Using high-frequency data to measure the resilience metrics for food security and women's dietary diversity in Uganda

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Note: I have interest to apply for the JRC and PARI scholarships

Abstract

Several debates and discussions have emerged in contemporary literature on the best method, data, and timing to measure the resilience concept. We contribute to this discussion by using high-frequency data collected in short spans of two to three months. We also validate if RIMA II can be used to estimate the resilience of rural households using high-frequency data collected within the year. We compare the resilience of families estimated using RIMA II with the subjective self-evaluated resilience score and the qualitative measures from focus group discussions and key informant interviews. Our qualitative and quantitative assessment establishes that the resilience concept does change within six months. The results are consistent when using two different weighting approaches to estimating the resilience capacity index using RIMA II. The resilience capacity index calculated from RIMA-II is also moderately comparable to the subjective self-evaluated resilience score estimated. Anecdotes from qualitative interviews also show that within the year, households can recover from some shocks and bounce back to their previous level of well-being using different coping strategies. Overall, this study reveals the possibility of employing the RIMA-II metrics for measuring resilience with data collected in six months durations to understand the dynamic and complex nature of resilience amongst rural households.

1. Introduction

Several donors, development agencies, and international Non-Governmental Organizations (NGOs), including USAID, DFID,UNDP, UN, and FAO, have embraced the concept of resilience (Béné et al., 2017), which is even more critical today in this era of the COVID-19 pandemic. The resilience of vulnerable households is crucial amidst increasing risk threatening their lives and ways of living. Resilience is the ability of families, individuals, or communities to withstand shocks and stressors to maintain a certain level of well-being (Alinovi et al., 2010) or their ability to bounce back or recover over time when exposed to stressors or a setback of some type (d'Errico et al., 2018; Vaitla et al., 2012). The ability of households or individuals to recover will depend on the available options to earn a living and manage risks (Béné et al., 2017). Being an unobserved concept makes resilience challenging to measure. Yet, the correct measurements for resilience are critical for the proper targeting, identification of hotspots, understanding of the drivers, and measuring the impact of any interventions (Jones & Tanner, 2017). So, there is a growing need for more evidence on its measurement and validation of the existing metrics. This apparent need motivates this research.

In recent years, studies focusing on the concept of resilience from an economic perspective have increased in published literature (Brück et al., 2018; d'Errico et al., 2020; d'Errico & di Giuseppe, 2018; FAO, 2016; Knippenberg et al., 2019). Nevertheless, there is no consensus on its measurements stemming from its complex and dynamic features, and it's being unobserved (d'Errico & di Giuseppe, 2018). First, there seems to be no consensus on whether qualitative or quantitative methods may be more appropriate to measure resilience, and authors have recommended using both approaches (Jones & Tanner, 2017). Second, several discussions ve centered on whether proxy indicators represent the resilience construct (d'Errico et al., 2018). Third, there is divergence in the type of approach or data employed in measurement. Specifically, the static techniques with cross-sectional datasets are adequate to reflect the unobserved concept (d'Errico et al., 2018), or they should be dynamic (FAO, 2016). Lastly, some methods have been tagged too "academic" and non-verifiable and require a high degree of unavailable data (Béné et al., 2017).

In this study, we propose to compare the Resilience Index Measurement and Analysis (RIMA-II) approach using high-frequency data with the subjective self-evaluated resilience score and the qualitative measures from focus group discussions and key informant interviews to examine the resilience of households. In this way, we also assess if RIMA II can be used to measure the resilience of families to short spans of exposure to shocks.

In 2008, the Food and Agriculture Organization (FAO) introduced the Resilience Index Measurement and Analysis (RIMA) technique to measure household resilience to shocks and stressors that may cause food and nutrition insecurity. In 2013, the Technical Working Group on resilience measurement constituting FAO, International Food Policy Research Institute (IFPRI), and World Food Program (WFP) updated RIMA to RIMA-II. To measure resilience, there is a need to be cognizant that as a concept, resilience (1) is an outcome-based concept for measuring welfare and in this case, food security and women's diet diversity (2) is measured based on exposure to stressors and or shocks (3) there are long-lasting effects on the outcome

(4) includes the agent's capacity to offset the negative consequences of the shocks through its ability to absorb, adapt and transform livelihood strategies (d'Errico et al., 2018).

Many recently published studies (Alinovi et al., 2010; Brück et al., 2018; d'Errico et al., 2017; d'Errico & di Giuseppe, 2018) have relied on the RIMA-II approach to measuring resilience in several contexts including Uganda, Tanzania, Senegal, Mauritania, Lesotho, and the Gaza strip in Palestine. In Uganda, 'Errico & Di Giuseppe, (2018) examined the resilience mobility of households using a two-year panel dataset. They use the RIMA-II approach and categorize households into least resilient, less resilient, and most resilient and analyze the factors affecting the household's probability of moving from one resilience category to another. In Lesotho, 'Errico et al., (2020) evaluate Lesotho's Child Grants Program's (CGP) impact on resilience following RIMA-II's two-step approach where they combine factorial analysis and structural equation modeling. In Uganda and Tanzania, d'Errico & di Giuseppe (2018), use a panel dataset and follow the conventional approach to estimating FAO's Resilience Capacity Index (RCI) and use probit models to test the relationship between resilience and food security outcomes.

Most of the above studies use panel datasets with a one-year recall to estimate resilience, so it is paramount to examine if they exclude some dynamic changes within the year (Alinovi et al., 2010; Brück et al., 2018; d'Errico et al., 2017; d'Errico & di Giuseppe, 2018). Households likely experience several shocks within the year, some of which resilient families quickly recover from while others persist. This tendency may not be reflected in annual panel surveys. Capturing these dynamic changes requires high-frequency data collected within these short spans, which is usually absent. High-frequency data allows researchers to track seasonality and short-term responses, which will enable one to study households' well-being and recovery path(Knippenberg et al., 2019).

I propose to examine if the RIMA-II technique can measure the intra- annual periodic changes in resilience. In the study, we ascertain two things; first, whether estimating resilience using RIMA –II approach correlates with the underlying changes in well-being resulting from short-span frequent exposures to shocks and stressors and household responses. Secondly, whether the resilience estimation using RIMA-II and high-frequency data compares closely with other alternative resilience measures. Despite its popularity and ease of gathering the required data for its measurement, the RIMA-II technique has not been used with such high-frequency data. High-frequency data minimizes recall bias in reporting shocks, changes in income, assets, and other factors that affect household food and nutrition security. Knippenberg et al. (2019) also quantify household resilience with high-frequency data collected monthly using three methodological approaches: shock persistence, stochastic distribution, and machine learning algorithms in the Malawian context. Although I propose using high-frequency data, I focus on the RIMA-II approach to measuring resilience in the Ugandan context. Resilience measures are context-specific and should be estimated on a case-by-case basis (d'Errico et al., 2020).

I corroborate the resilience of households estimated using RIMA II with that calculated using the subjective self-evaluated resilience score approach. In the latter method, we ask households about their perceptions of resilience in the different seasons and rate their responses based on a Linkert scale to questions representative of six different capacities associated with resilience, namely: (1) absorptive capacity, (2) adaptive capacity (3) financial capital (4) social capital (5) social capital (6) knowledge and learning. Subjective measures on theoretically framed questions allow participants to self asses their ability to cope and recover from risks they have been exposed to (Jones & d'Errico, 2019; Knippenberg et al., 2019). Jones & d'Errico, (2019) also combines the RIMA -II approach with a subjective measure of resilience. Although similar on several fronts to this study, including the use of RIMA II and applying it to the context of Uganda, major differences relate to the type of data used and how households' perspectives regarding their resilience are captured. Our study uses high-frequency data and covers Uganda's larger geographical span.

Indeed, our estimation of RIMA-II using high-frequency data reveals significant changes in household resilience to shocks experienced within two to three months. The results are consistent when using two different weighting approaches to estimating the resilience capacity index using RIMA II. The resilience capacity index calculated from RIMA-II is also moderately comparable to the one estimated using the subjective self-evaluated resilience score. There is a 13 percent correlation and some overlaps in the distribution of the score. Anecdotes from qualitative interviews also show that within the year, households can recover from some shocks and bounce back to their previous level of well-being using different coping strategies. Overall, this study reveals the possibility of employing the RIMA-II metrics for measuring resilience with high-frequency data collected to understand the dynamic and complex nature of resilience amongst rural households.

The rest of this paper is organized as follows. The next section reviews the literature on resilience. Section 3 discusses the data and methods, including the empirical strategy used. In section 4, we present the main results and discussion, and lastly, conclusions are presented in section 5.

2. Literature review

2.1 Innovation in analytical methods and metrics in measuring resilience

Resilience is used in several fields of study, including ecology, engineering, psychology, and epidemiology. It has also gained increasing usage in social sciences, for example, in understanding food and nutrition security (d'Errico et al., 2018). By definition, it is the ability of the household, community, or an individual to bounce back or recover over time when exposed to stressors or a setback of some type (d'Errico et al., 2018; Vaitla et al., 2012). However, given its unobserved nature, many discussions in the literature center on the suitable approaches for its measurement (Alinovi et al., 2008; d'Errico & di Giuseppe, 2018; Jones & d'Errico, 2019; Smith & Frankenberger, 2018; Vaitla et al., 2012). A recent paper by Upton et al., (2022) critiqued some of the methods used to measure the resilience concept as being unclear on exactly what they measure or what benefits they yield compared to other well being measures.

In quantitative measures for resilience, the argument is whether proxy indicators represent the resilience construct (d'Errico et al., 2018) and whether static approaches should be used to measure a dynamic concept like resilience. Some methods have been tagged too "academic," and data are demanding to assess the impacts of programs (Béné et al., 2017). Other studies have emphasized using qualitative methods such as focus group discussions and key informant interviews to understand the resilience concept better. Other studies have gone a notch higher and allowed for subjectivity (respondents internalize their situation of resilience) in responding to measures that have been generated objectively from the extensive literature (Jones & d'Errico, 2019; Jones & Tanner, 2017). The ultimate desire is to integrate pluralistic measures using quantitative and qualitative measures (Jones & d'Errico, 2019).

2.2 Quantitative measures for resilience:

Studies using quantitative measures of resilience have recently increased with differences in methods (Brück et al., 2018; Brück & d'Errico, 2019; d'Errico & di Giuseppe, 2018; Jones & d'Errico, 2019; Knippenberg, 2017; Knippenberg et al., 2019). Alinovi et al. (2008) use a two-stage factor analysis of observable variables to measure the resilience index as a latent variable but are limited by cross-sectional data. They also use proxies of shocks, such as the index of coping mechanism, which don't explicitly measure shocks (d'Errico et al., 2018). In another approach, Vaitla et al. (2012) use a livelihood change approach where households adopt different livelihood strategies per the assets owned. A limitation of their study is the cross-cross-sectional data used, which does not allow for measuring the changes in assets and household welfare over time. In 2008, FAO proposed an econometric approach, the Resilience Index Measurement and Analysis (RIMA), first implemented in Palestine and Kenya (d'Errico et al., 2018; d'Errico & di Giuseppe, 2018; FAO, 2016) maintaining the latent variable approach used by (Alinovi et al., 2008) through a two stage approach. RIMA allows for the estimation of the resilience index using factors analysis replacing structural equation modeling (d'Errico et al., 2018). In 2013, the Technical Working Group on Resilience Measurement set up by FAO, IFPRI, and WFP updated RIMA to RIMA-II, de-linking food and nutrition security from resilience capacity and thus allowing it to be more flexible in regards to other outcomes beyond food security. Studies have adopted the RIMA approach to estimate resilience in several contexts in Uganda, Tanzania, Senegal, Mauritania, Lesotho, and the Gaza strip in Palestine (Alinovi et al., 2010; Brück et al., 2018; d'Errico et al., 2017; d'Errico & di Giuseppe, 2018). In Uganda, 'Errico & di Giuseppe, (2018) examined the resilience mobility of households using a two-year panel dataset. Using the RIMA-II approach, they categorize households into least resilient, less resilient, and most resilient and analyze the factors affecting the household's probability of moving from one resilience category to another. In Lesotho, (d'Errico et al., 2020) evaluate Lesotho's Child Grants Program's (CGP) impact on resilience and follow RIMA-II's two-step approach combining factorial analysis and structural equation modeling. In Uganda and Tanzania, (d'Errico & di Giuseppe, 2018) uses panel data, follows the conventional approach to estimating FAO's Resilience Capacity Index (RCI), and uses probit models to test the relationship between resilience and food security outcomes. All the above studies use panel data with a year's recall period to measure resilience. Overall to measure resilience, there is a need to be mindful that as a concept, resilience (1) is an outcome-based concept for measuring wealth fare and, in this case, food security and women's diet diversity (2) measured based on exposure to stressors and or shocks (3) there are long-lasting effects on the outcome (4) includes the agent's capacity to offset the negative consequences of the shocks through its ability to absorb, adapt and transform livelihood strategies (d'Errico et al., 2018)..

3.0 Data and Methods

The study used a mixed methods approach using both quantitative and qualitative methods. Quantitative methods involved the computation of resilience by using the Resilience Index Measurement and Analysis (RIMA) technique introduced by the Food and Agricultural Organization and the Subjectively Self-Evaluated Score (SERS). For triangulation to help us understand the phenomenon of resilience within a year, we adopted the qualitative approach. Qualitative data collection involved (1) in-depth household interviews and (2) focus group discussions

3.1 Data

3.1.1 High-frequency data

We used high-frequency data to estimate RIMA-II. The high-frequency data was from surveys collected every two to three months, from June 2020 to August 2021. The sample consisted of eight districts in Ugandapurposively selected based on their past exposure to climatic and price shocks. The districts are Kole, Lira, Kamwenge, Kisoro, Kotido, Moroto, Sironko, and Bududa. From each of the eight districts, three -counties were randomly selected to be part of the study, and one sub-county was purposively selected based on past ad existing extreme weather events. The sampling frame for all the sub-counties was from the Uganda Bureau of statistics. All parishes in the selected -counties were liable to participate; overall, 25 percent of all villages in the parishes were selected. Using probability proportional to size sampling, 80 households were selected per district from the household listing to make a total of 640 households. The information collected from the households included questions on the household's food situation, maternal and children diets, household consumption expenditure, household social networks, sources of income and labor, livestock ownership and production, crop and livestock production, positive shock events, adverse shock events, health expenditures, the overall health status of the household members, changes in household assets and demographic and socioeconomic characteristics. The first survey wave was collected in June 2020, the second in August 2020, the third in December 2020, the fourth round in March 2021, the fifth round in May 2021 and the last round in August 2021. We also conducted phone interviews with half of the sampled respondents randomly selected from six districts: Kole, Lira, Kamwenge, Kisoro, Sironko, and Bududa.

Attrition: We checked out the dropout rates from our six rounds of data collected to ensure that the statistical power is not weakened and the dropout was nonrandom. Non-randomness may lead to biased estimates resulting from the correlation between the error terms and the observables. During data collection, households not interviewed in the previous phase were searched for in the subsequent rounds rather than dropping out entirely. In the first wave, 639 households were traced and interviewed. In the subsequent waves, all families were interviewed apart from the fifth wave, where we added two new households..

3.1.2 Qualitative data:

Qualitative data collection involved (1) in-depth household interviews and (2) focus group discussion. In-depth interviews were conducted with farmers, while focus group discussions were held with 10 to 12 farmers, including local leaders in the area. We conducted focus group discussions in the six districts from which primary high-frequency data was collected (Kamwenge, Kisoro, Kole, Lira, Bududa, Sironko). We randomly selected three sub-counties from each district, and from each of the sub-counties, we selected one nearby parish. We randomly selected three nearby villages from each parish and conducted four in-depth farmer interviews. We randomly selected farmers for the in-depth farmer interviews from the list of respondents who we interviewed during the high-frequency survey in that village. Each of the four selected interviews conducted in the village was from a different resilience category (computed from RIMAII). Twelve in-depth farmer interviews were conducted in three sub-counties. In total, 72 in-depth interviews were conducted in the six districts. 24 focus group discussions were conducted in all the selected districts (a total of 3 focus group discussions in each sub-county). Participants for the focus group discussion were selected with the assistance of the local leaders and snowball sampling while considering the representativeness based on age, income, ethnicity, and age. Each focus group had between 10 to 12 respondents. All sampled respondents were healthy and chosen from within the population without consideration for a particular population.

To triangulate some of the information collected from the high-frequency data, we conducted an in-depth farmer questionnaire to a balanced group of farmers in the first, second, third, and fourth estimated resilience quintile in either the first or second wave of data collection. The in-depth farmer questionnaire, for example, asked questions on household welfare and perception of welfare. For instance, we asked farmers how they felt in terms of (a) being cheerful and in good spirits, (b) being calm and relaxed, (c) being active and vigorous, (d) fresh and rested, (e) that their life half been filled with exciting things. In the farmer in-depth interviews and focus group discussions, we also asked farmers how their beliefs, power, identity, and social grouping affect the extent to which they can cope or recover from the shocks. In the quantitative estimation of resilience using the RIMA-II approach, the above variables associated with traditions, cultural elements, and social and institutional aspects are usually excluded because of data challenges (FAO, 2016).

3.2 Model specification and Estimation strategy using the RIMA II approach

Our interest is to validate RIMA-II as a measure of resilience with high-frequency data. In other words, we measure whether the concept of resilience may change in a short period (within two to three months) and the possibility of RIMA-II measuring these changes. We also verify and explain quantitative estimates with qualitative methods. We proceed as follows: First, we estimate whether certain pillars in the estimation of resilience change in two to three months. For example, households may withdraw or join new groups within this period, diversify their income sources, the number of assets may change, and distance to the markets may vary (due to floods that may make roads impassable). The number of shocks might also increase or decrease within a short period. Second, we corroborate the resilience constructed using RIMA-II with subjective measures of resilience (explained below) and qualitative data collected from in-depth farmer interviews and focus group discussions. Third, using the RIMA-II approach, we construct the resilience capacity index for each survey wave and estimate if there are significant differences between the waves. Through the estimated resilience capacity index, we know whether households withstand and bounce back to their previous well-being in the presence of shocks, including exposure to Covid-19 restrictions. Fourth, we compare the resilience capacity index estimated through RIMA II with the Subjective Self-Evaluated Resilience Score (SERS) to find synergies and validate whether the concept of resilience does change within short spans in the presence of some shocks. We use qualitative interview responses to explain the estimated resilience further.

3.2.1 Estimating Resilience using the RIMA II approach

We estimate resilience using FAO's RIMA-II approach, which combines factorial analysis and structural equation modeling. Most other studies have used annual data in the RIMA II approach, and this study is unique in using high-frequency data collected in a span of two to three months. The resilience concept is computed from four pillars (1) Access to basic services like schools, health centers, water, electricity, and markets (2) productive and nonproductive assets, for example, agriculture and non-agriculture equipment (3) Social Safety Nets and (4) Adaptive capacity which refers to the ability of households to adapt to any changes and absorb shock. We capture access to essential services by distance variables to these services measured in kilometers. Following d'Errico & Di Giuseppe (2018), we derive an infrastructure index by factorial analysis of household characteristics like the type of roof and floor, access to safe water and sanitation, and electricity. The agricultural wealth index is constructed from a factorial analysis of agriculture equipment and tools endowment. The non-agriculture wealth index is computed as a wealth index from factorial analysis of non-agriculture equipment such as the possession of a car, phone, land owned, and total livestock units. We ask households if they have acquired or sold off any assets since the last survey round.

The formal and informal transfers (or public and private) measure social safety nets that contribute to income and the household's overall welfare. Formal and informal transfers include remittances and aid, government transfers, friends and relatives, and reliance on social groups. We asked families if they had joined or left any new or old social groups and whether they still relied on these groups in every survey round. Variables that capture households' adaptive capacity include the years of education of the household head, the number of income-generating activities, and the dependency ratio (ratio of active to inactive people in the household). Every survey round asks families if there are new income-generating activities the family has engaged in or if they have left any since the last survey.

We measure income and food access by the weekly per adult equivalent food consumption expenditure and women's dietary diversity in the analysis. We construct the Women Dietary Diversity Score (WDDS) following FAO's guidelines for measuring household and individual dietary diversity (Kennedy et al., 2010). WDDS includes nine groups, namely (1) Starchy staples, (2) Dark green leafy vegetables, (3) Other vitamins A rich fruits and vegetables, (4) Other fruits and vegetables, (5) Organ meat, (6) Meat and fish,(7) Eggs (8) Legumes, nuts and seeds, (9) Milk and milk products. HDDS is constructed from 12 food groups, namely: (1) Cereals, (2) White tubers and roots, (3) Vegetables, (4) Fruits, (5) Meat, (6) Eggs, (7) Fish and other seafood (8) Legumes nuts and seeds (9) Milk and milk products (10) Oils and fats (11) Sweets (12) Spices, condiments and beverages. Women's dietary diversity is constructed as a binary variable equal to one if the caregiver in the household consumes five or more of the nine food groups following the guidelines by FAO and USAID.

The estimated Resilience capacity Index is a factor of pillars, namely access to basic services (ABS), Assets (AST), social networks (SSN), and Adaptive Capacity (AC) constructed from observable characteristics

$$RC1 = [\beta_1 \beta_2, \dots\dots \beta_n] * [ABS, AST, SSN, AC] + [\in_1]$$

Through the Resilience Capacity Index, the latent variables have a joint effect on well-being outcomes like per capita household consumption expenditure and women's dietary diversity

$$[W_1 , W_2, \dots\dots W_n] = [\propto_1 \propto_2, \dots\dots \propto_n] * RCI + \left[\in_{1,} \in_2, \dots, \in_n\right]$$

We also checked if the drivers of resilience constructed from RIMA-II and SERs are comparable. We estimate the equation below in which the dependent variable Y_i are resilience scores from RIMA- II and SERs scores, respectively.

Model specification:

$$Y_{it} = \alpha + \delta R_{it} + \beta X_{it} + \vartheta_i + \theta_t + \varepsilon_{it}$$

Where Y_{it} is the dependent variable, the resilience scores computed from RIMA II and the SERs. X are a vector of control variables like covariate shocks, district dummies, and household and village characteristics. ϑ_i Are time invariant unobserved household effects. θ_t are wave fixed effects, ε_{it} is the error term. Covariate shocks include illness, an increase in food prices, and death of a household member, and an index of climate risks. Household characteristics include the age of the household head (and its squared form), gender, household size (and its squared form), marital status, land size, and income activities in which the household is engaged. Village-level characteristics include distance to the nearest town, the presence of a village savings group, or a cooperative in the village.

Sensitivity Analysis

When estimating the resilience of households using RIMA II, in the first step that involves factorial analysis to generate the pillars, we follow 'Errico et al. (2020) and use two of the three approaches, which are differentiated by how the weights are computed and therefore how the resilience is defined. In the first approach, resilience is defined over time by having a constant weight. The weight is constructed by pooling all the variables that explain a given pillar across all the waves. Only the variables are allowed to vary. In the second approach, resilience is defined as time-dependent. In this case, the MIMIC model is estimated separately at different periods; therefore, the weights and the variables used to construct the pillars vary. We compare the constructed resilience index constructed using a constant wave across all the waves and the index constructed for each of the waves

3.2.2 Estimating resilience using a Subjective Self-Evaluated Resilience Score (SERS)

We also estimate resilience using a subjective score similar to the Subjective Self Evaluated Resilience Score (SERS) adopted by Jones & d'Errico, (2019). Using phone interviews and based on a Likert scale, we asked farmers to choose from whether they strongly agree to strongly disagree along six resilience measures categorized in literature as (1) coping capacity, (2) adaptive capacity, (3) financial capital (4) social capital (5) learning and (6) knowledge and information for two prevalent hazards/shocks that usually occur in the context of Uganda namely: (1) drought and floods and (2) pests and diseases. We compute a simple weighted single score by calculating the average mean score and principal component analysis. The resulting score computed is the resilience outcome which we compare with the standard Cronbach's Alpha score of 0.79 to assess the reliability or internal consistency of the SERs scores.

4.0 Results

4.1 Descriptive statistics

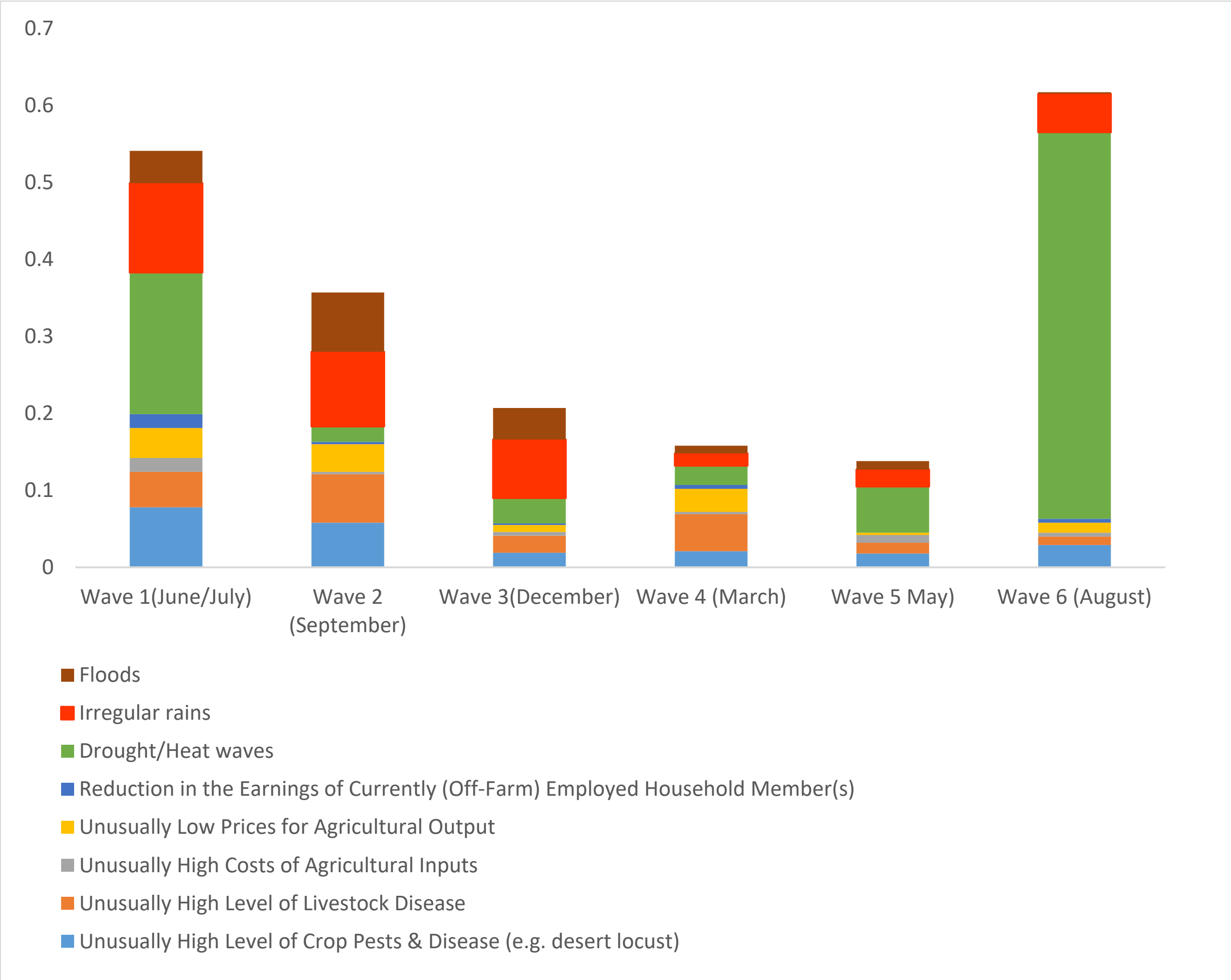
Table 1 shows that most shocks experienced by households were in the first wave of data collected in June 2020. On average, 18.4 percent experienced a drought in the first wave, 11.6 percent reported having irregular rains, and 11.9 percent reported having a severe illness or accident of a household member. The total number of reported shocks is 20. After two months, fewer shocks were reported in the second survey round, and fewer households reported these shocks. On average, families experienced twice the number of shocks in the first wave than in the second wave.

Table 1: Household experience of shocks in the different waves

Variable	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Drought/heat waves	0.184	0.02	0.033	0.025	0.006	0.502
Irregular Rains	0.116	0.097	0.076	0.016	0.022	0.05
Floods	0.042	0.077	0.041	0.01	0.011	0.002
Landslides	0.044	0.042	0.024	0	0	0.006
Erosion	0.024	0.035	0.019	0	0.029	0
Unusually High Level of Crop Pests & Diseases (e.g., desert locust)	0.078	0.058	0.019	0.021	0.018	0.029
Unusually High Level of Livestock Disease	0.046	0.063	0.022	0.048	0.014	0.011
Unusually High Costs of Agricultural Inputs	0.018	0.003	0.005	0.003	0.01	0.005
Unusually Low Prices for Agricultural Output	0.039	0.036	0.009	0.03	0.003	0.013
Reduction in the Earnings of Currently (Off-Farm) Employed Household Member(s)	0.018	0.003	0.002	0.005	0	0.005
Loss of Employment of Previously Employed Household Member(s)	0.008	0	0.003	0.002	0.002	0
Serious Illness or Accident of Income Earner	0.073	0.038	0.046	0.029	0.026	0.048
Serious Illness or Accident of Other Household Member	0.119	0.041	0.062	0.038	0.037	0.05
Death of Income Earner	0.021	0.002	0	0.005	0.002	0.003
Death of Other Household Member	0.09	0.008	0.021	0.022	0.008	0.011
Theft of Money/Valuables/Nonagricultural Assets	0.018	0.005	0.008	0.01	0.005	0.011
Theft of Agricultural Assets/Output (Crop or Livestock)	0.062	0.064	0.077	0.095	0.045	0.095
Conflict/Violence	0.042	0.011	0.016	0.014	0.005	0.01
Fire	0.007	0	0.005	0.002	0.002	0.002
Other shocks	0.103	0.074	0.027	0.04	0.021	0.034

The number of households reporting some shocks, such as drought, and irregular rains, reduced over the waves from the first time reported. Other shocks remain volatile, reducing and increasing at different points in time, for example, crop pests and diseases, livestock diseases, low prices of agricultural commodities, illnesses or accidents, and theft of agricultural produce. For shocks like drought, it is unsurprising that a high proportion of households report it in the baseline in June and then again in the last survey in August 2021. Such shocks might be subjectively reported depending on the effect that they might have on the welfare of the people. For example, the effects of drought might be felt at harvest time, usually between June and the end of August in Uganda. Many such shocks and their seasonal nature may be left unreported if we only rely on data collected annually. Other shocks remain constant or persistent throughout the year, for example, formerly employed earnings reductions, floods, landslides, and high cost of agriculture commodities. Generally, households in rural Sub-Saharan Africa are exposed to several shocks throughout the year against which they are not insured.

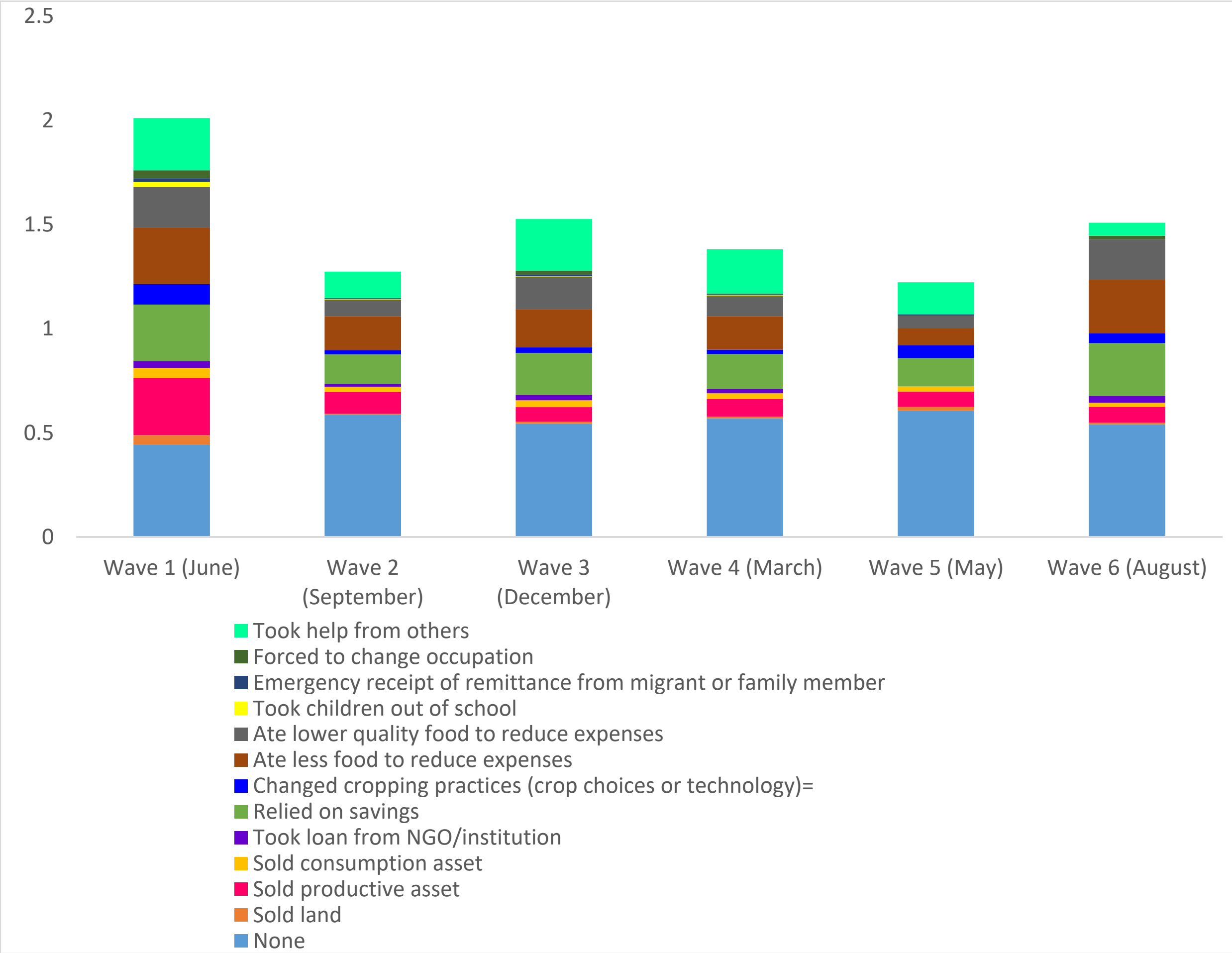
Figure 1: Variation in some selected shocks of households across the waves



Coping strategies of households across the waves

Figure 2 shows the different coping strategies that households adapted across the waves to cope with the shocks. There are incidences where the families reported that they did nothing to manage in regards to the shocks. Some of the coping strategies include selling productive assets (high at baseline), eating less food to reduce expenses (high in wave one and wave 6), relying on savings (relatively spread out across the seasons), and taking help from others (high in wave 1, 3 and 4).

Figure 2: Coping strategies by households across the survey waves



Differences in the constructed pillars and waves

Resilience pillars

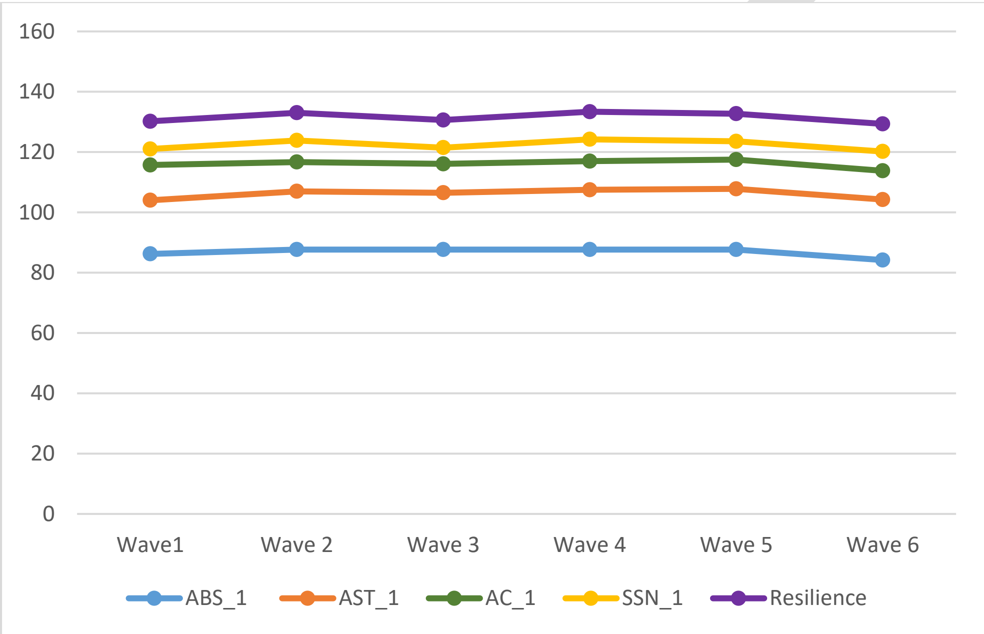
Table 2 and figure 3 shows the estimated pillars by the wave following the factorial analysis of observable variables described above.

Table 2: Estimated pillars and resilience across the waves

Pillar	Wave1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
ABS_1	86.226	87.656	87.656	87.656	87.656	84.185
AST_1	17.777	19.325	18.833	19.833	20.14	20.047
AC_1	11.692	9.709	9.57	9.481	9.697	9.546
SSN_1	5.31	7.166	5.397	7.238	6.047	6.395
Resilience	9.176	9.156	9.143	9.172	9.172	9.164

As is expected, there is minimal variation across the waves regarding access to the primary service and adaptive capacity pillars. These pillars will rarely change in a short span of two months or even in a year. For example, the access to essential services constructed from variables such as distance to social services and the nature of housing will rarely change within a year. Similarly, the adaptive capacity pillar constructed from variables such as the number of dependents and working-class family members, as well as the education level of the household members, may not change within a short time. The adaptive capacity index constructed might be the same for studies that use annual data where the years are not far apart. The social network pillars and asset pillars showed considerable variation within the short span of two to three months. Social networks, including groups, are very dynamic as new ones form, old ones perish, or people move in and out of these groups.

Figure 3: **Estimated pillars and resilience across the waves**



We further show the statistical differences in the pillars between waves (one, three, and six) in Tale 3 . Panel A shows the statistical difference in the pillars between waves one and wave three; Access to basic services and asset pillars were statistically lower in the first than in the third wave. The adaptive capacity showed a decrease in the third wave, most likely emanating from the temporary migration of some people within the household. There was no significant difference in the asset pillar between the first and third waves. Panel B shows the statistical difference in the pillars between the first and the sixth waves. Apart from the adaptive capacity and access to basic service pillars which reduce, the asset and network pillars show considerable statistical differences between the first and the sixth wave. Panel c shows the differences between the third and sixth waves; the asset and the social network pillars statistically increase from the third to the sixth while the access to the basic services reduces. There is no statistical difference in the adaptive capacity pillar between the third and the fourth pillars.

Table 3: t test results of the difference between pillars in waves 1, 3 and 6

	Wave 1	Wave 3	t
Panel A			
ABS_1	86.226	87.657	2.967***
AST_1	17.777	18.834	1.845*
AC_1	11.692	9.57	-7.993***
SSN_1	5.31	5.397	0.271
N		1279	
	Wave 1	Wave 6	t
Panel B			
ABS_1	86.226	84.186	-3.952***
AST_1	17.777	20.047	3.700***
AC_1	11.692	9.546	-8.019***
SSN_1	5.31	6.395	2.909***
N		1279	
	Wave 3	Wave 6	t
Panel C			
ABS_1	87.657	84.186	-6.674***
AST_1	18.834	20.047	2.038**
AC_1	9.57	9.546	-0.157
SSN_1	5.397	6.395	2.946***
N		1280	

4.2 Estimating household resilience capacity using RIMA II

Table 4 shows the results of the FAO-RIMA II model for the estimated resilience capacity. As described in the methodology section, the weights used to construct the pillars to estimate the resilience capacity index (Table 4) result from pooling all the variables that explain that given pillar across all the waves while allowing the observable variables to vary.

Panel A shows the relationship between the latent variables (pillars) and the resilience capacity. The assets, adaptive capacity, and socialnet coefficients are positive and statistically significant. A one standard deviation increase in assets results in an increase in the resilience capacity of households by 0.005. In contrast, a one standard deviation increase in access to basic services increases resilience capacity by 0.018. Lastly, a one standard deviation increase in the social safety net pillar increases households' resilience capacity by 0.009. Access to basic services is negative and statistically insignificant, showing the negligible effect of the adaptive capacity pillar. Across the waves, the observable variables used to construct resilience capacity remain relatively stable. Panel B of Table 4 shows the relationship between the structural model's estimated resilience and food security indicators: (1) women's dietary diversity and (2) per capita consumption expenditure. Following FAO (2016), the coefficient of per capita food consumption expenditure is constrained to unity to make the coefficient of women's dietary diversity interpretable. The results show that a one standard deviation increase in the resilience capacity of households leads to a 1.42 increase in the magnitude of women's dietary diversity. More resilient families have a better women's dietary diversity score. Panel c, Table 4 also reports the indirect effects of the pillars on women's dietary diversity. The results show that the social safety net pillar, the asset pillar, and the adaptive capacity pillars are important variables explaining women's dietary capacity. Panel C, Table 4 shows the goodness of fit statistics which all show that our model (MIMIC) is a good fit for the data.

Table 4: MIMIC model of estimating resilience capacity index

Panel A: Structural component	
Resilience	
Access to Basic Services (ABS)	-0.002*
	(0.001)
Assets (AST)	0.006***
	(0.001)
Adaptive Capacity (AC)	0.018***
	(0.004)
Social Safety Nets (SSN)	0.009***
	(0.002)
Panel B: Measurement component	
	Food consumption expenditure per capita
Resilience capacity index (RCI)	1
	(0.00)
	Women Dietary Diversity Score (WDD)
Resilience capacity index (RCI)	1.426***
	(0.321)
Indirect effects of resilience pillars	
Access to Basic Services (ABS)	-0.003*
	(0.001)
Assets (AST)	0.006***
	(0.0009)
Adaptive Capacity (AC)	0.018**
	(0.004)
Social Safety Nets (SSN)	0.002***
	(0.000)
Panel C: Good-of-fit statistics	
Likelihood ratio	91.42***
Root Mean Square Error of Approximation (RMSEA)	0.097
Prob RMSEA	0
Standardized root mean squared residual (SRMR)	0.034
Coefficient of determination	0.242
Comparative fit index (CFI)	0.65
Tucker-Lewis index (TLI)	-0.049
Observations	3,127

Is there an intra-annual change in resilience?

An important question is whether the resilience capacity index changes across waves and whether households transit from one resilience index to the other. Unlike previous data that relied on annual data, we use the RIMAII approach on high-frequency data collected every two to three months to determine if RIMAII applies to such data. Table 5 shows the t test in the difference of the means of the resilience capacity index between the waves. The resilience capacity between wave one and wave three is statistically significant, while wave one and wave six are statistically insignificant. Lastly, between waves three and six, it is statistically insignificant. Overall, there is a statistically significant reduction in the resilience of households between wave one, conducted in June, and wave three, conducted in September, and then a significant increase in the resilience capacity of families from wave 3 to wave 6. This result explains perhaps the behavior of rural households within the year concerning short-term shocks and short-term coping strategies adopted to cope with the shocks. So households likely recover from some shocks initially experienced within the year.

Table 5: t test results

	Wave 1	Wave 3	Wave 6	t
Resilience capacity index	9.177	9.143		4.360***
	9.177		9.164	1.534
		9.143	9.164	2.880***

Note: the resilience index is defined overtime by having a constant weight but variables used in RIMAII vary at each wave.

To further test these results' consistency, we estimate the MIMIC model separately for each wave and allow the weights and variables used to construct the pillars to vary (Table 6). This differs from the previous scenario were weights are pooled across all the waves and remain constant but the variables vary. The average resilience in all the waves does not deviate substantially from the resilience computed when the weights used to construct the pillars remain constant. The highest resilience index is reported in wave 1, followed by wave 3, and lastly, wave 6. There are also significant differences in the mean resilience between the waves showing that resilience does vary within the short span.

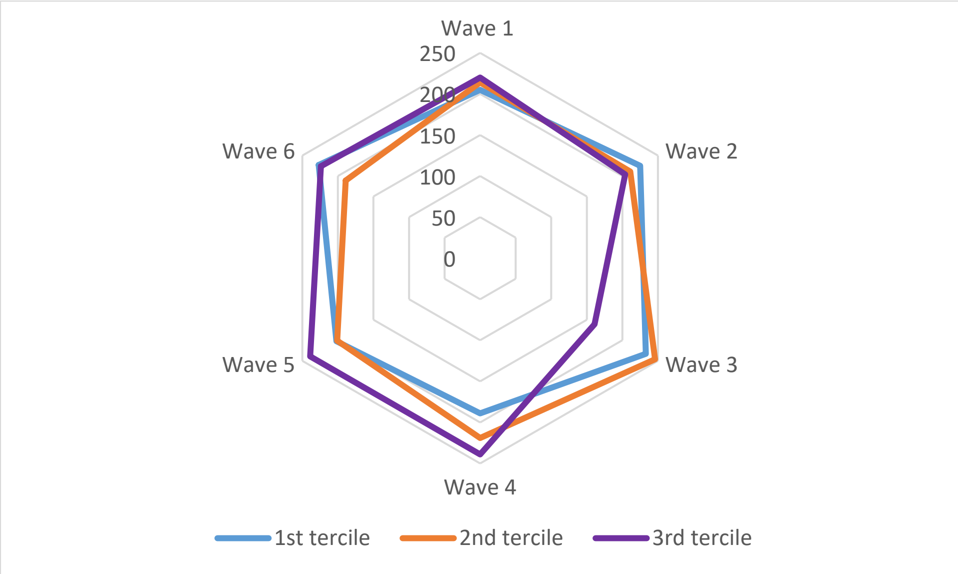
Table 6: t test results of the difference in the average resilience across households

	Wave1	Wave 3	Wave 6	t
Resilience Capacity Index	9.257	9.182		-8.638***
	9.257		9.096	-14.042***
		9.182	9.096	-8.035***

Note: The resilience index is constructed as time-dependent; therefore, the weights and variables used in RIMA II vary at each wave.

Figure 3 shows the changes in the resilience index of households across the waves. Families were equally distributed in the first wave of data collected in June/July 2021 across the first, second and third resilience tertiles. In the second and third waves, most households were in the first and second resilience tertiles, while in the fourth, fifth, and sixth waves, the highest number of families were in the third resilience tertile. The distribution of families across the resilience tertiles in the different waves substantiates the number of shocks reported in the various waves. Fewer shocks are reported in the third, fourth, and fifth waves, and most households in these waves also report doing nothing. In the fourth wave, where most families lie in the third and highest resilience tertile, fewer households also report being affected by drought or irregular rains compared to other waves. The third wave of data collected in December has the lowest proportion of homes in the highest resilience tertile compared to the other waves. This might be associated with the festive season, where households' high demand for improved consumption increases their aspiration for higher income and well-being.

Figure 4: Number of households by resilience terciles across the waves



4.3 Estimating the resilience capacity index using Subjective Self Evaluated Resilience Score (SERS)

Using factorial analysis, we computed a single weighted resilience score from six resilience categories in the literature. These include (1) coping capacity, (2) adaptive capacity, (3) financial capital, (4) social capital, (5) learning, and (6) knowledge and information for two prevalent hazards/shocks that usually occur in the Ugandan context namely: (1) drought and floods and (2) pests and diseases. We compared the computed single-weighted mean resilience score with the Cronbach alpha score, showing a high reliability or internal consistency (Cronbach's alpha value of 0.8585) measure of the resilience concept.

Next, we show that the resilience capacity index measured by the RIMA II for the different waves is closely associated with the resilience score calculated by SERS. Any overlaps, similar associations with relevant drivers of resilience, and similar trends and effects from the variables of interest show similarity in the two measures (Jones & d'Errico, 2019). Figure 5 shows the distribution of scores for RIMA II and SERS. The distribution for SERS scores is much broader than for the RIMA II, a finding similar to Jones & d'Errico, (2019), who also constructed a like-for-like comparison of RIMA II (using cross-sectional data collected for the year) and SERS.

Figure 5: Density scores of RIMA II and SERS scores

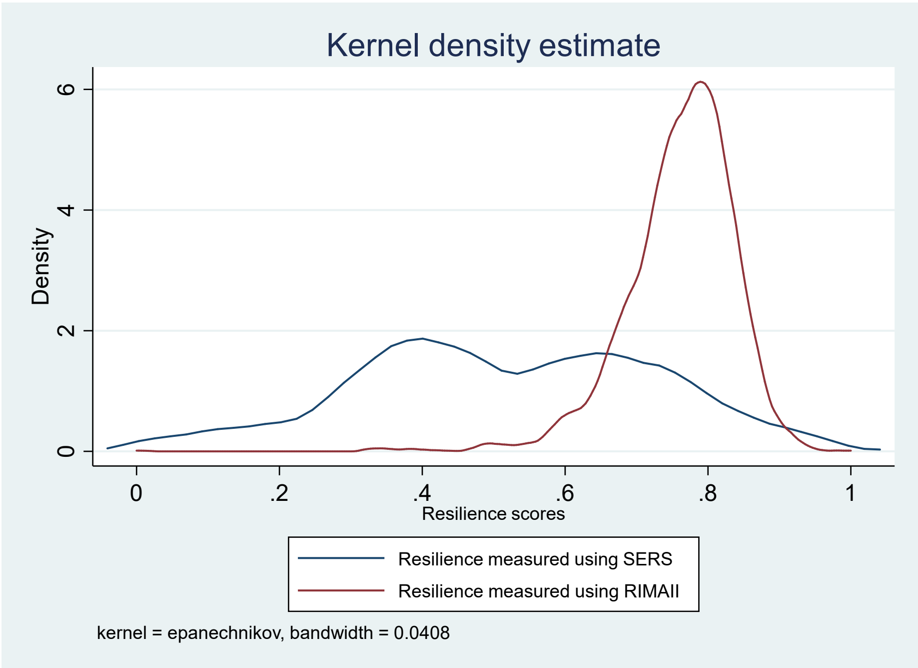


Figure 6 shows a simple association between SERS and RIMA II estimations for resilience. A linear relationship seems apparent; an increase in the RIMA II scores is associated with an increase in SERS. The fitted values and their confidence intervals are more precise at higher RIMA II and SERS levels.

Figure 6: Association between SERS and RIMA II estimations for resilience

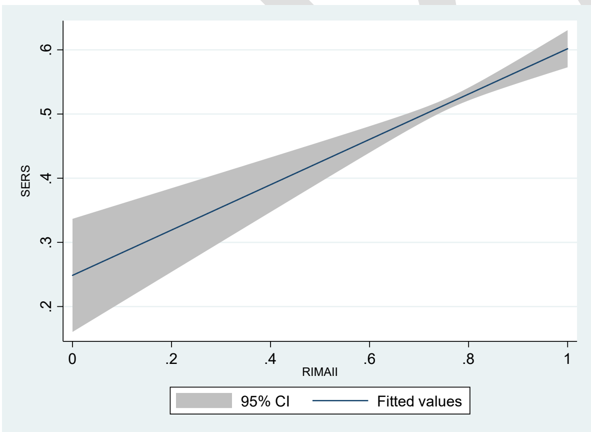


Table 7 shows the correlation matrix of SERS, RIMA II, and the categories of resilience used to construct SERS. There is a positive statistically significant association between the two measures of the resilience of about 13 percent. The RIMA II scores are also correlated to the pillars used to construct SERS within a range of 8 to 11 percent.

Table 7: Correlation matrix of SERS and RIMA II

	RIMA II	SERS	Copying capacity	Adaptive capacity	Finance capital	Social capital
RIMA II	1					
SERS	0.1303 0.000	1				
Copying capacity	0.0788 0.0003	0.551 0.000	1			
Adaptive capacity	0.0684 0.0017	0.6271 0.000	0.3692 0.000	1		
Finance capital	0.1079 0.000	0.65 0.000	0.3717 0.000	0.4375 0.000	1	
Social capital	0.08 0.0002	0.5448 0.000	0.2446 0.000	0.2422 0.000	0.2382 0.000	1

Table 8 compares the socioeconomic drivers of the resilience capacity of households computed from RIMA II and SERS scores using a pooled ordinary least square estimation. The wealth status of the family, the number of livestock units, education level, and the age of the household head are all positively related to resilience. In contrast, the number of dependents, household size, and the distance to the market are negatively associated with resilience. The findings reiterate the focus group discussions that cite ownership of livestock and wealth (ownership of nonagricultural assets like cars and houses) are some of the attributes of resilient households. Households with high resilience to shocks have landed properties, enough livestock, engage in alternative businesses and jobs apart from farming, and are highly educated. Other attributes of highly resilient households include the ability to afford medical bills, the capacity to control pest infestation through spraying pesticides, and paying for children's school fees. Some also use modern agriculture technology, like water tanks and electricity.

Table 8: Socioeconomic drivers of resilience for RIMA and SERS

VARIABLES	(1) RIMAII	(2) SERS
Sex of household head (1=Female)	-0.0155***	0.00602
	(0.00341)	(0.0300)
Marital status (1=Married)	-0.00271	0.00597
	(0.00379)	(0.0262)
Group index	0.0370***	-0.0237***
	(0.00143)	(0.00681)
Total Livestock Units	0.00376***	0.00519*
	(0.000353)	(0.00271)
Wealth index	0.00256***	0.00142
	(0.000159)	(0.00113)
Number of dependents	-0.00383***	-0.0193***
	(0.000962)	(0.00464)
Ownership of agricultural assets (index)	0.0140***	-0.00349
	(0.000779)	(0.00420)
Education level	0.00235***	0.00564***
	(0.000351)	(0.00175)
Age of the household head	0.000432***	0.00164***

	(9.66e-05)	(0.000431)
Distance to the nearest all-weather road?	-0.0112	0.122***
	(0.0105)	(0.0446)
Distance to the nearest agricultural market	-0.0924***	-0.283***
	(0.0170)	(0.102)
Household size	0.00230***	0.0136***
	(0.000653)	(0.00301)
Constant	0.240***	0.440***
	(0.0175)	(0.107)
Observations	2,171	1,263
R-squared	0.618	0.129

Notes: Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1; other control variables include: reported shocks by the households

5.0 Discussions

Resilience reflects the complex dynamic nature of welfare emanating from household exposure to shocks and their responses. Measurements of resilience are aimed at understanding or unpacking the relationship between shocks and well-being measures such as food insecurity. Given that it is unobserved, resilience is challenging to measure and usually proxied by a manifold of variables using qualitative and quantitative approaches. One of the metrics used to measure resilience in several economic literature is the Resilience Index Measurement and Analysis (RIMA) technique introduced by FAO in 2008 and later upgraded to RIMA-II in 2013. Most studies have used the RIMA-II method with annual cross-sectional or annual panel data and not with high-frequency data collected within the year. The main objective of this study was to assess to what extent RIMA II can be used to measure any changes in resilience within short spans in a year.

In this study, households face an array of shocks and stressors that undermine their food security and well-being within two to three months. Some families recover from shocks within the same period and return to their previous well-being. The use of annual data may fail to capture this dynamic tendency. And indeed, our estimation of RIMA-II using high-frequency data reveals the changes in resilience within a short span of six months, where we find statistically significant differences in resilience between the survey waves. The results are consistent when testing these differences using two weighting methods in estimating the resilience capacity index; one that allows for weights to remain constant and another that allows for the weights to be time-variant. The changes in resilience across the waves emanate from changes in resilience pillars such as social networks and assets. Social networks, including groups, are very dynamic as new ones form, old ones perish, or people move in and out of these groups. Findings reveal that social networks, such as membership in groups, are associated with more than a 10 percent reduction n average months of food security .

We find that the resilience scores constructed from RIMA-II are comparable to those estimated using the subjective self-evaluated resilience score used by Jones & d'Errico, (2019) and are backed by the findings from the focus group discussions and in-depth farmer interviews. For example, both approaches showed that the household's wealth status, the number of livestock units, education level, and age of the household head are positively related to resilience. Also, both methods show a positive association. Overall, this study has revealed the possibility of employing the RIMA-II metrics for measuring resilience with high frequency data collected on a two to three monthly basis as a way to understand the dynamic and complex nature of resilience.

6.0 Conclusion

The ability of households to recover from shocks such as drought or a disease pandemic and return to their previous level of well-being- resilience is an important concept given the current global situations of continually occurring shocks, including the Covid-19 pandemic and the Russian-Ukraine conflict. Several debates and discussions have emerged in contemporary literature on the best method, data, and timing to measure it. Studies use different methods and data, including panel and cross-section data and qualitative and quantitative assessment. We contribute to this discussion by using high-frequency data collected in short spans of two to three months. First, we established that the resilience concept does change within short spans in our qualitative and quantitative assessment. Certain pillars used in its construction, such as assets and social networks, will change within the short span, even if others, such as adaptive capacity, may or may not change. Whereas we used a high-frequency data set collected within two to three months, changes in resilience were most noticeable in spans of six months. We, therefore, recommend that researchers and practitioners interested in understanding changes in the resilience concept consider using six months duration. We also found overlaps in measuring resilience using RIMA II and methods such as the subjective self-evaluated resilience score measure resilience. The study shows complementarities in using qualitative and quantitative approaches to understand the complex dynamic definition of resilience.

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