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Building Resilience in Conflict Areas: Quasi-experimental Evidence from Borno State in North-east Nigeria

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Abstract
This paper provides novel evidence on the impacts of agricultural support programs in acute emergency settings, by studying resilience in mostly rural areas in the context of a multi-package intervention in conflict-affected Borno State, North-east Nigeria. We account for the challenging research environment in this insecure setting by carefully adapting our research design, thus generating empirical evidence on what works in areas previously considered off-limits to rigorous research designs. Combining a quasi-experimental design with unique panel survey data and fine-grained conflict event data, we find that resilience impacts are highly heterogeneous based on local conflict intensity during and after the implementation of the intervention. Our results suggest that even when local violence is high, programs can provide strong and much needed support for resilience, primarily by strengthening social safety nets and food security.

Keywords
Armed conflict, social protection, resilience, food security, emergency

JEL Classifications
D74, I32, I38, O12, Q18

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1 Introduction

How can we build resilience in places where people need it the most? Individuals and households in crisis settings face multiple adversities and constraints (Dercon, 2008; Justino, 2012a; Haushofer and Fehr 2014; Verwimp, et al., 2019). In these circumstances, human capabilities (such as agricultural skills) and non-human capabilities (such as agricultural assets) are often complements, and if both are below what is needed for positive change and equilibria, boosting one form of capabilities alone may not improve resilience. Therefore, it has now become apparent that effective support in crisis settings requires “much more than food aid” (Barrett, 2006: p. 1) and that multi-faceted interventions are needed to lift people effectively and sustainably out of hunger (Barrett et al., 2019; Buera et al., 2019; Malik et al, 2020; d’Errico et al., 2021).

In addition, the vast majority of people in crisis settings depend on agriculture. For example, up to 80 percent of people suffering or at risk of severe hunger rely directly on the agricultural sector for their livelihoods and survival (FAO, 2018). Accordingly, policies in crisis settings have moved to multifaceted agricultural interventions, bridging traditional programming divides, and bringing together humanitarian and development funds and actions at the Humanitarian-Development-Peace (HDP) nexus. However, quantitative micro-level evidence on the impacts of these interventions on behaviors and welfare remains scarce, in part because conducting rigorous empirical research in insecure settings can be challenging (Puri et al., 2017; Kayaoglu et al., 2023a,b).

We contribute to filling these methodological and knowledge gaps by studying resilience in North-east Nigeria, an acute humanitarian, development, and conflict crisis setting. Specifically, we estimate the resilience impacts of a complex agricultural intervention in Borno State, which was designed to protect and support individuals in the active conflict situation. The intervention was implemented as a Joint Action Programme by the Food and Agriculture Organization of the United Nations (FAO), UN WOMEN and the World Food Programme (WFP).

Since 2009, North-east Nigeria has been affected by extreme violence between armed groups and against civilians, primarily due to the emergence of the Boko Haram insurgency. The violent conflict has disrupted social networks, social cohesion, and value chains, and caused conflict-induced forced displacement, which puts already fragile host communities under additional stress. Specifically, measures adopted by the Government to contain violence (such as the prohibition to engage in certain types of agricultural activities), and fears of attacks and abduction have prevented farmers from working in their fields, leading to reduced harvests, incomes, and welfare. Combined with a fragile natural environment and volatile climate and weather conditions, these extreme forms of adversity have sharply increased the population's vulnerability and risks of food and nutrition insecurity, especially in remote areas. For 2022, the Cadre Harmonisé analysis estimated that more than fourteen million people were in critical states of food insecurity in Nigeria (CH, 2022).

The objective of the Joint Action Programme was to support the resilience of such conflict-affected people in Borno state. Specifically, the program aimed to provide people with the means to resume agriculture-based and other environment-friendly livelihoods, thereby allowing them to progressively sustain their own food and nutritional needs, which is building their resilience. To achieve these goals, the program delivered a multi-package intervention providing emergency assistance, asset provision, and skills training. The packages were designed to mitigate negative impacts of crisis stressors by investing in four key resilience dimensions: access to basic services, access to assets, social safety nets, and adaptive capacity. Interestingly, the Joint Action Programme was delivered at a time of ongoing violence in Borno State.

For the empirical analysis, we use a quasi-experimental design and combine unique panel survey data collected over a period of three years amidst an on-going violent conflict with local conflict event data. We analyze two waves of individual panel survey data collected based on a stratified, two-stage random sampling procedure. The baseline data were collected in July–August 2018, before the start of the intervention. The intervention took place from October 2018 to December 2019. The endline data were collected in December 2021, two years after the end of the intervention. The data in each wave were collected from program beneficiaries in Local Government Areas (LGAs) where the intervention was implemented and non-beneficiaries in comparable LGAs where the intervention was not implemented. We spatio-temporally match the panel survey data with conflict event data from the Armed Conflict Location & Event Data Project (ACLED), which allows us to assess conflict intensity at the local level at different points in time. Based on this setup, we estimate impacts of the support program on resilience using difference-in-difference and panel techniques, with a particular focus on the role of local conflict intensity in shaping program impacts and resilience outcomes.

Using these methods, we find that resilience impacts of the agricultural support program are highly heterogeneous based on the security situation and conflict intensity during and after the implementation of the intervention. We provide evidence that even when local conflict intensity is high, programs can still provide strong and much needed support for resilience, primarily by strengthening social safety nets and food security.

Our study makes two interconnected academic contributions. First, the paper contributes to the academic literature on the determinants of resilience and food security in crisis settings (Brück and d'Errico, 2019; Martin-Shields and Stojetz 2019; Shemyakina, 2022). Due to methodological and ethical challenges, most rigorous evidence on resilience outcomes and program effectiveness comes from non-conflict settings. A few recent studies quantify food security and the positive impacts of cash and food transfers in the context of large-scale interventions in poor and fragile contexts. These include experimental comparisons of different transfer modalities against each other (Schwab, 2019, 2020) and quasi-experimental comparisons against the counterfactual of receiving no transfer (Tranchant et al., 2019; Ecker and Maystadt, 2021). Bedoya et al. (2019) provide evidence from a small, randomized experiment that the new class of multifaceted interventions can significantly support the "ultra-poor" in a fragile setting (Afghanistan). Recent quasi-experimental studies of agricultural interventions in conflict settings focus on net program impacts (Malik et al., 2020; Baliki et al., 2018; Baliki et al., 2021; Kayaoglu et al., 2023a). Our study provides high-quality evidence on resilience and on the impact pathways of a large-scale agricultural multifaceted intervention in the midst of one of the world's most intense and complex conflict and emergency situations (North-east Nigeria).

Second, our paper adds to the growing literature on the microeconomic impacts of conflict. While the literature has made great strides in measuring households' and individuals' conflict exposure and its consequences (Brück et al., 2016; Verwimp et al., 2019; Vesco et al., 2024), the impacts of conflict on program effectiveness are very little understood (Weiffen et al., 2022). We provide novel evidence on the role of local conflict intensity and how it shapes program impacts and resilience outcomes in a high-intensity conflict setting.

Our findings are of particular policy interest as we study a dominant class of support programs in fragile contexts: multifaceted agricultural interventions (see above). Specifically, our findings can help policymakers and practitioners to design and implement interventions at the humanitarian–development–peacebuilding nexus that are more evidence-based, efficient and effective (Puri et al., 2017; Kayaoglu et al., 2023b).

The rest of the paper is organized as follows. Section 2 provides information on the study background. Section 3 outlines the research design. Section 4 presents and discusses the results. Section 5 provides concluding remarks.

2 Study background

Since 2009, Boko Haram has triggered bouts of violence in North-east Nigeria. The conflict has devastated agricultural livelihoods in several ways, including livestock losses, reduced access to fishing grounds, destruction of irrigation and farming facilities, the collapse of extension services and key agriculture-based value chains. Losses caused by Boko Haram imposed levies on transported production, market, and trade facilities (including fish markets), and reduced production due to mass displacement and limited access to markets.

Multiple factors contribute to the conflict in North-east Nigeria. The North-East Nigeria Recovery and Peace Building Assessment (RPBA) highlights the social, political, economic, and environmental drivers of the crisis (World Bank, 2015). Weak systems of governance are a driver of conflict and a constraint on effective responses to both conflict and displacement. Limited government support, poor management, and limited access to innovative technologies and inputs have contributed to erode rural livelihoods in agriculture, pastoralism, and fisheries. In addition, the lack of employment and livelihood opportunities is a possible 'push factor' towards violence, especially for young people. The fragility of the natural environment also undermines food security and causes social tensions.

Borno State has faced escalating levels of insecurity which led to massive population movements and food insecurity combined with human, social and economic losses. According to the International Organization for Migration (IOM), Borno is Nigeria's State most affected by conflict-related displacements as of August 2020, and still is today (IOM, 2020; IOM, 2022). In 2020, the IOM estimated that out of a total of 2,118,550 Internally Displaced People (IDPs), 1,566,011 of them (74 percent) were in Borno State. The steady increase in IDP numbers in Borno State and the high number of inaccessible LGAs in the state indicate that the humanitarian situation is continuously deteriorating.

As a result and in summary, lives and livelihoods in North-east Nigeria have been subject to a variety of serious challenges for years (Baliki et al., 2018; Ekhator-Mobayode et al., 2022; Stojetz and Brück, 2023a; Stojetz et al., 2024).

3 Research design

To study the impacts of the Joint Action Programme on resilience (see Online Appendix A.1), we use a quasi-experimental identification design, based on unique panel survey data collected over a period of three years, and spatio-temporally matched conflict event data.

3.1 Survey data

The baseline and endline surveys were fielded, respectively, in July–August 2018 and December 2021. The surveys were based on a comprehensive questionnaire, including standard modules on socio-demographic and socio-economic variables, but also on self-reported exposure to violence and other shocks. Specifically, the survey data by design allow to calculate state-of-art measures of food security and resilience.

Experimental studies based on random assignment to treatment is often considered the gold standard for program impact evaluation. However, designing and conducting a fully experimental impact evaluation in an acute emergency entails several ethical and operational challenges and was indeed not possible in this context. The beneficiaries were selected based on predetermined criteria to ensure targeting the households that needed assistance the most, and that would be able to appropriate the most the benefits of the project. Participants were selected according to the following criteria (partly based on the nature of support activities to be implemented and partly based on the nature of the intervention[1]): (i) having secure access to land; (ii) being able to engage in food processing, agribusiness or other income-generating activities; (iii) being able to cultivate a plot with the kits received; (iv) having access to a good source of water; (v) having access to livestock grazing land and space (for IDPs and returnee households); (vi) being engaged in livelihood or agro-pastoralism activities; (vi) being engaged in fishing activity; (vii) being engaged in agribusiness (for vulnerable

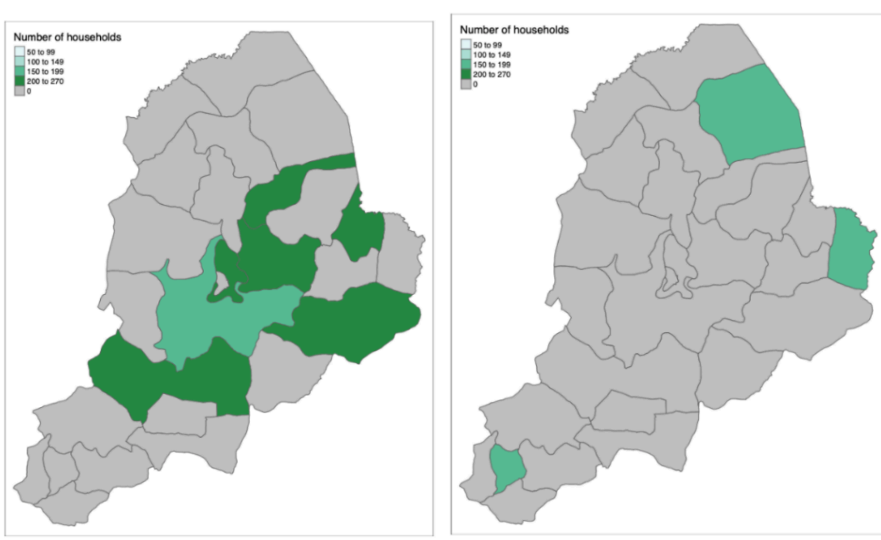
[1] In fact, each area of the intervention was associated with one of these characteristics, i.e. support for entrepreneurship and SME was part of the greater employment and economics opportunities area.

female-headed households). Furthermore, priority was given to beneficiaries of WFP programs or other food/cash assistance programs, female- and youth-headed households, households with a high dependency ratio, households with children under 5 years old and elderly, and households with presence of malnourished children. In addition, random selection of the households to receive support may exacerbate tensions in a context already affected by intense conflict.

Yet, there was scope for a quasi-experimental impact evaluation design. As part of the design, not only households in treated villages were surveyed, but also households in control villages from adjacent LGAs. Both groups were to be surveyed both before and after the intervention. The endline survey was conducted in December 2021, which means that we study program impacts two years after the end of the intervention. To ensure the statistical power of the panel dataset is sufficiently high to conduct the impact evaluation, and accounting for attrition, non-response rate and matching techniques, the baseline sample size was set at 2,049 households. These include 1,532 treatment and 517 control households. Figure 1 shows the spatial distribution across LGAs. Treatment households from seven LGAs were surveyed in Bama, Damboa, Jere, Konduga, Mafa, Monguno, and Ngala. Control households reside in the three LGAs of Kala/Balge, Kukawa and Kwaya Kusar.

Figure 1. Spatial distribution of baseline sample (across LGAs)

a) Treatment **b) Control**



Within treatment and control LGAs, households were selected into the survey through Probability Proportional to Size (PPS) techniques and a two-stage random sampling procedure. In the first stage, villages (Primary Sampling Units – PSU) were randomly selected for each LGA. In the second stage, households were randomly selected from each PSU. The sampling design was based on (i) the situation of food insecurity with reference to the Cadre Harmonisé (CH) classification, (ii) the coverage of the project (i.e., whether the intervention was implemented or not in an area), and (iii) the presence of IDPs. The surveys were based on Computer Assisted Personal Interviewing (CAPI), using digital tablets to conduct the interviews. In the endline survey, a significant share of households could not be re-interviewed. Table 1 reports the sample size for the two rounds of data collection. The total "attrition" rate is 37 percent from baseline to endline and is higher among the control group (49 percent) than among the treated (32 percent). We provide a detailed discussion of attrition in Section 3.5 below.

Table 1. Sample size (households)

	Baseline	Endline	Panel
Treatment	1,532	1,040	1,040
Control	517	253	253
Total	2,049	1,293	1,293

3.2 Resilience

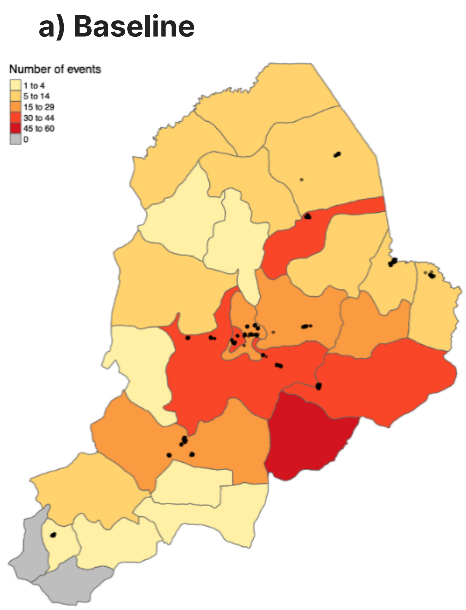
We follow Constas et al. (2014) to define resilience as "a capacity that ensures stressors and shocks do not have long-lasting adverse development consequences". Based on the survey data, we measure resilience via the Resilience Capacity Index (RCI) following FAO's Resilience Index Measurement and Analysis (RIMA) methodology (FAO, 2016a). Following the RIMA methodology, we calculate the RCI as our main outcome variable, which is an index score ranging from 0 (worst) to 100 (best). In Online Appendix A.2 we explain the RIMA methodology in detail and provide a full overview of all the variables used to calculate the RCI (Table A.1).

3.3 Conflict events

We spatio-temporally match the survey data with conflict event data from the Armed Conflict Location & Event Data Project (ACLED), using detailed geo- and time-tagged information on events of violence (Raleigh et al., 2010). Events reported by ACLED include various forms of violence, and we calculate local violence measures for multiple spatial and temporal horizons. Spatially, we calculate exposure at the LGA level, as well as in radii of 5, 25 and 50km from surveyed households. Temporally, we consider periods of 3, 6, 12 and 60 months prior to the baseline and endline surveys.

Figure 2 illustrates the distribution of conflict events at the LGA level that occurred in the 12 months before the baseline and endline surveys. The maps demonstrate that the whole region of North-east was affected by ongoing conflict, with varying intensity.

Figure 2. Spatial distribution of conflict events (across LGAs)

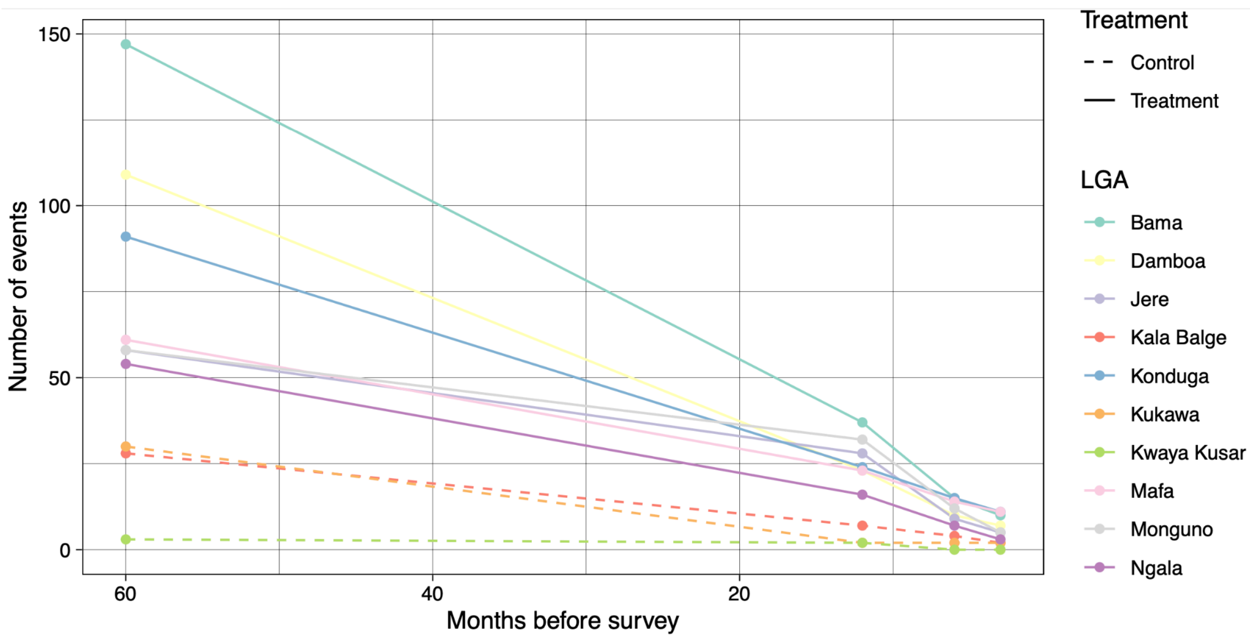


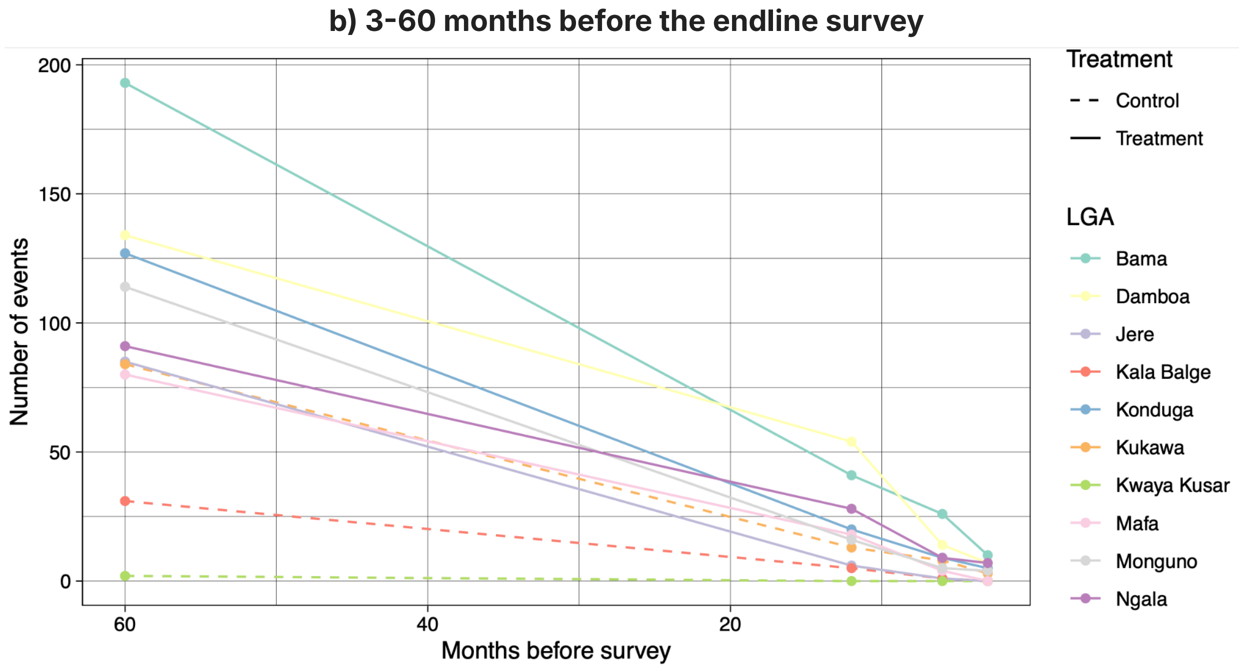
Note: Based on data from the Armed Conflict Location & Event Data Project (Raleigh et al., 2010). The black dots denote the location of surveyed households for the full sample (N = 2,049).

In Figure 3, we focus on different time periods and plot the cumulative number of conflict events that occurred in each surveyed LGA before the baseline and endline surveys. The graphics illustrate three important insights. First, before the baseline survey, control LGAs experienced consistently lower conflict intensity than treatment LGAs. This holds for any period ranging from 3 to 60 months before the baseline survey. Second, in the time during and after the intervention, conflict events were more prevalent than before the baseline. Third, these events were widespread and control LGAs were more comparable to treatment LGAs in terms of conflict events.

Figure 3. Cumulative number of conflict events at the LGA level

a) 3-60 months before the baseline survey





Note: Based on data from the Armed Conflict Location & Event Data Project (Raleigh et al. 2010) for the full sample (N = 2,049).

3.4 Baseline statistics

Table 3 provides descriptive statistics on resilience outcomes at baseline.

Table 3. Resilience at baseline (full sample)

	Mean	S.D.	Min.	Max.	N
Resilience and pillars					
RCI	43.96	19.05	0	100	2049
P1: Access to basic services (ABS)	-0.00	1.01	-1	29	2049
P2: Assets (AST)	0.00	1.04	-1	13	2049
P3: Adaptive capacity (AC)	-0.00	0.99	-2	4	2049
P4: Social safety nets (SSN)	0.00	1.79	-13	18	2049
P1: Access to basic services					
Improved sanitation	0.76	0.43	0	1	2049
Closeness to water source	0.25	0.79	0	10	2049
Closeness to school	0.11	0.19	0	3	2049
Closeness to hospital	0.11	0.46	0	10	2049
Closeness to agricultural market	0.10	0.44	0	10	2049
Closeness to livestock market	0.08	0.47	0	20	2049
P2: Access to assets					
Wealth index	0.14	0.12	0	1	2049
Agricultural wealth index	0.04	0.08	0	1	2049
Tropical Livestock Unit (TLU)	0.18	0.61	0	10	2049
Land	1.07	2.17	0	29	2049
House value	1304.09	2016.54	0	11080	2049
P3: Social safety nets					
Credit (value) per capita	2.69	10.07	0	172	2049
Formal transfers (value) per capita	0.00	1.00	-1	13	2049
Strategies relying on informal network(s)	3.50	4.11	0	28	2049
Associations	0.37	0.64	0	6	2049
P4: Adaptive capacity					
Average years of education	4.33	5.12	0	19	2049
Share of active members	0.50	0.21	0	1	2049
Number of income generating activities	1.86	1.10	0	6	2049
Participation in training	0.09	0.29	0	1	2049
Number of crops	0.90	1.22	0	10	2049
Food security					
HDDS	6.49	2.37	1	12	2049
Food expenditure per capita	10.71	9.49	0	116	2049

*Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Full sample (N = 2,049).*

Overall, the Resilience Capacity Index (RCI) did not differ significantly between control (mean RCI = 44.56) and treatment households (mean RCI = 43.75) at baseline (Table 4). The standardized indices for the four pillars of the RCI did not differ significantly, either, except for access to basic services (ABS), which is slightly higher in the treatment group. Yet, among the variables underpinning the ABS pillar, differences were very modest in magnitude.

Table 4. Resilience at baseline by group (full sample)

	Control	Treatment	Δ
Resilience and pillars			
RCI	44.56	43.75	0.81
P1: Access to basic services (ABS)	-0.12	0.04	-0.16***
P2: Assets (AST)	-0.03	0.01	-0.05
P3: Adaptive capacity (AC)	0.02	-0.01	0.02
P4: Social safety nets (SSN)	-0.05	0.02	-0.07
P1: Access to basic services			
Improved sanitation	0.74	0.77	-0.03
Closeness to water source	0.19	0.27	-0.08**
Closeness to school	0.08	0.12	-0.04***
Closeness to hospital	0.08	0.12	-0.03
Closeness to agricultural market	0.07	0.11	-0.04*
Closeness to livestock market	0.07	0.09	-0.02
P2: Access to assets			
Wealth index	0.15	0.14	0.00
Agricultural wealth index	0.03	0.04	-0.00
Tropical Livestock Unit (TLU)	0.24	0.16	0.08**
Land	0.72	1.19	-0.46***
House value	1291.12	1308.55	-17.43
P3: Social safety nets			
Credit (value) per capita	2.99	2.58	0.40
Formal transfers (value) per capita	-0.17	0.06	-0.23***
Strategies relying on informal network(s)	2.58	3.82	-1.24***
Associations	0.30	0.39	-0.09***
P4: Adaptive capacity			
Average years of education	4.87	4.15	0.72***
Share of active members	0.50	0.50	-0.00
Number of income generating activities	1.76	1.89	-0.13**
Participation in training	0.10	0.09	0.02
Number of crops	0.83	0.93	-0.10
Food security			
HDDS	6.63	6.44	0.19
Food expenditure per capita	9.91	10.98	-1.07**

*Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Full sample (N = 2,049).*

By contrast, the conflict event data suggest that the control and treatment groups differed significantly in terms of the conflict exposure. Consistent with Figure 3, treatment households were exposed to significantly more conflict events, measured at the LGA level. We observe that the same also holds for measures based on households' precise location, using multiple radii and multiple time periods.

Table 5. Event-based conflict exposure at baseline by group (full sample)

	Control	Treatment	Δ
A: LGA level			
Conflict events (3 months): LGA	1.38	7.14	-5.76***
Conflict events (6 months): LGA	2.03	11.50	-9.47***
Conflict events (12 months): LGA	3.62	25.89	-22.27***
Conflict events (60 months): LGA	21.00	80.55	-59.54***
B: Radius 5km			
Conflict events (3 months): r < 5 km	0.53	2.79	-2.27***
Conflict events (6 months): r < 5 km	1.23	5.20	-3.96***
Conflict events (12 months): r < 5 km	2.67	13.13	-10.46***
Conflict events (60 months): r < 5 km	15.99	42.11	-26.12***
C: Radius 25km			
Conflict events (3 months): r < 25 km	1.67	8.74	-7.08***
Conflict events (6 months): r < 25 km	2.50	13.69	-11.19***
Conflict events (12 months): r < 25 km	4.73	34.11	-29.38***
Conflict events (60 months): r < 25 km	24.50	129.50	-105.00***
D: Radius 50km			
Conflict events (3 months): r < 50 km	4.65	20.26	-15.61***
Conflict events (6 months): r < 50 km	7.45	33.41	-25.96***
Conflict events (12 months): r < 50 km	17.55	73.63	-56.08***
Conflict events (60 months): r < 50 km	79.57	278.60	-199.04***

*Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Full sample (N = 2,049).*

When we draw on the survey data on self-reported shocks and violence exposure, a different picture emerges. It appears that on the ground households from the two groups experienced similar levels of recent shock exposure, both in terms of the total number of shocks experienced (about one for each group) as well as in the likelihood of having experienced any shock (37 percent among control households and 33 percent among treatment households) (Table 6). When asked very broadly about having been exposed to conflict-related violence, we find no statistically significant difference between the treatment and control groups. Twenty-two percent of treatment households report such exposure compared to 19 percent in the control group.

Similarly, differences in the extent and likelihood of violence exposure (as measured by self-reported answers to the survey module) are statistically significant but very modest in magnitude. The mean reported number of total experiences of events of violence was .6 in the control group versus .8 in the treatment group. It is worth noting that subjective answers on personal exposure may suffer from underreporting. Yet, it seems unclear why the extent of underreporting would differ systematically across the control and treatment groups, leaving the tested differences largely unaffected.

The designated control and treatment households also differed only slightly in demographic outcomes and self-reported shock exposure (Table 6). For example, the average households in the two groups did not differ in terms of sex of the head, household size or the number of children. About 18 percent of households were headed by a female and the mean household had about 6.5 members, including 3.3 children. Treatment households were slightly more likely to be IDP households (49 percent among treatment versus 40 percent among control households) and to be farmers (75 percent among treatment versus 67 percent among control households), but the magnitudes of these differences are rather modest. Notably, only about one in five households reported having experienced a conflict-related violence shock with no significant difference between the treatment and control groups.

Table 6. Demographics and shock exposure at baseline by group (full sample)

	Control	Treatment	Δ
A: Household characteristics			
Female household head	0.17	0.18	-0.01
IDP household	0.40	0.49	-0.10***
Returnee household	0.27	0.34	-0.07***
Household size	6.47	6.51	-0.04
Number of children	3.31	3.29	0.03
Farming household	0.67	0.75	-0.07***
B: Shock exposure indices			
Shocks (any)	0.37	0.33	0.04*
Shocks (total)	1.07	1.11	-0.04
C: Shock exposure items (self-reported)			
Drought	0.11	0.17	-0.06***
Flood	0.00	0.01	-0.00
Water shortage	0.20	0.20	0.01
Crop disease	0.09	0.08	0.01
Livestock disease	0.01	0.02	-0.00
High prices for agric. inputs	0.01	0.04	-0.03***
Low prices for agric. outputs	0.01	0.00	0.01**
Illness/accident of earner	0.01	0.04	-0.03***
Illness/accident of non-earner	0.07	0.07	0.00
Death of household member	0.11	0.15	-0.03*
Theft of of money / non-agric. assets	0.02	0.06	-0.03***
Theft of agric. assets or output	0.01	0.05	-0.04***
Conflict/violence	0.22	0.19	0.03
Fire	0.17	0.03	0.13***
Other shock	0.01	0.02	-0.00

*Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Full sample (N = 2,049). The recall period for shock exposure is 12 months.*

In Table 7, we report the results from the specific module on experiences of conflict-related violence. Self-reported exposure to violence is slightly higher among treatment households, but the overall levels of exposure are low, and the differences are not sizable. In both groups, the average household experienced less than one out of eight probed forms of violence exposure (a total mean number of .61 in the control group versus .81 in the treatment group). 58 percent of households in the treatment experienced any (probed) form of conflict-related violence, and 48 percent of control households. In addition, across the eight items differences between the two groups are small in magnitude. While some differences are statistically significant, they are small in magnitude both for the items and for the index measures.

Table 7. Violence exposure at baseline (full sample)

	Control	Treatment	Δ
A: Indices			
Violence exposure (any)	0.48	0.58	-0.10***
Violence exposure (total)	0.61	0.81	-0.20***
B: Items (self-reported)			
Not feeling safe	0.23	0.27	-0.04*
Goods or property stolen	0.06	0.12	-0.06***
Threatened with violence or death	0.00	0.04	-0.04***
Been evicted from land	0.01	0.04	-0.02***
Denied access to farmland or pasture	0.06	0.04	0.02**
Witnessed violence	0.18	0.22	-0.04*
Being injured in violence	0.01	0.04	-0.03***
Household member injured or killed in conflict	0.05	0.05	-0.00

*Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Full sample (N = 2049).*

The comparisons based on the full sample of treatment and control households at baseline are important from a "program design perspective". In practice, much of our analysis will focus on the panel sample, for which we have observations at both baseline and endline. To that end, we also present key balance statistics for treatment and control households in the panel sample in Online Appendix Table A2. Overall, the comparisons are very similar to those using the full baseline sample, including household characteristics, shock exposure and exposure to local conflict events. Notably, in the panel sample the difference between treatment and control household in mean resilience is statistically significant (44.2 versus 49.3). Yet, as for the full sample, the sign of the difference varies across resilience dimensions and the overall difference in the RCI is small in size (4.9) given that the RCI has a large standard deviation of about 19 (Table 1).

3.5 Attrition

Due to the large attrition in our sample, it is important to understand the underlying causes. Conflict settings inherently cause forms of "attrition" that is different in nature from attrition in the usual statistical sense that individuals or households actively decide to leave the sample. In our case, the chief reason for the lower response rate at endline was not households actively "dropping out" but that several areas were not deemed safe to access. This was especially the case for several control communities, which were increasingly targeted by Boko Haram attacks. The conflict event data at the LGA level displayed in Figure 3 demonstrates an increase in violence before the endline in two of the three LGAs where control households were surveyed, namely Kala/Balge and Kukawa. In Kala/Balge, 49 percent of control households could not be re-interviewed at endline, and 71 percent of control households in Kukawa. By contrast, the treatment LGAs of Bama, Damboa and Konduga experienced high levels of conflict intensity but households could be surveyed. Within LGAs, non-responses were highly clustered geographically as illustrated by the "disappearance" of clusters (black dots) when comparing the spatial distribution of households locations in Figure 2. Table 8 provides the full LGA-level breakdown of the baseline and endline survey samples.

Table 8. Baseline and endline sample breakdown by LGA (households)

LGA	2018		2021	
	Treatment	Control	Treatment	Control
Bama	200	0	164	0
Damboa	205	0	146	0
Jere	200	0	149	0
Kala/Balge	0	170	0	86
Konduga	195	0	153	0
Kukawa	0	192	0	56
Kwaya Kusar	0	162	0	113
Mafa	201	0	129	0
Monguno	251	0	162	0
Ngala	266	0	135	0

Note: Full sample (N = 2049).

Thus, there is the important statistical issue of control households in high-intensity conflict areas that could disproportionately not be surveyed at the endline. Therefore, the probability that a household was not re-interviewed at the endline is significantly correlated with treatment status (Table 9). There is also a slight difference in resilience where households who could not be surveyed at the endline were less resilient on average (mean RCI values of 41.5 versus 45.4). Looking at households' characteristics, we find that self-reported exposure to conflict is 53 percent higher among households that could not be surveyed at endline (23 percent reporting exposure) compared to those that could be surveyed (15 percent reporting exposure). Also, households that were not re-interviewed are also slightly larger and have more children. While some of the differences in demographic outcomes, shock and violence exposure are statistically significant, overall very modest, both in terms of magnitude. We thus conclude that the observed strong attrition was systematic with respect to treatment status, but it was primarily due to factors beyond households' control and socio-economic characteristics, primarily their location.

Table 9. Attrition and baseline characteristics

	Not in endline	In endline	Δ
A: Resilience and treatment			
Treatment	0.64	0.80	-0.16***
RCI	41.54	45.37	-3.83***
B: Household characteristics (baseline)			
Female household head	0.19	0.16	0.03*
IDP household	0.46	0.47	-0.01
Returnee household	0.40	0.28	0.12***
Household size	5.93	6.84	-0.91***
Number of children	3.01	3.46	-0.46***
Farming household	0.70	0.74	-0.04**
C: Shock exposure (baseline)			
Shocks (any)	0.36	0.32	0.04*
Shocks (total)	1.02	1.15	-0.13***
Drought	0.11	0.18	-0.07***
Flood	0.00	0.01	-0.00
Water shortage	0.21	0.19	0.02
Crop disease	0.08	0.08	-0.01
Livestock disease	0.01	0.02	-0.00
High prices for agric. inputs	0.03	0.04	-0.01
Low prices for agric. outputs	0.01	0.00	0.00
Illness/accident of earner	0.03	0.03	-0.00
Illness/accident of non-earner	0.07	0.07	-0.01
Death of household member	0.14	0.14	0.00
Theft of of money / non-agric. assets	0.04	0.05	-0.00
Theft of agric. assets or output	0.04	0.04	0.00
Conflict/violence	0.15	0.23	-0.07***
Fire	0.09	0.06	0.03***
Other shock	0.01	0.02	-0.01
D: Violence exposure (baseline)			
Violence exposure (any)	0.55	0.56	-0.01
Violence exposure (total)	0.72	0.79	-0.07*

*Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Full sample (N = 2049).*

In summary, our impact analysis faces important challenges due to potential selection biases. First, control households resided in different LGAs than treatment households, and treatment households' LGAs had witnessed more conflict events, as measured by conflict event data at the LGA level. However, our detailed survey data suggests that in terms of personal background and vulnerability the two groups were similar at baseline, including in terms of resilience, demographic, shock, and violence exposure. On the other hand, attrition is very prevalent in our sample and significantly higher among the control group, primarily due to control households in high-intensity conflict areas that could not be surveyed. Thus, our data suggest that not being interviewed at endline was primarily determined by inaccessibility (and thus contextual factors) and not systematically related with personal characteristics and vulnerability.

3.6 Identification strategy

To assess program impacts, we employ a difference-in-differences approach by estimating fixed-effects models. In our main specifications, we exploit the panel structure of our data and estimate models for household *i* given by:

$$y_{it} = \gamma_i + \gamma_t + D_{it}\delta \ (+ \ z_{it}\beta) + \varepsilon_{ist} \qquad (4)$$

Where y_{it} is a resilience outcome household *i* at time *t* (i.e., RCI, pillars, food security indicators and resilience variables), γ_i denotes household-level fixed effects, γ_t denotes time fixed effects, D_{it} is the program treatment indicator, z_{it} is a flexible vector of time-varying control variables, and ε_{ist} is the error term. In the main specifications, standard errors are clustered at the household level to be as conservative as possible.

We take several measures to address potential selection biases. To start with, the fixed effects structure in our panel models allows us to control for unobserved time-invariant heterogeneity. We also estimate several models using matching techniques based on pre-treatment characteristics as a robustness check, including inverse-probability-weighted regression adjustment (IPWRA) and doubly robust difference-in-difference (DRDiD) estimators. Our identifying assumption is the parallel trends assumption that, in the absence of the intervention, the resilience capacity index would be similar across treated and untreated households.

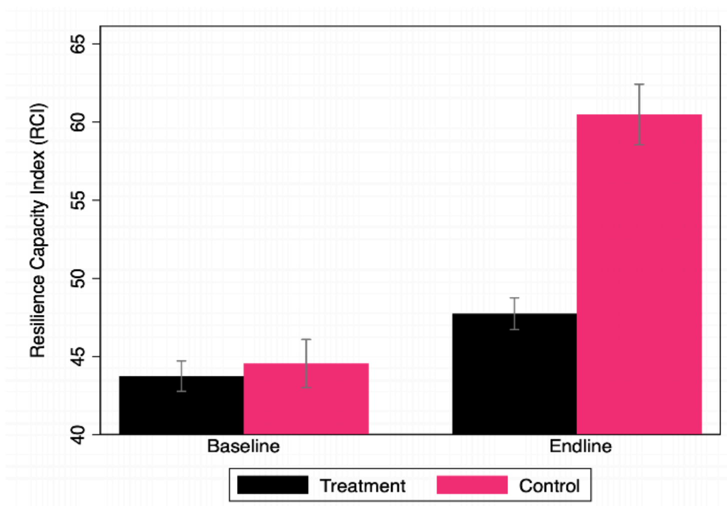
As we saw earlier, treatment status is likely correlated with conflict exposure. At the same time, conflict exposure usually strongly affects resilience capacity, which raises endogeneity concerns when estimating program impacts. Therefore, we will pay careful attention to conflict intensity during and after the intervention and specifically focus on impact analyses between control and treatment groups that both reside in areas that were affected by intense conflict before the endline survey.

4 Results

4.1 Basic impacts on resilience

Basic comparisons of resilience over time suggest that resilience increased for treated households (Figure 5). The mean resilience capacity slightly improved by 7 percent among treated households, from 44.4 at baseline to 47.6 at endline, and this difference is statistically significant at the 99% confidence level. However, we observe that at the same time there was a much stronger increase in resilience for control households, from 49.3 at baseline to 60.9 at endline (a 24 percent increase). As shown in

Figure 5. Resilience capacity at baseline and endline (full sample)

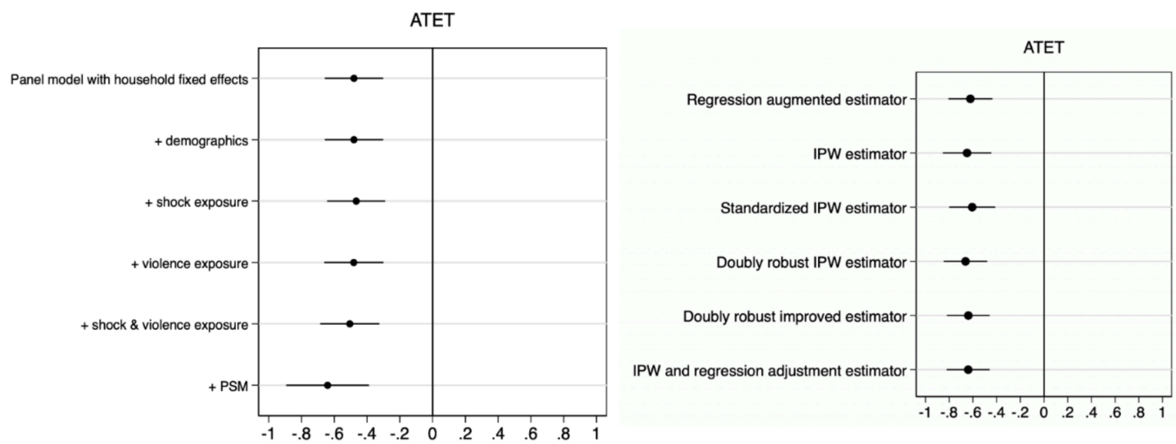


Note: 95% confidence intervals. Full sample (N = 2,049).

The seemingly negative impact of the intervention is confirmed by various panel estimators. The basic difference-in-difference model based on household-level fixed effects estimates a negative ATET on RCI of about .4 standard deviations (see Figure 6). This result is robust to the inclusion of various time-varying control variables, including demographic, self-reported shock exposure, and self-reported violence exposure variables, as well as propensity score matching based on pre-treatment demographics and exposure to shocks. As shown in Figure 6, the same result holds for other panel estimators using other matching algorithms.

Figure 6. Estimates of program impact from various models

a. Basic panel estimators **b. Additional matching estimators**



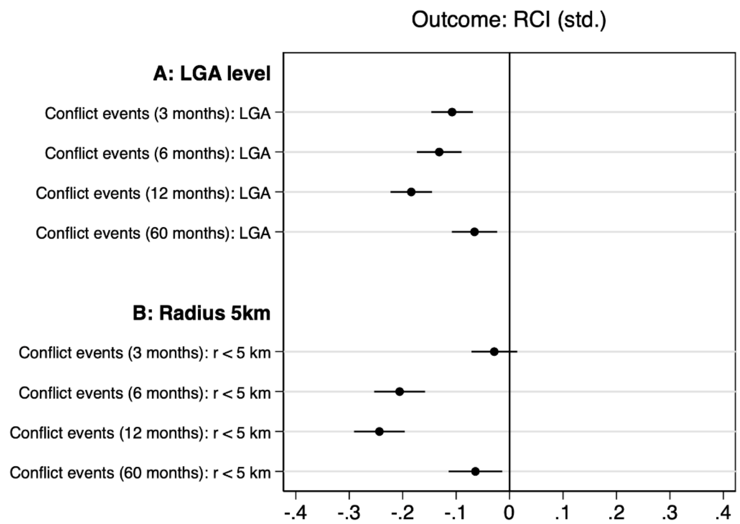
Note: 95% confidence intervals. Panel sample (N = 1,239).

What explains the result of seemingly negative resilience impacts of providing emergency support, assets, and training? We argue that – despite our statistical corrections – these results may not only capture program impacts but also the impacts of the violent conflict, which are difficult to disentangle in this case, as explained above. To tackle this issue, we study the critical role of local conflict intensity in detail in the following section.

4.2 The critical role of local conflict intensity

There is ample evidence that conflict has a strong negative impact on food security and resilience (Brück and d'Errico, 2019; Martin-Shields and Stojetz, 2019; Shemyakina, 2022). In Figure 7, we pool all our panel observations to inspect the link between local conflict intensity and resilience in our sample. We analyze LGA-level conflict intensity as well as a 5km radius around households' location, the smallest radius we can consider. Both the LGA and the 5km measures demonstrate the expected negative relationship of local conflict intensity and resilience. Considering 3- , 6- , 12- , and 60-month time horizons we observe that the number of conflict events that occur in the proximity of a household significantly weakens their resilience. Consistent across the LGA and the 5km levels, we find events that occur in the 6 and 12 months before a survey affect resilience the most .

Figure 7. Estimates of program impact from various models



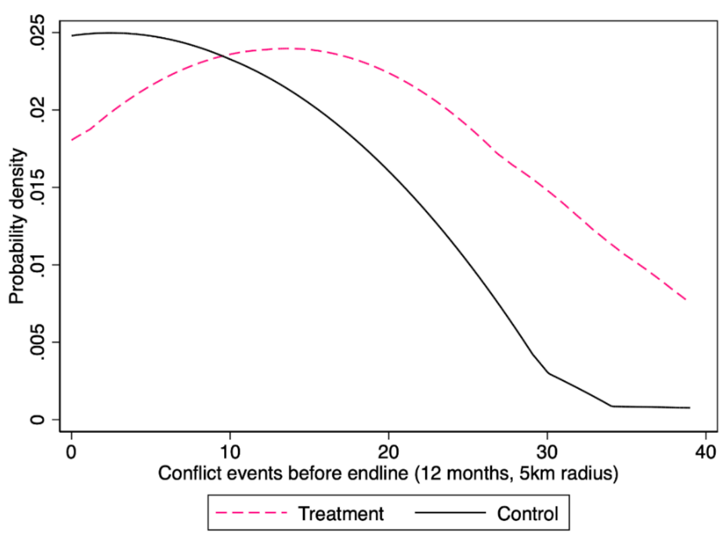
Note: 95% confidence intervals. Panel sample (N = 1,239).

Based on these insights, one factor that can help to explain our results above is the fact that treatment households were systematically exposed to higher levels of conflict intensity. Thus, we might pick up impacts of local conflict intensity as the scope and power of matching-based corrections is limited due to the strong, structural differences in exposure levels due to non-random attrition, which was concentrated among control households in areas of high conflict intensity during and after the intervention. Their absence is a plausible explanation for the relatively high mean resilience among control households at endline, which would likely be lower had the observed attrition not occurred and more control households from high-intensity conflict areas been surveyed at endline.

Related, there might have been the more intense humanitarian responses to conflict in control areas. In fact, many local partners, together with the Government, responded to the abovementioned escalation of violence in Kala/Balge and Kukawa, with several humanitarian activities (including food assistance, health, water, sanitation, and hygiene (WASH) and livelihood interventions) in these two control LGAs, which might have increased households' resilience capacity in those areas.

To tackle this concern and learn more about the "true" program impacts, we exploit the fact that conflict intensity was fairly high in many areas, not only the ones where households could not be surveyed. During and after the intervention, most sampled areas experienced some degree of local violence. In the 12 months before the endline survey, 80 percent of surveyed control households and 86 percent of treated households experienced at least one documented conflict event within a 5km radius. Figure 8 shows that for both groups the total number of events ranges from 0 to close to 40. As noted above, the majority of households surveyed at endline exposed to particularly high conflict intensity are treatment households. While the numbers are limited, we have observations from control households that were exposed to high levels of conflict, which allows us to compare treatment and control households and estimate program impacts across the spectrum of conflict intensity levels.

Figure 8. Local violence before endline

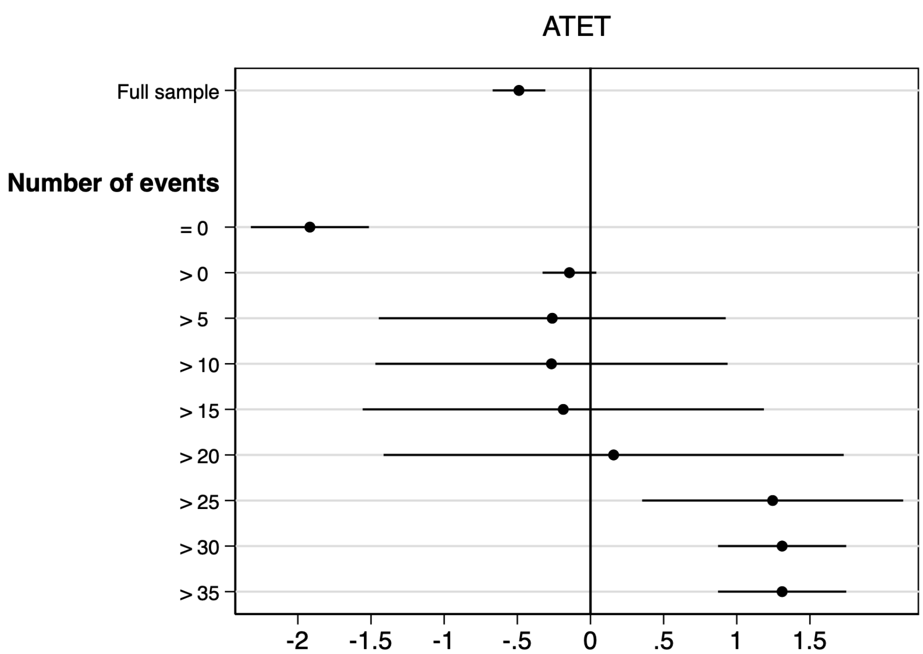


Note: 95% confidence intervals. Panel sample (N = 1,239).

Figure 9 presents our results on program impacts for households that reside in areas affected by conflict events in the year before the endline survey. We estimate our standard panel model with household-level fixed effects for various groups of treatment and comparable control households. These groups are defined by a minimum number of events that occurred in the 12 months in a 5km radius around them before the endline survey. In the model, we control for the actual level of (time-variant) violence that occurred in the 5km radius around a household's location over a 12-month period.

We find that the negative overall estimate is driven by the sub-sample of households for which no local conflict events were recorded in the 5km radius around them. When we compare all households that experienced any conflict events before the endline survey (the vast majority) and condition on the level of conflict intensity we find a precisely estimated null effect of the intervention. Once we focus further on the sub-sample to groups of households that were exposed to a certain minimum level of local conflict intensity, we see a clear pattern: the higher the threshold we use for conflict intensity the stronger and more positive the estimated program impact becomes. For households in areas with the highest levels of conflict intensity, we find evidence for strongly positive program impacts, again controlling for the actual level of intensity. These strongly positive impacts are stable across different thresholds of at least 25 conflict events, at least 30 conflict events, and at least 35 conflict events.[2]

Figure 9. Program impact on resilience, controlling for local conflict intensity



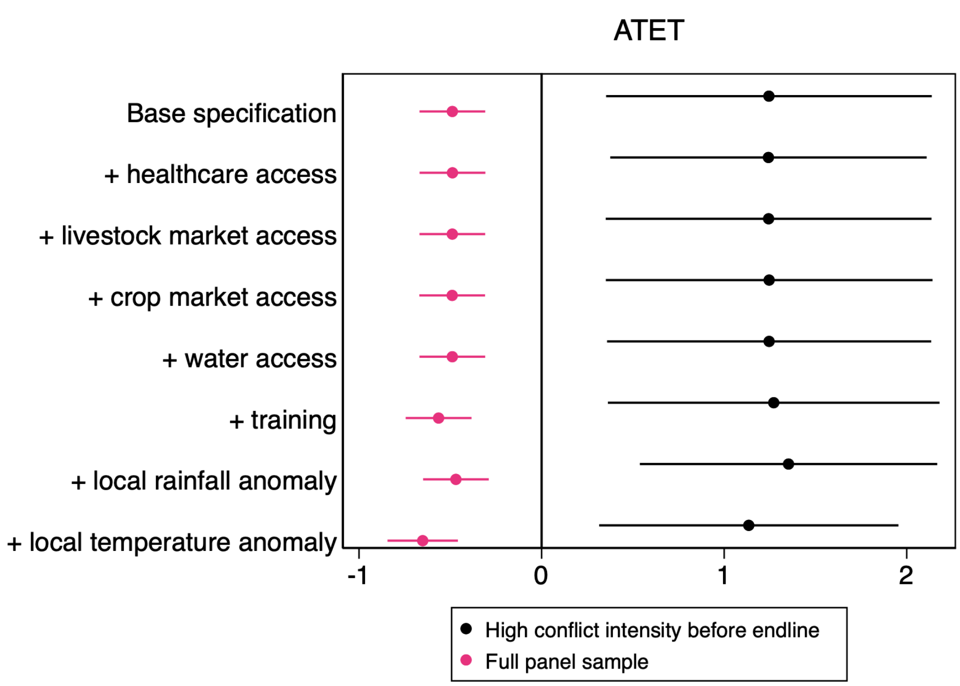
Note: 95% confidence intervals. Panel sample (N = 1,239).

[2] The increasingly limited number of control households that were exposed to higher levels of conflict intensity limits us in terms of the comparison groups. Therefore, we estimate models based on all households that were exposed to at least a given number of conflict events (e.g. more than 25 events) rather than program impacts for 'bands' (e.g. only households that were exposed to between 25 and 30 events).

4.3 Other potential intervening factors

Doubts may remain about a potentially influential role of 'other potential intervening factors', beyond shock and violence exposure. Our approach to addressing these concerns further is consistent with our broader attempt to distinguish 'local conflict conditions' from specific challenges and actions these may entail. In addition to violence and other shocks at the household level, we now also seek to look at changes at the more aggregate or institutional level, such as school closures, hospital closures, and changes in markets or training opportunities during our study period. To address these concerns empirically, we leverage additional survey data to check the role of changes in access to healthcare, livestock markets, crop markets, water; of training opportunities; and of local rainfall and temperature shocks. Figure 11 reports estimation results from adding these variables to the specification controlling for local conflict intensity (Figure 10). The estimates in the figure show clearly that these factors do not change our estimates for low- and high-intensity areas meaningfully, strengthen confidence in the critical role of local conflict intensity for our results.

Figure 10. Program impact on resilience, controlling for by degree of local conflict intensity



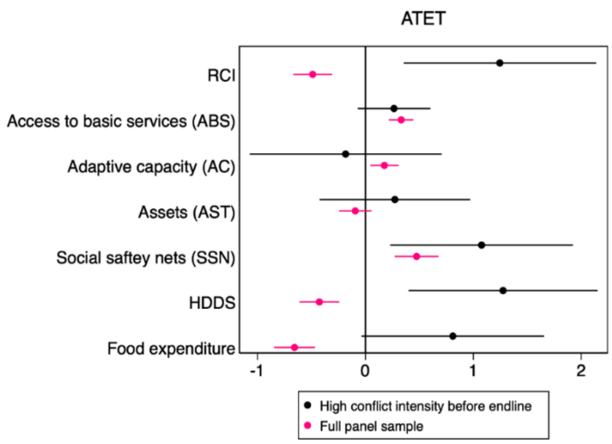
4.4 Mechanisms

In Figure 11a, we explore which dimensions of resilience benefit the most from the program when conflict intensity is high (more than 20 conflict events in a 5km before the endline survey). For completeness, we also report the results for the full panel sample. In all analyses, we control for the exact level of local conflict intensity. The results suggest that when local conflict intensity is high, treated households see an increase in their social safety nets, as well as increase in their food security indicators, especially their dietary diversity. Interestingly, the estimates for the full sample (which are likely confounded), suggest that the negative result for overall resilience capacity is almost entirely driven by food security variables. While very speculative, this may suggest that local conflict intensity before, during or after the intervention, which we believe is at the heart of selection bias, can be particularly detrimental for food security outcomes.[3] In Figure 11b, we study components of the social safety nets index separately. The estimates reveal that the positive program impacts on social safety nets are driven by increases in participation in associations. This insight suggests that when local conflict intensity is high, boosts in social capital can be a key factor for improved welfare outcomes, in the form of food security and resilience to food insecurity.

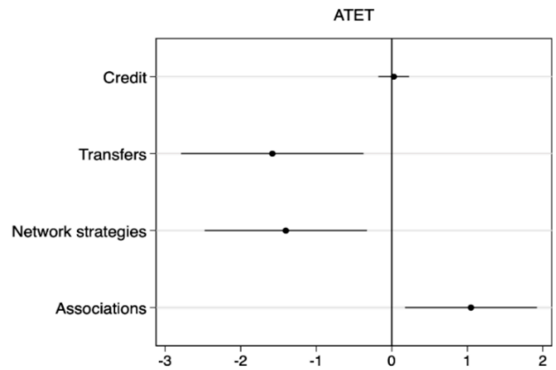
[3] There is ample evidence in the literature on the negative effects of violent conflict on food security (see, e.g., Justino, 2012b; Ecker, 2014; Bernstein et al., 2015; Justino, 2016; and Martin-Shields and Stojetz, 2019).

Figure 11. Resilience impacts under high local conflict intensity

a. Pillars of resilience



b. Pillars of of social safety nets



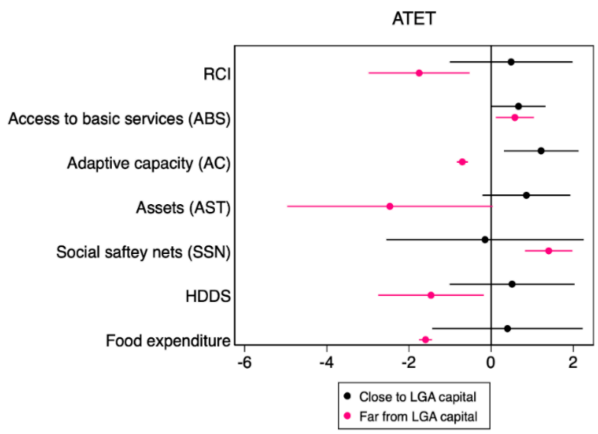
Note: 95% confidence intervals. Panel sample (N = 1,239).

In Figure 12, we study which groups of households benefit the most from multi-package program support under high conflict stress. We find that the gains in social safety nets are concentrated among households that live more than 15km from an LGA capital, which is the case for about one third of our sample (Figure 12a). This result emphasizes the particularly significant role resilience programs can play for remote areas, which are often particularly vulnerable when violence is high. We discuss this finding further in Discussion below (Section 5).

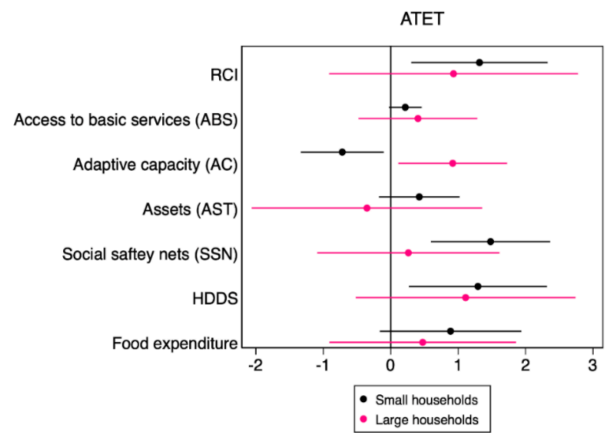
We find a similar pattern for smaller households, who benefit more in terms of social safety nets and resilience overall than larger households, for which we observe a markedly large degree of dispersion (Figure 12b). In Figure 12c, we group households by the sex of the head. While female-headed households are a small group (16 percent of households), we observe precisely estimated and strong positive impacts for those households when conflict stress is high. Interestingly, the gains in terms of social safety nets for female-headed households appear to be varied and not statistically significant while they are stronger and statistically significant among male-headed households. Rather, the group of female-headed households gain more clearly in terms of access to basic services, assets, and dietary diversity. This last result emphasizes that the positive impacts of multi-package programs in violent conflict zones are not only heterogeneous, but the pathways may also differ across benefitting groups.

Figure 12. Resilience impacts under high local conflict intensity

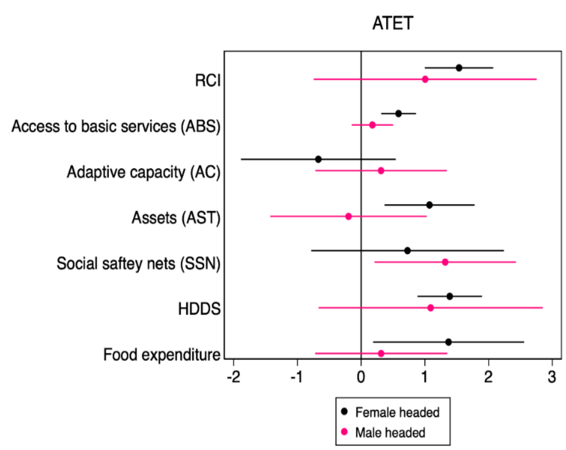
a. Distance of household to LGA capital



b. Household size



c. Sex of household head



Note: 95% confidence intervals. Panel sample (N = 1,239).

5 Discussion

Two of our findings are particularly striking and merit a more detailed discussion. First, while our results strongly suggest that the intervention had strongly positive impacts on resilience under high local conflict intensity, they also raise the question of why the program might have failed to support resilience and have had negative impacts when local conflict intensity is low. Second, when local conflict intensity is high, the gains in households' social safety nets, which drive the overall benefits in resilience, are concentrated among households in remote areas but these households are in fact made worse off by the program in terms of other dimensions of resilience. We discuss these two findings in turn below.

Negative program impacts when local conflict intensity is low. Negative program impacts might seem especially counterintuitive given the documented success of similar multi-faceted livelihood support programs in other contexts, sometimes also referred to as “big push” programs. For example, interventions deploying the “Ultra Poor Graduation Approach” had strongly positive impacts in poor contexts in Ethiopia, Ghana or Peru, among others (Banerjee et al., 2015; Banerjee et al., 2021). Yet, these results are typically from fragile but not active conflict settings, reflecting a general lack of evidence on support program impacts in crisis and humanitarian settings (Puri et al., 2017; Al Daccache et al., 2024).

There are reasons to expect that the impacts of such interventions, and the underlying pathways, may differ systematically across conflict and non-conflict situations. For example, being “poor” in an active conflict setting can be very different from being poor in a non-conflict setting due to the additional challenges and constraints created by conflict conditions. In addition, the structural conditions of local “peace” or absence of violence in a conflict setting can be very different from local structural conditions in a peaceful setting. In turn, this raises the question if we expect an intervention, that was designed as an emergency program providing support to conflict-affected households, works as intended when local conflict intensity is low. The possibility that it may not, is consistent with nascent evidence from Syria, where an emergency program providing agricultural assets did not improve food security in areas with low local conflict intensity (Weiffen et al., 2022).

So, what may explain the negative resilience impacts of the intervention in our case when local conflict intensity is relatively low? One potential explanation is that in less violent areas agricultural support programs may lead or enable beneficiaries to engage in activities that turn out to be less beneficial or profitable than intended. In areas with less conflict intensity, markets typically offer more opportunities, and the intervention may encourage people to engage in agricultural activities that are less profitable than alternatives, or it may induce them not to relocate in search of better opportunities. In this sense, the endowment effect would steer people's decisions towards less profitable options. By contrast, such a mechanism is less likely to occur in high conflict areas, where the economic fabric deteriorates, there might be less choices and the program serves as a lender of last resort by providing opportunities for self-employment and self-sufficiency. This idea is in line with the often-implicit assumption in economics that (free) market activities require strong institutions including respect for property rights

(Verwimp et al., 2019). Market interventions when in locations where there is violent conflict may make sense – while market interventions in "peaceful" locations may have an opportunity cost.

Another possibility is that in areas with less conflict events a sudden increase in supply occurs in a market that is not prepared to fully absorb the surplus production. Indeed, the aforementioned study from Syria finds that beneficiaries of a seed intervention living in areas less affected by the conflict had significantly more unsold and lost produce, compared to those living in high conflict intensity areas (Weiffen et al., 2022). In turn, this may drive an overall negative effect of an intervention. As for the previous explanation, such an effect is less likely to occur in areas where conflict is more intense and overall supply may be reduced significantly.

Lastly, our results may be explained by the specific design of the intervention. The intervention was designed to reach and support communities that were most affected by the conflict. Given that the intervention was intended to support post-conflict restoration and the reactivation of livelihood activities, it is plausible that more resources were allocated to the most severely affected areas in relative terms. That is, among treatment areas, treatment intensity might have been significantly higher in the most fragile areas. If there is a threshold of intensity that is required to change allocations and returns to change impacts from negative to positive, that may explain our results. Unfortunately, there is no information available on treatment intensity and we thus cannot rule out the possibility that the discrepancy between areas of high and low local conflict intensity may, in parts, be driven by difference in treatment intensity.

Mixed resilience impacts in remote, high conflict areas. What may be the reason that for households living in remote, high conflict areas the intervention strongly supported social safety nets but eroded other dimensions of resilience? While there is quite some variation, this especially concerns assets, and to some degree also adaptive capacity, which has a lot to do with the economic activity portfolio of a household.

A growing number of studies shows that exposure to conflict shapes social behaviors and outcomes among individuals, households, and communities. While conflict exposure is often associated with negative social impacts (Rohner et al., 2013; Stojetz & Brück, 2023b), there is strong evidence that is can also foster social cohesion and cooperation (Bauer et al. 2016; Oh et al., 2024).

Figure 11 shows that among components of social safety nets, participation in collective groups (associations) was particularly boosted by the intervention in high conflict areas, while reliance on informal economic coping strategies was reduced. In remote areas, the informal institutions behind these behaviors are often particularly important as formal institutions may be less strong and offer less support than in less remote areas.

Thus, in remote areas high levels of local conflict intensity may have created a particularly strong sense of solidarity and degree of social cohesion, leading recipient households to strongly interact with others, share assets, and adapt their economic activity in a way that leads to an effectively negative impact of the intervention on their assets and adaptive capacity.

While plausible, we would like to note that these explanations are speculative and should be investigated further in future research.

6 Conclusions

Our paper provides novel evidence on the impacts of agricultural interventions and conflict intensity in extreme emergency settings and contributes to the scarce knowledge base on the impacts of interventions in such settings. We find that the impacts of giving a combination of emergency assistance, assets, and skills training for resilience are strongly shaped by the security situation during and after the implementation of the intervention. We provide evidence that when local conflict intensity is high, such multi-faceted programs can provide strong and much needed support for resilience, primarily by strengthening social safety nets and food security. We document that impacts vary across groups of households, including pronounced positive impacts among particularly vulnerable groups, such as female-headed households and households in remote areas.

In challenging environments, rigorous learning is also challenging. Conflict settings inherently create challenges to data collection and to causal inference in impact evaluations. Our statistical analyses and findings showcase the challenges facing quasi-experimental impact evaluations in such settings. Specifically, it can be difficult to disentangle program impacts from selection effects based on conflict intensity. Yet, our study emphasizes the value of in-depth knowledge of households’ exposure to conflict for tackling these challenges, measured by survey modules on shocks and violence exposure (Brück et al., 2016) and via external conflict event data. Measuring and accounting for the extent of conflict exposure is key for conducting informed analyses, understanding selection biases, interpreting the findings, and orienting policymakers in their efforts to promote the Humanitarian-Development-Peacebuilding (HDP) nexus and avoid the activation of a vicious cycle in which conflict and food insecurity fuel each other, in turn reducing households’ resilience capacity in the longer-term (FAO, 2016b; USAID, 2014).

We took several lessons from conducting this research, which demonstrated that, despite multiple methodological challenges, rigorous learning can be accomplished. In our experience, learning must be integrated into the program from the start for such approaches to be successful. Impact evaluation design needs to be flexible in emergency contexts to allow capturing the effects of interventions even under crises and changing conditions. Finally, we find it important for research and practice to work together to overcome the challenges related to conducting impact evaluations in conflict and humanitarian emergency settings and to find innovative design and/or statistical methods and survey methods to overcome them.

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Online appendices

A.1 The intervention

We study the resilience impacts of a multi-package agricultural interventions in Borno State, implemented as a Joint Action Programme by the Food and Agriculture Organization of the United Nations (FAO), UN Women and the World Food Programme (WFP) in 2018.

The intervention took place from October 2018 to December 2019. It aimed to build the resilience of the conflict affected population and public sector institutions in Borno State by providing conflict-affected populations with the means to resume agriculture-based and other environment-friendly livelihoods, thereby allowing them to progressively sustain their own food and nutritional needs (FAO et al., 2018). In so doing, the action aims at setting the foundations for longer-term resilience building and sustainable economic and social development.

The intervention provided a combination of emergency assistance, asset provision, and skills training packages. The specific activities included:

- livestock distribution and vaccination;
- distribution of inputs and equipment for crop production, irrigation, aquaculture, and fish processing (e.g., seeds, fertilizers, tools, water pump, tube well, fish processing facility);
- agricultural trainings (fish processing and seed production);
- provision of equipment for business start-up;
- distribution of food preservation tools (fuel efficient cook stoves, seer pots);
- food distribution and cash transfers; and
- Village Savings and Loan Association (VSLA) support.

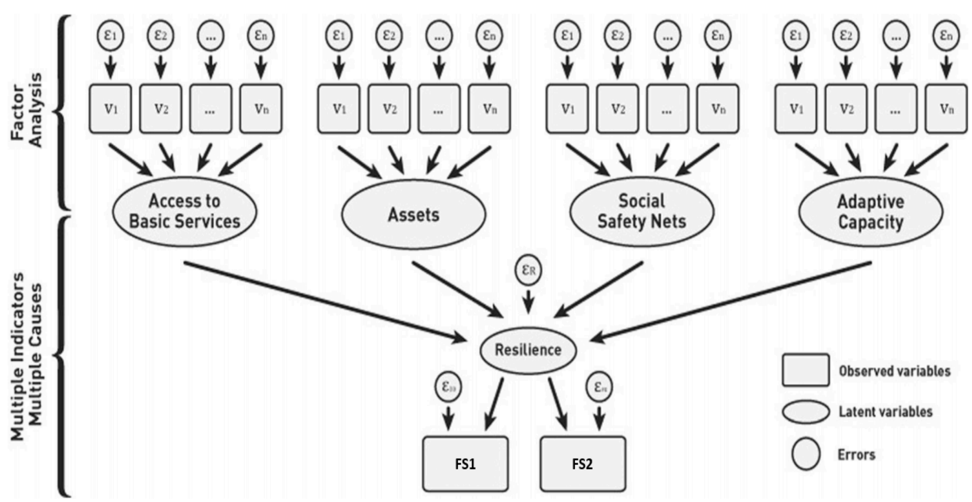
The expected results from resilience gains are threefold: (i) small holder farmers' (men, women and youth) have skills and knowledge to implement good agricultural, nutrition and gender practices; (ii) small holder farmers (men, women and youth) have diversified food source and income, and (iii) small holder farmers (men, women and youth) have opportunities for markets and business development.

A.2 Resilience measurement

To measure resilience, we adopt the innovative FAO-RIMA methodology (FAO 2016a), which generates the Resilience Capacity Index (RCI) as the main resilience measure. This approach is innovative for four reasons. First, it uses structural equation models for estimating a resilience capacity index through an extensive set of indicators that fit the analytical framework. Second, it adopts regression analysis to check the relevance and role of (idiosyncratic and covariate) shocks, socio-demographic characteristics, and other exogenous aspects to resilience. Third, it has been field-tested in many countries in Africa, Asia, and Latin America. Fourth, it has been demonstrated to be useful as an impact assessment indicator (see Brück et al., 2018; d'Errico et al., 2020; Malik et al., 2020).

The RIMA methodology is based on a two-stage procedure (Figure A1). 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)[4]. Only those factors able to explain at least 95 percent of the variance are considered.

Figure A1. Estimating resilience with the RIMA methodology



Source: Authors' own elaboration

[4] The choice of the employed pillars is based on consultations, literature review and previous analyses (FAO, 2016a).

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. (A1) – reflecting that the observed indicators of food security are imperfect indicators of resilience capacity – and the structural Eq. (A2), which correlates the estimated attributes to resilience:

$$[Food\ security\ indicator\ 1\ Food\ security\ indicator\ 2\ ] = [\Lambda_1, \Lambda_2] \times [\mathrm{RCI}] + [\varepsilon_1, \varepsilon_2] \quad \text{(A1)}$$

$$[\mathrm{RCI}] = [\beta 1, \beta 2, \beta 3, \beta 4] \times [ABS\ AST\ SSN\ AC\ ] + [\varepsilon 3] \quad \text{(A2)}$$

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 (Λ1) equal to 1, meaning that one standard deviation increase in RCI implies an increase of one standard deviation in food consumption. The scale defines the unit of measurement for the other outcome indicator (Λ2) 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:

$$RCI_h^* = \frac{RCI_h - RCI_{min}}{RCI_{max} - RCI_{min}} \times 100 \quad \text{(A3)}$$

where h represents the h^{th} household.

The variables employed to estimate the Resilience Capacity Index (RCI) are listed in Table A1, along with definitions.

Table A1. Definition of variables employed to calculate the Resilience Capacity Index

Variable	Definition
RCI	The RCI is the Resilience Capacity Index, ranging from 0 to 100.
Access to Basic Services	
Improved Sanitation	Dummy variable indicating access to improved toilet facility
Closeness to water source	Inverse distance to water source (minutes)
Closeness to school	Inverse distance to school (minutes)
Closeness to hospital	Inverse distance to hospital (minutes)
Closeness to agricultural market	Inverse distance to agricultural market (minutes)
Closeness to livestock market	Inverse distance to livestock market (minutes)

Access to Assets	
Wealth index	Index built through a factor analysis of all the wealth indicators in a dwelling
Agricultural asset index	Index built through factor analysis of ownership/use of agricultural assets/inputs
Tropical Livestock Unit (TLU)	Number of tropical livestock units owned by the household
Land	Total area cultivated by the household (hectares)
House value	Monetary value of the household dwelling (USD)
Social Safety Nets	
Credit (value) per capita	Total amount (USD) of loans received in the last twelve months
Formal transfers (value) per capita	Total amount of formal transfers received in the last twelve months (USD)
Informal network(s)	Number of days the household relies on informal network as coping strategy
Associations	Numbers of associations the household members participate in
Adaptive Capacity	
Average years of education	Average years of education of the household members
Share of active members	Share of household members in age of working (>15 and <64 years old)
Income generating activities	Sum of all the various sources of income-generating activities of the household
Participation in training	Dummy variable for participating in agricultural training courses
Number of crops	Sum of the different crops cultivated by the household during the last season
Food Security	
Food expenditure per capita	Monetary value (USD) of per capita food expenditure over the last month
Household Dietary Diversity Score (HDDS)	Monetary value (USD) of per capita food expenditure over the last month

A.3 Additional tables

Table A2. Baseline balance (panel sample)

	Control	Treatment	Δ
A: Resilience and food security			
RCI	49.30	44.42	4.88***
P1: Access to basic services (ABS)	-0.11	0.06	-0.17**
P2: Assets (AST)	0.25	0.06	0.19**
P3: Adaptive capacity (AC)	0.30	0.00	0.30***
P4: Social safety nets (SSN)	0.21	0.06	0.15
B: Household characteristics			
Female household head	0.15	0.16	-0.01
IDP household	0.33	0.51	-0.18***
Returnee household	0.18	0.30	-0.12***
Household size	7.33	6.72	0.61***
Number of children	3.71	3.40	0.31*
Farming household	0.69	0.76	-0.07**
C: Shock exposure			
Shocks (any)	0.66	0.69	-0.03
Shocks (total)	1.17	1.15	0.02
Drought	0.15	0.19	-0.04
Flood	0.00	0.01	-0.01
Water shortage	0.21	0.19	0.02
Crop disease	0.11	0.07	0.04*
Livestock disease	0.02	0.02	-0.00
High prices for agric. inputs	0.02	0.05	-0.03**
Low prices for agric. outputs	0.01	0.00	0.01***
Illness/accident of earner	0.01	0.04	-0.02*
Illness/accident of non-earner	0.08	0.07	0.01
Death of household member	0.10	0.15	-0.04*
Theft of of money / non-agric. assets	0.02	0.05	-0.04**
Theft of agric. assets or output	0.00	0.05	-0.05***
Conflict/violence	0.23	0.23	0.01
Fire	0.18	0.03	0.16***
Other shock	0.02	0.02	0.01
D: Conflict event exposure			
Conflict events (12 months): r < 5 km	3.13	13.60	-10.46***
Conflict events (12 months): LGA	3.97	26.46	-22.49***