a change in livelihoods; no matter what the solution adopted is, this will influence restoring or enhancing resilience policies. Consequently, associating reactions to shocks provides key instruments to fine-tune policies.

In the literature, shocks data are broadly self-reported (idiosyncratic) or derived from secondary data (e.g., GIS). It is no surprise that self-reported shocks carry biases. This bias is mainly experienced with poor households when the long recall periods are used (Das et al., 2012). Murendo et al. (2019) find that access to essential services and assets improves household nutrition in Malawi in the presence of shocks. Smith and Frankenberger (2018) find that in Bangladesh, social capital, human capital, exposure to information, and asset holding, among other things, help to mitigate the negative impact of floods on household food security. A study by Nikoloski et al. (2018) finds that in Uganda, households affected by diseases (human, livestock, or crop) in one year are more likely to experience a health shock in the following year, indicating that some shocks are persistent. Other studies by Dhanaraj (2016), Pradhan and Mukherjee (2018); Okamoto (2011); Khan (2010) find that in the presence of health shocks, households usually cope by taking credit. However, if the health shock affects the main head of household or the extremely poor households, the latter often respond by reducing food consumption or sending children to work. Similarly, Knight et al. (2015) found that (in KwaZulu-Natal, South Africa) health and economic shocks were commonly overcome by a contraction in consumption and general spending.

Evidence on the role of resilience to mitigate the effect of conflict on food security is found in Brück et al. (2019), von Uexkull et al. (2020), and Malik et al. (2020). The authors highlight the role of resilience enhancing intervention that restored assets and provided social protection intervention in the Gaza Strip (Brück et al., 2019), in the Democratic Republic of the Congo (Uexkull et al., 2020), and in Somalia (Malik et al., 2020). In any case, none of the above-mentioned references report cross-countries valid evidence.

As in Folke (2016), resilience can be seen as the capacity to sustain development in the face of expected and surprising change (i.e. shocks), and diverse pathways of development and potential thresholds between them. As such, it looks at how complex adaptive social-ecological systems (including households) react to shocks (e.g. drought) through coping strategies (e.g. reducing food). The interaction between resilience capacity, shocks, and adaptive capacity, is non-linear and rapidly evolving. In fact, resilience thinking has been characterized with the science of surprise (Folke, 2016);

Fig. 1 RIMA analytical Framework. Source FAO 2016



on one side it is not possible to predict the occurrence and magnitude of the shock with great precision, and on another side the interplay between the adaptive responses of the parts changes continuously (Levin et al., 2013).

There are not many studies in development economics that focus on how complex systems react to shocks (Béné et al., 2016); the few that exist largely focus on the relationship between vulnerability and shock (see for instance Hoddinott, 2006). We know that shocks affect resilience through various channels. Besides the immediate depletion of assets, there is the possibility of erosion of intrinsic resilience mechanisms due to the effect of recurrent shocks (Béné, 2020a, b). For example Smith and Frankenberger (2015) attribute the erosion of social support in communities in Ethiopia to the accumulative effects of repeated droughts.

Similarly, there are not many studies that look at how specific coping mechanisms enter into action when a shock occurs. Coping strategies are remedial actions employed by smallholders, mostly over short periods, to survive shocks (Bahta, 2020). Generally speaking, and together with Eriksen et al. (2005) we can consider coping strategies as the actions and activities happening to reduce economic, environmental, and social vulnerability. The authors identify preferred and less preferred coping mechanisms that can or cannot be adopted due to access or lack of skills, labor, and capital.

Overall, this paper sits within the analytical framework laid out in FAO (2016), and graphically presented in the Fig. 1.

In this framework, the disruptive role of shocks and the bouncing back mechanisms that enter into action through the coping strategies are framed between two points on time;

the pre- and post-shock. There is a resilience capacity and a food security level before and after the occurrence of the disturbance. The results of the interplay between the negative and the positive effects of shocks and coping strategies, will translate into one of the three possible outcomes: reduced, stable, or increased food security.

3 Data and methods

3.1 Data

This paper makes use of a large set of data from the Multiple Indicator Cluster Survey (MICS) produced by the United Nations International Children's Emergency Fund (UNICEF). The MICS data selected for this study covers 23 countries from various parts of the world. They are all nationally representative, except for Pakistan, which covers only the Punjab region. Table 8 describes the MICS datasets used in this paper. For each country, we employ two sets of data collected at two different points in time to investigate the determinants of households' resilience growth and contraction over time. As the MICS focus on issues affecting the lives of children and women, a specific RIMA analytical framework was designed to adapt with its structure. The variables adopted for the RIMA analyses in both RIMA and MICS datasets are listed in Table 9, along with definitions.

As the original MICS surveys are independent and cross-sectional, they cannot make a time-dependent comparison. To overcome this limitation, we employed pseudo-panels techniques to construct a synthetic longitudinal dataset for each country (D'Errico et al., 2019; Deaton, 1985).

Specifically, we grouped households that share some common characteristics into “cohorts” and treat the averages of these cohorts as observations instead of individual households. In one country, the criteria for forming cohorts are the following: (i) area (urban/rural); (ii) region; (iii) wealth level; (iv) average adult education level; and (v) household composition (from almost exclusively composed by men to composed mainly by women). The cohorts can be representative of the households from which they were drawn, since these households share similar characteristics (e.g., being in the same zone, have similar level of income, education, and household composition). They are likely to face similar shocks (e.g., rising food prices or natural shocks) that would affect the entire region instead of a single household, and can choose coping strategies similarly due to same constraints in capacity and resources. Then, it is possible to match the two datasets in different time points to create a balanced panel dataset. We retained only households living in the rural areas.² With the MICS datasets, pooling all the countries together allowed us to obtain a final sample of 18,125 households, from which we estimate the Resilience Capacity Index (RCI) at two points in time. This procedure allowed dynamic analyses to investigate the main determinants of a change in RCI over time and the role of shocks in this process. Specifically, since the MICS questionnaires were not designed to provide information on the occurrence of shocks, we used external data on price shocks and climate shocks. The price shock data are extracted from the WFP’s Alert for Price Spikes (ALPS indicator). This indicator provides detailed information on staple food price volatility. It monitors the extent to which a local food commodity market experienced unusually high food prices by comparing the level of monthly food prices (both actual and forecast) against estimated seasonal trends. The categories of shocks can be either standard, stress, alert, or crisis.³ Two dummy variables were created at the level of the region: (i) one variable for the occurrence of price shock, taking value 1 if “stress” or “alert” was detected, and (ii) one variable taking into consideration the *intensity* of the shock, taking

value 1 if “crisis” was detected. To investigate the impact of climate shocks (specifically, drought), we use the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) monthly (3-monthly) z-score dataset series⁴ and create a dummy variable taking value 1 if an abnormally dry climate is observed, 0 otherwise, as in Zaveri et al. (2019).

In this study, we combine the most recent RIMA datasets (individually employed as FAO reports and papers in peer-reviewed journals) to increase the statistical power and illustrate the diversity of resilient households living in different contexts. Specifically, we characterize the households based on RIMA pillars: (i) Access to Basic Services (ABS); (ii) Assets (AST); (iii) Social Safety Nets (SSN); and (iv) Adaptive Capacity (AC). As the RIMA questionnaire includes data on shocks, we also investigate the impact of different types of shocks (namely, natural shocks, health shocks, and shocks affecting households’ livelihoods) on resilience. Most surveys represent a specific region, and the period they cover extends from 2014 to 2020. In total, 12 (portions of) countries are represented – mostly the least developed and low-income countries in the African continent. Table A1 in the Appendix describes the RIMA datasets used in this paper.

To collect the data, questionnaires were administered to households and gather information on socio-demographic characteristics, expenditure, food consumption, distance to essential services, asset ownership, agricultural activity, family wealth, private transfers, labor market participation, and different types of shocks experienced by the household. Different countries might use questionnaires that included small different details; however, most of their contents were consistent, thus, guaranteeing cross-country comparability. The only disparities observed are the variables included under each pillar, that while largely overlapping, can have some differences from one dataset to another. This heterogeneity is due to the contextualization process of the questionnaires. Nevertheless, and in line with the ultimately limited context-driven differences observed, several variables⁵ can be identified as most used in the different analyses, which allows us to ensure a satisfactory level of comparability. Besides common pillars’ variables, we select three main food security indicators to add in the dataset. They are the Food Consumption Score (FCS), the Household Dietary Diversity Score (HDDS), and Food Expenditure. After combing all existing variables into a unique database, we perform additional

² Since FAO-RIMA data collections take place in rural areas, we include rural and “urban” households from the RIMA datasets; “urban” households in the RIMA datasets refer to households living in the village while maintaining agro-farming livelihoods conditions. On the contrary, the “urban” families included in the MICS surveys are more integrated in an urban way of life; therefore, we excluded these “urban” households from the final sample to grant consistency with the RIMA datasets.

³ For more information, visit: https://dataviz.vam.wfp.org/economic_explorer/price-forecasts-alerts

⁴ The z-score (or standard score) is the signed fractional number of standard deviations by which the value of an observation or data point is above the mean value of what is being observed or measured. Observed values above the mean have positive standard scores, while values below the mean have negative standard scores.

⁵ Namely, access to an improved source of water and sanitation facilities, access to the agricultural market, school and hospital, wealth index and agricultural wealth index (indexes of non-productive and productive asset ownership, respectively), land and livestock ownership (TLU), access to credit, formal and informal transfers, and social networks, crops diversification, level of education and work ratio (i.e., the inverse of dependency ratio).

Table 1 Frequency distribution for different profiles

| Profile | RIMA datasets | | | MICS datasets | | |
|---|---------------|---------|--------|---------------|---------|--------|
| | frequency | percent | total | frequency | percent | total |
| <i>Development level</i> | | | | | | |
| Least developed countries | 29,609 | 91.11 | 32,497 | 7,568 | 41.75 | 18,125 |
| Developing countries | 2,888 | 8.89 | | 9,845 | 54.32 | |
| Economies in transition | / | / | | 712 | 3.93 | |
| <i>Income level</i> | | | | | | |
| Low-income | 26,070 | 80.22 | 32,497 | 4,460 | 24.61 | 18,125 |
| Lower-middle-income | 5,588 | 17.20 | | 10,594 | 58.45 | |
| Upper-middle-income | 839 | 2.58 | | 3,071 | 16.94 | |
| <i>Country with a protracted crisis</i> | | | | | | |
| No | 11,270 | 34.68 | 32,497 | 14,063 | 77.59 | 18,125 |
| Yes | 21,227 | 65.32 | | 4,062 | 22.41 | |
| <i>Agro-ecological zone</i> | | | | | | |
| Hyper-arid/Arid | 6,630 | 20.40 | 32,497 | 7,277 | 40.15 | 18,125 |
| Dry semi-arid/Semi-arid | 5,980 | 18.40 | | 3,217 | 17.75 | |
| Moist semi-arid | 6,949 | 21.38 | | / | / | |
| Mixed | / | / | | 1,386 | 7.65 | |
| Sub-humid | 8,883 | 27.33 | | 3,393 | 18.72 | |
| Humid | 4,055 | 12.48 | | 2,852 | 15.74 | |
| <i>Main livelihood</i> | | | | | | |
| Farmer | 12,928 | 41.23 | 31,355 | 1919 | 29.54 | 6,496 |
| Agro-pastoralism | 8170 | 26.06 | | 541 | 8.33 | |
| Pastoralism | 10,257 | 32.71 | | 1395 | 21.47 | |

cleaning and generate various categories i (e.g., living context – country income and development level, country affected by a protracted crisis –, agro-ecological zone, and main livelihood) which allow us to further disaggregate the results.. Pooling all RIMA datasets together allows obtaining a total sample of 32,497 households, which offers an opportunity to compare household resilience across diverse contexts and identify the key variables contributing to household resilience capacity.

In total, this paper has used 63 datasets (17 FAO-RIMA and 46 UNICEF-MICS), with 50,622 households from no less than 35 different countries and has combined static analysis with dynamic analysis to picture household resilience most accurately and accounting for various contexts. For both RIMA and MICS data, the resilience profiles are based on the country's (i) level of development⁶; (ii) level of income of the country⁷; (iii) whether the country is affected

by a protracted crisis⁸; (iv) agro-ecological zones⁹; and (v) main livelihood.¹⁰ We disaggregated each profile to identify the key determinants of resilience for different contexts. Table 1 reports the frequency distribution for the different profiles analyzed with the RIMA and the MICS data. In all regression analyses, we controlled for profile heterogeneity.

3.2 Methods

We adopted the FAO's RIMA methodology (FAO, 2016) to estimate the Resilience Capacity Index (RCI) at the household level. This approach is based on a two-stage procedure (Fig. 2). In the first step, Factor Analysis (FA) is used to identify the attributes, or "pillars", that contribute to household resilience, starting from observed variables. The pillars analyzed under the RIMA model are (i) Access to Basic Services (ABS), (ii) Assets (AST), (iii) Social Safety Nets (SSN), and (iv) Adaptive Capacity (AC). Only those factors able to explain at least 95 percent of the variance are considered. In the second step, we use a Multiple Indicators Multiple Causes (MIMIC) model (Bollen et al., 2010). Specifically, a system of equations was constructed, specifying the relationships between an unobservable latent variable (resilience), a set of outcome indicators (food security indicators), and a set of attributes (pillars). The MIMIC model is made up of two components, namely the measurement Eq. (1) – reflecting

⁶ UN: https://www.un.org/development/desa/dpad/wp-content/uploads/sites/45/WESP2020_Annex.pdf

⁷ World Bank: <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups>

⁸ Based on FAO classification (2020).

⁹ Data provided by the Global Platform.

¹⁰ FEWSNET: <https://fews.net/fews-data/335>

that the observed indicators of food security are imperfect indicators of resilience capacity – and the structural Eq. (2), which correlates the estimated attributes to resilience:

$$\begin{bmatrix} \text{Food security indicator 1} \\ \text{Food security indicator 2} \\ \text{Food security indicator 3} \end{bmatrix} = [\Lambda_1, \Lambda_2, \Lambda_3] \times [\text{RCI}] + [\epsilon_1, \epsilon_2, \epsilon_3] \tag{1}$$

$$[\text{RCI}] = [\beta_1, \beta_2, \beta_3, \beta_4] \times \begin{bmatrix} \text{ABS} \\ \text{AST} \\ \text{SSN} \\ \text{AC} \end{bmatrix} + [\epsilon_3] \tag{2}$$

Since the estimated Resilience Capacity Index (RCI) is not anchored to any scale of measurement, a scale has been defined setting the coefficient of the food consumption loading (Λ_1) equal to 1, meaning that one standard deviation increase in RCI implies an increase of one standard deviation in food consumption. This scale also defines the unit of measurement for the other outcome indicator (Λ_2) and the variance of the two food security indicators.

Finally, to ease the understanding and interpretation of the results, the RCI has been standardized through a min–max scaling transformation, based on the following formula:

$$\text{RCI}_h^* = \frac{\text{RCI}_h - \text{RCI}_{\min}}{\text{RCI}_{\max} - \text{RCI}_{\min}} \times 100 \tag{3}$$

where h represents the h^{th} household.

To identify the most relevant aspects of households’ resilience capacity, we used two specific methods for Eqs. (4) to (6). The rationale of the equations is coming from the RIMA-II analytical framework (FAO, 2016) that explores the core ideas behind functional form and explanatory variables. First, we employed descriptive statistics using the RIMA datasets and looked at the structure of resilience at one point in time, and which components (pillars and variables) emerged as the most essential elements of resilience (static perspective). We then employed the MICS datasets organized as pseudo-panels to investigate which are the key drivers of resilience growth over time (dynamic perspective); we used the following regression model:

$$\Delta \text{RCI}_{h,t} = f(\Delta \text{Res}_{h,t}, C_{h,t}, \text{HG}_{h,t}, L_{h,t}, \text{AEZ}_{h,t}) + \epsilon \tag{4}$$

where the change in resilience capacity (ΔRCI) is seen as a function of changes in the resilience structure (ΔRes – i.e., pillars and variables), controlling for the country specificity (C), household gender composition (HG), main livelihood (L), and agro-ecological zones (AEZ). We run two separate models. In the first one (Model 1), the resilience structure is reflected by the pillars of resilience; in the second model (Model 2), the resilience variables are used as explanatory variables to reflect the resilience structure.

To explore whether shocks (particularly price shocks and weather shocks) can hinder resilience growth over time, we then look at the dynamic analysis. As mentioned above, we employ the MICS datasets, set under the synthetic panel approach. We model the growth of resilience as follows:

$$\Delta \text{RCI}_{h,t} = f(\Delta \text{Res}_{h,t}, C_{h,t}, \text{HG}_{h,t}, \text{AEZ}_{h,t}, \text{Prices}_t, \text{Weather}_t) + \epsilon \tag{5}$$

where an explanatory variable for the occurrence of price shocks (Prices) and weather shocks (Weather) is added to Eq. (4). As with Eq. 4, we run two separate models, first using the resilience pillars (Model 1) and then the resilience variables (Model 2) as components of the resilience structure.

As the RIMA datasets include data on self-reported shocks and coping strategies, we used descriptive statistics to identify the most frequent shocks affecting households’ well-being and the most adopted strategies used by the households to cope with these shocks. We then modeled the effect of the most frequently reported shocks (namely, natural shocks and livelihood-related shocks) and the most commonly adopted coping strategy (namely, the reduction in the quantity and quality of food consumed) on resilience by employing Ordinary Least Squares (OLS) regressions:

$$\text{RCI}_h = f(S_h, \text{HH}_h) + \epsilon \tag{6a}$$

$$\text{RCI}_h = f(S_h, \text{CS}_h, \text{HH}_h) + \epsilon \tag{6b}$$

where, in Eq. (6a), the Resilience Capacity Index (RCI) is a function of the occurrence of Shocks (S), controlling for household characteristics (HH) – namely, gender, household size, and livelihood. We then include the coping strategy (CS) in the previous specification to investigate how the effects of shocks on resilience capacity change – Eq. (6b). While acknowledging that resilience capacity and shocks do affect coping mechanisms, our focus was on understanding the impact of the two phenomena on RCI as explored by (Ansah et al., 2021).

We also conduct the power analysis of Cohen (1988) for the R-squared of each multiple linear regression model to see how changes in sample size affect the statistical significance of coefficients. The results of these tests are presented together with the regression outputs. The precise estimation of the power indicates the chance that the significance of all the coefficients is correctly identified based on a finite sample size.

Further, we test the endogeneity of S_h in Eq. (6a) using the Durbin–Wu–Hausman test (augmented regression test) to verify the consistency of the OLS model. We first specify Eq. (7a), then generate the residuals of S_h ($\text{res}S_h$) and specify Eq. (7b).

$$S_h = f(HH_h) + \varepsilon \quad (7a)$$

$$RCI_h = f(resS_h, HH_h) + \varepsilon \quad (7b)$$

As we identify endogeneity concerns, suggesting that the OLS estimator is not consistent (Table A8), we use an Instrumental variable (IV) estimator. Shocks might be endogenous due to omitted factors that affect both shocks, on one hand, and resilience, on the other, or because of a measurement error of shock exposure itself. Endogeneity arises when the explanatory variable (here, shock exposure) is jointly determined with the outcome of interest (here, the RCI) or is correlated with the error term. Therefore, the assumption of no covariance existing between one of the variables of the model and the error term is violated. The presence of endogeneity will bias the estimation of the parameters of interest.

Owing to the endogeneity of S_h with RCI_h , the coefficient of S_h in Eq. (6a) is biased. To overcome the endogeneity concerns related to the link between shocks and resilience, an Instrumental variable (IV) estimator can be used (see Brück et al., 2019; Knippenberg & Hoddinott, 2017; D'Errico & Pietrelli, 2017; Fichera & Savage, 2015; Hanandita & Tampubolon, 2014). We adopt the IV approach, measuring shock exposure using the geographic location of the household. Combining the country, region, and district where the household is located, we generate an identification variable associated with the specific location of the household. Geographical variables are often employed as instruments for resilience analysis, since they are most likely indirectly associated with resilience (e.g. Brück et al., 2019; Knippenberg & Hoddinott, 2017).

We estimate the IV model using a 2-Stage Least Squares (2SLS) specification. IV first stage equation:

$$S_h = f(HH_h, L_h) + \varepsilon \quad (8a)$$

where L represents the specific location of the household and HH are household characteristics – namely, gender, household size, and livelihood. The second stage equation is given by Eq. (8b):

$$RCI_h = f(\hat{S}_h, CS_h, HH_h) + \varepsilon \quad (8b)$$

4 Results

We approach RQ1 (i.e., if few and consistent elements determine actual resilience capacity) by looking at resilience structure (i.e., most relevant pillars and variables) by country¹¹ (Table 2).

Table 2 FAO-RIMA datasets: most important resilience pillars and variables by country

| Pillar | First Most Important | Second Most Important |
|--------|----------------------|-----------------------|
| AST | 7 | 6 |
| AC | 4 | 8 |
| ABS | 4 | 2 |
| SSN | 2 | 1 |

While Table 2 reports the number of times each pillar is the first or second most important pillar, Table A4 in the appendix provides the breakdown by country.

We observe that, for many countries, access to Assets (AST) is the first or second pillar in terms of contribution to resilience capacity. Access to productive and non-productive assets (including agricultural tools, land, and livestock) is critical to ensure households' capacity to bounce back after a shock. Adaptive Capacity (AC) is another critical component of resilience in most countries. In particular, the diversification of income sources and the level of education of the household members are relevant components of resilience. The third most important pillar is Access to Basic Services, with no relevance for any of the components of this pillar. Social Safety Nets is the *less frequently most relevant* pillar, which is in line with its nature of being an emergency pillar, therefore particularly relevant for humanitarian interventions and contexts.

We approach RQ2 (i.e., if there are few and consistently relevant elements that determine growth in resilience capacity) by employing the specification in Eq. (6). The dynamic analysis employs the MICS data and provides further evidence on the relevance of strengthening Adaptive Capacity (AC) for resilience building (Table 3). The corresponding power analysis on different sample sizes confirms the validation of conclusions drawn from our dataset.

We respond to RQ3 (i.e., what are the most recurrent shocks) by employing simple descriptive statistics using our 60,000 households sample (Table A5) and by employing Eq. (7) (Table A8). Table A5 reports, for each type of shock, the percentage of households who reported facing the shock over the last 12 months. The most frequently reported shocks are Natural disasters (including drought, flood, storm, fire, cyclones, armyworm, wind, locust, and landslides), Health shocks (illness, accident, or death of a household member), and shocks affecting households' livelihoods (crop damage or disease, livestock loss or disease, business failure, lousy harvest or fishing season, loss of agricultural or fishing inputs/equipment). Households less frequently report price, conflict, and shocks affecting their income and assets.

Table A8 explores whether price shocks and weather shocks can have long-term consequences in resilience building. As expected, the occurrence of price shocks is associated with a contraction of resilience capacity over time,

¹¹ RIMA datasets only.

Table 3 Determinants of RCI change over time (OLS regression) – MICS datasets

| | (Model 1) | (Model 2) |
|-------------------------------------|----------------------|----------------------|
| | ΔRCI | ΔRCI |
| Δ Access to toilet | | 0.379 (1.037) |
| Δ Access to water | | -0.976 (0.954) |
| Δ Access to electricity | | -1.865 (1.402) |
| Δ Access to energy | | -1.084 (2.490) |
| Δ Land Per Capita | | 0.0372 (0.262) |
| Δ Own house | | 1.779 (1.220) |
| Δ TLU ¹² Per Capita | | -0.725 (0.647) |
| Δ Wealth Score ¹³ | | 1.676 (1.596) |
| Δ Use of contraception | | 1.406 (0.992) |
| Δ Access to pre-natal care | | 0.389 (1.167) |
| Δ Support during delivery | | 2.187** (1.031) |
| Δ Avg level of education | | 0.601** (0.265) |
| Δ Active/non-Active work hh members | | 8.265** (3.848) |
| Δ Reading | | 2.382** (1.110) |
| The Gambia | 20.13 (14.42) | 19.26 (14.38) |
| Mali | 6.283*** (2.244) | 5.106** (2.390) |
| Mauritania | 9.708 (14.83) | 9.427 (14.95) |
| Nigeria | 13.92 (14.49) | 13.67 (14.35) |
| Sierra Leone | 5.200 (14.47) | 4.579 (14.31) |
| Sudan | 13.61 (14.80) | 12.47 (14.74) |
| Zimbabwe | 4.555 (14.47) | 3.492 (14.29) |
| HH: Mostly men | -0.645 (1.044) | -0.601 (1.046) |
| HH: Mixed | -2.674*** (1.010) | -2.696*** (1.012) |
| HH: Mostly women | -2.684** (1.233) | -2.697** (1.234) |
| Agro-pastoralism | 4.644 (10.32) | 4.552 (10.27) |
| Mixed | 13.40 | 13.59 |

Table 3 (continued)

| | (Model 1) | (Model 2) |
|--|---------------------|---------------------|
| | (14.45) | (14.29) |
| Pastoralism | 1.024 (10.63) | 1.251 (10.62) |
| Trade | 14.81 (13.85) | 14.22 (13.58) |
| AEZ: Humid | -1.228 (2.221) | -1.891 (2.234) |
| AEZ: Semiarid | -3.331** (1.584) | -3.178** (1.601) |
| AEZ: Sub-humid | 0.0918 (2.024) | -0.152 (2.044) |
| AEZ: Mixed | -2.310 (1.819) | -2.184 (1.848) |
| ΔABS | -0.109 (0.639) | |
| ΔAST | 0.491 (0.521) | |
| ΔSSN | 0.706** (0.333) | |
| ΔAC | 2.639*** (0.672) | |
| Constant | -11.33 (14.60) | -10.98 (14.47) |
| Observations | 6,496 | 6,496 |
| R-squared | 0.017 | 0.020 |
| Power analysis for the corresponding R-squared at $p=0.01$ | | |
| (Sample size) | (Power) | (Power) |
| - N = 100 | 0.027 | 0.031 |
| - N = 300 | 0.105 | 0.135 |
| - N = 500 | 0.236 | 0.304 |
| - N = 700 | 0.395 | 0.496 |
| - N = 1000 | 0.629 | 0.749 |
| - N = 2000 | 0.971 | 0.991 |
| - N = 5000 | 1.000 | 1.000 |
| - N = 6000 | 1.000 | 1.000 |

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ AC (in particular, the level of education of household members and the work ratio – indicating the potential number of income earners) is the primary driver of resilience growth over time. This finding suggests that if access to Assets (AST) is crucial to support households' resilience in the short term (humanitarian perspective) other types of interventions are needed to build resilience in the longer term (development perspective). In addition, we observe that living in **semi-arid zones** is associated with contractions in resilience capacity. Another relevant element of resilience growth is gender balance; in fact, we notice that households with a more significant majority of women are typically associated with resilience capacity contraction. Finally, a timely and regular provision of social protection interventions is another crucial determinant of resilience in the longer term

Note that our results are consistent when we run robustness checks using a fixed effects model as utilized by other researchers using cross country data with a time variation component. On top of the controls already presented in the main results, the FE also controls for regional disparities. (See in [Appendix](#)).

Table 4 Most frequently reported coping strategies for each type of shock faced – RIMA datasets

| | | Natural disaster | Livelihood-related | Health shocks |
|---------------------------------------|---|--|--|--|
| Most adopted coping strategies | 1 | Reduce quantity and quality of food consumed | Reduce quantity and quality of food consumed | Reduce quantity and quality of food consumed |
| | 2 | Seek extra jobs/increase labor | Ask for help from friends and relatives (e.g., borrowing food) | Take credit (mainly to buy food) |
| | 3 | Ask for help from friends and relatives (e.g., borrowing food) | Seek extra jobs/increase labor | Ask for help from friends and relatives (e.g., borrowing food) |
| | 4 | Selling productive and non-productive assets | Take credit (mainly to buy food) | Selling productive and non-productive assets |
| | 5 | Take credit (mainly to buy food) | Selling productive and non-productive assets | Seek extra jobs/increase labor |

especially when the shock is intense. When a household faces a price shock at time t , this inhibits its possibility to see its resilience capacity increasing at time $t + 1$, and this adverse effect is stronger when the shock faced at time t was particularly intense. Similarly, the occurrence of an abnormally dry climate (drought) hinders the possibility for a household to experience an increase in its resilience capacity in the future.

Our results for RQ4 (i.e., what are the most frequently adopted coping strategies) are reported in Table A6, which shows the percentage of households who adopted each type of coping strategy. Overall, most households resort to reducing the quantity and quality of food consumed (60 percent of households). Seeking an extra job and increasing the time spent at work is another frequent coping strategy (37 percent) and the sale of productive and non-productive assets (34 percent). In addition, a considerable proportion of households seek help from friends and relatives, e.g., borrowing food (32 percent), and many of them decide to take credit, especially to buy food (30 percent) in times of difficulties.

To further expand the analysis on RQ4, Table 4 reports the most adopted coping strategies associated with the type of shock faced.

For all shocks – natural disasters, livelihood-related, and health shocks –, reducing food consumption is the first adopted strategy. We observe then that many households increase their labor supply when natural disasters occur; they are more likely to take credit in the face of health shocks and finally ask for help from friends and relatives when a livelihood shock happens. The heterogeneous adoption of coping mechanisms suggests a 2-steps strategy that will be elaborated in the discussion section.

We finally respond to RQ5 (i.e., are the coping mechanisms sufficient to restore/maintain resilience capacity) by employing Eq. (6a) and Eq. (6b). We specified two models, one without (6a) and one with coping strategies (6b). The effects of natural shocks, livelihood-related shocks and health shocks are reported in Table A7. We observe that natural shocks and livelihood shocks have a significant harmful and

detrimental effect on resilience (Table A7). The occurrence of natural, livelihood and health shocks is associated with a reduction in RCI of (respectively) 60, 40 and 10 percent.

The results of Eq. (6b), which also includes the reduction of food consumption as coping strategy, are reported in Table 5. We observe that the reduction in the quality and quantity of food consumed allows to mitigate in part the negative effect of shocks on resilience.

The IV first-stage results (Eq. (8a)) for the instrumentation of shocks with household location is reported in

Table 5 Effect of shocks on resilience and the role of food consumption reduction

| | (1) | (2) | (3) | (4) |
|--------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Variables | RCI | RCI | RCI | RCI |
| Natural shock | -0.395*** (0.0405) | -0.323*** (0.0443) | | |
| Livelihood-related shock | | | -0.607*** (0.0464) | -0.668*** (0.0446) |
| Reduce food consumption | | 0.185*** (0.0447) | | 0.177*** (0.0433) |
| Agro-pastoralism | 1.586*** (0.0747) | 1.635*** (0.0607) | 1.769*** (0.0792) | 1.827*** (0.0673) |
| Pastoralism | -0.0267 (0.0348) | -0.0277 (0.0365) | 0.0882** (0.0343) | 0.186*** (0.0342) |
| Female-headed HH | -0.579*** (0.0520) | -0.696*** (0.0483) | -0.581*** (0.0519) | -0.705*** (0.0481) |
| HH size | 0.00635 (0.00633) | 0.00869 (0.00754) | 0.00508 (0.00638) | 0.0139* (0.00752) |
| Constant | 0.220*** (0.0647) | 0.116 (0.0835) | 0.196*** (0.0625) | 0.0908 (0.0807) |
| Observations | 31,403 | 26,910 | 31,403 | 26,910 |
| R-squared | 0.035 | 0.046 | 0.037 | 0.051 |

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 Effects of self-reported shocks on resilience and the role of food consumption reduction – RIMA datasets

| Variables | (1) RCI | (2) RCI |
|-------------------------|------------------------|-----------------------|
| Natural shock | -14.55*** (0.855) | |
| Livelihood shock | | -7.335*** (0.431) |
| Reduce food consumption | 0.0621 (0.0484) | 0.0621 (0.0484) |
| Agro-pastoralism | 1.114*** (0.0651) | 3.702*** (0.132) |
| Pastoralism | -0.740*** (0.0727) | 1.181*** (0.0879) |
| Female-headed HH | 0.106 (0.0705) | -0.472*** (0.0533) |
| HH size | 0.0453*** (0.00752) | 0.00481 (0.00723) |
| Constant | 5.172*** (0.310) | 1.454*** (0.108) |
| Observations | 26,910 | 26,910 |
| R-squared | 0.054 | 0.054 |

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Tables A9, A10 and A11. We observe a statistically significant association between the shocks and its household location, which confirms that the latter is a suitable instrument for shock exposure.

Table 6 shows the second-step results of the 2SLS approach. We observe that the impact of shocks on resilience is still negative but of smaller magnitude, and the reduction in food consumption actually does not permit to mitigate the negative effects of shocks on households' resilience.

These findings suggest that even adopting coping strategies does not counterbalance the adverse effects of shocks. Additionally, we sense that the disruptive mechanisms of a shock can jeopardize their detrimental effect on long-term development perspectives.

5 Discussion

Our analysis has shown that AST is the most critical pillar of resilience. Asset ownership is crucial to sustaining households' livelihoods and can be used as collateral for accessing credit. Moreover, assets are often used as a buffer when a shock occurs: selling productive and non-productive assets is a common coping strategy adopted by households to respond to shocks, especially by the poorest categories

(Barrett, 2002). However, this strategy can be hazardous. If households end up with an extremely low level of assets, they may fall into a poverty trap, unable to rebuild a living without external assistance (Banerjee & Duflo, 2011). Access to productive and non-productive assets (including agricultural tools, land, and livestock) is critical to ensure households' capacity to bounce back after a shock; restocking interventions might prevent falls into poverty traps.

The second most important pillar is AC. When a shock occurs that negatively affects households' well-being, the latter will adapt more quickly if they can rely (temporarily or not) on other source(s) of income, allowing them to maintain a decent level of food security. Similarly, looking for an extra job is another common coping strategy, and with a relatively high level of education, household members are more valued in the labor market. Improving people's access to education would allow them to have better access to the labor market and, in turn, better opportunities to expand their portfolio of options available as income-generating activities. In line with this, we observe that the work ratio (i.e., share of people in the age of working in the household) also emerges as an essential driver of resilience capacity, suggesting that the higher the number of potential income earners in the household, the more likely the latter is to resist shocks. This finding confirms the importance of income source diversification, both in income-generating activities and income-earning people in the household. These three resilience parameters, namely, diversified income-generating activities, diversified income-earning household members, and educational level, are strongly related. As mentioned above, a relatively high level of education among household members allows them to acquire a better position in the labor market. Not only can they access well-paid jobs (thus bringing relatively more money to their family), but they also have access to a wider variety of jobs, allowing them to diversify their sources of income.

ABS and SSN seem to have a marginal role in explaining the actual level of resilience. This finding should not surprise nor be associated with limited relevance to resilience per se. While ABS is, by definition, a pillar that tends to observe a prolonged change over time, SSN dramatically increases its relevance depending on where we are in the balance between humanitarian and development interventions. We believe our responses to RQ2 support the role of resilience in bridging these two aspects of international assistance. Overall, from a short-term (humanitarian) perspective, the results suggest that expanding access to productive and non-productive assets to help households restore (or maintain) their stock of assets would allow them to be better prepared to respond to future shocks.

Furthermore, in more remote areas and fragile contexts, building resilience urgently requires improving the availability and quality of primary services. From a longer-term

(developmental) perspective, improving access to education and post-education capacity-building projects (e.g., farmer field schools) would help build resilience through better access to the labor market and better opportunities for the diversification of income sources. While restocking can prevent humanitarian disasters, combining these interventions with improved and extended access to education and post-education grants better access to the labor market and better opportunities for diversification of income sources; this means bridging humanitarian and development interventions for building long-term resilience. An additional outcome is that efforts should be made to prevent households from engaging with harmful coping mechanisms that would jeopardize their well-being and food security levels. This is pretty in line with recent literature advocating the connection of resilience as a concept with sustainable Development Goal, as long-term perspective to wellbeing (Foltz 2022).

While there is a general agreement on the different persistency of diverse types of shocks (Knippenberg et al., 2019) even under non-linear assumptions (Phadera et al., 2019), we believe there is still a substantial gap in evidence. Therefore, another important message emerges from research questions 3 and 4. A 2-steps coping strategy mechanism seems to emerge when looking at the behavior of the sampled households. The initial reaction is to reduce food; this is then combined with a complementary strategy that changes according to the type of shock. We noticed that natural disasters are typically associated with searching for an alternative or extra job, while livelihood-related shocks are associated with the request for help from friends and relatives, and health shocks are associated with taking a loan (mostly to buy food). Recent literature questions about the long-term impact of cash transfers beyond the immediate support to consumption they provide. For instance, Pople et al. (2021) suggest that the immediate provision of cash transfers significantly reduced the depletion of assets in Bangladesh; Benè et al. (2020) identifies households in Niger that showed significant greater capacity to engage with positive strategies. Other evidence exists, however, that proves the failure of some resilience interventions' beneficiaries from engaging in negative strategies (Benè and Haque, 2022). Knippenberg et al (2019) mention the existence of key determinants of persistency of shocks (e.g., gender of household head, the presence of a ill member...), but they failed identifying a recurring pattern of two-steps approach as we did.

The adoption of the wrong (and detrimental) coping mechanisms can translate into further threat to long-term development. Contracting debt, reducing the quality and quantity of food consumed, and increasing working hours cannot be sustainable over the long term and creates burdens that might be unbearable to the households. Therefore, while these coping strategies might be functional in addressing short-period emergencies, more sustainable strategies must be facilitated. While evidence from resilience interventions is of interest for

the literature (Benè et al. 2017), the difference between short- and long-term impact is almost ignored (with few exceptions, e.g., Bene et al. 2020). We believe that this long-term depressing perspective can be explained by the disruption of productive assets, the contraction of income sources, and the interruption of access to essential services. An increase in social safety nets (through social protection interventions) does not suffice to counterbalance the negative effect of shocks on the other pillars of resilience. At the same time, investing in long-term social protection mechanisms can still enable the recovery and restoration of capacities. We notice however, and in line with other authors, that there is a lack of multiple time points before, as well as multiple time points after, the shock period (Smith & Frankenberger, 2022).

6 Conclusions

One limitation of the analysis is that it combines countries with quite different socio-economic and crisis profiles. Another limitation refers to the RIMA and MICS datasets, which are not perfectly comparable. Indeed, the MICS questionnaires are not designed to measure resilience, even though the variables collected still allow to estimate the RCI. Moreover, the use of pseudo-panels techniques means that the results overshadow the individual dimension of resilience. In fact, pseudo-panels observe cohorts (groups) of individuals, rather than individuals over time, and individual variables are replaced by their intra-cohort means. Instead of analyzing an individual effect, we analyze a cohort effect. In addition, the building of the cohorts is subject to a trade-off between bias and variance: on the one hand, the cohorts must be large enough to limit the extent of measurement error on intra-cohort variable means; on the other hand, increasing the size of the cohorts decreases the number of cohorts observed, which reduces the precision of the estimators (Guillerm, 2017). That said, we are confident that the statistical power we achieved (more than 50,000 households) suffices to give our findings a substantial impact on the design of resilience-enhancing interventions. Our results suggest that the most frequent shocks that threaten households' well-being and food security are natural, health, and livelihood related. We also have a clearer idea of what strategies are typically adopted to respond to diverse shocks; in fact, increasing working hours is usually associated with natural shocks, while greater access to credit and social networks is adopted vis-à-vis health issues. Furthermore, we confirm that covariate shocks (price shocks and weather shocks) have adverse effects on resilience growth. We advise bearing these findings in mind when designing resilience-enhancing interventions. In a context of increasing frequency and intensity of shocks, a timely and regular provision of social protection (promoting access to Social Safety Nets) is crucial to protecting resilience and preventing long-term developmental consequences.

Another limitation of the paper consists of the lack of country specificity. This is due primarily to the use of factor analysis and pseudo-panel approach that tend to wipe out any country-specific parameter. However, the objective of this paper is to obtain an overall picture of the main drivers of resilience. This is why, instead of looking at each country separately, we pool them all together so the overall picture can emerge. Moreover, for the sake of comparability, we adopt a consistent specification of the model in the selection of the variables, which is, by definition, not context-specific. Finally, our conceptual framework relies on the assumption of constant specification of the model over time (the model specification at time t is the same as that at time $t + 1$). If this ensures comparability over time, and, therefore, dynamic analyses, it does not allow to capture changes over time in the pillar composition. If we relax the constraint of constant specification over time, we fail comparing the resilience pillars composition over time, which is the objective of this paper.

The identification of 2-steps coping mechanisms, with a combination of coping strategies adopted by households, suggests that policymakers and donors must consider that the first reaction of the household is to reduce food consumption; therefore, they must fill this gap and the resulting potential risk of famine. The second level reaction, on the other hand, tends to threaten long-term development; therefore, interventions are required on distinct aspects to avoid negative consequences.

Coping mechanisms per se are not sufficient, in any case, to offset the disruptive effect of shocks on resilience. We need to advocate supporting mechanisms that consider the context-specificities (e.g., type of shocks; type of reactions; type of stressors; geographical zones; livelihoods; household composition; etc.) and at least two levels of interventions: in the long and the short period.

The main contribution of this paper is to provide a unique statistical power dataset composed of more than 50,000 households. We, therefore, assume that our findings can be quite generalizable. Under this perspective, and while recognizing the limitations of our analysis, we are convinced this analysis indicates that investing in resilience is made up of two significant aspects. There are essential elements of resilience that must be included in every program (diversification of income sources; access to productive assets; education). In addition, there are context-specific aspects required to fine-tune the intervention (e.g., the specificity of coping strategies).

There is ample room for further expanding our findings, especially on the determinants of growth of resilience and on the effect of great pandemics such as COVID-19. However, and bearing in mind the immense portfolio of investments made in building resilience and gathering data-driven evidence on the effectiveness of such efforts, we think this paper constitutes an important milestone in the current literature.

Appendix

Table A1 Description of the RIMA datasets

| Country | Coverage | Year | Sample |
|-------------|---|------|--------|
| Chad | National | 2015 | 6,949 |
| DRC | Rutshuru (Nord-Kivu) | 2017 | 1,719 |
| DRC | Rutshuru (Nord-Kivu) | 2019 | 1,643 |
| Mali | National | 2014 | 3,804 |
| Mauritania | National | 2017 | 2,826 |
| Myanmar | Rakhine State | 2019 | 304 |
| Niger | Maradi, Zinder | 2018 | 2,300 |
| Nigeria | Borno State | 2018 | 2,049 |
| Senegal | Matam | 2015 | 414 |
| Somalia | Jowhar district (Middle Shabelle) | 2019 | 599 |
| Somalia | Marka district (Lower Shabelle) | 2019 | 622 |
| South Sudan | Lakes State, Central Equatoria (Terekeka) | 2019 | 777 |
| Uganda | Karamoja | 2016 | 1,965 |
| Uganda | Karamoja | 2019 | 1,965 |
| Uganda | North | 2017 | 3,034 |
| Uganda | Southwest | 2018 | 705 |
| Venezuela | Portuguesa State | 2020 | 839 |

Table A2 Description of the MICS datasets

| Country | Coverage | Year 1 | Year 2 | Sample |
|---------------|----------|--------|--------|--------|
| Bangladesh | National | 2012 | 2019 | 1,109 |
| DRC | National | 2010 | 2017 | 748 |
| The Gambia | National | 2010 | 2018 | 520 |
| Ghana | National | 2011 | 2017 | 430 |
| Guinea-Bissau | National | 2014 | 2018 | 527 |
| Iraq | National | 2011 | 2018 | 2,190 |
| Kazakhstan | National | 2010 | 2015 | 313 |
| Kyrgyzstan | National | 2014 | 2016 | 307 |
| Laos | National | 2012 | 2017 | 1,186 |
| Mali | National | 2009 | 2015 | 885 |
| Mauritania | National | 2011 | 2015 | 543 |
| Mongolia | National | 2010 | 2018 | 252 |
| Nepal | National | 2014 | 2019 | 319 |
| Nigeria | National | 2011 | 2016 | 1,914 |
| Pakistan | Punjab | 2011 | 2017 | 3,728 |
| Serbia | National | 2010 | 2019 | 111 |
| Sierra Leone | National | 2010 | 2017 | 531 |
| Sudan | National | 2010 | 2014 | 878 |
| Thailand | National | 2012 | 2019 | 471 |
| Togo | National | 2010 | 2017 | 380 |
| Tunisia | National | 2011 | 2018 | 137 |
| Vietnam | National | 2010 | 2013 | 255 |
| Zimbabwe | National | 2014 | 2019 | 490 |

Note that for some nationally represented data, the small sample size is due to the grouping in pseudo analysis. Other observations were dropped due to the usual data cleaning processes

Table A3 Variables adopted for the RIMA analyses

| Variable | Definition | Datasets |
|-------------------|--|------------------------|
| abs toilet | Dummy for improved sanitation | RIMA (15) & MICS (All) |
| abs water | Dummy for improved water source | RIMA (14) & MICS (All) |
| abs electricity | Dummy if HH has access to electricity | RIMA (7) & MICS (All) |
| abs energy | Dummy for an improved energy source for cooking (electricity/ gas) | RIMA (5) & MICS (All) |
| abs closeness | Index for closeness to basic services | RIMA (5) |
| abs water | Closeness to a water source | RIMA (4) |
| abs school | Closeness to school | RIMA (10) |
| abs hospital | Closeness to hospital | RIMA (10) |
| Abs health center | Closeness to a health center | RIMA (3) |
| Abs transport | Closeness to public transportation | RIMA (5) |
| Abs Agri market | Closeness to the agricultural market | RIMA (11) |
| Ast wealth | Index for ownership of non-productive assets | RIMA (16) |
| Ast wscore | Wealth score provided by UNICEF | MICS (All) |
| Ast Agri wealth | Index for ownership of productive assets | RIMA (16) |
| Ast land | Land ownership | RIMA (15) & MICS (All) |
| Ast tlu | TLU (Tropical Livestock Unit) per capital | RIMA (14) & MICS (All) |
| Ast ownhouse | Dummy if any hh member own the dwelling | MICS (All) |
| Ssn formal | Formal transfers received by the household (dummy or value) | RIMA (14) |
| Ssn informal | Informal transfers received by the household (dummy or value) | RIMA (13) |
| Ssn credit | Access to credit (dummy or value) | RIMA (16) |
| Ssn network | Network of social relations households can rely on in case of need | RIMA (13) |
| Ssn contraception | Dummy if a woman in the household has access/use of contraception | MICS (All) |
| Ssn antenatal | Dummy if a woman received antenatal care by professionals during pregnancy | MICS (All) |
| Ssn delivery | Dummy if a woman received professional assistance during delivery | MICS (All) |
| Ac educave | Average years of education of household members | RIMA (12) & MICS (All) |
| Ac eduhead | Years of education of the household head | RIMA (3) |
| Ac lit head | Dummy if the household head can read and write | RIMA (5) |
| Ac read | Dummy if at least one woman in the household can read | MICS (All) |
| Ac income Div | Index for income diversification | RIMA (13) |
| Ac work ratio | Share of working members in the age of working | RIMA (12) & MICS (All) |
| Ac crop Div | Index for crop diversification | RIMA (11) |
| Ac training | Dummy if a household member participated in a training in agricultural practices | RIMA (6) |
| Fs fcs | Food Consumption Score | RIMA (15) |
| Fs foodexp | Food expenditures | RIMA (11) |
| Fs hdds | Household Dietary Diversity Score | RIMA (8) |
| Fs Shannon | Shannon index | RIMA (2) |
| Fs CSI | Coping Strategy Index | RIMA (2) |
| Fs no stunting | Share of not stunting children in the household | MICS (All) |
| Fs no wasting | Share of not wasting children in the household | MICS (All) |
| Fs nounderweight | Share of not underweight children in the household | MICS (All) |
| abs | Access to Basic Services – ABS pillar | All |
| Ast | Assets – AST pillar | All |
| ssn | Social Safety Nets – SSN pillar | All |
| ac | Adaptive Capacity – AC pillar | All |
| RCI | Resilience Capacity Index – RCI | All |

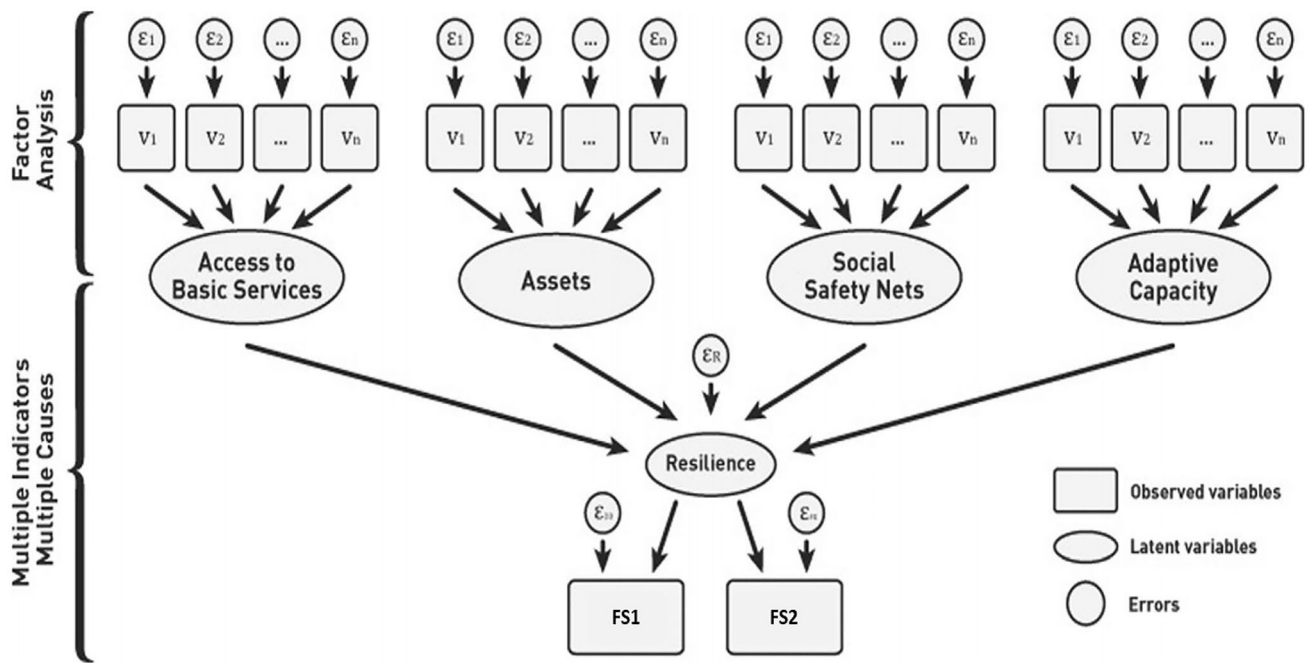


Fig. 2 Estimating resilience with the RIMA methodology

Table A4 FAO-RIMA datasets: resilience pillars and variables by country

| Country Coverage | Most important pillars and variables of resilience | | | |
|------------------------------------|--|--|--|---|
| | 1 | 2 | 3 | 4 |
| Chad <i>National</i> | AST Agri. wealth index; Wealth index; Land; TLU | ABS Energy; Water; Sanitation; Closeness to services | AC Income div.; Education | SSN Formal transfers; Credit; Informal transfers |
| DRC <i>Rutshuru (Nord-Kivu)</i> | AST Wealth index; TLU; Agri. wealth index; Land | AC Education; Work ratio; Income div.; Crop div | ABS Closeness to services; Sanitation; Electricity; Water | SSN Social network; Credit; Informal transfers; Formal transfers |
| DRC <i>Rutshuru (Nord-Kivu)</i> | AST Wealth index; TLU; Agri. wealth index; Land | AC Education; Crop div.; Work ratio; Agri. Training; Income div | ABS Sanitation; Electricity; Closeness to services; Water | SSN Social network; Credit; Informal transfers; Formal transfers |
| Mali <i>National</i> | ABS Electricity; Water; Energy; Sanitation | AST Wealth index | AC Education; Work ratio | SSN Social network; Credit |
| Mauritania <i>National</i> | ABS Electricity; Sanitation; Closeness to services (school, hospital, and agri. markets); Water | AC Education; Work ratio | AST Wealth index; TLU | SSN Credit; Social network; Formal transfers |
| Myanmar <i>Rakhine State</i> | AST Agri. wealth index; Wealth index | ABS Closeness to services | SSN Credit; Social network | AC Crop div.; Education |
| Niger <i>Maradi, Zinder</i> | SSN Credit; Formal transfers; Informal transfers | AST Land; TLU; Wealth index | AC Education; Crop div.; Work ratio | ABS Closeness; Water; Sanitation; Electricity |

Table A4 (continued)

| Country Coverage | Most important pillars and variables of resilience | | | |
|--|---|---|--|---|
| | 1 | 2 | 3 | 4 |
| Nigeria | AST | AC | SSN | ABS |
| <i>Borno State</i> | Wealth index; Land; TLU; Agri. wealth index | Education; Income div.; Crop div.; Agri. training; Work ratio | Social Network; Credit | Closeness; Sanitation |
| Senegal | ABS | AC | SSN | AST |
| <i>Matam</i> | Closeness to services (school, hospital, and agri. markets); Electricity; Sanitation | Education; Work ratio | Credit; Social network; Informal transfers; Formal transfers | Wealth index; Land; Agri. wealth index; TLU |
| Somalia | SSN | AC | AST | ABS |
| <i>Jowhar district (Middle Shabelle)</i> | Credit; Social network; Formal transfers | Education | Agri. wealth index; Wealth index; Land; TLU | Energy; Closeness to services; Sanitation; Water |
| Somalia | ABS | SSN | AST | AC |
| <i>Marka district (Lower Shabelle)</i> | Water; Sanitation; Energy | Informal transfers; Social network; Formal transfers; Credit | Agri. wealth index; Wealth index; Land | Income div.; Education |
| South Sudan | AC | AST | SSN | ABS |
| <i>Lakes State, Central Equatoria (Terekeka)</i> | Education; Agri. training; Income div | Agri. Wealth index; TLU; Wealth index | Formal transfers; Credit; Informal transfers; Social network | Water; Energy |
| Uganda | AC | AST | ABS | SSN |
| <i>Karamoja</i> | Crop div.; Income div.; Work ratio; Education | TLU; Wealth index; Land; Agri. wealth index | Water; Closeness to services | Credit |
| Uganda | AC | AST | SSN | ABS |
| <i>Karamoja</i> | Income div.; Education; Crop div.; Work ratio | Land; TLU; Agri. Wealth index; Wealth index | Credit | Closeness to services; Water |
| Uganda | AC | AST | SSN | ABS |
| <i>North</i> | Education; Crop div.; Work ratio; Income div | Agri. wealth index; Wealth index; Land; TLU | Credit; Informal transfers; Social network; Formal transfers | Closeness to services; Sanitation; Water |
| Uganda | AST | AC | SSN | ABS |
| <i>Southwest</i> | Wealth index; Agri. wealth index; Land; TLU | Work ratio; Agri. training; Education; Income div | Credit; Formal transfers | Water; Closeness to services |
| Venezuela | AST | AC | ABS | SSN |
| | Land | Income div | Closeness to services; Sanitation | Informal transfers; Formal transfers; Social network |

The pillars and variables of resilience are reported in order of importance (i.e., from highest to lowest contribution to the RCI)

Table A5 Most frequently reported shocks by profile (%) – RIMA datasets

| Profile | Natural disaster | Livelihood-related | Health shocks | Price shocks | Conflict-related | Income/Asset-related |
|-----------------------------|------------------|--------------------|---------------|--------------|------------------|----------------------|
| <i>Development level</i> | | | | | | |
| Developing countries | 33.62 | 38.68 | 28.81 | 2.49 | 39.51 | 0.00 |
| Least developed countries | 36.30 | 31.98 | 16.20 | 14.94 | 6.5 | 5.41 |
| <i>Income level</i> | | | | | | |
| LICs | 39.30 | 31.42 | 17.23 | 14.98 | 7.29 | 5.06 |
| LMICs | 17.13 | 33.55 | 13.10 | 10.58 | 8.86 | 5.06 |
| UMass | 61.62 | 62.22 | 48.15 | 0.00 | 79.86 | 0.00 |
| <i>Protracted crisis</i> | | | | | | |
| No | 59.69 | 44.92 | 22.85 | 18.50 | 10.82 | 3.40 |
| Yes | 23.52 | 26.02 | 14.38 | 11.37 | 8.70 | 5.74 |
| <i>Agro-ecological zone</i> | | | | | | |
| Hyper-arid | 31.07 | 25.01 | 12.82 | 26.38 | 6.56 | 5.54 |
| Dry semi-arid | 29.41 | 44.23 | 11.17 | 9.18 | 16.29 | 7.09 |
| Moist semi-arid | 12.66 | 7.41 | 8.30 | 0.98 | 3.91 | 0.13 |
| Sub-humid | 67.39 | 49.23 | 22.1 | 20.85 | 10.32 | 3.4 |
| Humid | 25.52 | 34.43 | 38.72 | 6.97 | 11.5 | 12.26 |
| <i>Main livelihood</i> | | | | | | |
| Farmer | 38.09 | 19.4 | 13.14 | 9.47 | 6.18 | 0.22 |
| Agro-pastoralism | 35.34 | 47.53 | 28.38 | 9.31 | 8.18 | 11.65 |
| Pastoralism | 32.68 | 34.73 | 11.53 | 22.92 | 8.87 | 6.04 |
| Overall | 36.04 | 32.61 | 17.39 | 13.84 | 9.43 | 4.93 |

Table A6 Most frequently reported coping strategies by profile (for each type of coping strategy, percent of households who reported relying on it in the past year) – RIMA datasets

| Profile | Food | Asset | Exp | Child | Credit | Help | Beg | Job | Migr | Barter |
|-----------------------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|--------------|
| <i>Development level</i> | | | | | | | | | | |
| Developing countries | 87.02 | 39.09 | / | / | 55.49 | 50.71 | 16.54 | / | / | / |
| Least developed countries | 58.89 | 29.43 | 7.61 | 3.46 | 27.46 | 30.59 | 21.57 | 36.39 | 14.29 | 17.3 |
| <i>Income level</i> | | | | | | | | | | |
| LICs | 56.93 | 31.57 | 7.61 | 3.46 | 25.96 | 29.65 | 21.23 | 39.13 | 13.69 | 17.76 |
| LMICs | 79.55 | 23.82 | / | / | 46.03 | 43.08 | 20.9 | 22.93 | 17.48 | 16.17 |
| UMass | / | / | / | / | / | / | / | / | / | / |
| <i>Protracted crisis</i> | | | | | | | | | | |
| No | 92.11 | 31.05 | / | / | 32.75 | 40.81 | 15.76 | 37.87 | 8.25 | 25.68 |
| Yes | 43.46 | 29.67 | 7.61 | 3.46 | 27.82 | 26.96 | 24.45 | 35.14 | 18.8 | 12.03 |
| <i>Agro-ecological zone</i> | | | | | | | | | | |
| Hyper-arid | 74.13 | 12.74 | / | / | 39.17 | 37.54 | 24.06 | 22.93 | 17.48 | 16.17 |
| Dry semi-arid | 64.76 | 30.84 | 11.22 | 9.00 | 35.82 | 48.91 | 16.12 | 35.61 | 14.74 | / |
| Moist semi-arid | 5.19 | 32.45 | 5.74 | 0.85 | 9.28 | 3.78 | 31.7 | / | / | / |
| Sub-humid | 85.87 | 31.57 | 13.64 | 10.42 | 25.71 | 36.97 | 15.88 | 38.73 | 9.68 | 26.99 |
| Humid | 97.10 | 35.07 | / | / | 58.26 | 51.20 | 16.32 | 42.08 | 20.84 | 10.43 |
| <i>Main livelihood</i> | | | | | | | | | | |
| Farmer | 44.92 | 34.38 | 5.74 | 0.85 | 21.86 | 23.10 | 25.22 | 48.91 | 12.57 | / |
| Agro-pastoralist | 81.55 | 30.28 | 13.64 | 10.42 | 40.70 | 42.37 | 15.19 | 35.84 | 13.79 | 17.5 |
| Pastoralist | 69.36 | 21.60 | 11.22 | 9.00 | 32.16 | 40.28 | 19.26 | 28.61 | 15.92 | 16.94 |
| Overall | 59.52 | 33.81 | 9.63 | 3.17 | 30.44 | 31.97 | 25.21 | 37.01 | 14.23 | 17.25 |
| Observations | 26,910 | 26,910 | 10,026 | 10,026 | 26,910 | 27,189 | 25,689 | 27,189 | 17,912 | 9,684 |

Table A7 Effects of self-reported shocks on resilience (OLS regression) – RIMA datasets

| Variables | (1) RCI | (2) RCI | (3) RCI |
|------------------|-----------------------|-----------------------|-----------------------|
| Natural shock | -0.395*** (0.0458) | | |
| Livelihood shock | | -0.607*** (0.0484) | |
| Health shock | | | -0.0985* (0.0599) |
| Agro-pastoralism | 1.586*** (0.0554) | 1.769*** (0.0569) | 1.617*** (0.0562) |
| Pastoralism | -0.0267 (0.0514) | 0.0882* (0.0518) | -0.00668 (0.0514) |
| Female-headed HH | -0.579*** (0.0529) | -0.581*** (0.0528) | -0.601*** (0.0529) |
| HH size | 0.00635 (0.00564) | 0.00508 (0.00563) | 0.00536 (0.00565) |
| Constant | 0.220*** (0.0568) | 0.196*** (0.0552) | 0.0935* (0.0551) |
| Observations | 31,403 | 31,403 | 31,403 |
| R-squared | 0.035 | 0.037 | 0.032 |

Power analysis for the corresponding R-squared at $p=0.01$

| (Sample size) | (Power) | (Power) | (Power) | (Power) | (Power) |
|---------------|---------|---------|---------|---------|---------|
| - N = 100 | 0.064 | 0.024 | 0.030 | 0.018 | 0.013 |
| - N = 500 | 0.711 | 0.193 | 0.281 | 0.089 | 0.034 |
| - N = 1000 | 0.988 | 0.542 | 0.706 | 0.259 | 0.076 |
| - N = 5000 | 1.000 | 1.000 | 1.000 | 0.997 | 0.736 |
| - N = 10,000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.990 |
| - N = 15,000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| - N = 20,000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| - N = 25,000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| - N = 30,000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A8 Consistency of OLS model: endogeneity test

| | (1) | (2) | (3) | (4) |
|------------------|--------------------------|-----------------------|-------------------------|-----------------------|
| Variables | Natural shock | RCI | Livelihood shock | RCI |
| Agro-pastoralism | -0.0386*** (0.00680) | 1.601*** (0.0749) | 0.276*** (0.00657) | 1.601*** (0.0746) |
| Pastoralism | -0.0546*** (0.00629) | -0.00508 (0.0341) | 0.154*** (0.00585) | -0.00508 (0.0342) |
| Female-headed HH | 0.0566*** (0.00654) | -0.602*** (0.0521) | 0.0335*** (0.00620) | -0.602*** (0.0521) |
| HH size | 0.00258*** (0.000705) | 0.00533 (0.00634) | -0.000408 (0.000637) | 0.00533 (0.00637) |
| Residuals (1) | | -0.395*** (0.0405) | | |
| Residuals (2) | | | | -0.607*** (0.0464) |
| Constant | 0.352*** (0.00692) | 0.0809 (0.0599) | 0.190*** (0.00611) | 0.0809 (0.0601) |
| Observations | 31,403 | 31,403 | 31,403 | 31,403 |
| R-squared | 0.005 | 0.035 | 0.061 | 0.037 |

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A9 First-stage: Instrumenting regression results for Shock Exposure

| Variables | (1) | (2) |
|------------------|---------------------------|---------------------------|
| | Natural shock | Livelihood shock |
| Location | 1.48e-07*** (1.57e-08) | 2.93e-07*** (1.48e-08) |
| Agro-pastoralism | -0.0619*** (0.00726) | 0.230*** (0.00682) |
| Pastoralism | -0.0504*** (0.00633) | 0.162*** (0.00595) |
| Female-headed HH | 0.0572*** (0.00650) | 0.0348*** (0.00611) |
| HH size | 0.00243*** (0.000694) | -0.000714 (0.000653) |
| Constant | 0.344*** (0.00675) | 0.176*** (0.00634) |
| Observations | 31,403 | 31,403 |
| R-squared | 0.008 | 0.073 |

Standard errors in parentheses
 *** p < 0.01, ** p < 0.05, * p < 0.1

Table A10 Impact of price shocks and weather shocks on resilience change over time (OLS regression) – MICS datasets

| Variables | (Model 1) ΔRCI | (Model 2) ΔRCI |
|---------------------|-------------------|-------------------|
| Δ abs toilet | | 0.586 -1.44 |
| Δ abs water | | 0.0336 -1.274 |
| Δ abs electricity | | -3.176* -1.642 |
| Δ abs energy | | 3.843 -2.85 |
| Δ ast landpc | | 0.482 -0.331 |
| Δ ast ownhouse | | 3.371** -1.676 |
| Δ ast tlupc | | -0.446 -0.958 |
| Δ ast wscore | | -0.985 -2.026 |
| Δ ssn contraception | | 2.053 -1.523 |
| Δ ssn antenatal | | 1.249 -1.443 |
| Δ ssn delivery | | 1.783 -1.425 |
| Δ ac educ ave | | 0.517* -0.312 |
| Δ ac work ratio | | 1.98 -5.313 |
| Δ ac read | | 3.223** -1.503 |

Table A10 (continued)

| Variables | (Model 1) ΔRCI | (Model 2) ΔRCI |
|--|---------------------|---------------------|
| Mauritania | 4.123 -24 | 5.313 -23.55 |
| Nigeria | 0.976 -21.66 | 0.634 -21.25 |
| Sudan | 13.24 -24.09 | 13.5 -23.5 |
| Zimbabwe | -5.899 -22.21 | -4.326 -21.69 |
| HH: Mostly men | -1.438 -1.351 | -1.332 -1.35 |
| HH: Mixed | -2.561* -1.325 | -2.637** -1.329 |
| HH: Mostly women | -1.047 -1.663 | -1.136 -1.658 |
| Agro-pastoralism | 4.871 -12.27 | 3.542 -12.16 |
| Mixed | 16.78 -21.51 | 15.53 -21.05 |
| Pastoralism | -2.511 -12.36 | -3.391 -12.08 |
| Trade | 15.33 -15.61 | 13.22 -15.28 |
| Price shock | -7.536*** -1.971 | -7.496*** -2.035 |
| Price shock (intense) | -11.26*** -3.178 | -10.81*** -3.214 |
| Dry anomaly | -3.254*** -1.101 | -3.084*** -1.11 |
| ΔABS | -0.659 -0.815 | |
| ΔAST | 0.517 -0.517 | |
| ΔSSN | 1.195** -0.54 | |
| ΔAC | 2.381*** -0.88 | |
| Constant | 4.804 -21.8 | 4.654 -21.36 |
| Observations | 3,806 | 3,806 |
| R-squared | 0.026 | 0.031 |
| Power analysis for the corresponding R-squared at p = 0.01 | | |
| (Sample size) | (Power) | (Power) |
| - N = 100 | 0.040 | 0.040 |
| - N = 300 | 0.204 | 0.204 |
| - N = 500 | 0.449 | 0.449 |
| - N = 700 | 0.679 | 0.679 |
| - N = 1000 | 0.890 | 0.890 |
| - N = 2000 | 0.999 | 0.999 |
| - N = 3000 | 1.000 | 1.000 |
| - N = 4000 | 1.000 | 1.000 |

Robust standard errors in parentheses
 *** p < 0.01, ** p < 0.05, * p < 0.1

Robustness checks

Table A11 Determinants of RCI over time (Fixed effects) – MICS datasets

| | Model 1 | Model 2 |
|-----------------------------------|-------------------|-------------------|
| | RCI | RCI |
| Agro-pastoralism | 4.95 (0.31) | 4.74 (0.33) |
| Mixed | -6.32 (0.31) | -6.51 (0.30) |
| Pastoralism | -2.59 (0.60) | -2.80 (0.57) |
| Trade | 4.89 (0.36) | 4.85 (0.36) |
| abs | 1.21*** (0.00) | |
| ast | 0.09 (0.71) | |
| ssn | 1.10*** (0.00) | |
| ac | 2.61*** (0.00) | |
| Access to toilet | | -0.92 (0.18) |
| Access to water | | -0.36 (0.55) |
| Access to electricity | | -0.76 (0.39) |
| Access to energy | | -2.56* (0.03) |
| Land per capita | | 0.17 (0.17) |
| Own house | | 1.06 (0.19) |
| TLU per capita | | -0.30 (0.52) |
| Wealth score | | 3.45*** (0.00) |
| Use of contraception | | 1.93** (0.00) |
| Access to pre-natal care | | 1.99** (0.01) |
| Support during delivery | | 1.89** (0.00) |
| Average level of education | | 0.26 (0.12) |
| Education of household head | | 0.25* (0.02) |
| Active/non-Active work hh members | | 8.51*** (0.00) |

Table A11 (continued)

| | Model 1 | Model 2 |
|---------------------------------------|--------------------|-------------------|
| Reading | | 1.79* (0.01) |
| Constant | 60.62*** (0.00) | 53.00** (0.00) |
| Controlling for regions | YES | |
| Controlling for household composition | YES | |
| Controlling for AEZ | YES | |

Declarations

Conflict of interest statement We wish to confirm that there are no known conflicts of interest associated with this publication. There has been no significant financial support for this work that could have influenced its outcome. We confirm that the manuscript has been read and approved by all named authors and that there are no other people who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property. We further confirm that any aspect of the work covered in this manuscript that has involved either experimental animals or human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript. We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author, and which has been configured to accept email from (marco.derrico@fao.org).

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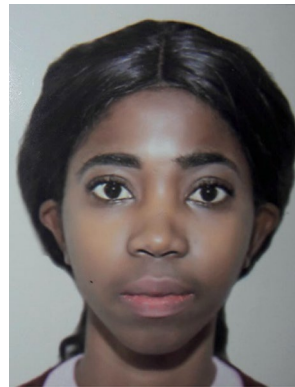
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Marco d'Errico holds a Ph.D. in Economics and is an economist at the Food and Agriculture Organization (FAO) of the United Nations. He joined FAO in 2009 and since then he has collaborated with World Bank, IFAD, and UNICEF. He is currently Head of the RIMA (Resilience Index Measurement and Analysis) team, and coordinator of the Impact Evaluation Task Force in the Agriculture and Development Division (ESA).



Jeanne Pinay holds an MSc in Development Economics and is an economist at the Food and Agriculture Organization (FAO) of the United Nations. She joined FAO in 2020 and works on resilience and food security analyses, with a particular focus on African countries.



Ellestina Jumbe holds two masters' degrees in Economics and International public finance and has since 2020 been working at FAO as an Economist. Her work involves country support in resilience analysis and measurement within the RIMA team- including extended support to a select countries in Africa under the Malabo declaration agenda.



Anh Hong Luu holds a Ph.D. in Applied Economics and is an economist in the RIMA (Resilience Index Measurement and Analysis) team at the Food and Agriculture Organization (FAO) of the United Nations. She specializes in household resilience, prices of agriculture products, and models built using the R and STATA programming language. She is currently working on different projects of FAO and World Bank to improve the livelihoods of poor rural households and enhance their resilience.