Building resilience and ensuring food security in Ethiopia amid multiple shocks

By

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B.S., Alemaya Uniersity, 2005
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AN ABSTRACT OF A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2026

Abstract

This thesis examines household resilience, shock exposure, and food security in Ethiopia under overlapping climatic, economic, health, and political shocks. Using nationally representative panel data from the Ethiopia Socioeconomic Survey (ESPS/LSMS–ISA) for 2018/19 and 2021/22, the study analyzes how resilience is constructed, how it relates to food security outcomes, and whether its effects vary across rural and urban contexts. The analysis is grounded in the Food and Agriculture Organization of the United Nations' Resilience Index Measurement and Analysis (RIMA-II) framework and conceptualizes resilience as a multidimensional capacity shaped by access to basic services, assets, social safety nets, and adaptive capacity.

The first part of the thesis develops a multidimensional Resilience Capacity Index (RCI) for Ethiopia using structural equation modeling and related multivariate techniques. The findings show that household resilience during prolonged crises is driven primarily by structural factors, especially material assets and access to basic services. By contrast, informal and community-based social safety nets weakened substantially under covariate shocks such as drought, conflict, and pandemic-related disruptions. Adaptive capacity shows mixed and, in some cases, negative associations with resilience, suggesting that diversification, technology adoption, and engagement with extension services may often reflect distress-driven responses rather than proactive adaptation. The results also reveal marked regional disparities, with households in Somali, Afar, and Benishangul-Gumuz exhibiting significantly lower resilience than households in other regions.

The second part of the thesis examines the relationship between resilience capacity, shock exposure, and food security outcomes. Multiple food security indicators are considered, including food expenditure share, household dietary diversity, daily caloric adequacy, food insecurity experiences, and household hunger. The results show that higher resilience capacity is generally associated with better food security outcomes, particularly lower food budget pressure, more diverse diets, and fewer food insecurity experiences. At the same time, shocks such as drought, health shocks, and food price increases are strongly associated with worsening food insecurity and hunger, especially during the 2021/22 survey wave, which reflects a substantially harsher food security environment. Interaction estimates suggest that the buffering role of resilience is present but limited and highly shock specific. Drought, input-price inflation, and political shocks weaken some of the protective advantages associated with resilience.

The third part of the thesis introduces a spatially disaggregated analysis of urban–rural heterogeneity in resilience and food security. The results show that resilience is both context-specific and multidimensional. Rural households are more exposed to climatic and production-related shocks, while urban households are more vulnerable to market- and income-related shocks. The structure of resilience also differs across settings: in rural areas, resilience is driven more strongly by adaptive capacity, access to basic services, and productive assets, whereas in urban areas assets and social safety nets play a larger role. Resilience improves food security in both contexts, but the channels through which it operates differ. In rural areas, resilience works mainly through production stabilization and asset protection, while in urban areas it operates more strongly through income stability, service access, and market participation.

Overall, the thesis demonstrates that resilience is not a fixed household trait but a context-dependent capacity whose determinants and effects vary across shock environments, livelihood systems, and institutional settings. The findings underscore the importance of multidimensional and shock-aware approaches to resilience measurement and suggest that improving food security in Ethiopia requires spatially differentiated strategies that combine household-level resilience building with responsive social protection, climate adaptation, market stabilization, and stronger institutional support.

Keywords

Household resilience; food security; shock exposure; Resilience Capacity Index; RIMA-II; Ethiopia; rural livelihoods; urban–rural heterogeneity; covariate shocks; panel data

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Acknowledgements

I would like to sincerely thank my advisor, Professor Timothy J. Dalton, for his guidance, patience, and constant encouragement throughout this research. I am also grateful to my committee members for their valuable feedback and thoughtful suggestions, which significantly improved this work.

I am deeply thankful to my colleagues and friends who supported me throughout this process. Their encouragement and shared experiences made this journey more meaningful. Above all, I am profoundly grateful to my family for their unconditional support, understanding, and belief in me.

This study was made possible by the support of the American People provided to the Feed the Future Innovation Lab for Collaborative Research on Sorghum and Millet through the United States Agency for International Development (USAID) under Cooperative Agreement No. AID-OAA-A-13-00047.

Dedication

To my family,

for their love, patience, sacrifices, and faith in me throughout this journey.

This work is as much yours as it is mine.

Overview of the Dissertation and Linkages Across Essays

This dissertation examines household resilience, exposure to shocks, and food security outcomes in Ethiopia within a context of overlapping climatic, economic, health, and political disturbances. While each empirical chapter addresses a distinct research question, the three essays are unified by a common conceptual foundation that views resilience as a multidimensional capacity influencing households' ability to withstand, adapt to, and recover from shocks. The analysis is grounded in the Food and Agriculture Organization's Resilience Index Measurement and Analysis (RIMA-II) framework and adopts a resilience-as-capacity approach, emphasizing the role of structural and institutional factors in shaping welfare outcomes.

A central motivation of this dissertation is that food security outcomes cannot be fully understood without jointly considering both the incidence of shocks and the capacity of households to respond to them. In shock-prone environments such as Ethiopia, households face recurrent droughts, price volatility, conflict-related disruptions, and health crises. These shocks affect food security both directly through income loss, asset depletion, and market disruptions and indirectly, by weakening key resilience capacities. Consequently, resilience is not only a determinant of welfare but also a mediating mechanism through which shocks translate into food security outcomes.

The dissertation is organized into three interrelated essays that collectively provide a comprehensive analysis of resilience and food security dynamics. The first essay focuses on the measurement of resilience by constructing a multidimensional Resilience Capacity Index (RCI) using nationally representative panel data from the Ethiopia Socioeconomic Survey (2018/19 and 2021/22). Drawing on the RIMA-II framework, resilience is modeled as a latent construct determined by four pillars: access to basic services (ABS), assets (ASS), adaptive capacity (AC), and social safety nets (SSN). Structural equation modeling is employed to capture the relationships among these dimensions while explicitly accounting for measurement error. This essay establishes the empirical foundation of the dissertation by providing a rigorous and policy-relevant measure of household resilience.

Building on this foundation, the second essay examines the effects of shocks and resilience on multiple food security outcomes, including food expenditure share, dietary diversity, calorie adequacy, and experiential measures of food insecurity. The empirical strategy models food security as a function of shock exposure, resilience capacity, and their interaction, allowing for the identification of both direct shock effects and the buffering role of resilience. This approach provides evidence on whether and to what extent higher resilience mitigates the adverse impacts of shocks on household welfare. By integrating resilience into the analysis of food security outcomes, the essay contributes to a more nuanced understanding of vulnerability and welfare dynamics in the presence of repeated shocks.

The third essay extends the analysis by examining heterogeneity in resilience and its effects across rural and urban contexts. Recognizing that the determinants and transmission channels of resilience differ by livelihood systems, this essay re-estimates the resilience index separately for rural and urban households and investigates how the relative importance of resilience pillars varies across these settings. In rural areas, resilience is closely linked to production systems, natural capital, and agricultural assets, while in urban areas it is more strongly associated with income stability, market access, and service provision. This essay highlights the context-specific nature of resilience and underscores the importance of tailored policy interventions.

Taken together, the three essays are interconnected along both conceptual and empirical dimensions. Conceptually, all essays are anchored in the same resilience framework, where resilience capacity serves as a central mechanism linking shocks to food security outcomes. Empirically, the resilience index developed in the first essay is consistently applied in subsequent analyses, ensuring coherence across chapters. The second and third essays build directly on the measurement framework by examining the implications of resilience for welfare outcomes and by exploring how these relationships vary across contexts.

This integrated approach allows the dissertation to make three key contributions. First, it provides a robust and multidimensional measurement of household resilience in Ethiopia using advanced econometric techniques. Second, it offers empirical evidence on the role of resilience in mitigating the adverse effects of shocks on food security. Third, it demonstrates that resilience is inherently context-specific, with distinct determinants and transmission channels across rural and urban settings. By linking measurement, impact analysis, and heterogeneity, the dissertation advances both the conceptual and empirical literature on resilience and provides policy-relevant insights for strengthening food security in shock-prone environments.

1 Chapter One: Constructing a Multidimensional Resilience Capacity Index for Ethiopia under Compounding Shocks: Evidence from National Panel Data

Abstract

This study examines the determinants of household resilience in Ethiopia during a period of overlapping climatic, economic, and political shocks. Using the nationally representative LSMS–ISA panel data from 2018/19–2021/22 combined with the FAO Resilience Index Measurement and Analysis (RIMA-II) framework, we construct a multidimensional Resilience Capacity Index (RCI). The index is estimated using structural equation modeling to assess how assets, access to basic services, social safety nets, and adaptive capacity jointly shape household resilience under crisis conditions.

The results indicate that resilience during sustained shocks is driven by structural factors, particularly material assets, and access to basic services. In contrast, informal and community-based social safety nets deteriorated sharply in response to covariate shocks, including drought, armed conflict, and pandemic-related disruptions. Adaptive capacity exhibits a mixed and frequently negative association with resilience, suggesting that diversification, technology adoption, and engagement with extension services often reflect reactive, distress-driven responses rather than proactive adaptation. Substantial spatial disparities are observed, with households in Somali, Afar, and Benishangul-Gumuz regions experiencing pronounced declines in resilience relative to other areas.

These findings stress the importance of shock-aware and multidimensional approaches to resilience measurement and demonstrate that the contribution of individual resilience pillars shifts under prolonged crisis. The study emphasizes the need for policies that address structural inequalities and institutional fragility, while strengthening the enabling conditions for anticipatory and transformative adaptation in rural livelihoods.

Keywords

Household resilience; Rural livelihoods; Covariate shocks; Spatial inequality; Ethiopia; RIMA-II; Panel data.

1.1. Introduction

1.1.1. Context of Vulnerability and Shocks in Ethiopia

Ethiopia remains among the world's poorest countries, with per-capita gross national income (GNI) of about US$1,020 and a population of 130 million (World Bank, 2024). Agriculture is the backbone of the economy and the primary livelihood for rural households. It contributes approximately 34.6% to national GDP, accounts for 90% of export earnings, and employs around 80% of the labor force (FAO, 2017a; World Bank, 2024). Beyond its economic role, agriculture supports food security and the social and institutional fabric of rural communities (FAO, 2017a).

The country has achieved notable progress in growth and poverty reduction over the past two decades: national poverty declined from 44.2% in 2000 to 24% in 2016 (Mekasha and Tarp, 2021; World Bank, 2020). Yet these gains remain fragile. Between 2018 and 2022, Ethiopia experienced repeated droughts, conflict, and economic shocks that left more than 20 million people in need of food assistance (WFP, 2022). At the same time, rapid inflation and rising food prices significantly eroded household purchasing power, intensifying food insecurity, particularly among poor households (IGC, 2022).

Since 2019, Ethiopia has been affected by a series of overlapping climate, health, economic, and political shocks (Figure 1). The eastern Horn of Africa experienced extreme rainfall, flooding, and a prolonged drought (UNDRR, 2024). The COVID-19 pandemic further disrupted mobility, supply chains, and labor markets, contributing to declines in key sectors such as tourism, transport, and exports (Bogale et al., 2020; Gebreeyesus and Tekleselassie, 2021). These stresses were compounded by a two-year internal conflict that displaced millions, damaged infrastructure, and curtailed agricultural production (Diao et al., 2022). In the most affected areas, by mid-2021, 61% of households faced acute food insecurity, driven by market fragmentation, rising price volatility, and widespread asset losses (FEWSNET, 2022; IPC, 2021). More recently, global price shocks associated with the Russia–Ukraine conflict intensified domestic food and fertilizer price inflation, further eroding purchasing power (AERC, 2023; Steinbach, 2023). Economy-wide simulations estimate a 3.1% decline in consumption and a 1.2% reduction in real GDP due to food price shock related to the Russia-Ukraine conflict (Diao et al., 2022).

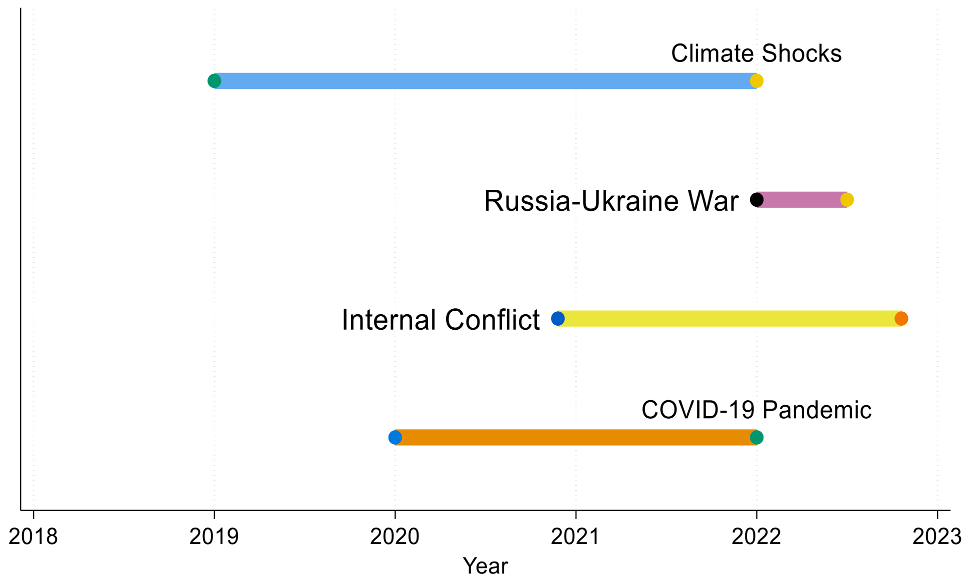

Figure 1-1: Timeline of major shocks in Ethiopia (2019-2022)

Rural households tend to be poorer, more dependent on rain-fed agriculture, and have limited access to markets and services, leaving them particularly exposed to such shocks (Dercon, 2004; Mekasha and Tarp, 2021) Common coping strategies include distress asset sales, borrowing, and reductions in food intake (Little et al., 2006). While providing short-term relief, these strategies often undermine future productive capacity and deepen vulnerability. Severe shocks, such as conflict and displacement, can further push households into poverty traps and trigger long-term socioeconomic disruption (Barrett and Carter, 2013; Verwimp et al., 2019).

These conditions stress the urgency of measuring household resilience and understanding how households mobilize assets, capacities, and support systems to withstand, adapt to, and recover from increasingly frequent and compounding shocks.

1.1.2. Measuring Resilience at the Household Level

Traditional welfare indicators such as consumption, income, or caloric intake capture current well-being but fail to reflect households' underlying capacity to manage or recover from shocks. This limitation is particularly relevant in Ethiopia, where short-term welfare improvements often mask deeper structural vulnerabilities (Barrett and Constas, 2014; Dercon, 2004; Headey and Jayne, 2014). As a result, policy and research have shifted toward resilience-based approaches that take a forward-looking perspective grounded in household capacities.

Resilience is typically measured using multidimensional indices that integrate key livelihood components. Prominent frameworks include FAO's Resilience Index Measurement and Analysis (RIMA-II) (FAO, 2016)(FAO, 2016)(FAO, 2016)(FAO, 2016), the Sustainable Livelihoods Framework (SLF) (Ian Scoones, 1998)(Ian Scoones, 1998)(Ian Scoones, 1998)(Ian Scoones, 1998), the Climate Resilience Index (CRI) (Sharma and Patwardhan, 2008)(Sharma and Patwardhan, 2008)(Sharma and Patwardhan, 2008)(Sharma and Patwardhan, 2008) and Livelihood Vulnerability Index (LVI) (Hahn et al., 2009)(Hahn et al., 2009)(Hahn et al., 2009)(Hahn et al., 2009). Despite methodological differences, these frameworks share the objective of assessing household capabilities within dynamic social–ecological systems.

FAO's assessment using (Living Standards Measurement Study – Integrated Surveys on Agriculture) (LSMS-ISA) of the Ethiopia socioeconomic panel survey (ESS) data (2011–2018) identifies substantial regional disparities in resilience, driven by differences in assets, education, and access to services (FAO, 2022) Further studies show that higher resilience scores are associated with improved dietary diversity and more stable food security under climatic stress (Belete et al., 2023; Haile et al., 2022). Yet most analyses remain cross-sectional or geographically narrow, limiting understanding of how resilience evolves over time.

This study therefore applies the RIMA-II framework to a nationally representative ESS panel data set (2018/19–2021/22) to generate a comparable Resilience Capacity Index (RCI) between survey waves and examine resilience trajectories during a period of exceptional shock exposure.

This paper constructs a Resilience Capacity Index (RCI) using the RIMA-II framework and then employs it to compare resilience over time and across rural and urban households. The analysis then assesses how various shocks impact each pillar of resilience before identifying policy pathways that can strengthen household resilience. By integrating RIMA-II with nationally representative panel data, this study provides one of the first comprehensive assessments of household resilience in Ethiopia during a period marked by multiple and overlapping shocks. We address identification by combining household fixed effects, focusing on plausibly exogenous covariate shocks, validating self-reported shocks with external data like rainfall and conflict events, and using lag structures and rich controls to reduce simultaneity and omitted variable bias.

1.2. Literature Review

1.2.1. Conceptualizing Household Resilience

Household resilience refers to the capacity of households to withstand, adapt to, and recover from shocks while maintaining acceptable levels of well-being. Barrett and Constas (2014) define development resilience as the ability to sustain well-being trajectories above a critical threshold despite recurrent stressors highlighting the dynamic nature of welfare and the importance of capacities that shape households' responses to risk. In this study, household well-being is defined primarily in terms of food security, reflecting both economic access to food and nutritional adequacy. Specifically, well-being is operationalized using multiple complementary indicators, including Food Expenditure Share (FES) as a measure of economic access, Household Dietary Diversity (HDDS) as an indicator of diet quality, Household Daily Calorie Intake (HDCI) as a measure of energy sufficiency, and experiential measures such as the Food Insecurity Experience Scale (FIES) and the Household Hunger Scale (HHS), which capture perceived and severe forms of food deprivation. By adopting a multidimensional approach, the analysis captures both objective and subjective dimensions of welfare, allowing for a more comprehensive assessment of households' ability to maintain acceptable living standards in the face of shocks.

Across the food-security and livelihood literature, resilience is commonly framed through three interlinked capacities. Absorptive capacity reflects households' ability to reduce exposure to shocks and buffer their immediate impacts using existing resources or coping strategies. Adaptive capacity captures medium-term adjustments such as livelihood diversification, technology adoption, and investment decisions that help households manage evolving risks. Transformative capacity represents deeper structural shifts in governance, market access, infrastructure, or social protection systems that reduce systemic vulnerability and create welfare-enhancing livelihood opportunities (Béné et al., 2012; Jeans et al., 2017).

More recent advances in resilience measurement extends this framing to include anticipative and preventive dimensions, in addition to absorptive, adaptive, and transformative dimensions. Anticipative capacity concerns the ability to act early based on risk information (e.g., early warning) to reduce expected losses, while preventive capacity reflects actions that reduce underlying risk by lowering exposure and vulnerability before shocks occur (FAO, 2023). This five-capacity lens clarifies that resilience is not equivalent to coping alone: households may smooth consumption in the short run yet remain unable to anticipate or prevent future losses, adapt to repeated shocks, or transition out of chronic vulnerability.

These capacities are especially salient in low-income agrarian economies such as Ethiopia, where households depend heavily on rain-fed agriculture and face repeated exposure to droughts, price shocks, and conflict-related disruptions. Extensive evidence shows that structural constraints, including underdeveloped financial and insurance markets, infrastructure, and weak social protection, systematically reduce households' ability to manage shocks (Carter and Barrett, 2006; Dercon, 2004; Hoddinott, 2006). As a result, conventional welfare indicators such as income or consumption capture current well-being but not the underlying capacity to withstand or recover from shocks. This divergence between short-term welfare and underlying resilience features the need for multidimensional metrics (FAO, 2016; FSIN, 2014; Ian Scoones, 1998).

The RIMA-II framework aligns well with this capacity-based conceptual foundation. It measures resilience through a composite Resilience Capacity Index (RCI) constructed from four empirically identified pillars as Access to Basic Services (ABS), Assets (ASS), Social Safety Nets (SSN), and Adaptive Capacity (AC) and has been widely used in shock-prone and low-income settings (FAO, 2016). Rather than measuring each resilience capacity as a separate latent construct, RIMA-II translates broad theoretical concepts into observable household conditions, resources, and institutional linkages. This makes the framework especially useful in low-income and shock-prone settings, where resilience must be assessed using measurable indicators that reflect households’ ability to prepare for, withstand, respond to, and recover from adverse events.

Conceptually, these four pillars provide practical entry points for understanding the five resilience capacities. Preventive and anticipative capacities are reflected primarily through ABS and selected components of AC, since access to education, health services, markets, transport, financial services, information, and preparedness mechanisms enables households to reduce exposure to risk and act early when threats emerge. Absorptive capacity is most closely linked to SSN and asset holdings, as households often rely on transfers, informal support, savings, livestock, and other buffer resources to stabilize consumption and protect welfare in the immediate aftermath of shocks. Adaptive capacity is captured more directly through AC and productive asset portfolios, which shape the ability of households to diversify livelihoods, adjust production and labor decisions, adopt new strategies, and respond flexibly to changing conditions. Transformative capacity is less directly observable at the household level, but it is reflected indirectly through sustained improvements in service access, institutional support, and livelihood opportunities that enable households to move beyond repeated crisis management and transition out of chronic vulnerability (Bahadur et al., 2015; FAO, 2023).

Accordingly, the RCI is used in this study not only to compare resilience across regions and between rural and urban households, but also to examine how different shocks affect each underlying pillar. This pillar-based approach makes it possible to identify which dimensions of resilience are most constrained under different forms of stress and where policy interventions may be most effective. In the empirical analysis, variation in pillar performance and differential shock effects are therefore interpreted as evidence of the strengthening or erosion of preventive, anticipative, absorptive, adaptive, and indirectly transformative resilience capacities.

1.2.2. Empirical Measurement of Resilience Using RIMA-II

Building on this conceptual foundation, the next step is to operationalize resilience empirically in a way that is both theoretically grounded and measurable using household survey data. The RIMA-II framework is a widely used approach for quantifying household resilience to shocks in rural and low-income settings. It operationalizes resilience as a second-order latent construct composed of four first-order pillars. The empirical strategy uses principal component analysis (PCA) for initial structure detection and factor analysis (FA) for pillar construction and to estimate the second-order latent construct the RCI. This strategy is consistent with the multidimensional nature of resilience and improves comparability across different contexts.

In Ethiopia, applications of RIMA-II are emerging but remain limited. A key contribution is FAO's national assessment using LSMS-ISA/ ESS data (2011–2018), which identifies wide spatial disparities and demonstrates strong associations between RCI and food-security outcomes (FAO, 2022). Importantly, the study validates the RCI against multiple food-security indicators, demonstrating that resilience is strongly associated with dietary diversity, caloric adequacy, and reduction in poverty outcomes.

Haile et al. (2022) show that households with higher resilience capacity experience more stable food and nutrition security under climatic stress, underscoring the role of adaptive behaviors and asset buffers. Using ESS data, Belete et al. (2023), find that resilience capacity reduces households' risk of multidimensional destitution and vulnerability to becoming destitute, particularly in the presence of recurrent and concurrent shocks. Their findings indicate that shocks such as drought, conflict, price volatility, and other household-level stressors increase the likelihood of destitution, as captured by indicators of education, nutrition, and standard of living, whereas stronger resilience capacity mitigates these effects and enhances households' ability to avoid or move out of persistent deprivation.

Subnational studies further highlight localized drivers of resilience, emphasizing social capital, livestock ownership, irrigation, education, diversification, and institutional support, though these analyses remain geographically narrow and cross-sectional (Beyene and Senapathy, 2022; Guyu and Muluneh, 2015; Mossie et al., 2024). This literature demonstrates that multidimensional, statistically derived measures of resilience provide explanatory power beyond conventional welfare indicators. Nevertheless, although RIMA-II offers a rigorous framework for quantifying resilience, nationally representative longitudinal applications remain scarce, leaving the temporal dynamics of resilience, particularly under multiple and overlapping shocks, insufficiently understood.

1.2.3. Evidence on Shocks and Resilience in Ethiopia

Ethiopia has experienced a convergence of severe shocks in recent years, each with significant implications for rural livelihoods and resilience dynamics. The COVID-19 pandemic disrupted mobility, supply chains, and employment, leading to income losses and rising food-price inflation (Bogale et al., 2020; Gebreeyesus and Tekleselassie, 2021). The northern conflict in Ethiopia (2020–2022) further increased vulnerability through displacement, asset destruction, and disruptions to markets and agricultural systems, with assessments indicating high levels of acute food insecurity in affected regions (FEWSNET, 2022; IPC, 2021).

Global supply disruptions, including the Russia–Ukraine conflict, amplified domestic food and fertilizer price inflation, and reduced real incomes and production capacity (AERC, 2023; Steinbach, 2023). Concurrently, recurrent climatic shocks, particularly prolonged drought cycles, continue to erode agricultural and pastoral systems (UNDRR, 2024). Evidence consistently shows that households with greater assets, better access to services, diversified livelihoods, and stronger social networks exhibit higher resilience in the face of such shocks. Existing studies are largely cross-sectional or geographically limited, providing limited insight into how resilience evolves through prolonged or multiple shocks.

Critically, to our knowledge, no published study for Ethiopia combines RIMA-II with nationally representative panel data to estimate resilience as a SEM-based second-order latent construct and simultaneously examine how shocks map onto the individual pillars. Addressing this gap is essential for understanding resilience trajectories and for designing policies that strengthen households' ability to manage shocks in an increasingly uncertain environment.

This study responds to this need by applying the RIMA-II framework to nationally representative ESS data (2018/19–2021/22) to construct a multidimensional Resilience Capacity Index and examine how household resilience evolved across space and time during one of the most shock-intensive periods in Ethiopia's recent history.

1.3. Data

This study uses microdata from the Ethiopia Socioeconomic Survey (ESS), a nationally representative panel survey implemented by the Central Statistical Agency (CSA) in partnership with the World Bank's LSMS–ISA program. The ESS collects detailed information on household demographics, agricultural production, assets, consumption, access to services, social networks, and exposure to shocks features that make it well suited for the construction of multidimensional resilience indicators.

1.3.1. Survey Waves and Coverage

The analysis is based on two consecutive ESS waves: Wave 4 (2018/19) provides a nationally representative pre-shock baseline covering 6,770 households in 565 enumeration areas across all nine regional states and the two federal cities. Wave 5 (2021/22) was collected during a period characterized by COVID-19 disruptions, regional conflict, and sharp food and fertilizer price inflation. The survey successfully re-contacted 4,999 households in 438 enumeration areas; however, the Tigray Region was excluded because of conflict-related inaccessibility.

After harmonizing variables and addressing missing data on core indicators, the final balanced panel comprises 4,849 households observed in both waves. The two rounds capture conditions before and after a period of overlapping climate, health, economic, and political shocks, allowing for an examination of changes in resilience capacity over time. A few moderate positive correlations are observed, particularly between drought and livestock death, and between food price increases and input price increases, reflecting plausible environmental and market linkages. Overall, the results indicate that the shock measures capture related but distinct dimensions of household risk exposure and can therefore be modeled separately, while acknowledging the possibility of concurrent shocks.

1.3.2. RIMA-II and Integrating conceptual framework

The RIMA-II framework conceptualizes resilience as a multidimensional latent construct reflecting households' capacity to anticipate, prevent, absorb, adapt to, and transform in the face of shocks while maintaining acceptable levels of well-being. RIMA-II consists of four first-order pillars representing distinct yet interrelated dimensions, each grounded in the sustainable livelihoods and development of resilience literature (Barrett and Constas, 2014; Béné et al., 2012; FAO, 2016). In empirical applications, these capacities are captured indirectly through the four pillars that combine a strong theoretical foundation with data-driven estimation.

Figure 1.2 illustrates this conceptual framework linking observed indicators to resilience. Household-level indicators map into the four first-order pillars which jointly define the latent RCI.

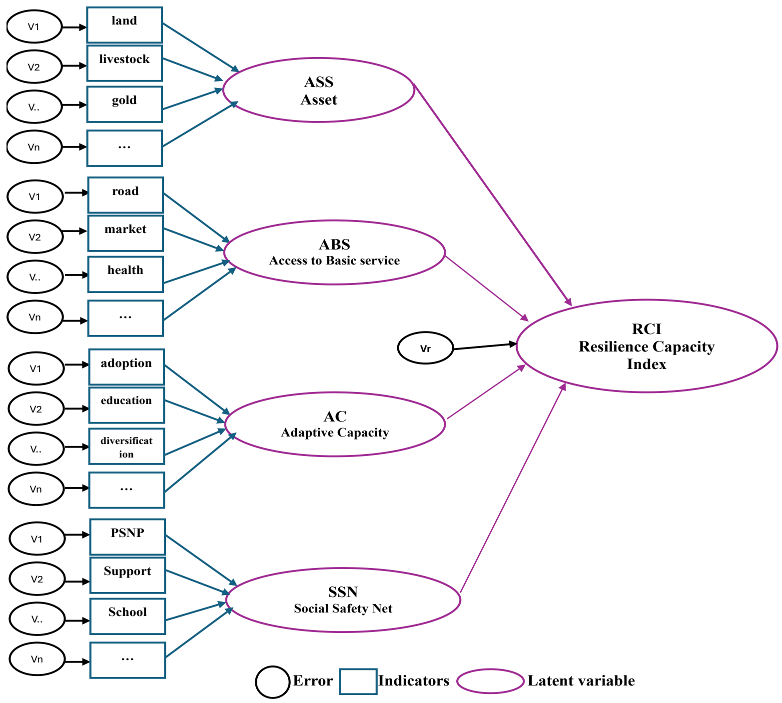

Figure 1-2: Conceptual framework for measuring household resilience capacity.

The estimated pillars consist of:

1. Access to Basic Services (ABS): Physical and institutional access to markets, schools, health centers, water sources, financial institutions, and administrative bodies. Improved service access reduces information asymmetries, strengthens absorptive capacity, and enhances opportunities for adaptation.
2. Assets (ASS): Stocks of productive, durable, and financial assets that buffer shocks and enable recovery directly influencing both absorptive and adaptive capacities.
3. Adaptive Capacity (AC): education, skills, technology adoption, off-farm work, and access to information that support long-term adjustments in response to changing conditions.
4. Social Safety Nets (SSN): Formal transfers and informal social support systems that stabilize welfare during crises. It enables households to share risks and buffers during crises.

These pillars reflect the theoretical view that resilience emerges from the interaction of household resources, capacities, and enabling environments, and that well-being trajectories depend on this ability. Thus, the RIMA-II framework aligns with the broader resilience literature by emphasizing capacities rather than static outcomes, adopting a forward-looking perspective, and focusing on households' ability to maintain or improve their capacity over time in the presence of risk and uncertainty (Barrett & Constas, 2014; FSIN, 2014; FAO, 2016).

The framework is particularly appropriate for Ethiopia's rural context, where livelihoods depend heavily on rain-fed agriculture, exposure to climate and market shocks is recurrent, and access to formal insurance and credit markets remains limited. The ESS provides consistent and detailed information that allows these four pillars to be operationalized over time, enabling a dynamic assessment of resilience capacity.

1.3.3. Link to Household Welfare

RIMA-II explicitly models the structural drivers of resilience and the capacity of households to remain above or below a specified welfare threshold. The framework has been validated across multiple countries, demonstrating strong associations between resilience capacity and food security and reduced vulnerability to poverty (D'Errico and Lisa C., 2020; FAO, 2022). In Ethiopia, empirical studies show that households with higher resilience scores experience more stable food consumption, improved nutrition, and lower welfare volatility during climatic and economic shocks (Belete et al., 2023; Haile et al., 2022).

1.3.4. Indicator Selection & Preprocessing

Indicators were selected based on theoretical relevance, data availability, and statistical adequacy following FAO (2016) guidelines. Only variables consistently collected across both waves were included to ensure comparability.

Each indicator was mapped to its associated RIMA-II pillar based on theoretical function. Also, we performed diagnostic assessment on distributional properties, multicollinearity, and correlation patterns to ensure suitability for PCA and SEM. Appendix Table A.1 lists all indicators and definitions, minimum and maximum values. In addition, missing values, outliers, and coding errors were handled while minimizing distortion of underlying variance.

1.4. Methods

1.4.1. Principal Component Analysis (PCA)

To construct efficient and parsimonious indices, candidate indicators were first screened using pairwise correlations to reduce redundancy and exclude weak contributors. Specifically, variables exhibiting high (> 0.70) and very low correlation with other indicators (< 0.20) were carefully reviewed, with exclusions guided by both statistical criteria and conceptual relevance.

Principal Component Analysis (PCA) was then applied separately to each of the four RIMA-II pillars. For each pillar, the first principal component (PC1) was retained as a unidimensional index summarizing the shared variation across indicators. Table 1-1 presents the indicators included in each pillar together with their corresponding PC1 loadings. This mapping provides transparency on variable contributions and allows assessment of whether the retained component captures a coherent underlying dimension.

The PCA results reveal important differences in the internal structure of the four pillars. The ABS indicators exhibit a strong and coherent unidimensional structure, with uniformly positive loadings and relatively high explained variance, indicating a well-defined latent construct. In contrast, the SSN, AC, and ASS pillars display more heterogeneous loading patterns, with mixed signs reflecting the presence of underlying sub-dimensions and contrasting mechanisms.

Specifically, the SSN pillar distinguishes between informal support systems and formal transfer programs, the AC pillar captures differences between production-based and human capital–based adaptation strategies, and the ASS pillar reflects a contrast between productive and consumption-oriented asset portfolios. Despite this multidimensionality, the first principal component is retained for all pillars to ensure comparability and maintain a parsimonious representation consistent with the RIMA-II framework.

Despite this multidimensionality, the first principal component is retained for all pillars to ensure comparability and maintain a parsimonious representation consistent with the RIMA-II framework. Because PCA loadings are scale- and sign-dependent, the direction of components is normalized such that higher values consistently reflect greater resilience capacity.

Table 1-1: PCA loadings for RIMA-II pillar construction

ABS Indicators	Description	PC1 Loading
z_ABS_Road_Type	Road type / quality of road access	0.343
z_ABS_Asphalt_Rs	Access to asphalt (paved) road	0.304
z_ABS_PubTrans	Access to public transport	0.234
z_ABS_Bus_Rs	Access to bus services	0.276
z_ABS_Market_Dist	Access to markets	0.179
z_ABS_Health_Facility	Access to health facilities	0.279
z_ABS_Microfinance	Access to microfinance services	0.287
z_ABS_Water_Service	Access to water services	0.315
z_ABS_Electricity	Access to electricity	0.345
z_ABS_Bank_Dist	Access to banking services	0.329
z_ABS_Secondary_School	Access to secondary education	0.280
z_ABS_Agent_Dist	Access to extension/agent services	0.249
SSN Indicators		
z_SSN_Insurance	Access to insurance mechanisms	0.294
z_SSN_SACCO	Participation in SACCO/cooperatives	0.419
z_SSN_Social_Support	Informal social support networks	0.410
z_SSN_Church	Support from religious institutions	0.352
z_SSN_PSNP	Participation in PSNP (public safety net)	-0.135
z_SSN_Assistance	Institutional assistance (gov/NGO)	-0.195
z_SSN_PrimarySchool_religious	Religious-based primary support/services	0.452
z_SSN_SecondarySchool_religious	Religious-based secondary support/services	0.430
AC Indicators		
z_AC_HHHRemit	Household remittance access	-0.147
z_AC_HighEdu	Highest education level	-0.278
z_AC_Phone	Access to phone/communication	-0.202
z_AC_Num_children	Household size / dependency	0.410
z_AC_Imp_Agr	Improved agricultural practices	0.313
z_AC_Vac_animal	Livestock vaccination	0.311
z_AC_Ext_Reach	Extension service access	0.444
z_AC_coop_member	Cooperative membership	-0.264
z_AC_Fin_service	Access to financial services	0.410
z_AC_Machinery	Use of agricultural machinery	0.188
z_AC_Income_sources	Income diversification	0.167
Ass Indicator		
z_ASS_TLU_owned	Livestock holdings (TLU)	-0.229
z_ASS_Land_owned	Land owned	-0.219
z_ASS_Ownership	Ownership status (housing/land)	-0.230
z_Ass1_Stove	Improved stove	0.394
z_Ass2_Electricity	Electricity access (asset)	0.409
z_Ass3_Livestock_products	Livestock-related assets/products	0.388
z_Ass4_Kitchen	Kitchen/household facilities	0.400
z_Ass5_GoldSavings	Gold/savings assets	0.198
z_Ass6_FarmTools	Farm tools/equipment	-0.340
z_Ass7_OtherAssets	Other productive assets	-0.141
z_Ass8_Transport	Transport assets	0.199

PCA suitability was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. All pillars satisfy standard adequacy thresholds, with KMO values exceeding 0.60 and Bartlett's test strongly rejecting the null hypothesis of an identity correlation matrix ($p < 0.001$), confirming sufficient correlation among indicators (Table 1-2).

Table 1-2: PCA Fit stat

Statistic	ABS	SSN	ASS	AC
Eigenvalue (PC1)	4.558	2.38	3.97	3.70
Variance explained	37.98	29.75	36.07	33.59
Number of indicators	12	8	11	11
KMO	0.8831	07101	0.8683	0.8213
Bartlett	0.0001	0.0001	0.0001	0.0001

Component loadings were examined to verify internal consistency, and sensitivity analyses were conducted to assess robustness to indicator exclusion (Appendix Figure A1). The retained PC1 scores were then standardized (mean = 0, standard deviation = 1) to ensure comparability across pillars and survey waves. These standardized indices: ABS, ASS, AC, and SSN serve as inputs to the subsequent structural equation model (SEM) used to estimate the composite Resilience Capacity Index (RCI).

1.4.2. RCI Estimation via SEM

A second-order Structural Equation Model (SEM) was estimated to derive the composite RCI. SEM is well suited for resilience measurement as it explicitly models latent constructs, allows hierarchical factor structures, and accounts for measurement error, thereby yielding consistent estimates of multidimensional capacity indices (Barrett and Constas, 2014; Bollen, 1989).

Model specification

Household resilience capacity is conceptualized as a latent construct reflecting the shared variation across four empirically derived pillar indices: Access to Basic Services (ABS), Assets (ASS), Adaptive Capacity (AC), and Social Safety Nets (SSN). These pillar scores are constructed in a first stage using Principal Component Analysis (PCA), as described above.

In the second stage, the Resilience Capacity Index (RCI) is estimated within a reduced-form SEM framework by treating the four pillar scores as observed indicators of a single latent resilience construct. Formally for household i, the measurement model is specified as:

$$P_{ij} = \lambda_j \, \boldsymbol{RC_i} + \varepsilon_{ij}, \text{j} \in \{\text{ABS, ASS, AC, SSN}\}$$

Where:

- P_{ij} denotes the observed score for pillar j,
- λ_j is the loading of pillar j on the latent Resilience Capacity Index, and
- ε_{ij} is a pillar-specific error term capturing measurement error and idiosyncratic variation and RCI_i represents the underlying capacity common to the four pillars.

This specification constitutes a reduced-form latent measurement model, where the SEM captures the common covariance structure across the four pillar indices rather than estimating a full item-level confirmatory factor model. The approach therefore combines data reduction at the indicator level (via PCA) with latent variable modeling at the aggregate level, consistent with the multidimensional and theory-driven nature of resilience in the RIMA-II framework.

Each pillar is treated as an observed endogenous indicator of the latent RCI, with measurement error explicitly modeled within the SEM framework.

Estimation Strategy

The Structural Equation Model (SEM) is estimated using Maximum Likelihood with Missing Values (MLMV), which allows the inclusion of incomplete observations under the assumption that data are missing at random (MAR). This approach exploits all available information, improving efficiency relative to listwise deletion and yielding consistent parameter estimates in the presence of missing data.

A second-order confirmatory factor model (hierarchical CFA) is specified to construct the Resilience Capacity Index (RCI). Household resilience is modeled as a higher-order latent construct reflected by the four first-order dimensions pillars. In empirical implementation, these four dimensions are represented by composite indices derived from principal component analysis and are treated as observed indicators of the higher-order latent variable. The model therefore captures the shared variation across these pillars as manifestations of underlying resilience capacity.

Formally, the measurement structure of the second-order model can be expressed as:

$$\text{ABS} = \gamma_1\text{RCI} + \delta_1,\ \text{ASS} = \gamma_2\text{RCI} + \delta_2,\ \text{SSN} = \gamma_3\text{RCI} + \delta_3,\ \text{AC} = \gamma_4\text{RCI} + \delta_4$$

Where

- γ_k denote factor loadings and
- δ_k are measurement disturbances.

Predicted latent factor scores for RCI are obtained from the fitted model using the post-estimation prediction command (e.g., predict RCI_hat, latent). These scores represent household-specific estimates of resilience capacity and are subsequently used as key explanatory variables in the econometric analysis of food security outcomes.

Model Fit and Validation

Model adequacy is evaluated using multiple goodness-of-fit indices (Table 1-3) following established guidelines Hu and Bentler (1999), including: Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR)

Table 1-3: SEM model fit statistics

Fit Statistic	Full Sample (Pooled)	Wave 4	Wave 5	Interpretation
X^2	742.74 ($P < 0.001$)	380.27 ($P < 0.001$)	393.50 ($P < 0.001$)	Good fit
RMSEA (90% CI)	0.195 (0.184–0.207)	0.198 (0.181–0.214)	0.201 (0.184–0.218)	Suggest Specification Error.
CFI (≥ 0.95)	0.961	0.962	0.957	Very Good Relative Fit.
TLI (> 0.90)	0.882	0.887	0.871	Marginal Parsimony.
SRMR (< 0.08)	0.036	0.035	0.037	Acceptable Residual Fit.
CD (> 0.85)	0.877	0.884	0.874	Strong overall explanatory power.

The results indicate mixed but generally acceptable model fit. CFI and SRMR suggest strong relative and residual fit, while RMSEA and TLI indicate some degree of model misspecification or limited parsimony.

Such patterns are not uncommon in reduced-form SEMs based on composite indices. The elevated RMSEA likely reflects both the use of pre-constructed pillar scores and the complexity of representing resilience as a single latent dimension. Accordingly, model fit is interpreted jointly across indices, with greater weight placed on CFI and SRMR.

Standardization and Index Construction

Predicted latent factor scores for RCI are extracted from the SEM and standardized to z-scores:

$$Z_i = \frac{X_i - \bar{X}}{s}$$

This transformation places the index on a common scale, facilitating comparison across households, survey waves, and improves interpretability in regression analysis by expressing effects in standard deviation units. Standardization is performed using the pooled sample to ensure temporal comparability.

Resilience Classification

For descriptive and spatial analysis, households are classified into four resilience categories based on standardized thresholds (RCI ≥ +1→High, 0≤ RCI<+1→Moderate, -1≤ RCI<0 →Low & RCI < -1→ Very Low). These cutoffs are distribution-based and reflect deviations from the sample mean. The ±1 standard deviation threshold is a conventional statistical benchmark for identifying households that are meaningfully above or below average. The classification is therefore relative rather than policy-defined and is intended to support interpretation while preserving the continuous nature of the RCI.

1.4.3. Regional and Rural–Urban Disaggregation

Given pronounced spatial heterogeneity in livelihoods, infrastructure, and shock exposure, we examine RCI distributions across (i) major regions: Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, SNNP, Sidama, Gambella, Harari, Dire Dawa, and Addis Ababa and (ii) rural versus urban areas, reflecting distinct livelihood systems. Tigray is excluded from the pooled analysis because it is not observed in Wave 5.

Tests of spatial differences

We assess wave, geographic and rural–urban disparities using mean-comparison tests and distributional diagnostics. Rural–urban differences are tested using two-sample t-tests. Regional differences are evaluated using one-way ANOVA with Tukey's HSD post-hoc pairwise comparisons. Together, these tests identify statistically significant gaps in average resilience and highlight spatial inequalities in resilience capacity across Ethiopia.

1.5. Results

1.5.1. Descriptive Patterns of Household Characteristics and Shock Exposure

The descriptive statistics reveal clear temporal and spatial differences in household characteristics and shock exposure (Table 1-4**)**. Over time, households in Wave 5 experienced significantly higher exposure to all shock types reflecting the intensification of climatic, economic, and conflict-related stressors between 2018/19 and 2021/22. Total shock exposure more than doubled, and several individual shocks show substantial and statistically significant increases.

Table 1-4: Patterns of Household Characteristics and Shock Exposure

Variable	Mean Urban	Mean Rural	Diff	Mean W5	Mean W4	Diff
Household head Sex (1=Male)	0.678	0.771	-0.093***	0.686	0.688	-0.003
Age of Household head (yrs)	41.586	45.56	-3.974***	45.43	42.89	2.535***
Household Size (No)	3.965	5.104	-1.139***	4.604	4.506	0.097**
Adult equivalent	3.329	4.060	-0.730***	3.813	3.593	0.220***
Agriculture practice (0=non-agriculture, 1=crop / livestock, 2=mixed)	0.000	1.646	-1.646***	0.674	0.652	0.022
Dependency	0.297	0.422	-0.125***	0.372	0.381	-0.008
Total number of Shock	0.776	1.241	-0.464***	1.293	0.581	0.713***
Health shocks (1=Yes)	0.184	0.230	-0.046**	0.214	0.185	0.028***
Job Loss (1=Yes)	0.012	0.009	0.004	0.010	0.006	0.004**
Drought (1=Yes)	0.068	0.159	-0.092***	0.170	0.071	0.099***
Excess Rain (1=Yes)	0.042	0.114	-0.072***	0.092	0.038	0.054***
Output Price fall (1=Yes)	0.005	0.017	-0.012*	0.014	0.005	0.009***
Food Price Rise (1=Yes)	0.292	0.284	0.008	0.402	0.133	0.268***
Input Price Rise (1=Yes)	0.095	0.258	-0.163***	0.217	0.053	0.164***
Livestock Death (1=Yes)	0.018	0.091	-0.074***	0.083	0.037	0.046***
Political Shock (1=Yes)	0.056	0.061	-0.005	0.078	0.048	0.030***

Notes: Weighted means reported. *Stars denote significance of the difference tests (Y5–Y4 or Urban–Rural): *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Diff(U–R) < 0 indicates rural values are higher; Diff(Y5–Y4) > 0. Adult equivalent Follows a calorie-requirement equivalents formula which assign a kcal requirement for each household member from an age–sex requirement table. (Age 15-59) male=1, women=0.85, age<=4=0.4, 5<age,10=0.6, 10<age<14=0.8(male) & 0.75(female), 60+(male) =0.9 & 0.8(female. Dependency Ratio Calculated as (total number households – number of households aged between 15-64)/ Total number of households.*

Spatial differences are similarly pronounced. Rural households report significantly larger household sizes, higher dependency ratios, and far greater reliance on agriculture than urban households. They also face consistently higher incidence of climatic and agricultural shocks, including drought, rainfall variability, input-price spikes, and livestock losses, all of which show large and highly significant rural–urban gaps. Urban households, by contrast, exhibit slightly higher job-loss exposure, but few other shock indicators differ meaningfully. Together, these temporal and spatial patterns highlight the cumulative shock environment of Wave 5 and underscore the heavier shock burden borne by rural households relative to their urban counterparts.

1.5.2. Contributions of Indicators to the RCI and PCA Diagnostics

To examine the internal structure of resilience, survey-weighted (probability weighing) regressions of standardized RCI scores on individual standardized indicators followed by PCA diagnostics (KMO and Bartlett's tests) were estimated (Table 1-5). These associations offer descriptive insight into the indicators most strongly correlated with household resilience. The PCA diagnostics demonstrate strong internal coherence within each pillar. All KMO values exceed the conventional threshold of 0.60, with particularly high values for ABS and ASS (>0.87), signaling that indicators within these pillars are highly interrelated. Bartlett's tests are significant at $p < 0.001$ for all pillars, confirming that the correlation matrices are suitable for data reduction. Factor loadings on the first principal component range from 0.64 to 0.92 across pillars, suggesting that individual indicators contribute meaningfully and in expected directions to their respective latent domains. These results provide empirical support for the conceptual structure of the RIMA-II pillars within the Ethiopian context.

Indicators within the ABS pillar show consistently strong positive associations with resilience. Proximity to markets and services, improved infrastructure, physical connectivity, and access to financial institutions all correlate with higher resilience scores. These results emphasize the foundational role of spatial and institutional access in shaping households' capacity to anticipate, absorb, and respond to shocks.

SSN indicators exhibit a dual pattern. Informal community-based support such as assistance from neighbors or religious groups correlates positively with resilience, underscoring the continued relevance of horizontal safety-net structures in rural and peri-urban areas. However, receipts of formal assistance or NGO transfers are negatively associated with the RCI. This pattern is consistent with program targeting design rather than a causal effect, as assistance is typically directed toward households experiencing acute distress and lower underlying resilience capacities.

Table 1-5: Indices contribution to the RCI and KMO result (standardized & weighted)

Pillar	Variable	Coefficient	Std. Err.	KMO
ABS	Road Type	0.0453***	0.0005	0.8984
	Asphalt Dis	0.0423***	0.0005	0.8533
	Public Transport Passable Months	0.0322***	0.0004	0.8984
	Bus Station Distance	0.0390***	0.0005	0.8285
	Market Distance	0.0252***	0.0004	0.9062
	Health Facility Availability	0.0401***	0.0006	0.8724
	Micro Finance Availability	0.0393***	0.0006	0.9053
	Water service Availability	0.0432***	0.0006	0.8976
	Electricity Availability	0.0485***	0.0008	0.9219
	Bank Distance	0.0456***	0.0005	0.8655
	Secondary School number	0.0380***	0.0003	0.8639
	Financial Agent Distance	0.0349***	0.0006	0.8693
	ABS			**0.8811**
SSN	Insurance Availability	0.0344***	0.0011	0.6432
	SACCO membership	0.0473***	0.0004	0.6835
	Received Social Support	0.0453***	0.0012	0.7814
	Church number	0.0401***	0.0006	0.7636
	PSNP (Productive Safety Net Programme)	−0.0168***	0.0003	0.6652
	Assistance received	−0.0224***	0.0004	0.7437
	Religious Primary School number	0.0526***	0.0025	0.6813
	Religious Secondary School number	0.0509***	0.0010	0.7074
	SSN			**0.7071**
AC	HH Read and Write	0.0170***	0.0003	0.6475
	HH member Highest Education level attained	0.0431***	0.0009	0.7457
	Mobile Phone access	0.0262***	0.0005	0.8602
	Crops grown number	−0.0539***	0.0004	0.853
	Use of Improved Agricultural practice	−0.0413***	0.0002	0.8782
	Vaccine animal	−0.0411***	0.0003	0.885
	Agricultural Extension Reach	−0.0588***	0.0005	0.8199
	Community Cooperative membership	0.0349***	0.0007	0.9138
	Receive Financial advice	−0.0543***	0.0006	0.8628
	Use of any Machinery	−0.0242***	0.0003	0.9062
	Income Sources number	−0.0206***	0.0007	0.8850
	AC			**0.8352**
ASS	TLU	−0.0507***	0.0006	0.9187
	Land size	−0.0493***	0.0004	0.8148
	Ownership of House	−0.0487***	0.0006	0.8217
	Stove assets	0.0890***	0.0010	0.8959
	Electronics assets	0.0925***	0.0009	0.9030
	Living Room assets	0.0894***	0.0009	0.8705
	Kitchen use assets	0.0970***	0.0017	0.8603
	Gold and silver	0.0470***	0.0005	0.9205
	Farm tool	−0.0730***	0.0009	0.8292
	Other farm tool	−0.0295***	0.0004	0.8485
	Vehicle	-	-	0.9124
	ASS			**0.8717**
Fit stat	**Population (Weighted)**	36,176,838		
	Obs.	9698		

Indicators in the AC pillar highlight both proactive and reactive features. Human capital, information access, and cooperative membership correlate positively with resilience, reflecting their role in expanding adaptive opportunities. However, income diversification and adoption of improved practices correlate negatively with the RCI. In rural contexts, these behaviors may reflect reactive adjustments undertaken in response to stress rather than deliberate longer-term strategies, suggesting that adaptive actions are not uniformly indicative of higher resilience.

Indicators associated with ASS show the most pronounced contrast. Modern household assets and liquid wealth (e.g., appliances, improved housing materials, gold/silver holdings) correlate positively with resilience, while traditional agricultural assets (e.g., livestock, farm tools) correlate negatively. This pattern likely reflects the heightened exposure of agrarian assets to climatic variability, disease outbreaks, and conflict-related losses during the study period. Or also the inability of these assets to provide the capacity needed to mitigate or absorb such shocks.

Taken together, the indicator-level associations suggest that infrastructure, reliable access to services, strong community networks, and diversified, particularly non-agricultural asset portfolios underpin higher resilience, whereas indicators reflecting reactive or vulnerability-driven behaviors are more prevalent among less resilient households.

1.5.3. Principal Component Analysis

1. Pillar Movements Over Time

Wave-to-wave comparisons of pillar indices (Table 1-6) reveal heterogeneous yet informative shifts. The only pillar showing a statistically significant decline is the SSN, consistent with reductions in cooperative membership, church-based support, and other community mechanisms.

Table 1-6: Weighted Pillar movements

Pillar	Mean (W4)	Mean (W5)	Diff (W5–W4)	95% CI
ABS	−0.35 (0.912)	−0.42 (0.882)	−0.069	[−0.156, 0.018]
SSN	−0.27 (0.766)	−0.36 (0.645)	−0.085**	[−0.155, −0.014]
AC	0.62 (1.180)	0.61 (0.998)	−0.010	[−0.100, 0.079]
ASS	−0.51 (0.864)	−0.48 (0.772)	0.027	[−0.010, 0.065]
RCI	−0.401	−0.416	−0.015	[−0.050, 0.019]

*Asterisks denote statistical significance of the mean difference: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*
"Diff (W5–W4)" reports mean values Δ between waves: 95% confidence intervals provided in brackets.

By contrast, ABS, AC and ASS pillars are not statistically significant. The ABS falls slightly, driven by the reduction in access to transport and financial services, and offsets by improvements in road conditions. AC is unchanged, implying gains in education and mobile phone ownership likely to compensate for reduced cooperative participation and agricultural support. The relative increases in ASS, alongside improvements in certain assets, reflects the gradual asset rebuilding.

Combined, these patterns indicate that resilience pathways diverged during the study period: households experienced erosion in some of the service access and social-support systems indicators while simultaneously maintaining or improving aspects of human capital and asset bases. This divergence is later reflected in the composite RCI.

2. Rural–Urban Differences in Pillar Distributions

The weighted kernel density plots (figure 1-3) reveal pronounced rural–urban disparities across all four RIMA-II resilience pillars. The distributions show not only clear level differences but also structural contrasts in dispersion and skewness, indicating heterogeneity in how rural and urban households accumulate capacities that underlie resilience.

ABS displays the starkest divide in its distribution. Urban households cluster tightly around higher standardized scores, with a narrow and negatively skewed distribution. Rural households, in contrast, show a broader distribution, centered on negative values and skewed towards very low values. This reflects systematic differences in proximity to markets, transport infrastructure, health facilities, financial institutions, and administrative services. The large gap in central tendencies and dispersion indicates that service access is not only lower but also more uneven in rural areas. This pattern underscores the spatially concentrated nature of service provision in Ethiopia.

SSN distributions also differ markedly, though less sharply than ABS. Rural households show a dense trimodal concentration around negative SSN scores, suggesting reliance on limited or weaker communities and institutional support. Urban households exhibit more dispersion with positive skewness, reflecting greater access to diverse formal and informal support institutions. The longer right tail for urban areas indicates that a subset of households benefits from stronger safety-net environments. These patterns align with known geographic differences in institutional density and social protection reach.

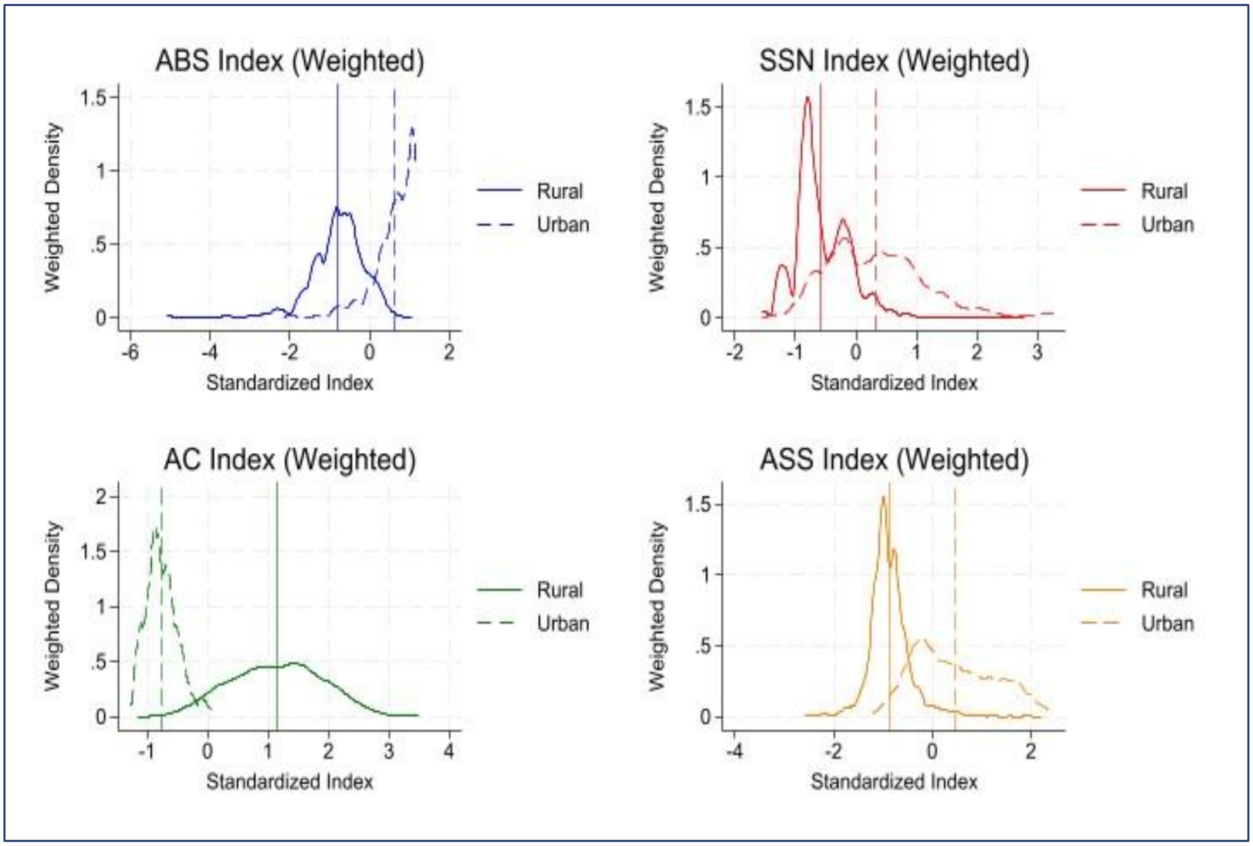

Figure 1-3: Distribution of pillars between households over Wave 4 and Wave 5.

AC reveals a different comparative pattern of distribution relative to ABS and SSN: urban households cluster narrowly around lower AC values, while rural households show a much wider distribution extending toward higher scores. This suggests that although average urban adaptive capacity is lower, variability is far more pronounced among rural households. Rural adaptive capacity appears to be driven by heterogeneity in education, information access, cooperative participation, and agricultural engagement. The broad rural distribution may reflect both proactive investment (e.g., education, cooperatives) and reactive strategies (e.g., diversification) among different groups.

ASS distributions show greater overlap between rural and urban households but still reveal a substantial urban advantage. Urban households cluster around higher standardized scores with relatively wider dispersion, reflecting greater access to assets and wealth, as well as a more heterogeneous distribution of asset holdings. In contrast, rural households exhibit a left-skewed distribution dominated by lower values, consistent with their reliance on traditional agricultural assets whose productivity is more vulnerable to climatic and economic shocks. The pronounced left tail in the rural distribution highlights the depth of asset poverty outside urban centers, while the extended right tail indicates that a small group of rural households possess relatively higher levels of asset holdings.

3. Regional Differences in Pillar Distributions

Figure 1.3 highlights substantial spatial heterogeneity in pillar levels and changes between Wave 4 and Wave 5. Addis Ababa and Dire Dawa consistently exhibit above-average performance in ABS and ASS and are the only regions with positive SSN scores, indicating stronger access to services, higher asset endowments, and comparatively better formal and informal protection. In contrast, several agrarian and pastoral regions most notably Somali, Afar, and Benishangul-Gumuz remain below the national mean in ABS, SSN, and ASS.

Temporal dynamics differ sharply across regions. ABS deteriorates most strongly in Somali, implying a widening deficit in service access, whereas SNNP and Harar show modest improvements. SSN declines in Dire Dawa and Afar, suggesting weakening shock-buffering capacity. ASS improves in Harar, Benishangul-Gumuz, Addis Ababa, and Gambela, consistent with gains in household productive and/or liquid assets. Patterns for AC are mixed: Oromia improves, while Amhara, Harar, Afar, and Gambela experience declines, indicating uneven changes in households' ability to adjust livelihood strategies under compounding stressors.

Within-region wave-to-wave changes further underscore this heterogeneity. Afar pillar values declines across ABS, SSN, and AC, and Somali declines in SSN and ASS, pointing to simultaneous weakening of protection and asset bases. By contrast, SNNP and Gambela improve in ABS and ASS, potentially reflecting localized recovery and improved market connectivity. Oromia and Amhara exhibit mixed movements, consistent with subregional variation in conflict exposure and mobility constraints.

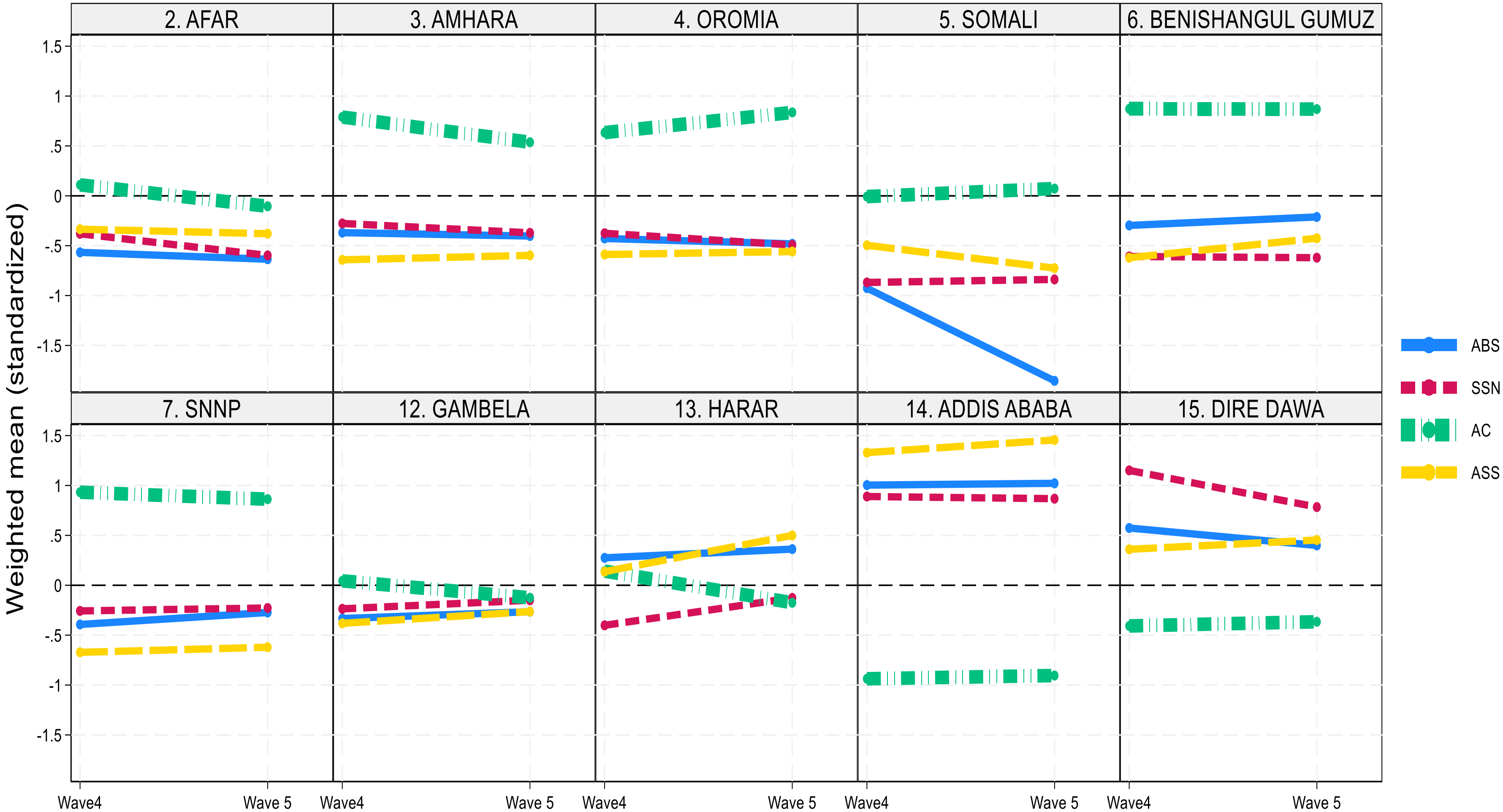

Figure 1-4: Pillar distribution and changes across regions

1.5.4. SEM Model and Pillar Fit

Pillar Contributions

SEM results (Table 1.7) indicate that all four pillars contribute significantly to the latent resilience construction. ASS exhibits the strongest contribution (λ ≈ 0.86–0.88), highlighting the central role of material wealth in buffering and recovering from shocks. ABS also contributes substantially (λ ≈ 0.71–0.79), although its influence declines slightly between waves, consistent with observed reductions in service access.

Table 1-7: Standardized Loadings of each Pillar Contributes to the RCI

Pillar	Pooled λ	R^2	Wave 4 λ	R^2	Wave 5 λ	R^2	Lr χ^2
ABS	0.74*** (0.033)	0.55	0.79*** (0.030)	0.629	0.71*** (0.041)	0.506	18.35***
SSN	0.63*** (0.034)	0.40	0.62*** (0.045)	0.386	0.64*** (0.041)	0.414	1.09
AC	–0.75*** (0.021)	0.557	–0.81*** (0.020)	0.652	–0.70*** (0.027)	0.486	96.97***
ASS	0.87*** (0.026)	0.755	0.86*** (0.025)	0.742	0.88*** (0.030)	0.765	13.04***
Average R^2 (indicators)		0.862		0.876		0.856	129.44***

Note: *λ denotes standardized factor loadings from the SEM, with standard errors in parentheses. R^2 represents the proportion of variance in each observed pillar index explained by the latent RCI. "Average R^2 (indicators)" reports the mean explained variance across the four pillars and should not be interpreted as a global model fit measure. LR χ^2 reports likelihood-ratio tests of equality of factor loadings across Wave 4 and Wave 5. *** $p < 0.01$.*

SSN maintains moderate, positive loadings (λ ≈ 0.63), reflecting the continued relevance of informal and formal support systems in stabilizing resilience. AC, in contrast, loads negatively (λ ≈ –0.70 to –0.81). This finding is consistent with descriptive evidence suggesting that certain adaptive behaviors such as diversification are undertaken reactively in response to stress, especially among vulnerable households.

Tests of equality of factor loadings across waves reveal significant structural changes in resilience composition. The loadings for ABS, AC, and ASS differ significantly between Wave 4 and Wave 5, while SSN remains statistically stable. Notably, adaptive capacity exhibits the largest shift (LR $\chi^2 = 96.97$, $p < 0.01$), highlighting its dynamic and context-dependent role during periods of compounded shocks.

Taken together, the four pillars account for a large share of the variance in the observed indices (average $R^2 \approx 0.86$), indicating a strong and coherent latent structure.

Pillar Patterns

Figure 1-5 shows scatterplots of standardized pillar indices against the RCI. Several clear patterns emerge. shows a strong positive association with the RCI, with observations relatively tightly clustered around the fitted relationship. Regression results further indicate that this relationship is convex, implying increasing marginal returns to improvements in service access. This pattern is consistent with complementarities among infrastructure, connectivity, and service provision, such that gains in resilience become larger once households reach higher levels of access.

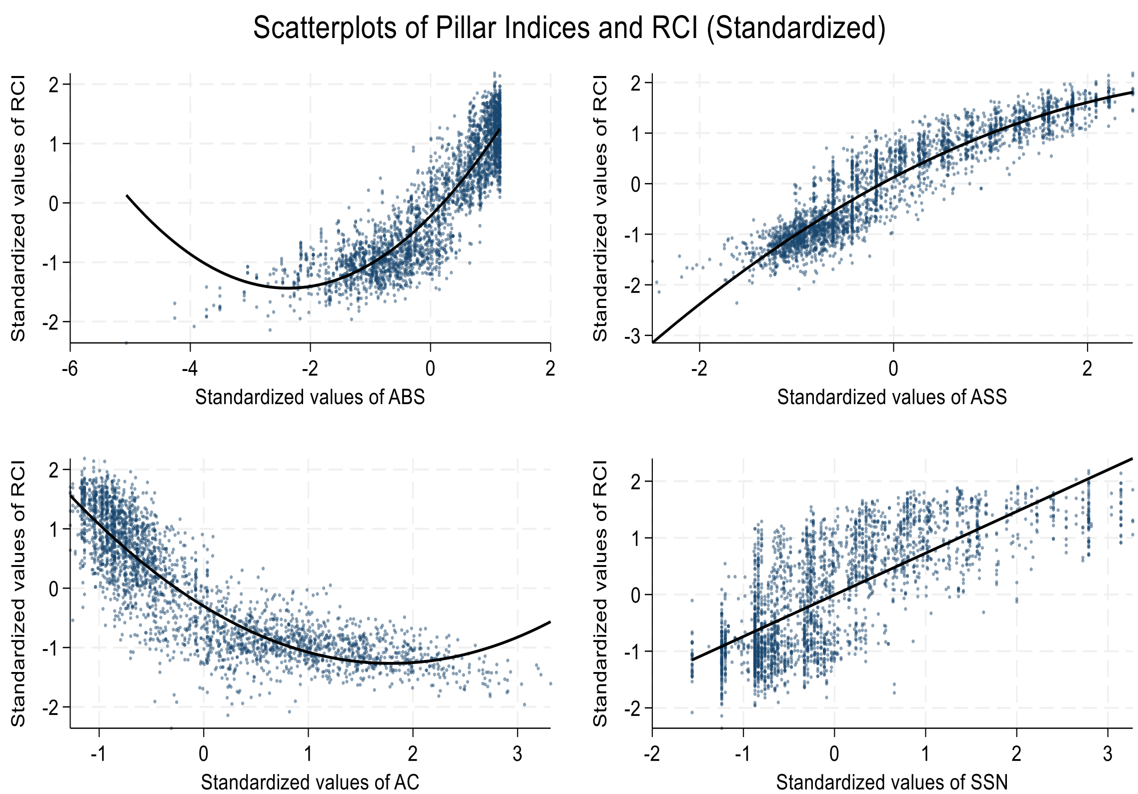

Figure 1-5: Scatterplots of Pillar Indices and RCI (Standardized).

Assets (ASS) also exhibit a strong positive association with the RCI and account for a substantial share of cross-household variation in resilience. However, unlike ABS, the regression results indicate a concave relationship, suggesting diminishing marginal contributions at higher levels of asset ownership. This implies that additional asset accumulation yields larger resilience gains for asset-poor households than for those already better endowed.

Social Safety Nets (SSN) are positively associated with the RCI but display greater dispersion and visible clustering at discrete values, reflecting the episodic and program-based nature of transfers and support mechanisms. The regression evidence suggests that this relationship is approximately linear, with no statistically significant nonlinear effect. This indicates that SSN contributes to resilience in a stable but more limited and uneven manner across households.

Adaptive Capacity (AC) displays the most distinct pattern. The scatterplots show a generally inverse association, with higher AC values concentrated among households with lower resilience scores. The regression results confirm a U-shaped relationship, characterized by a negative linear term and a positive quadratic term. This suggests that adaptive behaviors at low levels of capacity are often associated with distress-driven coping, whereas at higher levels they become more effective and resilience-enhancing. In this sense, AC appears to capture both reactive adjustment and more productive adaptation, depending on households' broader resource base and context.

Taken together, these results indicate that the pillars do not relate to resilience in uniform ways. ABS and ASS serve as the main structural anchors of resilience, while SSN and AC play more context-dependent roles that vary across households and levels of vulnerability.

Structural Redistribution of Pillar Influence

Comparisons across waves (Figure 1-6) reveal a modest redistribution in pillar contributions. The relative importance of ABS and SSN increases, while the importance of AC and ASS declines slightly.

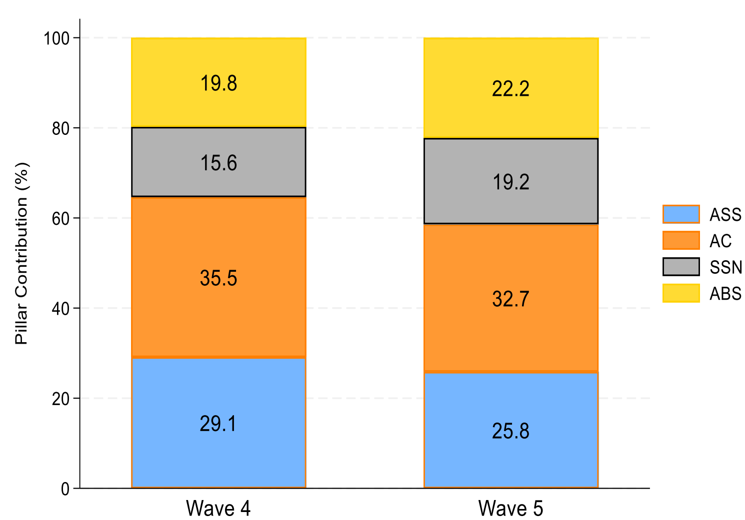

Figure 1-6: Weighted Contribution of Pillars to the Composite RCI (%)

This pattern suggests that during intense and overlapping shocks, households may rely more heavily on immediate support systems and access to services than on longer-term adaptive strategies or asset accumulation. While such rebalancing enhances short-term protection, it may weaken longer-term resilience pathways.

1.5.5. Distribution and Spatial Patterns of the Composite RCI

1. National RCI Distribution

Kernel density estimates (Figure 1-7) show a persistent bimodal distribution in resilience capacity, characterized by a large low-resilience cluster and a smaller high-resilience cluster. Weighted densities emphasize the lower tail, consistent with Ethiopia's predominantly rural and low-income population.

The mean RCI declines slightly between waves, indicating a marginal deterioration in overall resilience during the shock period. At the same time, dispersion narrows modestly. However, increased skewness and kurtosis imply that only a small share of households experienced substantial resilience gains, while many remained clustered at low levels.

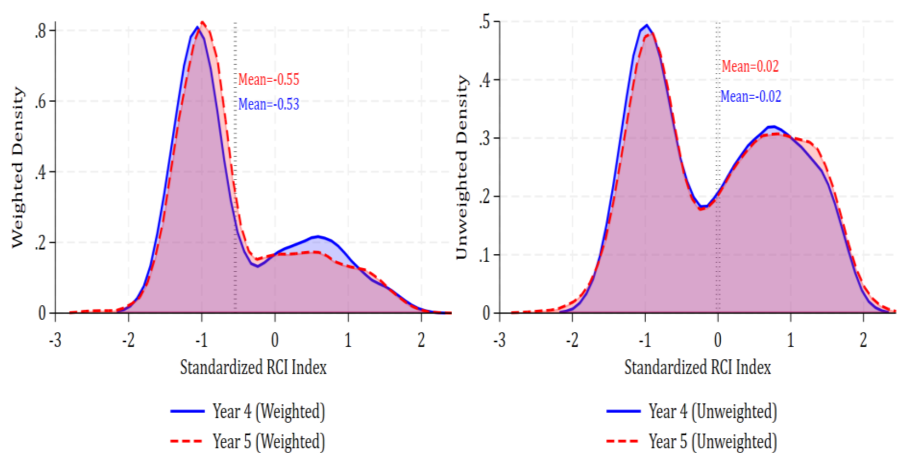

Figure 1-7: Weighted and unweighted Density plot of the RCI by Year

2. Rural–Urban Differences

The rural–urban divide in resilience is also evident in the distribution of the underlying pillar indices. Rural households exhibit markedly lower distributions ABS, with the median and interquartile range concentrated well below zero, reflecting persistent deficits in infrastructure, market connectivity, and service access. By contrast, urban households show substantially higher ABS values, consistent with better access to roads, transport, education, health, and financial services. A similar contrast emerges for Assets (ASS): urban households display a higher median and broader upper distribution, indicating stronger material endowments and a greater concentration of households in the upper tail of the asset distribution.

The pattern for AC differs sharply. Rural households show substantially higher AC values than urban households, with the distribution centered above zero, whereas the urban AC distribution is concentrated below zero. This finding is consistent with earlier results suggesting that adaptive capacity in this context partly captures reactive coping and stress-induced diversification rather than purely ex-ante resilience. In other words, higher rural AC scores may reflect greater reliance on adjustment strategies in response to exposure and vulnerability, rather than stronger structural capacity. SSN show a more moderate rural–urban difference, though urban households display a slightly higher and more dispersed distribution, suggesting somewhat broader access to formal and informal support systems.

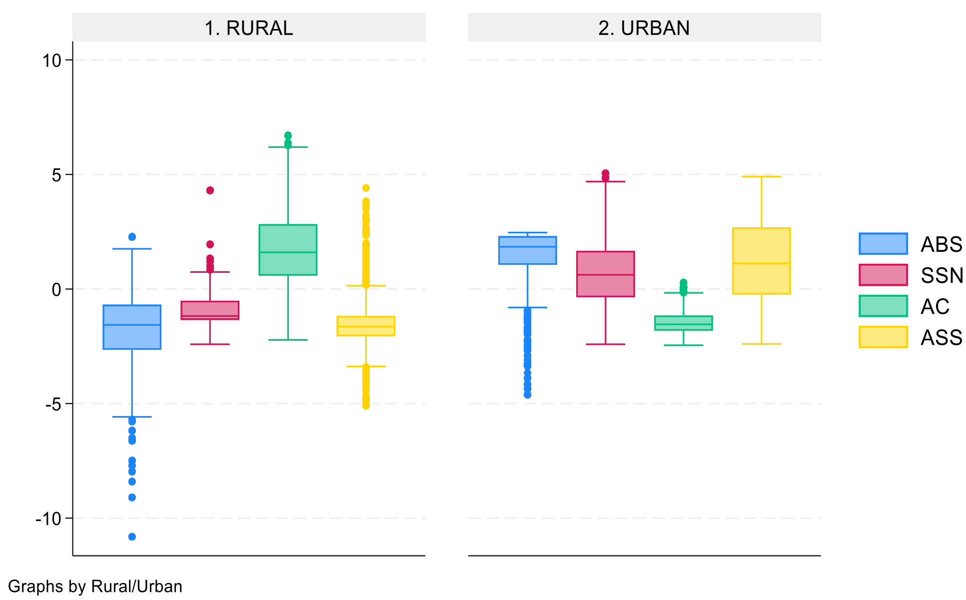

Figure 1-8: Rural Urban pillar comparison

Taken together, Figure 1-8 reinforces the broader finding that resilience is shaped by distinct structural conditions across space. Urban resilience appears to be anchored primarily in stronger access to services and asset holdings, whereas rural households remain disadvantaged in these foundational pillars and rely more heavily on adaptive responses. This contrast helps explain why rural households are disproportionately concentrated in lower resilience categories, while urban households are more frequently observed in the upper tail of the resilience distribution.

3. Regional RCI Patterns

Table 1-8 reveals a clear spatial hierarchy. Rural and pastoral regions (Somali, Afar, Benishangul-Gumuz, and SNNP) consistently exhibit the lowest resilience. Somali records the steepest decline (Δ = –0.295***), reflecting severe drought cycles and restricted mobility. By contrast, urban regions (Addis Ababa, Dire Dawa, and Harar) show high and in some cases improving resilience. Harar's substantial increase (Δ = +0.238***) reflects relative insulation from climate shocks and stronger institutional presence.

Mixed-farming regions (Amhara, Oromia, SNNP) remain persistently below zero, with limited temporal change, suggesting that while the shocks did not uniformly worsen conditions, they reinforced long-standing rural disadvantages. The moderate increases observed in Gambela (Δ = +0.098***) reflect the increase in AC, ASS and SSN values.

These findings point to widening spatial inequalities in resilience capacity: rural structural deficits compound the effects of climate and market shocks, while urban areas have a better advantage.

Table 1-8: Adjusted Mean RCI by Region (Year 4 vs. Year 5)

Region	Pooled mean RCI	Year 4 mean	Year 5 mean	DIFF (Y5 – Y4)
Afar	–0.324* (0.169)	–0.309 (0.184)	–0.327 (0.170)	–0.018
Amhara	–0.458*** (0.112)	–0.482 (0.124)	–0.439 (0.104)	+0.043
Oromia	–0.492*** (0.104)	–0.461 (0.112)	–0.517 (0.098)	–0.056
Somali	–0.657*** (0.086)	–0.485 (0.049)	–0.780 (0.120)	–0.295***
Benishangul-Gumuz	–0.459*** (0.132)	–0.518 (0.147)	–0.435 (0.130)	+0.084
SNNP	–0.490*** (0.111)	–0.522 (0.119)	–0.461 (0.106)	+0.062
Gambela	–0.182** (0.082)	–0.241 (0.093)	–0.143 (0.078)	+0.098***
Harar	0.160 (0.124)	0.027 (0.108)	0.264 (0.134)	+0.238***
Addis Ababa	0.982*** (0.013)	0.962 (0.014)	0.999 (0.016)	+0.037**
Dire Dawa	0.440*** (0.152)	0.478 (0.147)	0.413 (0.160)	–0.065

*Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$*

4. Synthesis

Taken together, the results reveal complex and uneven resilience trajectories in Ethiopia between 2018/19 and 2021/22. While some households strengthened elements of their human capital and asset portfolios, others experienced pronounced declines in service access and weakening of community-based support systems. These trends unfolded alongside marked spatial inequalities, with peripheral regions and rural areas disproportionately affected. The findings underscore the need for geographically targeted and multi-pillar resilience strategies that integrate infrastructure rehabilitation, social protection strengthening, and sustain support for adaptive capacities and diversified asset accumulation.

1.6. Discussion

The results provide new evidence on the determinants of household resilience in Ethiopia during a period of overlapping climatic, economic, and political shocks. Four patterns stand out: the dominant role of assets and basic services, the fragility of community safety nets under covariate stress, the reactive nature of much observed adaptive capacity, and wide spatial disparities shaped by infrastructure and institutional inequalities.

Taken together, these findings indicate that resilience in low-income agrarian settings is shaped primarily by structural conditions particularly access to services and asset endowments rather than by isolated coping behaviors. Household-level responses, including adaptive strategies and safety net participation, play complementary but context-dependent roles that vary with exposure to shocks and underlying resource constraints.

1.6.1. Why Assets and Basic Services Drive Resilience the Most

The strongest contributors to the composite RCI are ASS and ABS pillars, underscoring the foundational role of material endowments and structural access conditions in shaping welfare trajectories (Barrett and Constas, 2014; Carter and Barrett, 2006; FAO, 2016). In rural Ethiopia, where credit and insurance markets remain thin, assets act as de facto insurance by smoothing consumption, supporting production, and enabling recovery from shocks (Carter and Barrett, 2006).

A notable finding is the divergence within the asset portfolio. Modern and liquid assets (electronics, household durables, gold/silver) are positively associated with resilience, whereas agricultural assets including livestock and land load negatively. This reflects the specific draught and production shock environment that caused substantial agricultural losses (FEWSNET, 2022). The pattern also captures underlying socioeconomic differentiation where households with stronger resilience tend to hold more diversified and liquid assets, while land and livestock ownership is concentrated among poorer, agriculture-dependent groups (Vyas and Kumaranayake, 2006). Consistent with broader evidence from rural Ethiopia, livestock- or farm-dominant portfolios characterize as less diversified and more vulnerable households, explaining the negative loadings observed in the model (Pica-Ciamarra et al., 2011; Rogg, 2006).

ABS exerts a similarly strong effect. Proximity to markets, schools, health services, financial institutions, and all-weather roads enhances absorptive and adaptive capacities by lowering transaction costs and increasing information and mobility. The strong positive contribution of ABS in the SEM is consistent with FAO's RIMA-II applications in Africa and with evidence on spatial inequality in services and welfare trajectories in Ethiopia (FAO, 2022, 2016; Headey et al., 2018). Spatial disparities in service access exacerbated in conflict-affected regions such as Afar, Somali, and parts of Oromia mirror differences in resilience outcomes (Gutema et al., 2023; Headey et al., 2018; IPSS, 2020). Overall, these results indicate that resilience is anchored in structural opportunity environments, rather than discrete household-level strategies.

1.6.2. Institutional Fragility and the Decline of Community Safety Nets

The SSN pillar declines markedly between 2018/19 and 2021/22, driven by weakening informal support systems ($\Delta SSN = -0.085^{**}$). Reciprocal arrangements such as grain borrowing, informal credit, labor exchange, and religious or community assistance historically helped households manage idiosyncratic shocks. However, such systems are intrinsically vulnerable when entire communities are simultaneously affected, the capacity to share risk collapses (Dercon, 2004; Little et al., 2006).

The COVID-19 pandemic, conflict, and severe drought disrupted local institutions and administrative structures, limited physical access, leading to declining community support and cooperative participation. The negative association between formal assistance (PSNP) and the RCI is consistent with program targeting, which directs support toward households already experiencing acute vulnerability (D'Errico and Lisa C., 2020).

These trends indicate a shift from horizontal to vertical risk-sharing: as community-based systems weaken, households rely more on externally financed safety nets. While essential for preventing destitution, the erosion of local social protection mechanisms raises concerns about longer-term resilience pathways.

1.6.3. Why Adaptive Capacity Presents a Mixed, Often Reactive Pattern

The AC pillar shows a mixed relationship with resilience. Education, information access, and cooperative membership are positively associated with resilience, while diversification, use of improved technologies, extension contact, and machinery use are negatively associated. This pattern reflects the prevalence of reactive adaptation, where behaviors arise from exposure and constraint rather than opportunity (Gao and Mills, 2018; Gebeyehu et al., 2021; Matewos, 2020).

In Ethiopia's shock-prone rural economy, diversification into casual labor, seasonal work, or petty trade provides short-term liquidity but is widely recognized as distress-driven, undertaken by households with depleted buffers rather than as part of upward livelihood strategies (Barrett and Constas, 2014; Bezu and Barrett, 2012). A similar dynamic appears in agricultural technology adoption. Drought-tolerant or short-maturity varieties are often adopted by liquidity-constrained or climate-exposed households during periods of stress (Dercon and Christiaensen, 2011; Di Falco and Veronesi, 2014). Their performance remains modest due to limited complementary inputs and weak extension systems, reinforcing their function as risk-minimizing rather than productivity-enhancing technologies (FAO, 2017b; Hodson et al., 2020; Jaleta et al., 2019).

These constraints were amplified during the COVID-19 period and northern conflict, which disrupted extension services, input delivery, and market access, limiting farmers' ability to benefit from new practices (Gutema et al., 2023; Juliet et al., 2023). Consequently, several AC indicators capture behavioral responses of already vulnerable households, rather than genuine adaptive capacity. This helps explain why the latent AC factor loads negatively on the RCI: in a context of repeated shocks, "adaptive" behaviors may signal exposure and constraint rather than resilience.

1.6.4. Consistency and Divergence from Previous Literature

Overall, the findings are broadly consistent with the resilience literature, which emphasizes the foundational role of assets, services, and institutional support in shaping households' capacity to manage and recover from shocks. The strong contributions of the ASS and ABS pillars align with evidence from Ethiopia and other low-income agrarian settings showing that material endowments and spatial access conditions underpin both absorptive and adaptive capacities (Barrett and Constas, 2014; Belete et al., 2023; FAO, 2022, 2016; Haile et al., 2022). The erosion of community-based safety nets under repeated shocks also reflects established insights on the limits of informal insurance when entire communities are simultaneously affected (Dercon, 2004; Little et al., 2006).

At the same time, the results diverge from studies that associate diversification and technology adoption with greater resilience. In the 2018–2022 context, such behaviors are driven by exposure and constraints rather than opportunity, consistent with emerging evidence on distress-driven adaptation in shock-prone environments (Bezu and Barrett, 2012; Dercon and Christiaensen, 2011). The negative association between agricultural technology use and the RCI also contrasts with narratives that frame improved varieties and machinery as uniform resilience-enhancing. Instead, these results highlight the importance of complementary inputs, functioning markets, and extension support for these technologies to generate meaningful gains.

Finally, the pronounced spatial disparities in resilience outcomes, particularly the sharp deterioration in Somali and the persistent deficits in Afar and Benishangul-Gumuz, are more pronounced than in earlier LSMS-ISA analyses conducted during less shock-intensive periods (Bogale et al., 2020; Haile et al., 2022). This highlights the importance of longitudinal, shock-aware measurements for capturing how crises reshape regional resilience trajectories. The findings also reflect deep structural inequalities in service provision and market connectivity, consistent with recent work documenting the geographic concentration of vulnerability in Ethiopia (Headey et al., 2018; Mekasha and Tarp, 2021). These divergences suggest that, in periods of intense and overlapping shocks, the determinants of resilience differ markedly from those observed in more stable contexts, underscoring the need for context-sensitive interpretations of adaptive capacity and livelihood strategies.

1.7. Policy Implications

The findings carry several implications for strengthening resilience in Ethiopia and comparable shock-affected settings.

1. **Address Spatial Inequalities in Infrastructure and Services**

The strong contribution of ABS to resilience points to the need for territorially targeted investments in roads, markets, health and education services, and financial access in lagging regions such as Afar, Somali, Benishangul-Gumuz, and rural Oromia. Enhancing these structural conditions expands households' opportunity sets and reduces exposure to covariate shocks.

2. **Rebuilding Community-Based Institutions and Safety Nets**

The decline in informal support mechanisms highlights the fragility of horizontal risk-sharing under large-scale shocks. Revitalizing cooperatives, savings groups, and local governance structures can help restore community-based protection systems that complement formal social protection.

3. **Support Adaptive Capacity Through Enabling Conditions, Not Coping Pressures**

The negative association between diversification, extension contact, and technology uptake with resilience indicates that these behaviors often reflect distress rather than opportunity. Strengthening extension systems, stabilizing input markets, and easing liquidity constraints can shift households from reactive to proactive adaptation by improving their ability to act **before** shocks translate into major losses. Extension services lower information barriers and help translate climate and agronomic knowledge into actionable farm decisions, while reliable input markets ensure that recommended responses are feasible in practice. Relaxing liquidity constraints enable households to finance preventive investments at the beginning of the production cycle, rather than relying on ex post coping once shocks occur. Under these conditions, adaptive behavior is more likely to reflect forward-looking risk management than distress-driven adjustment

4. **Develop Integrated, Shock-Responsive Early-Warning Systems**

The recommendation for integrated, shock-responsive early-warning systems follows directly from the pillar results. The decline in SSN indicates that informal and community-based support weakens under covariate stress, while the regression results show that shock exposure is associated with deterioration in ABS. At the same time, the nonlinear pattern of AC suggests that many household responses are activated only after shocks occur. These findings imply that resilience interventions need to begin earlier, before stress translates into service disruption, distress coping, and asset erosion. Early-warning systems that combine climate, price, and conflict indicators with local reporting, and that are linked to pre-arranged financing and flexible delivery channels, would therefore help protect the very pillars shown here to underpin resilience.

5. **Scale and Adapt Social Protection to Multi-Shock Environments**

The association between formal assistance and lower resilience reflects effective targeting but also highlights persistent vulnerability. Expanding shock-responsive social protection, ensuring continuity in conflict-affected regions, and linking beneficiaries to asset-building and livelihood programs can mitigate negative coping and support recovery.

Summary

Overall, the results depict a resilience landscape shaped by structural access to services and assets, yet increasingly strained by institutional fragility, reactive adaptation, and widening spatial disparities. This underscores the value of multidimensional, capacity-based resilience metrics such as RIMA-II, while showing that the contribution of specific pillars shifts under extreme and overlapping shocks. Rebuilding resilience in Ethiopia's rural peripheries will require territorially differentiated, multi-pillar strategies that integrate infrastructure investment, institutional rehabilitation, and adaptive, shock-responsive social protection.

1.8. Conclusion

This study examined the structural and dynamic drivers of household resilience in Ethiopia during a period of overlapping climatic, economic, and political shocks. Using a multidimensional resilience framework and nationally representative panel data, the analysis shows that resilience is shaped by underlying asset endowments and access to basic services, while community-based safety nets weakened under covariate stress. Adaptive capacity emerges as a mixed and often reactive domain: many behaviors conventionally viewed as adaptive such as diversification or technology adoption are revealed to reflect exposure and constraint rather than enhanced capability. These patterns are further amplified in peripheral and conflict-affected regions, where deteriorating infrastructure, limited institutional presence, and constrained market access reinforce spatial inequalities in resilience outcomes.

The findings contribute to ongoing debates on the meaning and measurement of resilience in low-income agrarian settings by demonstrating that resilience capacities do not operate uniformly across contexts, and that their interpretation can shift markedly during crisis episodes. They highlight the value of longitudinal, shock-aware approaches that capture how households adjust within rapidly changing opportunity structures. More broadly, the results underscore the centrality of structural conditions assets, services, institutions, and territory in shaping resilience trajectories, and the limits of inferring resilience from behavioral indicators alone. These insights offer an empirical basis for designing resilience-building strategies that are sensitive to context, risk environments, and differentiated regional realities.

1.9. Limitations and Future Research

This study has several limitations that suggest directions for future research. First, while the panel structure allows analysis of changes in resilience over time, the empirical strategy remains primarily associational. The regressions identify systematic relationships between household characteristics, shocks, and resilience outcomes, but do not establish causal effects. Future work could strengthen identification by exploiting quasi-experimental variation in shocks, policy exposure, or infrastructure expansion.

Second, the measurement of resilience relies on latent constructs derived from observed indicators. While the RIMA-based framework captures multiple dimensions of resilience, some indicators—particularly within the adaptive capacity pillar may reflect both ex ante capability and ex post coping behavior. As the results show, this dual interpretation can complicate inference. Future research could refine measurement by distinguishing more explicitly between preventive capacity and reactive responses, potentially through higher-frequency data or behavioral modules.

Third, the analysis is constrained by data availability on local institutional dynamics and service quality. While the study captures access to services and infrastructure, it cannot fully account for variation in the reliability, timing, or effectiveness of these systems, which are likely to influence resilience outcomes. Integrating administrative data, geospatial indicators, or service delivery metrics would improve the ability to link structural conditions to resilience trajectories.

Fourth, although spatial heterogeneity is documented across regions and rural–urban contexts, the analysis does not explicitly model spillovers, market integration, or conflict dynamics at finer spatial scales. Given the importance of these factors in Ethiopia, future work could combine household data with spatially explicit information on conflict exposure, market connectivity, and climate variability to better understand how shocks propagate across regions.

Finally, the study focuses on medium-term changes between two survey waves, which may not fully capture shorter-term adjustment dynamics or longer-term recovery paths. Future research using higher-frequency panel data would help distinguish between transient coping responses and sustained improvements in resilience.

2 Chapter two: When does resilience protect household food security? Evidence from Ethiopia

Abstract

Food insecurity in Ethiopia remains widespread and is increasingly shaped by overlapping climatic, market, health, and political shocks. This paper tests whether, and under what conditions, household resilience capacity is associated with better food-security outcomes and whether it moderates the impacts of shocks. Using nationally representative panel data from the Ethiopia Socioeconomic Survey Waves 4 (2018/19) and 5 (2021/22), we construct a multidimensional Resilience Capacity Index consistent with the Food and Agriculture Organization of the United Nations RIMA-II framework. We analyze complementary food-security indicators capturing economic access (food expenditure share), utilization (dietary diversity and calorie-adequacy categories), and experiential food insecurity and hunger (FIES and HHS), and estimate outcome-appropriate models with resilience–shock interactions. Shocks, especially health shocks, drought, and food price increases, are strongly associated with worse experiential food insecurity and hunger, and the 2021/22 wave reflects a markedly harsher food-security environment. Higher resilience is associated with lower food budget pressure, higher dietary diversity, and fewer food-insecurity experiences, while severe hunger is primarily shock-driven. Interaction results show limited, shock-specific moderation: drought reshapes expenditure patterns; input-cost shocks erode dietary-diversity advantages among more resilient households, and political shocks weaken resilience-linked stability. These findings imply that household resilience capacity building should be paired with shock-responsive social protection and measures that address covariate risks such as drought and price instability.

Key Word:

Resilience Capacity Index (RCI); Food Security Outcomes; Shock Exposure; RIMA-II Framework; Ethiopia; Panel Data Analysis.

2.1. Introduction

Food insecurity remains a persistent and multidimensional challenge in many low-income countries, where livelihoods are highly exposed to climate, economic, health, and conflict-related shocks. In predominantly agrarian economies, such shocks disrupt production, incomes, and market access, pushing vulnerable households into transitory or chronic food insecurity (Barrett and Carter, 2013; Dercon, 2004). Because food security is increasingly understood as a dynamic welfare outcome and one that depends on stability “at all times,” the central question is not only whether households are food secure on average, but how quickly and how severely their welfare deteriorates when shocks occur (FAO, 2016). Global monitoring continues to document persistent hunger and acute food insecurity in shock-prone settings, reinforced by macroeconomic pressures and conflict dynamics (FAO IFAD UNICEF WFP and WHO, 2023; FSIN and GNAFC, 2024).

Ethiopia exemplifies these dynamics. Although the country has experienced periods of economic growth and poverty reduction, food insecurity remains widespread and highly sensitive to rainfall variability, drought, conflict-related disruptions, and macroeconomic stress (FAO IFAD UNICEF WFP and WHO, 2023; World Bank Group, 2022). With a large share of the population reliant on rain-fed smallholder agriculture and livestock, climate shocks can translate rapidly into production and income shortfalls. These effects are often compounded by displacement and political insecurity, displacement, and market disruptions that erode purchasing power, reduce labor availability, and constrain mobility and trade (Barrett and Constas, 2014; Dercon, 2004). Recent crisis assessments indicate that more than 20 million Ethiopians required emergency food assistance in 2023, underscoring the scale of vulnerability under intensified stress (FSIN and GNAFC, 2024).

These conditions motivate resilience-oriented policy aimed at strengthening the capacities that allow households to absorb, cope with, and adapt to adverse events without persistent welfare losses (Barrett and Constas, 2014; Béné et al., 2016). These capacities are often understood as encompassing absorptive capacity, which enables households to withstand and smooth the immediate effects of shocks; adaptive capacity, which allows them to adjust livelihoods and behavior in response to changing conditions; and transformative capacity, which reflects the broader institutional and structural changes needed to create more resilient livelihood systems. Yet compounding shocks such as widespread drought, conflict, and macroeconomic instability can overwhelm household-level coping strategies, implying the need for complementary system-level measures including shock-responsive social protections, market stabilization, and disaster risk management programs (FSIN and GNAFC, 2024). This raises a practical empirical question: which resilience capacities matter most for protecting food security and do protective effects differ between shocks?

Three gaps limit current evidence. First, many studies rely on single proxies or ad hoc indices that do not fully capture resilience as a multidimensional capacity (Upton et al., 2016). Such indices are typically assembled by combining heterogeneous indicators using arbitrary weighting schemes or equal weights, with limited attention to underlying latent structure, correlation among variables, or measurement error, thereby reducing comparability and interpretability. Second, empirical work often abstracts from the fact that households face multiple shock types that may operate through distinct channels and interact in shaping outcomes (Hallegatte et al., 2015). Third, and most critically, relatively few studies directly test the buffering hypothesis by estimating resilience–shock interactions, leaving uncertainty about whether resilience actively mitigates shock impacts or simply correlates with higher baseline welfare (Barrett and Constas, 2014; Cissé and Barrett, 2018).

This paper addresses these gaps by examining whether and under what conditions household resilience capacity protects or improves food security in Ethiopia using nationally representative panel data from the Ethiopia Socioeconomic Survey (ESS). We test whether resilience improves food-security outcomes directly (level effects) and whether it moderates the impacts of climatic, economic, health, and conflict-related shocks (buffering effects). By integrating a multidimensional resilience measure with multiple food-security indicators capturing experiential, economic, and dietary dimensions, the analysis provides policy-relevant evidence to inform the design, targeting, and sequencing of food-security and shock-responsive interventions in shock-prone settings.

The remainder of the paper proceeds as follows: Section 2 presents the conceptual framework; Section 3 describes the methods; Section 4 reports the results; Section 5 discusses implications; and Section 6 presents the policy implication and finally section 7 concludes.

2.2. Conceptual Framework

This study adopts a dynamic view of food security in which household welfare evolves over time under repeated exposure to shocks. Rather than treating food insecurity as a static condition, the framework focuses on how exogenous stressors interact with households' resilience to shape both (i) baseline food-security levels and (ii) the sensitivity of food-security outcomes when shocks occur. In line with the resilience-as-capacity literature, resilience is treated not only as a correlation of higher average welfare, but also as a conditioning mechanism that can attenuate the marginal impacts of shocks across food-security domains (Barrett and Constas, 2014; Béné et al., 2016).

2.2.1. Food Security as a Dynamic Outcome Under Shocks

Food security exists when "all people, at all times" have physical, social, and economic access to sufficient, safe, and nutritious food (FAO, 1996). Because food security is multidimensional (availability, access, utilization, and stability), shocks can affect it through multiple channels (FAO, 2008). In shock-prone environments, repeated stressors can increase volatility in consumption and diets, weaken coping capacity, and shift households onto lower welfare trajectories.

Food insecurity in low-income countries commonly reflects the interaction between structural vulnerabilities (poverty, reliance on rain-fed agriculture, limited market integration, weak institutions) and recurrent climatic, price, and conflict shocks (Dercon, 2004; Barrett and Carter, 2013; Skoufias, 2003; Hill and Porter, 2017; Martin-Shields and Stojetz, 2019). A key distinction is the covariance structure of shocks. Idiosyncratic events (e.g., illness, job loss) may be partially smoothed through assets and social networks, whereas repeated shocks (e.g., drought, widespread price surges, conflict) affect many households simultaneously and can overwhelm local risk-sharing arrangements and markets (Barrett and Constas, 2014; Carter et al., 2007). Under repeated covariate shocks, short-run coping responses may protect current consumption but erode future capacity through distress asset sales, reduced diet quality, and foregone productive investments generating intertemporal trade-offs that weaken longer-run food security (Maxwell et al., 2015). As a result, transitory food insecurity can become chronic, with slower recovery and deeper welfare losses (Carter et al., 2007).

2.2.2. Resilience Capacity and the Shock–Food Security Relationship

Resilience is defined as the capacity to withstand and recover from shocks without compromising long-term well-being (Barrett and Constas, 2014; FAO, 2016). We operationalize resilience using FAO's RIMA-II framework, which models resilience capacity as a latent construct shaped by four pillars including assets, access to basic services, adaptive capacity, and social safety nets (FAO, 2016). These pillars capture complementary mechanisms: resources and transfers support short-run smoothing, services and adaptive capabilities expand households' ability to adjust livelihoods and reduce vulnerability over time, while access to service and infrastructure reflects longer-run structural conditions such as education, physical infrastructure, and institutional access that reduce exposure and expand opportunity sets (Béné et al., 2016).

Within this framework, resilience affects food security through two pathways.

- Level effect: Higher resilience capacity is associated with better baseline food-security outcomes.
- Buffering effect: Resilience moderates shock impacts, such that households with higher resilience experience smaller welfare losses when exposed to shocks.

This distinction is central for policy: level effects indicate whether resilience aligns with better outcomes on average, while buffering effects indicate whether resilience investments reduce vulnerability under stress over time and whether this protection differs between shocks.

2.2.3. Evidence and contribution to literature

Ethiopia provides a relevant context where climatic variability, price volatility, conflict, and health risks intersect and place disproportionate burdens on vulnerable households. Drought and rainfall variability reduce agricultural production and income, while price volatility and macroeconomic shocks erode purchasing power and constrain food access often with larger effects among rural, asset-poor, and market-constrained households (Dercon, 2004; Hill and Porter, 2017). Conflict and insecurity further compound these effects by disrupting markets and mobility and increasing displacement (Martin-Shields and Stojetz, 2019).

Evidence from Ethiopia's Productive Safety Net Programme (PSNP) and related transfers suggests that predictable support can improve consumption smoothing and reduce distress coping, though widespread covariate shocks can strain local networks and institutions and limit household-level coping especially when crises are systemic rather than localized (Abay et al., 2023; Gilligan et al., 2009; Guush Berhane et al., 2014; Hoddinott, 2006).

These considerations motivate direct tests of both the level effect of resilience on food security and its buffering effect under shock exposure. Observing higher food security among more resilient households does not by itself demonstrate buffering: buffering is a conditional prediction that should be most visible when shocks occur and requires testing whether the marginal shock effect varies with resilience. Accordingly, the framework generates four testable hypotheses that guide empirical analysis:

- **H1** (Level effect): Higher resilience capacity is associated with better food-security outcomes, on average.
- **H2** (Shock effect): Exposure to shocks worsens food-security outcomes.
- **H3** (Buffering): Resilience moderates the adverse effect of shocks on food security, consistent with reduced sensitivity at higher resilience.
- **H4** (Heterogeneity): Buffering varies by shock type and food-security indicators.
    - **H4a (Idiosyncratic shocks).** Resilience is expected to provide stronger buffering effects against shocks, such as illness or job loss, because these shocks can be partially smoothed through savings, private coping, and informal insurance.
    - **H4b (Covariate shocks).** Resilience is expected to provide weaker or more limited buffering effects against shocks, such as drought, widespread food-price increases, and conflict, because these shocks affect many households simultaneously and place greater strain on markets, institutions, and risk-sharing mechanisms.
    - **H4c (Outcome heterogeneity).** The buffering effect of resilience is expected to differ across food-security indicators, reflecting differences in transmission channels, adjustment margins, and the time horizon over which shocks affect food access, diet quality, caloric adequacy, and experiential food insecurity.

Together, these hypotheses guide the interpretation of results and motivate an empirical strategy that estimates both direct resilience effects and resilience–shock interactions using outcome-appropriate models.

2.3. Data and variable management

This chapter draws on Waves 4 (2018/19) and 5 (2021/22) of the Ethiopia Socioeconomic Survey (ESS), as introduced in Chapter One. The analysis uses the same standardized indicators and resilience framework developed in the national-level analysis in Chapter One but extends that framework to examine multiple food-security outcomes.

All analyses apply household sampling weights provided in the ESS/ESPS. These weights adjust for the survey's stratified two-stage sampling design, unequal probabilities of selection, non-response, and panel attrition across waves. In panel analysis, longitudinal weights are used to preserve the representativeness of households observed in both waves. Accordingly, weighted estimates are interpreted as representative of the relevant household population covered by the survey design.

The analysis focuses on three main groups of variables. The first is the Resilience Capacity Index (RCI), constructed as described in Chapter One. The second is shock exposure, which includes both covariate shocks such as drought, rainfall irregularities, rising input prices, food price changes, livestock mortality, and political instability and idiosyncratic shocks, including health shocks and job loss. The third is food security outcomes, captured through five complementary indicators.

2.3.1. Survey design and panel structure

We analyze a balanced two-wave household panels constructed from Wave 4 and Wave 5 of the ESS. Both waves are part of the LSMS-ISA program and use a stratified two-stage probability sampling design, with enumeration areas serving as primary sampling units and households sampled within them.

Survey weights are applied to preserve population representativeness. In survey-weighted specifications, we implement the declared complex design using the survey primary sampling unit and strata variables together with probability weights and compute standard errors using Taylor-series linearization. Thus, this ensures that variance estimates correctly reflect clustering and stratification in the sampling process, thereby yielding valid statistical inference. Stata's survey procedures are designed for this purpose through svyset and the svy: estimation prefix.

Because observations are repeated for the same household across waves, standard errors are clustered at the household level in non-svy panel estimators to account for within-household correlation over time. For fixed-effects estimators where full survey linearization is not implemented in the preferred specification, we apply probability weights and cluster at the household level; these estimates are treated as robustness checks rather than the primary basis for population-level inference.

2.3.2. Variable Operationalization

Food security outcomes

We use a set of complementary indicators capturing distinct dimensions of food security: experiential food insecurity, consumption adequacy, dietary diversity, food budget pressure, and hunger severity. These measures are widely used in the food security and nutrition literature and together provide a multidimensional assessment of household food access and utilization. Together, they capture complementary dimensions of food security, including access, diet quality, consumption adequacy, and severe deprivation.

— **Food Insecurity Experience Scale (FIES):** FIES is an experience-based measure developed by the Food and Agriculture Organization of the United Nations to capture the severity of food insecurity based on households' reported experiences of constrained food access (e.g., worrying about food, reducing meal size, or going without eating). It is constructed from a set of binary (yes/no) questions and typically ranges from 0 to 8, where higher values indicate more severe food insecurity. It captures access-related and psychological dimensions of food insecurity.

— **Household Dietary Diversity Score (HDDS):** HDDS, also developed by Food and Agriculture Organization of the United Nations, measures the number of distinct food groups consumed by the household over a reference period (in a week). It ranges from 0 to 12 food groups, with higher values indicating greater dietary diversity and better diet quality and economic access to food.

- **Household Daily Calory Intake (HDCI):** HDCI classifies households into food consumption adequacy categories based on per capita caloric intake, following thresholds consistent with methodologies used by the World Food Programme and related food consumption frameworks. It is an ordinal variable with three categories: 1 = poor, 2 = borderline, 3 = acceptable. It captures overall food consumption adequacy. In the analysis, interpretation focuses on the predicted probability of being in the acceptable category.
- **Food Expenditure Share (FES):** FES is defined as the ratio of household food expenditure to total household expenditure. It is a continuous variable bounded between 0 and 1 (or a percentage). Higher values indicate that a larger share of the household budget is devoted to food, reflecting greater economic vulnerability and food access pressure.
- **Household Hunger Scale (HHS):** HHS, developed by the Food and Nutrition Technical Assistance Project, is a standardized measure of severe food deprivation based on reported hunger experiences. It is constructed from three occurrence questions with frequency responses and ranges from 0 to 9, where higher values indicate more severe hunger. It captures severe food insecurity and deprivation.

Resilience Capacity Index (RCI)

The index is constructed independently of food-security outcomes to minimize mechanical overlap. Methods and definitions are provided in Chapter 1.

Shock exposure

Shock exposure is captured using binary indicators and organized into two conceptually distinct groups. Endogenous (idiosyncratic) shocks arise largely within the household and include health (serious illness or death) and job loss. Exogenous (covariate) shocks originate outside the household and affect many households simultaneously; these include climatic shocks (drought, irregular rainfall), and price (input or food price changes), and political or conflict-related shocks.

Controls

All models include time-varying demographic and socioeconomic covariates (e.g., household size, dependency ratio, head age/sex), while household fixed effects absorb time-invariant characteristics and wave fixed effects capture common macro shifts between survey rounds. We also include regional fixed effects where possible.

2.4. Methods

2.4.1. Analytical Framework: shocks, resilience, and buffering

Household food security is conceptualized as a welfare outcome jointly determined by shock exposure and underlying resilience capacity. Shocks can impair food security by disrupting agricultural production, income generation, labor availability, and market access thereby reducing households' ability to acquire sufficient and nutritious food while increasing the likelihood of dietary compromise and hunger.

Resilience capacity is defined as the ability to withstand, cope with, and adapt to adverse events without persistent welfare losses. In the RIMA II framework (figure 2-1), resilience operates through two complementary channels.

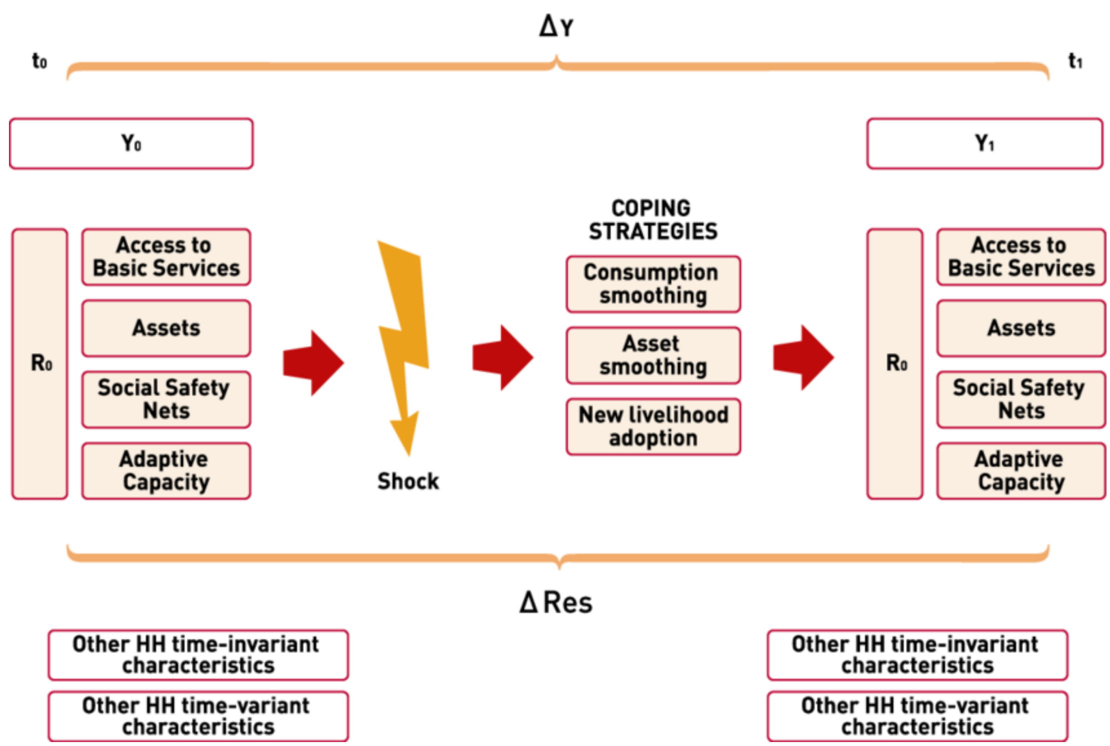

Figure 2-1: The RIMA II conceptual framework: Source: FAO (2018, p. 9).

Note: *Let Y_{it} denote food security and R_{it} denote resilience capacity for household i at time t. Resilience is constructed from four pillars ABS, ASS, SSN, and AC. Households are exposed to shocks $Shock_{it}$, which trigger coping responses CS_{it} and lead to changes in resilience (ΔR_i) and food security (ΔY_i).*

First, a level effect: households with higher resilience attain better food-security outcomes even in the absence of shocks, reflecting stronger assets, access to services, livelihood diversification, and adaptive capacity. Second, a buffering effect: resilience reduces the sensitivity of food security to shocks by enabling consumption smoothing, labor reallocation, and livelihood adjustments without resorting to erosive coping strategies that undermine future welfare. This conceptual structure follows the RIMA-II framework (FAO, 2018).

Because households with higher resilience may differ systematically in unobserved characteristics correlated with food security, resilience–food security correlations alone do not establish protection against shocks. The buffering hypothesis is inherently conditional: resilience should matter most when shocks occur. Accordingly, we estimate models that include interactions between shock exposure and resilience capacity and interpret interaction effects using marginal effects and predicted probabilities.

2.4.2. Empirical Specification

We estimate panel models linking food-security outcomes to shock exposure, resilience capacity, and their interaction:

$$\boldsymbol{g}(\boldsymbol{E}[\boldsymbol{FS_{it}}|\boldsymbol{Shock_{it}}, \boldsymbol{RCI_{it}}, \boldsymbol{x_{it}}]) = \boldsymbol{\alpha} + \boldsymbol{\beta_1 Shock_{it}} + \boldsymbol{\beta_2 RCI_{it}} + \boldsymbol{\beta_3}(\boldsymbol{Shock_{it}}\ \boldsymbol{x}\ \boldsymbol{RCI_{it}}) + \dot{\boldsymbol{x}}_{\boldsymbol{it}}\theta + \mu_{\boldsymbol{i}} + \boldsymbol{\tau_t} + \varepsilon_{\boldsymbol{it}}$$

Where:

— FS_{it}: denotes the relevant food-security outcome for household $i$at time t.
— $Shock_{it}$: Exposure to a specific shock.
— RCI_{it}: Resilience Capacity Index.
— $Shock_{it}\ X\ RCI_{it}$: The interaction term is used to test the buffering effect of resilience.
— $\dot{x}_{it}$: a vector of time-varying controls (e.g., size, sex and age of household head).
— μ_i: Household fixed effects, controlling for time-invariant unobservable characteristics.
— $\boldsymbol{\tau}_t$: Wave fixed effects to control time-specific shocks or trends and ε_i is the error term.

The interaction term tests whether resilience buffers the adverse effect of shocks on food security. Because the food-security outcomes differ in scale and distribution, the models are estimated separately using outcome-specific estimators rather than as a single SEM or system. SEM is used in the first stage to construct the latent RCI, while the second stage estimates the level and buffering effects of resilience on each food-security outcome.

The parameters of primary interest are $\boldsymbol{\beta_1}$(average shock effect), $\boldsymbol{\beta_2}$(resilience level effect), and $\boldsymbol{\beta_3}$(buffering/moderating effect). For linear specifications, the marginal effect of a shock is:

$$\frac{\partial \boldsymbol{FS_{it}}}{\partial \boldsymbol{Shock_{it}}} = \boldsymbol{\beta_1} + \boldsymbol{\beta_3 RCI_{it}},$$

For nonlinear models (ordered logit; count models), buffering is evaluated using predicted margins and (where relevant) the predicted probability of being food secure, computed at substantively meaningful values of RCI(e.g., −2, −1, 0, +1, +2 SD).

2.4.3. Estimator choice and identification

Food-security outcomes differ in scale and distribution; therefore, we match estimators to each outcome (Appendix Table B.0). For outcomes where linear fixed-effects estimation is appropriate, identification relies on within-household changes in shocks and resilience across waves, net of time-invariant household heterogeneity (μ_i) and common period shifts (τ_t).

For nonlinear outcomes where standard fixed-effects estimators are infeasible or potentially biased in short panels (e.g., incidental-parameters concerns in ordered-response and over-dispersed count models), our main estimates use survey-weighted pooled specifications that preserve population representativeness and are interpreted as conditional associations. To strengthen credibility, we complement these main specifications with stricter within-household comparisons where feasible, first differences and Poisson Pseudo–Maximum Likelihood (PPML) with household fixed effects reported as sensitivity checks.

2.4.4. Robustness and sensitivity checks

We assess robustness in five ways. First, we re-estimate each outcome using alternative functional forms consistent with its support (e.g., Poisson vs negative binomial, for counts; linear FE vs fractional response for bounded shares). Second, we test sensitivity to survey design and inference by comparing survey-weight versus alternative weighting/variance implementations where relevant. Third, we assess sensitivity to identification by comparing main specifications with within-household estimators where feasible (first differences; PPML with household fixed effects). Fourth, we test sensitivity to timing by estimating models with predetermined (lagged) resilience where feasible. Appendix Tables B.2–B.6 summarize these checks.

2.5. Results

2.5.1. Descriptive Patterns

Table 2-1 presents survey-weighted descriptive statistics for household characteristics, resilience capacity, shock exposure, and food security outcomes, disaggregated by survey waves (wave 4 and wave 5) and residence (urban and rural).

Table 2-1: Weighted Mean differences in key variables by Wave and Residence

Variable	Wave5	Wave4	Diff (5–4)	Urban	Rural	Diff (U–R)
Household Demography						
Household Sex (Male = 1)	75.0%	73.7%	1.3%	67.8%	77.1 %	−9.3%***
Household Age (Yrs.)	45.4	43.3	2.1***	41.6	45.6	−4.0***
Household size (No.)	4.77	4.79	−0.02	3.97	5.10	−1.14***
Adult equivalent	3.95	3.73	0.22***	3.33	4.06	−0.73***
Agriculture (0=Non agriculture, 1=Crop/livestock, 2=Mixed)	1.21	1.15	0.07*	0.00	1.65	−1.65***
Dependency Ratio	0.37	0.413	−0.05***	0.30	0.42	−0.13***
RCI						
Resilience Capacity Index	−0.42	−0.40	−0.015	0.48	−0.76	1.24***
Food security outcomes						
FES	0.82	0.82	0.01	0.73	0.85	−0.12***
HDCI Group (1–3)	2.32	2.45	−0.14***	2.32	2.40	−0.08
HDDS (1-12)	7.26	6.56	0.70***	7.73	6.65	1.08***
FIES (0-8)	2.99	1.20	1.80***	1.90	2.32	−0.42**
HHS (0-9)	0.88	0.15	0.73***	0.48	0.58	−0.10
Total no of Shocks (0-9)	1.50	0.615	0.887***	0.78	1.24	−0.46***

Note: *Differences (Diff) are survey-weighted; significance is based on design-adjusted tests with standard errors clustered at household; p values given as (*** p<0.01, ** p<0.05, * p<0.10). Adult equivalent Follows a calorie-requirement equivalents formula which assign a kcal requirement for each household member from an age–sex requirement table. (Age 15-59) male=1, women=0.85, age<=4=0.4, 5<age,10=0.6, 10<age<14=0.8(male) & 0.75(female), 60+(male) =0.9 & 0.8(female. Dependency Ratio Calculated as (total number households – number of households aged between 15-64)/ Total number of households*

Household demographic characteristics remain broadly stable across survey waves. The average age of household heads increases modestly, while household size and adult-equivalent measures show little change. The dependency ratio declines significantly, indicating a slight improvement in labor availability. Strong rural–urban differences persist, with rural households being larger, older, and substantially more dependent on agriculture than urban households.

Resilience capacity exhibits marked spatial inequality. Urban households consistently display higher resilience capacity than rural households, reflecting stronger access to infrastructure, markets, financial services, and information.

Food security outcomes evolve unevenly across dimensions. Dietary diversity (HDDS) improves significantly between waves, particularly in urban areas. In contrast, experiential indicators (FIES and HHS) worsen sharply, signaling increased instability in food access despite improvements in diet variety. FES remains broadly stable between the two waves but is consistently higher among rural households, indicating greater economic vulnerability for rural livelihoods.

Shock exposure increases substantially between waves. The average number of reported shocks is more than double, consistent with overlapping crises during the period (COVID-19, conflict, and food/input price inflation). Figure 2-2 compares shock prevalence. Overall, wave 5 reflects a substantially harsher environment dominated by market and input-cost shocks and compounded by climate-livestock pressures, with rural households experiencing larger increases.

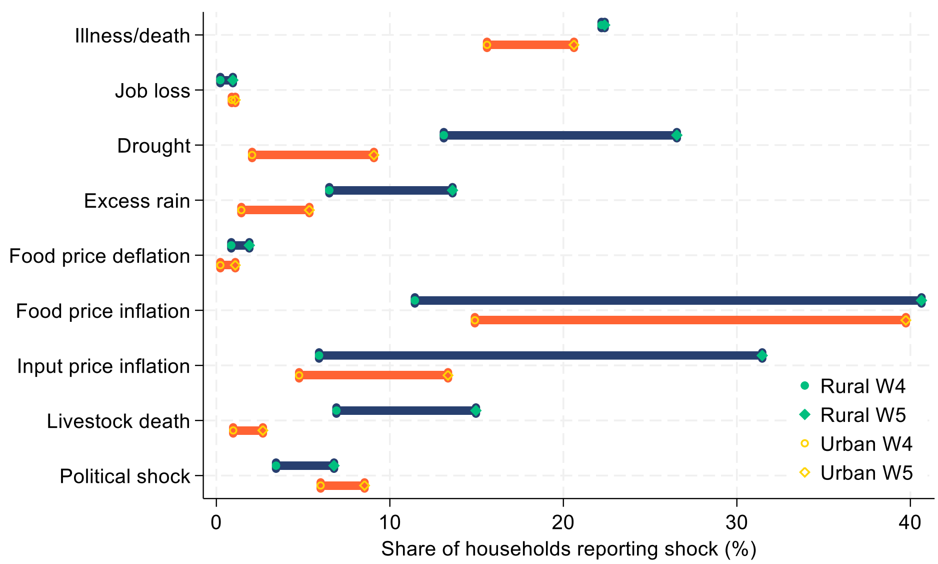

Figure 2-2: Prevalence of shocks by wave and residence

The increase is driven mainly by economy-wide price pressures in both rural and urban areas, while input price inflation expands far more in rural communities than in cities. Climate and production risks also intensify and remain strongly rural-skewed: drought and rainfall shocks increase in both locations but at consistently higher rural levels, and livestock deaths more than double in rural areas while remaining rare in urban settings.

In contrast, shocks linked to labor markets and insecurity show weaker spatial differences. Job loss remains uncommon but increases slightly, with a marginally larger rise in urban areas, and political shocks are reported more frequently in cities in both waves. Health shocks remain widespread; the rural–urban gap narrows as urban prevalence rises while rural prevalence stays persistently high. Overall, the figure indicates a shift toward a substantially harsher shock environment in wave 5 dominated by market and input-cost shocks and compounded by worsening climate-livestock pressures, with rural households bearing the largest increases.

2.5.2. Bivariate Associations

Shocks vs Food Security

Shock exposure is consistently associated with poorer food security outcomes, particularly for food access and stability indicators. Table 2-2 presents the bivariate patterns in food security indicators between households exposed to shocks and those otherwise.

Table 2-2: Mean differences in food security indicators by shock exposure

Shock	FIES	HHS	FES	HDDS	HDCI
Health shock	0.849***	0.212**	0.015***	−0.156	0.037
Job loss	1.270***	0.278	−0.003	0.776***	0.159
Drought	1.534***	0.775***	0.025**	0.060	−0.186**
Rain-related shock	1.358***	0.523***	0.033***	0.012	0.075
Output price deflation	2.307**	0.872***	0.044***	0.281	0.134
Food Price inflation	1.455***	0.538***	−0.018**	0.299***	−0.081
Input price inflation	1.288***	0.469***	0.008	0.343***	0.017
Livestock death	1.532***	0.581***	-	−0.022	−0.146*
Political instability	0.303	0.030	-	−0.014	−0.026

*(Difference = mean among shocked households − mean among non-shocked households. Significance: *** p<0.01, ** p<0.05, * p<0.10).*

Across most shock types, exposed households report significantly higher FIES and HHS, with particularly large differences for climatic shocks (drought and rain-related shocks), livestock losses, and food and input price shocks. In contrast, associations with economic vulnerability (FES) and utilization outcomes (HDDS and HDCI) are weaker and occasionally positive. These patterns may reflect short-run adjustment and coping responses rather than sustained welfare improvements, and they reinforce the value of analyzing multiple food-security dimensions.

Resilience vs Food Security

Table 2.3 further characterizes heterogeneity by resilience status. Among low-resilience households, correlations across food security indicators are weak and fragmented. In contrast, high-resilience households display stronger and more coherent correlations across indicators, suggesting more integrated and stable welfare outcomes. The stronger and more consistent co-movement of food-security indicators among high-resilience households suggests that higher resilience is associated with systematically better food-security outcomes (level effect). At the same time, the fragmentation observed among low-resilience households is consistent with greater sensitivity to shocks, where different dimensions of food security deteriorate unevenly. This implies that resilience may reduce the extent to which shocks disrupt multiple welfare dimensions simultaneously (buffering effect).

Table 2-3: Correlation matrices of food security indicators, by resilience group

Indicators	Low Resilience (n=4,870)				High Resilience (n=4,767)			
	FES	HDCI	HDDS	FIES	FES	HDCI	HDDS	FIES
HDCI	**0.231**	1.00			**0.199**	1.00		
HDDS	0.031	**0.160**	1.00		0.002	**0.311**	1.00	
FIES	0.068	**−0.112**	−0.04	1.00	0.010	**−0.120**	**−0.180**	1.00
HHS	0.012	−0.097	−0.001	**0.697**	0.081	−0.082	**−0.104**	**0.695**

The result shows that resilience capacity is systematically associated with food security outcomes. Households with higher resilience capacity exhibit lower experiential food insecurity and hunger and higher dietary diversity and caloric adequacy, suggesting more stable and integrated food security outcomes. Resilience is also negatively associated with exposure to several major shocks, particularly drought, livestock death, and input price increases, indicating that repeated exposure to adverse events is correlated with lower underlying resilience.

2.5.3. Regression Results

Across the five models, the results are coherent when organized around economic access, utilization, and experiential access/stability. Table 2.4 presents the main model result for each of the models. In general, higher resilience capacity is associated with improved food-security outcomes, while shocks, especially health shocks, drought, and food-price increases are associated with worse food security. We interpret main coefficients as conditional associations and use sensitivity tests.

Table 2-4: Panel estimates of the effect of resilience, shock, and resilience–shock interactions across food security outcomes

	Economic Access	Utilization		Experiential access / stress	
Variable	**(1) FES *(reghdfe)***	**(2) HDCI *(OLOG_SVY)***	**(3) HDDS *(POI_SVY)***	**(4) *FIES* *(SVY_NB)***	**(5) HHS *(SVY_NB)***
Main Effect					
RCI (standardized)	-0.018* (0.01)	-0.225*** (0.07)	0.103*** (0.01)	-0.160** (0.06)	-0.118 (0.12)
Health shock=1	-0.001 (0.01)	0.105 (0.10)	0.002 (0.01)	0.254*** (0.05)	0.301*** (0.11)
Job Loss=1	-0.032* (0.02)	-0.056 (0.40)	0.082*** (0.03)	0.397** (0.18)	0.474 (0.33)
Drought=1	0.005 (0.01)	-0.544* (0.28)	-0.018 (0.03)	0.274** (0.12)	0.603** (0.24)
Excess rain =1	0.004 (0.01)	0.185 (0.19)	0.012 (0.02)	0.286** (0.13)	0.408 (0.28)
Output Price deflation=1	-0.019 (0.03)	0.099 (0.38)	0.031 (0.04)	0.335 (0.221)	0.627* (0.33)
Food Price inflation=1	-0.008 (0.01)	-0.085 (0.11)	-0.017 (0.01)	0.346*** (0.07)	0.389*** (0.13)
Input Price inflation =1	-0.006 (0.01)	0.336** (0.14)	0.009 (0.02)	-0.033 (0.09)	-0.185 (0.17)
Livestock death=1	-0.025 (0.02)	0.138 (0.43)	0.007 (0.03)	0.138 (0.15)	0.130 (0.26)
Political Shock=1	-0.033*** (0.01)	-0.013 (0.18)	-0.016 (0.02)	0.030 (0.13)	-0.196 (0.24)
Interaction					
Health shock × RCI	-0.004 (0.01)	0.048 (0.11)	0.022* (0.01)	-0.083 (0.06)	-0.101 (0.14)
Job Loss × RCI	-0.024 (0.02)	-0.989* (0.57)	-0.021 (0.04)	0.299 (0.21)	0.464 (0.46)
Drought × RCI	0.032*** (0.01)	-0.166 (0.24)	-0.041* (0.02)	0.020 (0.11)	0.026 (0.25)
Excess rain × RCI	0.012 (0.01)	-0.152 (0.20)	0.002 (0.02)	0.101 (0.13)	0.122 (0.27)
Output Price deflation × RCI	-0.015 (0.02)	-0.110 (0.39)	-0.006 (0.04)	-0.125 (0.20)	-0.033 (0.27)
Food Price inflation × RCI	0.001 (0.01)	0.054 (0.11)	0.003 (0.01)	0.013 (0.08)	0.012 (0.12)
Input Price inflation × RCI	0.002 (0.01)	0.176 (0.17)	-0.053*** (0.02)	0.016 (0.09)	-0.118 (0.14)
Livestock death × RCI	-0.007 (0.02)	0.420 (0.36)	-0.013 (0.03)	-0.035 (0.12)	0.044 (0.24)
Political Shock × RCI	-0.011 (0.01)	0.070 (0.19)	0.015 (0.02)	0.197** (0.10)	0.295 (0.25)
Controls					
Household head Age (yrs)	-0.000 (0.00)	-0.008*** (0.00)	-0.000 (0.00)	-0.002* (0.00)	-0.001 (0.00)
Household head Sex (Male=1)	0.007 (0.01)	-0.328*** (0.09)	0.036*** (0.01)	-0.297*** (0.06)	-0.464*** (0.10)
Wave =5 (2021/2022)		-0.327** (0.13)	0.091*** (0.02)	0.805*** (0.08)	1.613*** (0.14)
Constant	0.820*** (0.02)		1.915*** (0.02)	0.207** (0.09)	-1.853*** (0.15)
N (Number of observation)	9698	9698	9637	9698	9698
HH (Number of households)	4849	4849	4789	4849	4849

Note: *The table reports associations between household resilience capacity and food-security outcomes across economic access (food expenditure share, FES), utilization (calorie adequacy categories, HDCI; dietary diversity, HDDS), and stability (Food Insecurity Experience Scale, FIES; Household Hunger Scale, HHS). RCI is the standardized resilience index (mean 0, SD 1). Shock indicators equal 1 if the household reports the shock in the reference period. Interaction terms (Shock × RCI) test whether the resilience gradient differs by shock exposure; in models with interactions, the reported "shock main effect" is interpreted at RCI = 0 (the sample mean).*

Estimation: *Column (1) is a household fixed-effects model (household and year fixed effects) estimated with weights and standard errors clustered at the household level. Column (2) is a survey-weighted ordered logit for HDCI (poor/borderline/acceptable). Column (3) is a survey-weighted Poisson model for HDDS (count). Columns (4) – (5) are survey-weighted negative binomial models for FIES and HHS (counts). Survey-weighted models implement the declared complex design (PSU/strata) with linearized variance estimation.*

*Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.*

1. Economic access: Food Expenditure Share (FES)

We proxy economic access using food expenditure share (FES), interpreted as food-budget pressure and crowding out of non-food essentials. In the household fixed-effects specification, resilience is associated with improved affordability: RCI is negative and statistically significant (−0.018, $p<0.10$), indicating that identification comes from within-household changes between waves in the FE specification, higher resilience corresponds to a lower share of total expenditure devoted to food.

Shock main effects are generally modest in the FES model. However, drought significantly moderates the resilience gradient. The Drought × RCI interaction is positive and significant (0.032, $p<0.01$), implying that drought reshapes how resilience maps into expenditure allocation. Predictive margins (Figure 2-3) indicate that under drought, FES increases more at higher resilience levels. A consistent interpretation is protective reallocation: more resilient households may sustain food spending by compressing non-food expenditures, mechanically raising the food share during drought. By contrast, low-resilience households may be unable to maintain food purchases, so the food share does not rise and may even fall.

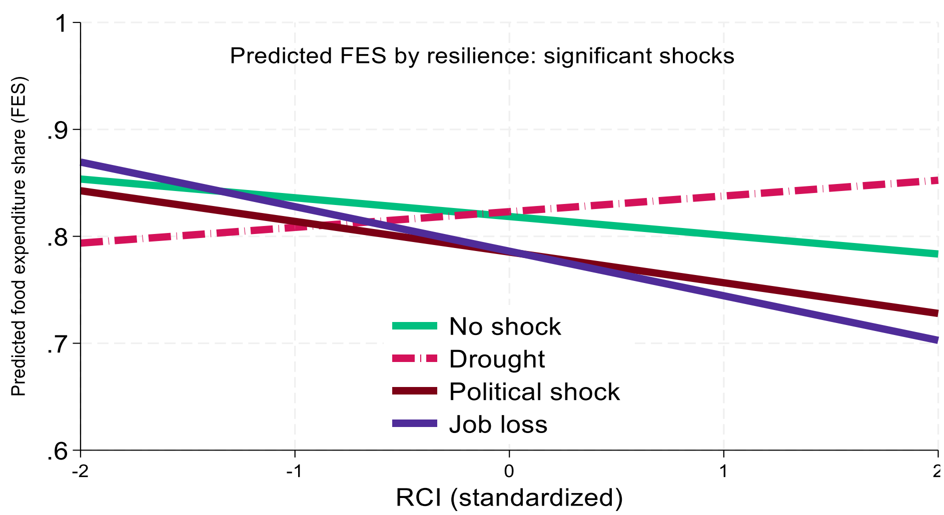

Figure 2-3: Predicted FES by RCI

2. Utilization: calorie adequacy and diet quality

1.1. Household Daily Calorie Intake (HDCI)

To capture the utilization dimension of food security, we estimate a survey-weighted ordered logit model for HDCI (poor/borderline/acceptable). The association between resilience and HDCI is negative and statistically significant (−0.225, $p<0.01$), implying lower odds of being in a higher calorie-adequacy category at higher measured resilience. Because the HDCI gradient is counterintuitive, we treat it as descriptive and emphasize predicted probabilities and correlated random effect (CRE) decomposition. Appendix Table B.3 suggests this gradient is sensitive to between-household composition: in the correlated random-effects (Mundlak) specification, the within-household component of RCI is small and statistically insignificant, consistent with unobserved household traits correlated with both RCI and calorie adequacy shaping the pooled association.

Figure 2-4 presents significant shock effect under HDCI. Drought is associated with lower calorie adequacy (−0.544, $p<0.10$). Input price increases are positively associated with HDCI (0.336, $p<0.01$), plausibly reflecting selection/market participation, where households purchasing modern inputs are more likely to report input-price shocks and may have higher baseline consumption. We also find heterogeneity under labor-market shocks: Job loss × RCI is negative and weakly significant (−0.989, $p<0.10$), indicating that among job-loss households, the probability of being in the acceptable HDCI category declines more sharply as RCI rises.

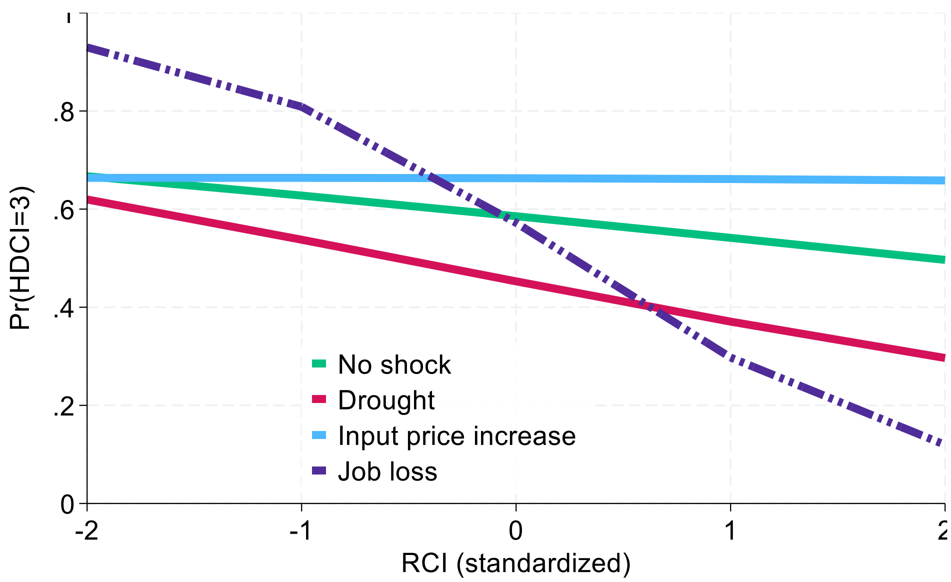

Figure 2-4: Predicted (HDCI =Acceptable) for drought, input price inflation and job loss

1.2.Diet quality (HDDS)

We measure diet quality using HDDS (count of food groups consumed) and estimate a survey-weighted Poisson model. Resilience is strongly and positively associated with dietary diversity

(0.103, p<0.01), indicating that higher resilience is associated with a higher expected number of food groups consumed.

Among shocks, only job loss is positively associated with HDDS (0.082, p<0.01). This pattern is consistent with compositional coping ("thin diversification"): households may spread constrained resources across more food groups in smaller quantities, which can coexist with deteriorating experiential outcomes (FIES/HHS). Moderation results indicate that the resilience–HDDS gradient is shock-contingent (Figure 2-5). The interaction with health shocks is positive and weakly significant (Health × RCI = 0.022, p<0.10), suggesting resilient households better maintain diversity during illness. Drought weakens the resilience advantage (Drought × RCI = −0.041, p<0.10). The strongest heterogeneity is for input price increases (Input price × RCI = −0.053, p<0.01), implying that rising input costs substantially erode the diet-diversity gains associated with resilience, consistent with a cost-exposure channel for more market-oriented households.

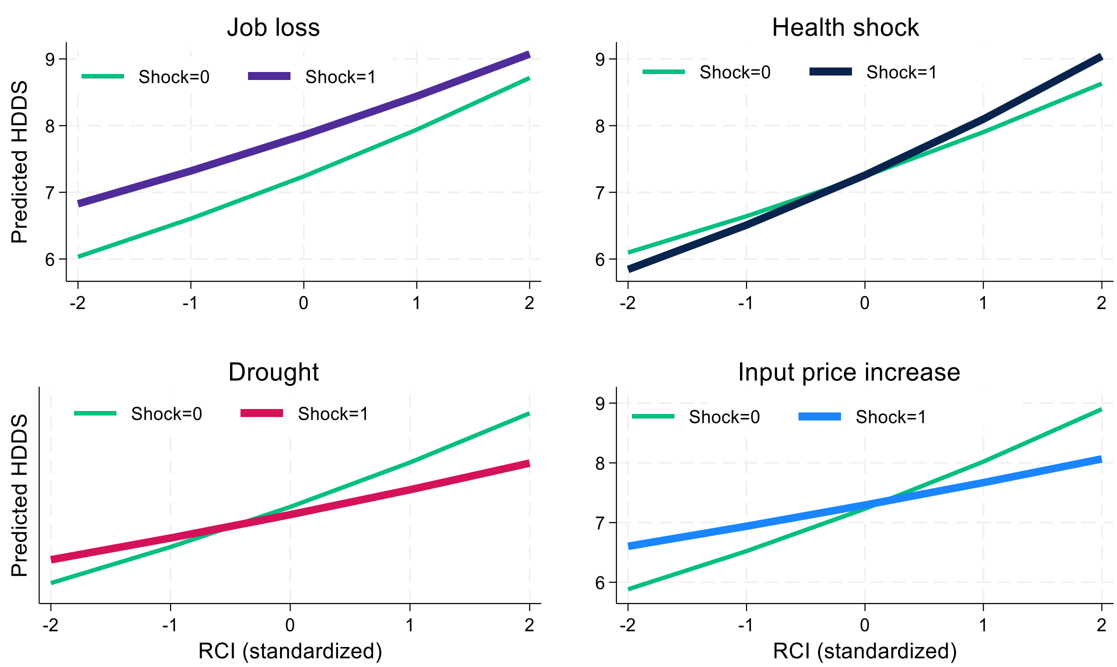

Figure 2-5: Predicted HDDS by RCI for main shocks

2. Stability: food insecurity and hunger severity

2.1. Experiential food insecurity (FIES)

FIES assess stability and estimated with a survey-weighted negative binomial model. Resilience is stabilizing (−0.160, p<0.05), implying fewer expected food-insecurity experiences among more resilient households. Multiple shocks significantly increase FIES: health (0.254, $p<0.01$), job loss (0.397, $p<0.05$), drought (0.274, $p<0.05$), excess rain (0.286, $p<0.05$), and food price increases (0.346, $p<0.01$). The later wave also shows substantially higher food insecurity (Wave 5 = 0.805, $p<0.01$), indicating a deterioration in stability between 2018/19 and 2021/22 (Figure 2-6).

Most shock × resilience interactions are statistically insignificant, suggesting limited evidence of systematic buffering in FIES. One exception is political disruption: Political shock × RCI is positive and significant (0.197, $p<0.05$), implying that the stabilizing association of resilience weakens under political shocks. A plausible interpretation is that political disruptions operate through market and institutional channels (mobility constraints, insecurity, displacement, and supply disruptions) that can overwhelm household-level capacities. Appendix Table B.5 further shows that resilience is most consistently associated with the probability of any food insecurity (extensive margin) rather than the severity conditional on being food insecure (intensive margin).

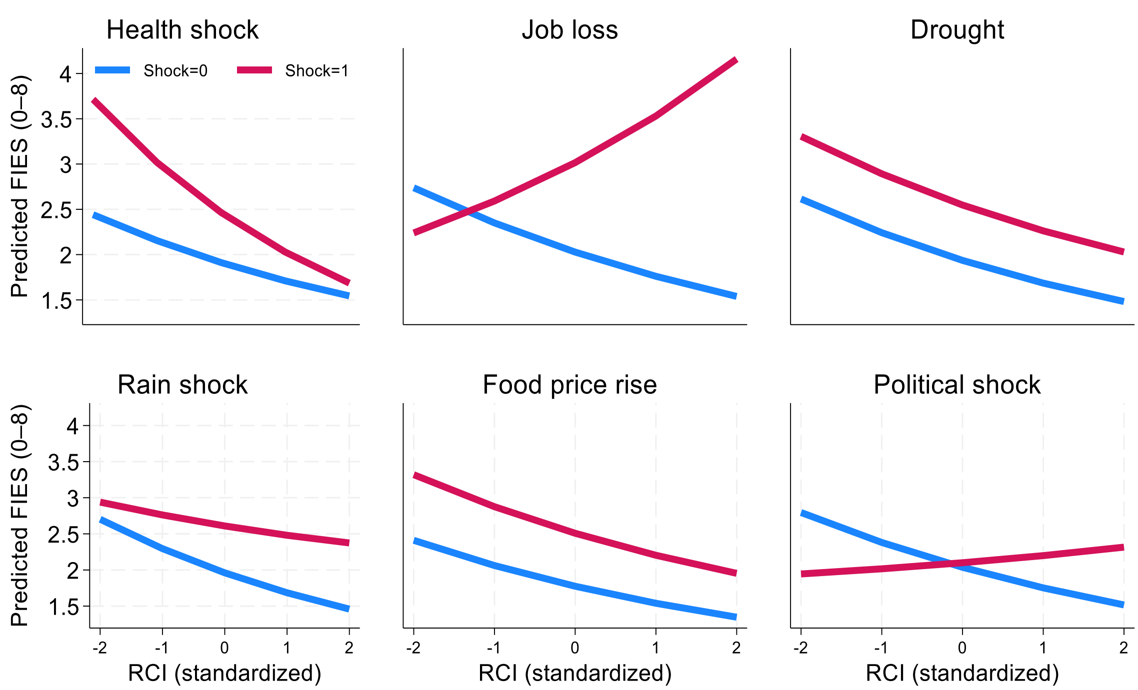

Figure 2-6: Predicted FIES count by RCI for key shocks

2.2.Hunger severity (HHS)

We next examine severe instability using HHS. Resilience is negative but not statistically significant (−0.118, n.s.), suggesting that resilience may reduce moderate food insecurity but does not reliably prevent severe hunger once major shocks and broader disruptions occur. Severe hunger is primarily shock-driven: health shocks (0.301, $p<0.01$), drought (0.603, $p<0.05$), and food price inflation (0.389, $p<0.01$) increase HHS. Also, the later wave is strongly associated with higher HHS (Wave 5 = 1.613, $p<0.01$), indicating a marked worsening of severe hunger in 2021/22. Figure 2-7 reports predicted HHS at low versus high resilience under significant shocks. Appendix Table B.6 indicates that shocks predominantly shift households into hunger (0→>0) rather than intensifying severity among those already hungry (hurdle results).

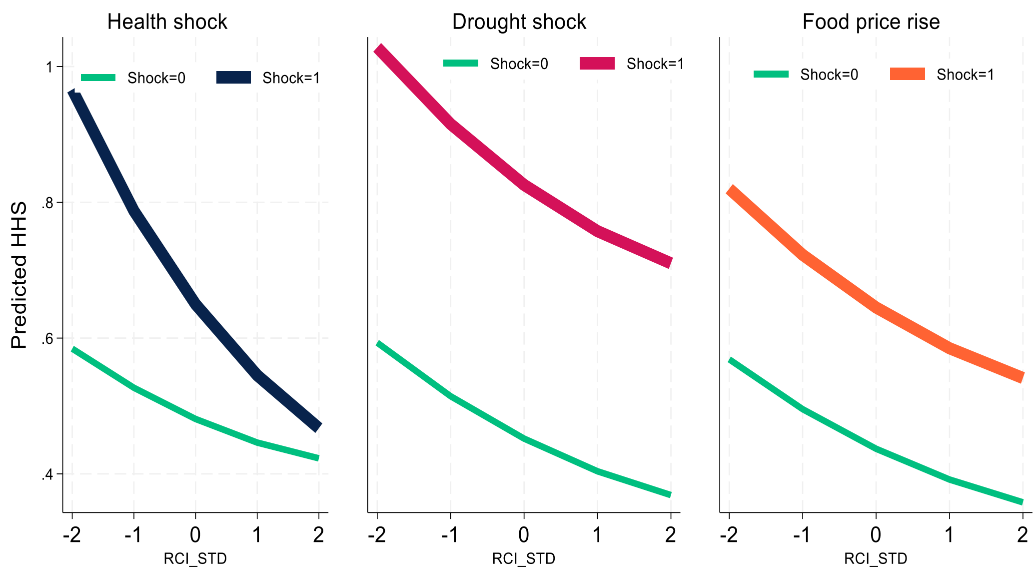

Figure 2-7: Predicted HHS by RCI for drought, health shock, and food price inflation

2.5.4. Summary across dimensions

Across domains, resilience is associated with better food security, but its role is outcome- and shock-dependent. For economic access, resilience is associated with lower food budget pressure under normal conditions, yet drought alters allocation behavior in a way consistent with protective reallocation away from non-food essentials. For utilization, resilience strongly predicts diet quality (HDDS), but drought and especially input price increases weaken the resilience advantage, highlighting vulnerability to rising production costs among market-oriented households. For experiential access/stability, resilience is associated with fewer reported food-insecurity experiences (FIES), while severe hunger (HHS) is driven mainly by large shocks especially health, drought, and food-price shocks and worsens sharply in the later wave.

2.5.5. Robustness and credibility checks

We assess whether three core conclusions are sensitive to modeling choices, survey design, and sample composition: (i) resilience is associated with improved food security, (ii) shocks are associated with worse food security, and (iii) selected interactions indicate heterogeneity in the resilience gradient. First, we examine functional-form sensitivity by re-estimating outcomes using alternative specifications and comparing signs and substantive implications (including marginal effects). Second, we assess sensitivity to alternative variance estimation consistent with survey design and panel structure. Third, we test robustness to alternative resilience timing (contemporaneous versus lagged RCI) and panel estimators (first-difference, PPML-FE, and CRE/Mundlak where feasible). Finally, we estimate models on balanced-panel households to reduce sensitivity to attrition. Across checks, the main patterns in Table 2-5 remain stable.

2.6. Discussion

This study shows that the resilience–food security relationship is multi-dimensional and shock-contingent: resilience is associated with improved outcomes in some domains (economic access and diet quality), while severe food insecurity and hunger are highly influenced by large shocks and period-wide disruptions.

Across access and diet-quality measures, higher resilience is generally protective: resilience is associated with lower food expenditure share (FES), lower experiential food insecurity (FIES), and higher dietary diversity (HDDS), consistent with resilience-as-capacity frameworks that conceptualize resilience as an ex-ante ability to absorb and adapt to shocks without compromising welfare (Barrett and Constas, 2014; FAO, 2016; Upton et al., 2016). Importantly, these associations are observed using population-representative survey-weighted models and remain qualitatively stable under alternative estimators and panel-based sensitivity checks.

In contrast, results for calorie adequacy (HDCI) are more sensitive to specification and appear partly driven by between-household composition. The correlated random-effects (CRE/Mundlak) decomposition indicates that this pattern is driven primarily by between-household (compositional) differences correlated with the resilience index rather than within-household increases in resilience worsening calorie adequacy; an interpretation consistent with concerns in resilience measurement and estimation work emphasizing heterogeneity and identification (Cissé and Barrett, 2018; Constas et al., 2022). Accordingly, we emphasize predicted probabilities and treat the pooled HDCI gradient as a descriptive pattern rather than a definitive causal effect.

A central contribution is evidence that shocks change not only the level of food security but also the translation of resilience into outcomes. The drought–resilience interaction in the FES model suggests that under covariate climate stress, households with greater capacity may protect food consumption by compressing nonfood spending, mechanically increasing food expenditure share even when overall welfare is strained. This pattern is consistent with buffering concepts and the broader evidence that resilience impacts depend on the type, scale, and persistence of shocks (Barrett and Constas, 2014; Smith and Frankenberger, 2018; Ranucci et al., 2025). Rather than indicating improved welfare, this interaction likely reflects how households adjust: resilient households may sustain food purchases by reducing spending on health, education, or productive inputs, an adjustment that can protect short-term food access while risking longer-term welfare.

Similarly, the job loss × resilience interaction in the HDCI model indicates that employment shocks can impose a larger calorie-adequacy penalty at higher measured resilience, consistent with heterogeneity in exposure when shocks operate through labor and markets (Ansah et al., 2023). This suggests that structural advantages (assets, market integration) can moderate shock impacts, but that moderation may weaken or even reverse under market-mediated or systemic stressors that exceed household-level coping capacity (Smith and Frankenberger, 2018; Ansah et al., 2023).

Divergence across indicators also matters for interpretation and policy. HDDS captures dietary variety rather than quantities or food-related stress, so short-run reallocation across food groups can coexist with increased experiential insecurity (FIES) or weaker calorie adequacy (HDCI). This reinforces the value of multidimensional food-security measurement in resilience analysis, particularly in shock-prone settings where coping can change the composition of diets without improving overall adequacy (FAO, 2016; Upton et al., 2016). Together, the findings imply that resilience-building improves average conditions, but severe food insecurity and hunger are primarily shaped by the intensity of shocks and broader macro/market disruptions that exceed household-level coping capacity.

Overall, the results support resilience as a meaningful correlational predictor of food security, while emphasizing that (i) some estimated gradients reflect structural differences across households, and (ii) buffering is not universal but depends on shock type and on whether outcomes capture stress, access, or diet composition. Thes highlights the value of decompositions and robustness checks in applied resilience work (Cissé and Barrett, 2018; Constas et al., 2022; Tasnim et al., 2025).

2.7. Policy implications

1. Scale shock-responsive social protection for health shocks.

The strong association of health shocks with food insecurity and hunger supports rapid-response instruments (temporary cash top-ups, fee waivers, and protection against catastrophic health costs) to prevent health shocks from cascading into food insecurity (Haile et al., 2022; Knippenberg et al., 2019). Because health-shock buffering appears more visible in some specifications, integrating health-related assistance with existing safety nets can yield high payoffs.

2. Pair drought response with protection of nonfood essentials.

The drought–resilience interaction in FES suggests that households may protect food spending by compressing non-food expenditures. Drought assistance (cash/food, scalable public works, and complementary risk-management tools where feasible) should therefore be bundled with measures that protect health, education, and productive spending, consistent with evidence that covariate shocks can overwhelm household coping and require system-level scalability (Smith and Frankenberger, 2018; Tasnim et al., 2025.

3. Address labor-market shocks with dedicated stabilization instruments.

The job loss × resilience evidence suggests that "capacity building" alone may not prevent utilization losses under employment shocks. Policies that stabilize earnings and consumption during job disruptions, especially in urban/peri-urban contexts, are warranted (Ansah et al., 2023; Haile et al., 2022). Where feasible, linking temporary income support to job-search or enterprise recovery services may reduce persistent scarring.

4. Target price and input cost measures by exposure as well as capacity.

The consistent importance of food-price shocks for experiential insecurity, together with evidence that input-price increases erode the diet-diversity gains of resilient (more market-oriented) households, suggests the need for instruments that explicitly address price volatility. Targeting should then be based on exposure profiles. This involves distinguishing households that are primarily harmed by rising prices and input costs from those that are more market-integrated and therefore more exposed to cost passthrough. This enables time-bound support packages, such as temporary vouchers or cash top-ups for net buyers, credit-smoothing for working capital constraints, and targeted input support where input-market tightening threatens production and price stability (FAO, 2016; Tasnim et al., 2025). This is especially relevant where input markets tighten and pass-through to food prices is rapid.

In summary, the policy message is not only that resilience matters, but that its protective value is conditional: household capacity improves average outcomes, yet severe food insecurity and hunger are largely determined by shocks and systemic disruptions calling for scalable, timely, and shock-specific responses alongside longer-term resilience investments.

2.8. Conclusion

This study uses nationally representative two-wave panel data from Ethiopia and a RIMA-II-based resilience index to examine how resilience relates to multiple food-security outcomes under a worsening shock environment. Resilience is consistently associated with improved outcomes for food budget pressure (FES), dietary diversity (HDDS), and experiential food insecurity (FIES), while major shocks, especially health, drought, and food-price shocks are strongly associated with deteriorations in experiential food security and hunger.

A key result is that resilience is not a uniform "shield." Interactions indicate that climate and market shocks can weaken (and in some cases reshape) the resilience advantage, consistent with the idea that household capacities may be insufficient under covariate stressors that operate through broader market and institutional channels.

Policy implications following resilience-building investments remain important but should be paired with shock-responsive systems particularly rapid protection against health shocks, scalable drought response that protects non-food essentials, and measures that cushion households from market and input-price volatility. More broadly, the divergence across indicators reinforces the value of multidimensional food-security measurement when evaluating resilience in shock-prone settings.

2.9. Limitations and Future Research

This study has several limitations that point to directions for future research. First, while the panel structure allows analysis of changes over time, the empirical strategy remains primarily associational. Although the models control observed characteristics and household-level heterogeneity, the estimates should not be interpreted as strictly causal. Future work could strengthen identification by exploiting exogenous variation in shocks, policy exposure, or infrastructure expansion.

Second, resilience is measured as a latent construct derived from observed indicators using the RIMA-II framework. While this approach captures multiple dimensions of capacity, some indicators particularly within the adaptive capacity pillar may reflect both ex ante capability and ex post coping behavior. As the results suggest, this dual interpretation complicates inference. Future research could refine measurement by distinguishing more explicitly between preventive capacity and reactive responses, potentially using higher-frequency data or modules that capture timing of adaptation.

Third, the analysis is based on two survey waves, which limit the ability to capture short-run adjustment dynamics and longer-term recovery trajectories. Resilience is inherently dynamic, and future work using higher-frequency panel data would help distinguish temporary coping from sustained improvements in welfare.

Fourth, although the study documents substantial heterogeneity across shock types and outcome measures, it does not fully model spatial spillovers, market integration, or conflict dynamics at finer geographic scales. Integrating household data with geospatial information on climate variability, conflict exposure, and market access would improve understanding of how covariate shocks propagate across regions.

Finally, while multiple food-security indicators are used, each capture only a specific dimension of welfare. The divergence across outcomes observed in this study highlights the need for further work on integrating multidimensional measures into unified frameworks that better reflect the joint dynamics of food security under stress.

3 Chapter Three: Subgroup Analysis: Urban–Rural Disparities in Resilience and Food Security

Abstract

This chapter examines urban–rural heterogeneity in the relationship between resilience capacity, shock exposure, and food security outcomes in Ethiopia. Building on the national-level analysis in Chapter Two, the chapter introduces a spatially disaggregated perspective to assess whether the composition, transmission channels, and buffering role of resilience differ across rural and urban livelihood systems. Using data from Waves 4 (2018/19) and 5 (2021/22) of the Ethiopia Socioeconomic Survey Panel Survey (ESPS), the analysis re-estimates the Resilience Capacity Index (RCI) separately for rural and urban households following the RIMA-II framework. This allows the relative contribution of resilience pillars to reflect context-specific structures rather than a single national model.

The chapter combines descriptive analysis with econometric models estimated separately for rural and urban households. Five food security indicators are examined: food expenditure share, household daily caloric intake, household dietary diversity score, food insecurity experience scale, and household hunger scale. The results reveal substantial spatial heterogeneity in resilience composition and shock transmission. In rural areas, resilience is driven more strongly by adaptive capacity, access to basic services, and productive assets, while urban resilience depends more on assets and social safety nets. Rural households face greater exposure to climatic and production-related shocks, particularly drought, whereas urban households are more vulnerable to price-related and labor-market shocks.

The regression results further show that resilience capacity is positively associated with improved food security outcomes in both settings, especially through better dietary diversity and reduced food insecurity experiences. However, the channels through which resilience operates differ by residence type. In rural areas, resilience mainly works through production stabilization and asset protection, whereas in urban areas it operates more strongly through income stability, service access, and market participation. The buffering effect of resilience is also shock-specific: resilience is more effective in moderating idiosyncratic shocks than large covariate shocks such as drought and widespread food-price inflation.

Overall, the chapter demonstrates that resilience is both context-specific and multidimensional. The findings underscore the importance of spatially differentiated resilience-building strategies and suggest that policies aimed at improving food security in Ethiopia should reflect the distinct risk environments, livelihood systems, and institutional conditions that characterize rural and urban households.

Keywords

Urban–rural heterogeneity; Ethiopia; shocks; Resilience Capacity Index; dietary diversity; food insecurity; social protection.

3.1. Introduction

Chapter Two demonstrated that household resilience capacity, measured through the Resilience Capacity Index (RCI), significantly improves food security outcomes at the national level. However, national averages may conceal important spatial heterogeneity. Resilience is inherently context-specific and shaped by livelihood systems, asset structures, institutional access, and exposure to risk (Barrett & Constas, 2014; Béné et al., 2016). In Ethiopia's dual economic structure, predominantly rural, agriculture-based livelihoods coexist alongside increasingly urban, market-oriented systems. As a result, the mechanisms through which resilience capacity influences food security are unlikely to be uniform across residence types.

Rural households depend largely on rain-fed agriculture and livestock production. Their welfare is therefore closely tied to climatic stability, access to agricultural inputs, and local market conditions. Drought, rainfall variability, livestock mortality, and input-price increases can directly reduce production and income. Structural limitations such as weaker infrastructure, limited financial access, and constrained institutional support may further restrict rural households' resilience capacity (Dercon, 2004; World Bank, 2008).

Urban households, by contrast, are less directly exposed to production risks but are more dependent on labor markets and purchased food. As a result, employment instability, inflation, and food-price volatility may pose more immediate threats to food access. Evidence from Ethiopia shows that food-price inflation can significantly erode real wages among urban workers, highlighting the central role of purchasing power in determining food security outcomes (Birhane et al., 2014; Headey et al., 2012). Although urban households typically benefit from stronger infrastructure and service availability, their reliance on market purchases makes them particularly vulnerable to price shocks.

Because these structural conditions differ substantially, resilience capacity may vary not only in magnitude across residence types but also in composition and transmission channels. This chapter re-estimates the relationship between food security, shocks and RCI separately for rural and urban households using identical procedures as in Chapter 2. Estimating the index separately allows the relative contribution of each resilience pillar to reflect context-specific structures rather than imposing a uniform national model. Consequently, RCI values are interpreted as relative positions within each subgroup and are not directly comparable in absolute terms across rural and urban households.

This chapter examines three dimensions of spatial heterogeneity: differences in resilience composition, differential shock impacts, and variation in the buffering role of resilience. The following section outlines the conceptual framework guiding the analysis.

3.2. Conceptual Framework

Resilience capacity is expected to operate differently across spatial contexts because exposure to shocks, livelihood strategies, and institutional environments vary systematically between rural and urban households. These structural differences shape both the composition of resilience and the channels through which it influences welfare outcomes. This chapter therefore examines how the structure and effects of resilience diverge across Ethiopia's rural and urban households. The analytical framework links resilience capacity, shock exposure, and food security outcomes through both direct and interaction (moderated) effects, allowing these relationships to vary by residence.

3.2.1. Structural Differences in Resilience Drivers

Rural and urban households differ substantially in both their exposure to risk and the resources they can mobilize in response to shocks. Rural livelihoods in Ethiopia remain predominantly agriculture-based, leaving households highly exposed to covariate shocks such as drought, rainfall variability, and livestock losses (Mekasha & Tarp, 2021). Rural resilience therefore depends strongly on productive and natural-capital-linked channels, including assets (ASS), access to basic services (ABS), and adaptive capacity (AC) through diversification, technology adoption, and improved farm management (FAO, 2016; Ciani et al., 2020). However, limited market integration, weaker infrastructure, and institutional constraints can restrict rural households' ability to anticipate, absorb, and recover from shocks, increasing the risk of persistent welfare losses and poverty traps (Barrett & Carter, 2013; Verwimp et al., 2019).

By contrast, urban households face lower exposure to direct climatic production risks but greater vulnerability to market and institutional disruptions (Headey et al., 2022; World Bank, 2020). Urban livelihoods rely more on wage employment, self-employment, and market purchases of food, making them especially sensitive to job loss, food-price inflation, and governance-related disruptions. Urban resilience is thus more closely tied to the stability and functionality of markets and services, with access to basic services, social safety nets, and adaptive capacity playing larger roles through infrastructure, formal institutions, education, financial services, and labor mobility

(Béné et al., 2016; Frankenberger et al., 2014). At the same time, resilient outcomes remain contingent on institutional effectiveness and the coverage and adequacy of social protection.

3.2.2. Transmission Channels

The framework distinguishes between dominant rural and urban transmission channels. Figure 3-1 summarizes the conceptual pathways linking resilience capacity, shocks, and food security outcomes across rural and urban settings. Shocks can affect food security directly by reducing incomes, damaging assets, disrupting markets, or constraining mobility, and indirectly through the resilience pillars that shape households' RCI. The framework also recognizes dynamic feedback: maintaining food security during shocks protects assets and human capital, which may strengthen resilience capacity in subsequent periods (FAO, 2016; Barrett & Constas, 2014).

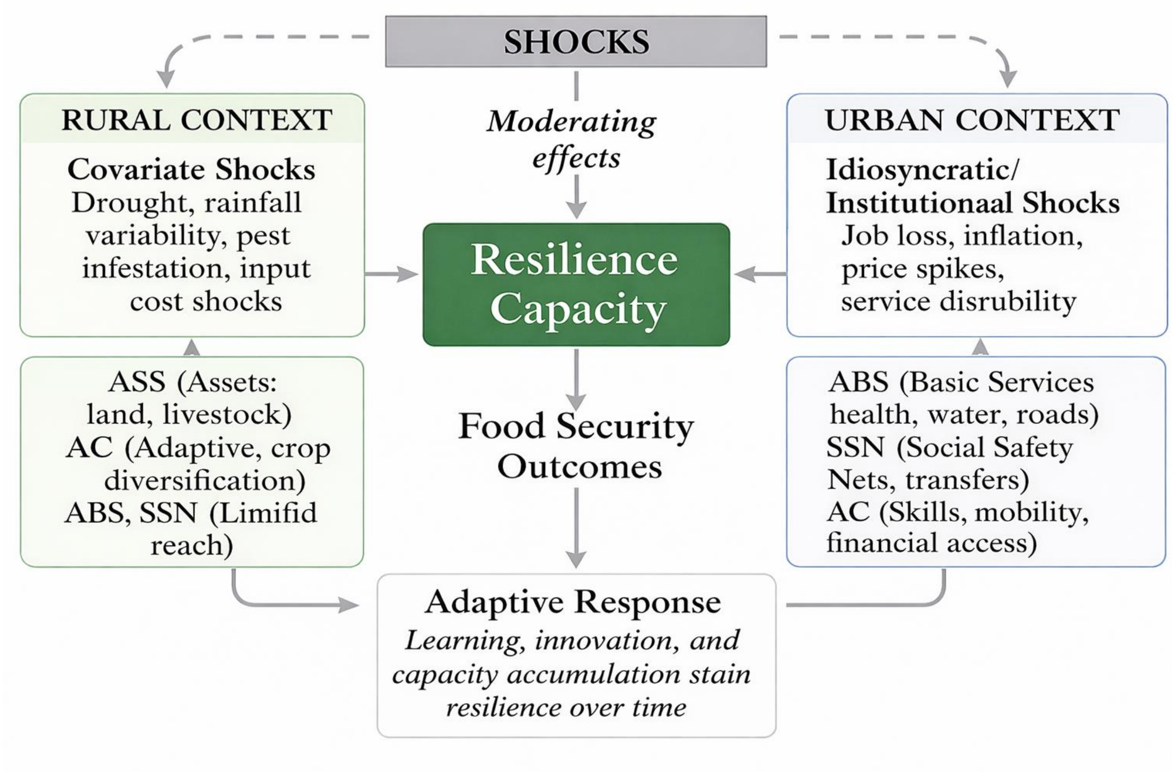

Figure 3-1: Rural-Urban Resilience Pathways

I. Rural Pathway – Production and Natural Capital Driven

In rural areas, resilience operates primarily through productive, environmental, and infrastructural channels. Improved road connectivity, irrigation, and market access strengthen the ABS and ASS pillars by stabilizing output and facilitating market participation. Households with diversified crop portfolios or livestock holdings are better able to smooth consumption during shocks. Adaptive capacity through technology adoption and resource conservation helps sustain caloric adequacy (HDCI) and dietary diversity (HDDS) under climatic stress (Headey & Ecker, 2013; Mekasha & Tarp, 2021). Informal safety nets and the Productive Safety Net Programme (PSNP) may buffer temporary shortages, although covariate shocks such as drought and erratic rainfall remain dominant threats.

II. Urban Pathway – Market and Institutional Capital Driven

In urban settings, shocks affect food security primarily through income and market channels. Employment shocks, inflation, and supply disruptions reduce real purchasing power and food access. Here, ABS, SSN, and AC are expected to play dominant roles by stabilizing income flows and enabling households to smooth consumption during periods of price and employment instability (FAO, 2016; Smith & Frankenberger, 2018; Abay et al., 2022). These mechanisms are especially relevant for access- and experience-based outcomes such as food expenditure stress, food insecurity experiences, and hunger severity.

3.2.3. Hypotheses

Based on these differentiated livelihood structures and transmission mechanisms, the empirical analysis tests four hypotheses:

— **H1:** Resilience composition differs across rural and urban households. Separate estimation of the RCI is expected to reveal different pillar contributions in rural and urban settings, reflecting context-specific livelihood systems and institutional environments.

— **H2:** The dominant transmission channel of resilience differs by residence. In rural areas, resilience effects are expected to operate primarily through production stabilization and asset-based mechanisms. In urban areas, resilience effects are expected to operate primarily through income and market-access channels.

— **H3:** The buffering effect of resilience differs by shock type and residence. Resilience is expected to mitigate climatic and agricultural shocks more effectively in rural areas, while buffering income and price shocks more effectively in urban areas.

— **H4:** Shock transmission into food security is spatially heterogeneous. Identical shocks are expected to generate different magnitudes and patterns of food security outcomes across rural and urban households.

3.3. Data and Method

Households are classified as rural or urban based on the official designation provided in the Ethiopia Socioeconomic Survey (ESS/ESPS). This classification follows the Central Statistical Agency sampling frame, in which enumeration areas are pre-classified as rural or urban according to administrative criteria, including settlement characteristics, infrastructure, and population density. The rural–urban indicator is therefore treated as exogenous to the analysis and reflects the survey design rather than a constructed threshold.

3.3.1. Data

This chapter uses data from the ESPS, Waves 4 (2018/19) and 5 (2021/22) survey, as described in Chapters One and Two. The analysis applies the same standardized indicators and resilience framework developed in the national level analysis but introduces spatial differentiation by estimating resilience and outcome models separately for rural and urban households.

Three groups of variables are central to the analysis:

1. Resilience Capacity Index (RCI): Constructed following FAO's RIMA-II framework and incorporates the four pillars. For this chapter, the RCI is re-estimated separately for rural and urban households to allow pillar contributions to vary by rural or urban residency. Variables included in each subgroup-specific index are selected based on contextual relevance and data availability.
2. Shock Exposure Variables: capture both covariate and idiosyncratic shocks as presented in chapter two.
3. Food Security Indicators: capture multiple dimensions of food security: FES, HDCI, HDDS, FIES and HHS. All estimates use household sampling weights, and all models are estimated separately for rural and urban households.

3.3.2. Analytical Framework for Urban–Rural Resilience Differentiation

This chapter builds on the national framework and introduces a spatially differentiated analytical framework that explains how resilience operates through distinct livelihood and market systems in rural and urban Ethiopia. The analytical structure integrates four components: structural context, shock exposure, resilience capacity, and food security outcomes.

1. **Structural Context and Livelihood Systems**

Residence type shapes both exposure to risk and the channels through which resilience translates into welfare outcomes. Rural households rely predominantly on agriculture and natural capital, making food security sensitive to production stability and environmental conditions. Urban households depend more heavily on wage labor and market purchases, making purchasing power and income stability central determinants of food access. These structural differences imply that resilience may influence food security through distinct mechanisms across residence types.

2. **Shock Typology**

To clarify transmission channels, shocks are grouped into two broad categories. Idiosyncratic shocks include health shocks and job or income loss. Covariate shocks include drought, rainfall irregularities, food-price changes, input-price increases, livestock mortality, and political instability. Covariate shocks are expected to generate broader welfare effects because they simultaneously affect markets and production systems, whereas idiosyncratic shocks primarily affect individual households.

3. **Resilience Capacity as a Moderating Mechanism**

Resilience capacity, measured through the RCI, affects food security through two channels. First, higher resilience improves average welfare outcomes directly. Second, resilience moderates the adverse effects of shocks. Because covariate shocks affect entire systems, resilience is expected to be more effective in buffering idiosyncratic shocks than large-scale systemic shocks.

4. **Outcome Domains and Transmission Channels**

The five food security indicators capture economic, utilization, and experiential dimensions of food security. In rural settings, resilience is expected to influence food security primarily through production stabilization and expenditure smoothing. In urban settings, resilience is expected to operate mainly through income stabilization and market-access mechanisms.

3.3.3. Econometric Specification

To evaluate how resilience influences food security under varying shock conditions, the following model is estimated separately for rural and urban households:

$$FS_{it}^{(u,r)} = \beta_0 + \beta_1 Shock_{it}{}^{(u,r)} + \beta_2 RCI_{it}{}^{(u,r)} + \beta_3 (shock_{it}\ X\ RCI_{it})^{(u,r)} + \dot{x}_{it}\alpha^{(u,r)} + \delta_i + \lambda_t + \varepsilon_{it}$$

Where:

— $FS_{it}^{(u,r)}$ represents each food-security outcome for urban u and rural r sub-populations.

— $RCI_{it}{}^{(u,r)}$ denotes resilience capacity.

— $shock_{it}$ capture exposure and

— $\grave{x}_{it}$ is a vector of controls.

— δ_i and λ_t captures unobserved time and household effects respectively.

Estimating the model separately for rural and urban households allows the magnitude, direction, and statistical significance of resilience and shock effects to differ across residence types. This is appropriate given the substantial differences in livelihood systems, market dependence, and shock exposure between rural and urban households.

3.3.4. Model Selection

Model selection is guided by the measurement properties of each food security outcome and follows the same framework used in the pooled analysis. Because the outcomes differ in scale and distribution, we employ outcome-specific estimators. Food Expenditure Share (FES), a continuous ratio, is estimated using a linear model with household fixed effects. The caloric adequacy category (HDCI), an ordinal variable, is estimated using a survey-weighted ordered logit model. Dietary diversity (HDDS), a non-negative count, is estimated using a survey-weighted Poisson model. Experiential food insecurity (FIES) and hunger severity (HHS), which exhibit over-dispersion, are estimated using survey-weighted negative binomial models.

All models are estimated separately for rural and urban households. Survey weights, primary sampling units, and strata are incorporated to account for the complex sampling design, and standard errors are computed using Taylor linearization. For specifications where full survey linearization is not feasible (e.g., fixed-effects models), probability weights are applied and standard errors are clustered at the household level to account for within-household correlation over time.

Comparing coefficients and marginal effects across rural and urban models allows the analysis to identify spatial heterogeneity in both the direct (level) and moderating (buffering) effects of resilience capacity.

3.4. Results and Discussion

3.4.1. Descriptive Analysis of Urban–Rural Differences

A descriptive comparison of household characteristics, livelihoods, and the Resilience Capacity Index (RCI) between urban and rural households highlights the spatial heterogeneity shaping resilience and food security outcomes in Ethiopia.

3.4.1.1. Demographic and Livelihood Characteristics

Rural households are characterized by significantly higher average dependency ratios and lower levels of education than their urban counterparts. Nearly 77 percent of rural households are male headed, compared with 68 percent in urban areas, and rural household heads also tend to be older, averaging 46 years compared with 42 years in urban settings. Household size and adult-equivalent measures are likewise markedly higher in rural areas, indicating greater demographic pressure and consumption needs. These findings are consistent with previous national surveys showing that rural households in Ethiopia typically have larger family sizes, higher dependency ratios, and older heads than urban households (CSA & World Bank, 2015; CSA & ICF, 2016; FAO, 2020).

Education indicators reveal a substantial urban advantage. About 92 percent of urban household heads can read and write, compared with 78 percent in rural areas, and the average years of schooling among the most educated household members in urban areas (10.7 years) is nearly double that of rural households (5.8 years). This urban advantage mirrors previous evidence from Ethiopia and Sub-Saharan Africa, where persistent rural–urban education gaps reflect structural inequalities in access to schools, educational quality, and broader opportunity structures (Barrett et al., 2017; Mekasha & Tarp, 2021).

Livelihood structures further reinforce this divide. Agriculture remains the dominant source of livelihood for rural households, primarily through mixed farming systems that combine crop and livestock production, whereas almost no urban households depend on agricultural activities. This pattern reflects Ethiopia’s dual economic structure, in which rural livelihoods remain largely subsistence-based and heavily dependent on rain-fed agriculture, while urban households rely more on wage employment, trade, and services. Similar rural–urban livelihood divides have been documented in Ethiopia and across Sub-Saharan Africa (CSA & World Bank, 2015; Wossen et al., 2018; FAO, 2016).

3.4.1.2. Structural Differences in Resilience Composition

Figure 3.2 presents the distribution of pillar contributions to the separately estimated RCI for rural and urban households. The stacked distributions reveal clear structural heterogeneity in resilience composition, consistent with the view that resilience is context-specific and shaped by livelihood systems and institutional environments (Barrett & Constas, 2014; Béné et al., 2016).

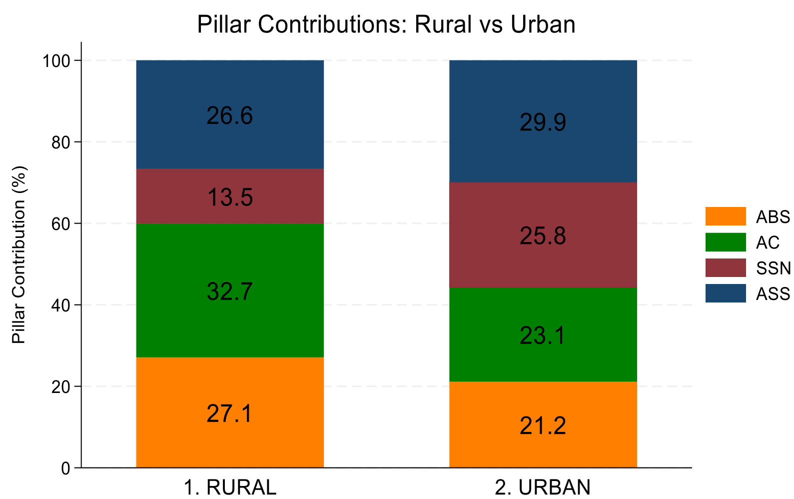

Figure 3-2: Rural-urban Resilience pillar distribution

In rural areas, resilience is primarily driven by adaptive capacity (32.7 percent), followed by access to basic services (27.1 percent) and assets (26.6 percent), while social safety nets contribute the smallest share (13.5 percent). This distribution reflects the underlying structure of the RCI, where pillar contributions are determined by the loadings of their constituent indicators in the factor model. In particular, the prominence of adaptive capacity is driven by indicators such as education, mobile phone access, cooperative membership, and livelihood diversification, which exhibit relatively strong loadings and capture households' ability to adjust production and income strategies in response to climatic variability. Similarly, the contributions of access to basic services and assets reflect strong loadings on infrastructure- and wealth-related indicators, including electricity access, water services, road connectivity, and durable asset ownership, which facilitate production and market participation. By contrast, the relatively smaller contribution of social safety nets reflects both weaker loadings and more limited variation in indicators such as formal assistance, insurance access, and program participation, suggesting that these mechanisms play a more constrained role in shaping resilience in rural contexts.

In urban areas, resilience exhibits a distinct composition. Assets (29.9 percent) and social safety nets (25.8 percent) account for the largest shares, while adaptive capacity (23.1 percent) and access to basic services (21.2 percent) contribute relatively less. This pattern is consistent with an indicator structure in which financial and asset-based measures such as ownership of durable goods, housing quality, and access to financial services carry stronger loadings, alongside social protection and transfer-related indicators. These components reflect the importance of purchasing power, income stability, and institutional support in buffering urban households against labor-market and price shocks. In contrast, indicators of adaptive capacity related to agricultural adjustment and production diversification play a comparatively smaller role, consistent with the reduced importance of own production in urban livelihoods.

Overall, these results confirm that resilience formation is not structurally uniform across space. Estimating the RCI separately by place of residence reveals meaningful heterogeneity in both the composition and relative importance of resilience pillars, driven by differences in the underlying indicator loadings. This reinforces the need for spatially differentiated resilience-building strategies that align with distinct livelihood systems, risk environments, and institutional contexts in Ethiopia (Barrett & Constas, 2014; d'Errico et al., 2021).

3.4.1.3. Shock Exposure and Vulnerability Patterns

The weighted distribution of shock exposure between waves as shown in Figure 3-3 reveals clear spatial differences in both the frequency and composition of shocks experienced by rural and urban households. Rural households experience a higher average number of shocks and are disproportionately affected by climatic and production-related events, including drought, erratic rainfall, livestock losses, and input price increases. These shocks directly undermine agricultural production and income stability, reflecting the structural vulnerability of livelihoods that depend heavily on rain-fed farming systems. The recurrent and covariate nature of these shocks further intensifies rural vulnerability, as entire communities may be affected simultaneously, thereby weakening the effectiveness of informal coping mechanisms.

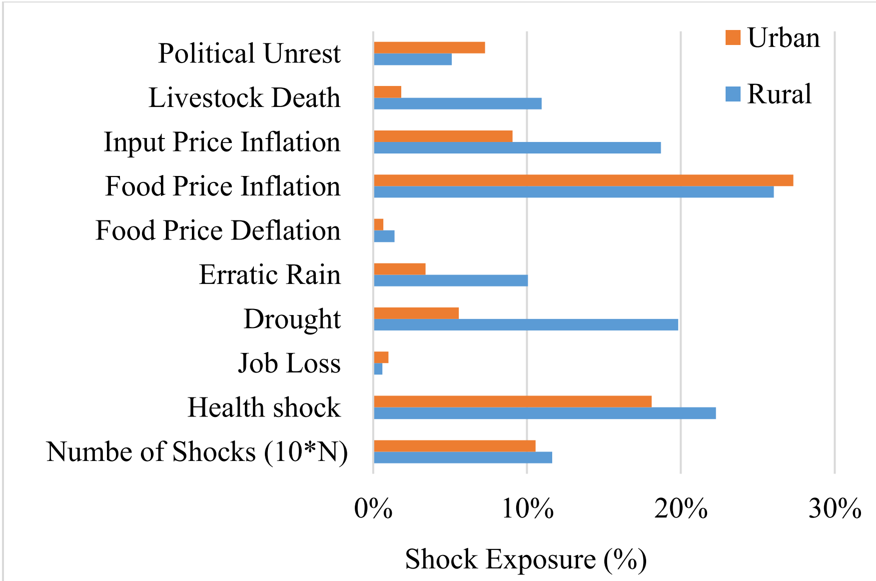

Figure 3-3: Shock exposure between rural vs urban

By contrast, urban households are more exposed to labor market and macroeconomic shocks, particularly job loss and food price increases. These shocks primarily affect purchasing power and food access rather than production capacity. Although generally less frequent than rural production shocks, urban economic shocks can generate immediate consumption stress because urban households rely heavily on purchased food and cash-based livelihoods.

Taken together, the results reveal a dual vulnerability structure: rural exposure is dominated by climatic and production-related shocks, whereas urban exposure is shaped primarily by income and market volatility. These findings underscore that vulnerability is structured differently across rural and urban settings, highlighting the importance of context-specific policy responses to strengthen resilience.

3.4.1.4. Food Security Outcomes

Table 3-1 presents a weighted comparison of food security indicators between rural and urban households. The results reveal clear spatial disparities in household food security outcomes, indicating that the level and dimensions of food security vary systematically by place of residence.

Table 3-1: Weighted Rural–Urban Comparison of Food Security Outcomes

Food Security Indicator	Urban	Rural	Diff (Urban–Rural)
Food Expenditure Share (FES)	0.73	0.85	−0.123***
Daily Caloric Intake (HDCI)	2.32	2.40	−0.085
Dietary Diversity Score (HDDS)	7.73	6.65	1.082***
Food Insecurity Experience (FIES)	1.90	2.32	−0.419*
Household Hunger Score (HHS)	0.48	0.58	−0.104

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Rural households allocate a significantly larger share of their total expenditure to food than urban households (FAO, 2016), as reflected in the higher food expenditure share. This suggests a greater degree of economic vulnerability, since households that spend a large proportion of their budget on food are generally more exposed to income and price shocks. At the same time, rural households record slightly higher daily caloric intake than urban households, although the difference is not statistically significant. This may reflect the role of own production in sustaining calories in rural areas, even where other dimensions of food security remain constrained (Barrett, 2010).

Urban households, however, perform better in terms of dietary quality and food security experience. The household dietary diversity score is significantly higher in urban areas, indicating that urban households consume a wider variety of food groups than rural households. This pattern is consistent with evidence from Ethiopia showing pronounced rural–urban differences in dietary diversity, with urban households generally consuming more diverse diets than rural households Hirvonen (2016). Likewise, the lower food insecurity score among urban households suggests that they face fewer constraints related to uncertainty and insufficiency in food access. Although the household hunger score is also lower in urban areas, the difference appears more modest.

Taken together, these results point to an important rural–urban contrast in food security. Rural households may maintain calorie consumption through subsistence production and staple-based diets, but they remain disadvantaged in terms of dietary diversity and broader food access. Urban households, by contrast, appear to benefit from more diversified diets and relatively better food access, although they may still be vulnerable to market-based shocks that affect affordability. These results point out that food security disparities across residence are multidimensional and cannot be captured by a single indicator alone.

3.4.2. Regression Results

Table 3-2 presents the regression results examining the relationship between shock exposure, resilience capacity, and food security outcomes separately for rural and urban households. The results reveal substantial heterogeneity in how different shocks affect food security across settlement types, as well as in the role of resilience capacity in moderating these effects.

Overall, the results suggest that climatic and production-related shocks exert stronger adverse effects in rural areas, whereas market- and income-related shocks play a more prominent role in shaping urban food security outcomes. Among climatic shocks, drought has particularly strong effects in rural areas. It significantly reduces food expenditure share, but more importantly increases food insecurity experience and household hunger, indicating worsening food security among drought-affected rural households. In urban areas, drought mainly reduces caloric intake, suggesting that climatic shocks are transmitted more indirectly through market channels than through direct production losses. These findings are consistent with the greater dependence of rural households on rain-fed agriculture and climate-sensitive livelihoods (Barrett et al., 2017; FAO, 2016).

Price-related shocks also exhibit important spatial differences. Food-price inflation significantly worsens food insecurity experiences in both rural and urban areas, with especially strong adverse effects in urban areas, where it also raises household hunger. This pattern reflects urban households' stronger dependence on purchased food and their greater exposure to fluctuations in market prices (Headey & Martin, 2016; Ivanic et al., 2012). Input-price inflation likewise has significant effects in urban areas, where it increases caloric intake but reduces household hunger, suggesting complex transmission channels that may reflect short-run adjustments in market supply, substitution in consumption, or differences in how households respond to changing prices. Job loss also shows stronger adverse effects in urban settings, where it significantly increases food insecurity experience, highlighting the vulnerability of wage-dependent households to labor-market disruptions. In contrast, job loss in rural areas is associated with higher caloric intake and dietary diversity, possibly reflecting the role of subsistence production, informal support, or temporary reallocation of labor toward own-farm activities.

Table 3-2: Regression Results for rural and urban food security outcomes

Variable	FES Rural	FES Urban	HDCI Rural	HDCI Urban	HDDS Rural	HDDS Urban	FIES Rural	FIES Urban	HHS Rural	HHS Urban
Main effects										
Health shock=1	0.002	0.002	0.094	0.140	-0.016	0.020	0.284***	0.157*	0.213	0.193
Job loss=1	-0.006	-0.037	2.390***	-0.957	0.170**	0.036	-0.040	0.611***	-0.644	0.709
Drought=1	-0.034***	0.015	-0.166	-0.714**	0.059**	0.025	0.203*	0.123	0.573**	0.325
Excess Rain=1	-0.006	-0.008	0.298	0.195	-0.008	-0.003	0.164	0.060	0.254	0.075
Food Price Deflation=1	-0.001	-0.019	0.141	-0.517	0.019	0.013	0.359**	0.044	0.308	0.604
Food price Inflation=1	-0.013*	-0.009	-0.154	-0.115	-0.016	-0.023	0.224***	0.464***	0.226*	0.663***
Input price Inflation=1	-0.007	-0.004	0.021	0.560**	0.019	0.008	0.141	-0.121	0.203	-0.489**
Livestock Death=1	-0.011	-0.128**	-0.100	-0.139	0.027	0.008	0.121	0.247	-0.075	0.048
Political Shock=1	-0.026**	-0.024	-0.153	-0.010	-0.013	-0.033*	-0.279*	0.376**	-0.632**	0.456
Interaction										
RCI (centered/std)			0.263***	-0.084	0.097***	0.112***	-0.205***	-0.489***	-0.126	-0.684***
Interactions										
Health shock × RCI	0.005	-0.004	-0.122	0.243	0.001	0.041**	0.046	-0.044	0.128	-0.176
Job loss × RCI	-0.008	0.015	-2.305**	-0.394	-0.130*	-0.032	0.073	0.288*	0.634	0.275
Drought × RCI	-0.023**	-0.016	0.027	-0.025	-0.057**	-0.009	0.134	0.265**	0.198	0.363
Excess Rain × RCI	-0.002	-0.001	0.183	-0.336	0.035**	-0.065***	0.050	-0.140	0.023	-0.132
Food Price Deflation × RCI	-0.056*	-0.044	0.102	0.091	-0.020	0.091***	0.296***	0.213	0.609***	0.831*
Food price Inflation × RCI	0.032***	-0.024**	0.196	-0.015	0.008	-0.020	0.024	0.157*	-0.131	0.069
Input price Inflation × RCI	0.011	-0.003	-0.042	-0.745***	-0.011	-0.042*	-0.055	-0.021	-0.126	-0.151
Livestock Death × RCI	-0.009	-0.092**	-0.038	0.283	-0.031	-0.011	-0.037	0.008	-0.141	-0.257
Political Shock × RCI	-0.003	0.009	0.237	0.078	0.004	0.003	-0.009	0.182	-0.219	0.323
Controls										
Age of HH head	-0.000	-0.001	-0.008**	-0.010***	-0.001	-0.001	-0.002	-0.000	-0.000	0.000
Male	0.002	0.017	-0.505***	-0.151	0.005	0.012	-0.177***	-0.228***	-0.441***	-0.215
Wave 5 (2021/22)			-0.506***	-0.121	0.101***	0.047***	0.807***	0.785***	1.795***	1.314***
Constant	0.870***	0.746***			1.818***	2.048***	0.287***	-0.060	-1.911***	-2.105***
cut1 (HDCI)			-2.355***	-1.719***						
cut2 (HDCI)			-1.517***	-0.851***						
Observations	4424	5154	4424	5154	4424	5154	4424	5154	4424	5154

Note: **** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.,*

For FES, FIES, and HHS higher values indicate worse food security outcomes, while higher values of HDCI and HDDS indicate improved food security.

The results also highlight the protective role of resilience capacity. Higher RCI is significantly associated with better food security outcomes in several models, particularly through higher caloric intake and dietary diversity and lower food insecurity experience. However, the strength and direction of these effects vary across residence and indicator. Interaction effects provide further evidence of the buffering role of resilience. In rural areas, resilience moderates the adverse effects of drought by lowering food expenditure share and improving dietary diversity, indicating that more resilient households are better able to smooth consumption and maintain diet quality under climatic stress. In urban areas, resilience interacts significantly with several price-related shocks, especially food-price inflation, food-price deflation, and input-price inflation, suggesting that assets, services, and social protection mechanisms help households cope with market volatility. Taken together, the findings confirm that both shock exposure and resilience capacity play critical roles in shaping food security, consistent with resilience frameworks emphasizing the role of assets, adaptive capacity, and institutional support in enabling households to absorb and recover from shocks (Barrett & Constas, 2014; d'Errico et al., 2018).

3.4.3. Synthesis of Urban–Rural Heterogeneity

The results presented in this chapter reveal substantial heterogeneity in the structure of vulnerability, resilience, and food security outcomes between rural and urban households in Ethiopia. The descriptive analysis highlights important structural differences in demographic characteristics and livelihood systems. Rural households tend to have larger household sizes, higher dependency ratios, and lower levels of education, while urban households benefit from stronger human capital and better access to services. These structural differences are reflected in the composition of resilience capacity, where rural resilience relies more strongly on adaptive capacity and access to basic services, whereas urban resilience is driven more by assets and social safety nets.

The analysis of shock exposure further illustrates how vulnerability differs across settlement types. Rural households are more exposed to climatic and production-related shocks such as drought, erratic rainfall, and livestock losses, reflecting their dependence on rain-fed agriculture and natural-resource–based livelihoods. Urban households, in contrast, face greater exposure to market and income shocks, including food-price inflation and job loss, which primarily affect purchasing power and food access. These differences in shock exposure are also reflected in food security outcomes. Rural households tend to maintain slightly higher caloric intake through own-production and staple consumption, while urban households exhibit higher dietary diversity and lower levels of food insecurity experience, reflecting greater access to markets and more diversified consumption patterns.

The regression results reinforce these patterns and demonstrate that the effects of shocks on food security differ systematically across locations. Climatic shocks have stronger adverse effects in rural areas, whereas price-related and labor-market shocks play a more prominent role in shaping urban food security outcomes. At the same time, resilience capacity plays an important protective role in mitigating these impacts. Higher resilience capacity is associated with improved food security outcomes, particularly through higher dietary diversity and lower food insecurity experiences. Interaction effects further indicate that resilience moderates the effects of shocks through different mechanisms across contexts. In rural areas, resilience primarily buffers climatic shocks by supporting consumption smoothing and protecting diet quality. In urban areas, resilience plays a more important role in moderating the effects of market volatility by stabilizing household purchasing power and food access.

Overall, the findings highlight that resilience and vulnerability are structured differently across rural and urban environments. Because households face distinct risk profiles and livelihood constraints, resilience-building strategies must be tailored to local contexts. Policies aimed at strengthening rural resilience should focus on climate adaptation, agricultural risk management, and improved access to productive services. In urban areas, strengthening social protection systems, stabilizing food markets, and supporting income security are likely to be more effective in protecting household food security. These results underscore the importance of spatially differentiated approaches to resilience-building to address the diverse sources of vulnerability affecting households across Ethiopia.

3.5. Policy implications

The findings of this study highlight important policy implications for strengthening household resilience and improving food security in Ethiopia. The results show that rural and urban households face fundamentally different types of shocks and rely on different mechanisms to cope with them. As a result, policies aimed at strengthening resilience should be tailored to the specific vulnerability profiles associated with each household type rather than applying uniform approaches across contexts.

In rural areas, climatic and production-related shocks particularly drought and rainfall variability remain the dominant drivers of food insecurity. These shocks directly affect agricultural production, household income, and food availability. Strengthening rural resilience therefore requires policies that enhance climate adaptation and agricultural risk management. Investments in irrigation, climate-resilient crop varieties, agricultural extension services, and improved access to productive inputs can help reduce vulnerability to climatic variability. In addition, expanding rural infrastructure, including roads, markets, and financial services, can improve access to basic services and strengthen households' adaptive capacity.

In urban areas, food security is more strongly influenced by market and income-related shocks such as food-price inflation and job loss. Because urban households rely heavily on purchased food, fluctuations in food prices and labor market instability can quickly translate into food insecurity. Policies aimed at strengthening urban resilience should therefore focus on stabilizing household purchasing power. Expanding social protection programs, strengthening labor market opportunities, and improving access to affordable food through market stabilization measures can play an important role in protecting urban households from price volatility and income shocks.

Finally, the results underscore the critical role of resilience capacity in mitigating the effects of shocks across both rural and urban settings. Households with higher resilience capacity are better able to maintain food consumption and dietary quality when faced with adverse events. This highlights the importance of integrated resilience-building strategies that strengthen household assets, improve access to services, and enhance adaptive capacity. By addressing the distinct risk environments faced by rural and urban households, policymakers can design more targeted interventions that effectively protect food security and support long-term resilience.

3.6. Conclusion

This chapter examined how resilience capacity and shock exposure influence food security outcomes across rural and urban households in Ethiopia. Building on the national-level analysis presented in Chapter Two, the chapter introduced a spatially disaggregated perspective to assess whether the structure and effects of resilience differ across livelihood systems.

The results reveal substantial heterogeneity in both shock transmission and resilience mechanisms. Climatic shocks, particularly drought, exert stronger effects on rural households, reflecting the continued dependence of rural livelihoods on rain-fed agricultural production. In contrast, urban households are more sensitive to price-related and income shocks because of their greater reliance on market purchases for food consumption.

The findings also demonstrate that resilience capacity plays an important role in improving food security across both settings. Households with higher resilience levels tend to maintain more diverse diets and experience lower levels of food insecurity. However, the magnitude and channels through which resilience capacity operate differ across rural and urban contexts. In rural areas, resilience functions mainly through production stabilization and asset protection, whereas in urban areas it operates more strongly through income stability, service access, and market participation.

At the same time, the moderating role of resilience varies across shock types. While resilience helps households mitigate the effects of several idiosyncratic shocks, its buffering capacity is more limited in the face of large covariate shocks such as drought or widespread food-price inflation. These findings highlight the importance of complementing household-level resilience with broader institutional and policy responses during systemic crises.

Overall, the results demonstrate that resilience is both context-specific and multidimensional. Recognizing the structural differences between rural and urban livelihood systems is therefore essential for designing effective resilience-building policies.

3.7. Limitations and Future Work

While this study provides important insights into the relationship between resilience, shock exposure, and food security across rural and urban households in Ethiopia, several limitations should be acknowledged. First, the analysis relies on survey-based indicators of shocks and food security, which may be subject to measurement error and recall bias. Second, although the study exploits nationally representative panel data, the analysis captures resilience and food security outcomes over a relatively short time horizon and may not fully reflect longer-term dynamics in household resilience. Third, the empirical models focus on observable household characteristics and resilience indicators, and therefore may not fully capture unobserved institutional, community-level, or behavioral factors that also influence households' capacity to cope with shocks.

Future research could extend this work in several directions. First, incorporating longer-term panel data would allow a more dynamic assessment of resilience trajectories and recovery pathways following shocks. Second, future studies could explore the role of community-level institutions, social networks, and local governance structures in shaping resilience outcomes across different spatial contexts. Finally, integrating climate, market, and geospatial data could provide deeper insights into how environmental and economic shocks interact to influence household food security and resilience over time.

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Appendix A

1.1. Data

To ensure conceptual alignment, statistical consistency, and comparability across waves, we followed the following three steps in data management:

1. Sampling Design and Representativeness

The ESS follows a two-stage, stratified probability sampling design.

— Stage 1: Selection of EAs

The 2018 pre-census EA frame serves as the sampling base, stratified by region and rural–urban residence. Both rural and urban EAs were selected using probability proportional to population size (PPS). Rural EAs were drawn primarily from the Agricultural Sample Survey frame, while urban EAs were selected systematically using PPS based on population size.

— Stage 2: Selection of households

Households were sampled systematically from updated EA listings: 12 households (10 agricultural and 2 non-agricultural) in rural EAs and 15 households in urban EAs. This structure captures heterogeneity in livelihood systems, market integration, and exposure to shocks that are the key elements of resilience analysis.

2. Weights and Panel Structure

CSA-provided survey weights, adjusted for non-response and inter-wave attrition, are used for descriptive statistics. The survey design is declared using “svyset”. Yet PCA and SEM are unweighted estimatates following standard practice for latent-variable modelling, as sampling weights can distort covariance structures. Weighted SEMs were estimated as robust checks and confirmed the stability of the factor structure and model fit. Thus, the panel structure enables analysis of how pre-shock capacities shaped household outcomes during the shock-intensive (2018/19–2021/22) period, an advantage not afforded by cross-sectional surveys.

3. Data Preprocessing Procedures

- Missing data. Handled with Hot-deck imputation which is applied within the EA level to preserve local distributional properties and Last Observation Carried Forward (LOCF) for conceptually stable panel variables in addition to variables with excessive or inconsistent missingness were excluded.
- Outlier treatment. Continuous variables were screened for extreme values using variable-specific distributional limits. Implausible values were winsorized, while extreme but plausible values (e.g. large landholdings or livestock holdings) were retained after verification.
- Directional alignment. Indicators specifically related to distances were re-oriented so that higher values (Shorter distance) consistently represented greater access.
- Standardization. Continuous variables were standardized into z-scores (mean = 0, SD = 1) to eliminate scale effects. Binary and categorical indicators retained their original coding.

1.2. Appendix Tables

Table A. 1: Descriptive Statistics and Measurement of Indicators Used in Constructing RIMA-II Pillars.

IPillar	Variable / Indicator	Measurement	Description	Mean	Std. Dev.	Min	Max
Access to Basic Services (ABS)	Road type	Categorical (1 = Dirt, 4 =All-weather)	Quality of road infrastructure	2.579	1.281	1	4
	Distance to Asphalt Road	Continuous (km)	Proxy for transport connectivity	−16.191	29.661	−170	0
	Public transport passable months	Count (1–12)	Indicates mobility and service accessibility	10.260	3.670	0	12
	Distance to bus stop	Continuous (km)	Reflects local transport availability	−6.249	11.030	−70	0
	Distance to market	Continuous (km)	Ease of market participation and food access	−4.686	12.788	−75	0
	Access to health facility	Count (0–2)	Availability of pharmacy / hospital services	1.411	0.744	0	2
	Access to microfinance institution	Binary (0–1)	Availability of financial services	0.460	0.498	0	1
	Access to improved water	Binary (0–1)	Measures access to piped or safe water	0.593	0.491	0	1
	Access to electricity	Binary (0–1)	Indicates electric power connection	0.555	0.497	0	1
	Distance to bank	Continuous (km)	financial inclusion and economic connectivity	−15.130	27.983	−150	0
	Distance to secondary school	Continuous (km)	Proxy for human capital development	−4.192	6.594	−70	0
	Distance to financial agent	Continuous (km)	Access to agent-based financial services	−20.071	39.243	−450	0
Social Safety Nets (SSN)	Access to insurance	Binary (0–1)	Access to formal safety mechanisms	0.186	0.389	0	1
	Membership of SACCO	Binary (0–1)	Local savings and credit access	0.512	0.500	0	1
	Participation in social network	Binary (0–1)	Proxy for informal social support and solidarity	0.324	0.468	0	1
	Number of churches	Count	Informal religious and community support	4.379	6.250	0	40
	PSNP participation	Binary (0–1)	Public safety net program beneficiary	0.079	0.269	0	1
	Received assistance	Binary (0–1)	Household received aid or relief	0.140	0.347	0	1
	Number of religious primary school	Count	Community-based education participation	0.602	1.201	0	8
	Number of religious secondary school	Count	Reflects extended educational support	0.166	0.515	0	3
	Household head literacy	Binary (0–1)	Proxy for human capital and decision-making ability	0.848	0.359	0	1

Adaptive Capacity (AC)	Highest education level	Continuous (years)	Indicates potential for innovation and resilience	8.664	5.997	0	20
	Household owns mobile phone	Binary (0–1)	Access to information and communication	0.604	0.489	0	1
	Number of crops grown	Count	Crop diversity for food and income security	1.730	3.204	0	22
	Adoption of improved agricultural practice	Ordinal (0–2)	Use of improved seed, breed, or technique	0.078	0.223	0	2
	Livestock vaccination	Binary (0–1)	Preventive animal health management	0.120	0.324	0	1
	Level of extension service received	Categorical (0=none, 3=on farm Demo)	Institutional support for adaptation	0.674	1.007	0	3
	Membership in cooperative	Binary (0–1)	Collective capacity and resource sharing	0.345	0.475	0	1
	Financial training/advice	Ordinal (1–5)	Participation in financial awareness activities	1.085	1.470	0	5
	Use of machinery / irrigation	Binary (0–1)	Use of modern production equipment	0.056	0.229	0	1
	Number of income sources	Count (0–4)	Income diversification for risk management	1.155	0.776	0	4
Assets (ASS)	Tropical Livestock Units (TLU)	Continuous	Livestock wealth and productive assets	2.656	5.799	0	90
	Land size (ha)	Continuous (ha)	Agricultural capacity and food production base	0.325	0.810	0	13
	Owns dwelling house	Binary (0–1)	Long-term asset security	0.689	0.463	0	1
	Ownership of improved stove type	categorical (0–2)	Proxy for wealth and living standard	0.558	0.829	0	2
	Ownership of electric appliances type	categorical (0–3)	Indicator of household modernity	1.276	1.383	0	3
	Ownership of living-room furniture type	categorical (0–2)	Proxy for household comfort level	0.518	0.755	0	2
	Ownership of kitchen items type	categorical (0–2)	Reflects household well-being and food preparation	0.356	0.683	0	2
	Ownership of jewelry/gold/silver	Binary (0–1)	Liquid assets for shock coping	0.221	0.415	0	1
	Ownership of farm tools type	categorical (0–3)	Agricultural productivity assets	0.820	0.862	0	3
	Ownership of other durable goods	Binary (0–1)	Residual household durables	0.181	0.385	0	1
	Ownership of transport assets (vehicle, bike,..)	Binary (0–1)	Improves market access and mobility	0.075	0.263	0	1

Table A.2: Survey-Weighted Regional Pillar scores (Standardized and Weighted)

Region	ABS Y4	ABS Y5	ABSΔ (Y5-Y4)	SSN Y4	SSN Y5	SSNΔ (Y5-Y4)	AC Y4	AC Y5	ACΔ (Y5-Y4)	ASS Y4	ASS Y5	ASSΔ (Y5-Y4)
Afar	-0.252	-0.315	-0.063*	-0.362	-0.530	-0.168**	-0.061	-0.264	-0.203***	-0.156	-0.117	+
Amhara	-0.272	-0.227	+	-0.241	-0.283	-	0.579	0.313	-0.266***	-0.520	-0.413	0.107*
Oromia	-0.214	-0.197	+	-0.279	-0.295	-	0.402	0.442	+	-0.419	-0.281	0.139*
Somali	-0.767	-1.285	-0.518***	-0.761	-0.685	0.076*	−0.116	−0.104	+	-0.416	-0.479	-0.063*
Benishangul -Gumuz	-0.086	-0.107	-	-0.543	-0.600	-0.057*	0.529	0.489	-	-0.457	-0.326	0.131*
SNNP	-0.211	-0.080	0.131**	-0.106	-0.090	+	0.613	0.542	-0.072*	-0.525	-0.449	0.077*
Gambela	-0.210	-0.217	-	-0.076	0.018	0.095*	−0.131	−0.306	-0.176**	-0.304	-0.179	0.124*
Harar	0.367	0.326	-	-0.378	-0.073	0.305***	−0.007	−0.070	-	0.289	0.384	0.095*
Addis Ababa	1.012	1.018	+	0.900	0.892	-	−0.938	−0.910	+	1.339	1.450	0.111*
Dire Dawa	0.626	0.515	-0.111*	1.186	0.907	-0.280**	−0.424	−0.444	-	0.387	0.529	0.142*

Note: *Pillars are weighted according to their contribution to the RCI. Regions with significant negative changes in pillars are highlighted in red to indicate elevated vulnerability.*

1.3. Appendix Figures

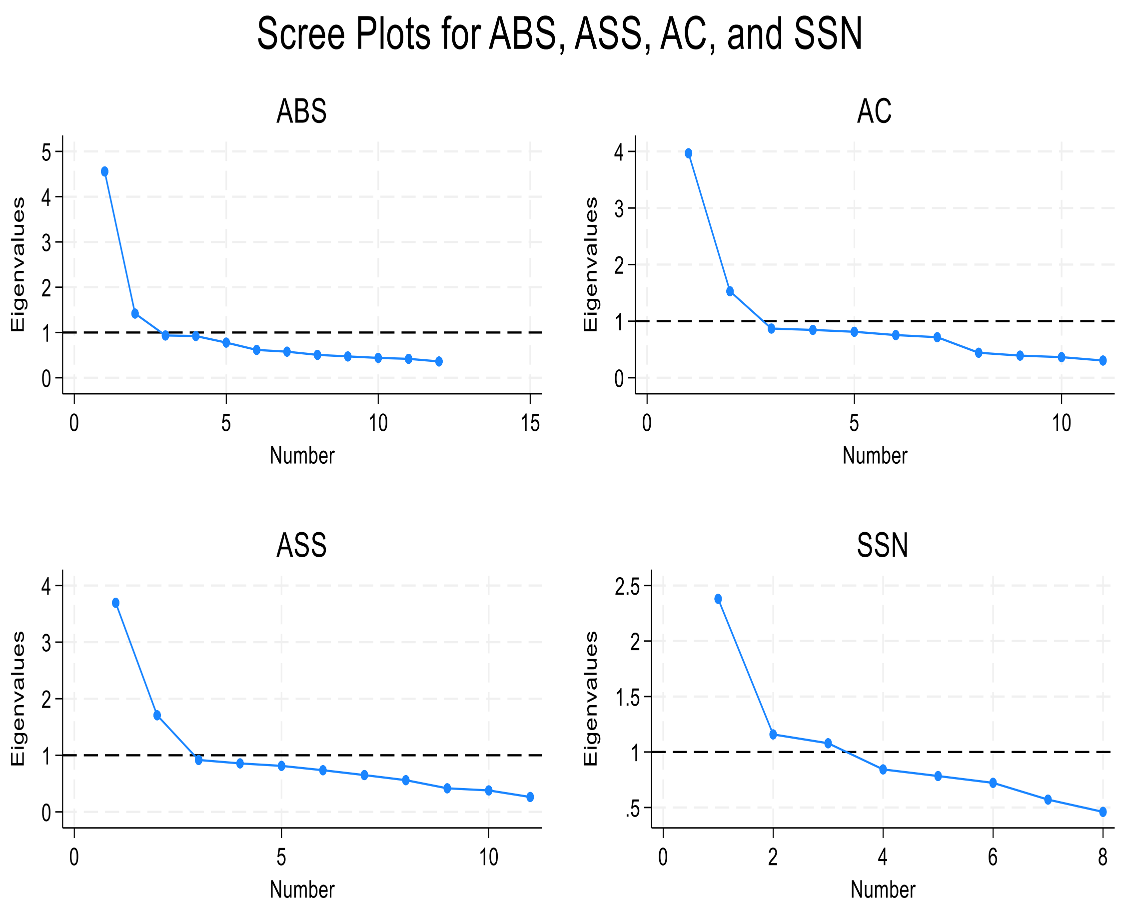

Figure A 1: Scree Plots for PCA of the RIMA-II Pillars (Eigenvalue plots)

Note: Each panel displays the eigenvalues associated with the principal components for a given RIMA-II pillar. The sharp decline after the first component in all four pillars supports the retention of PC1 as the unidimensional index for each pillar, consistent with theoretical expectations and PCA adequacy criteria.

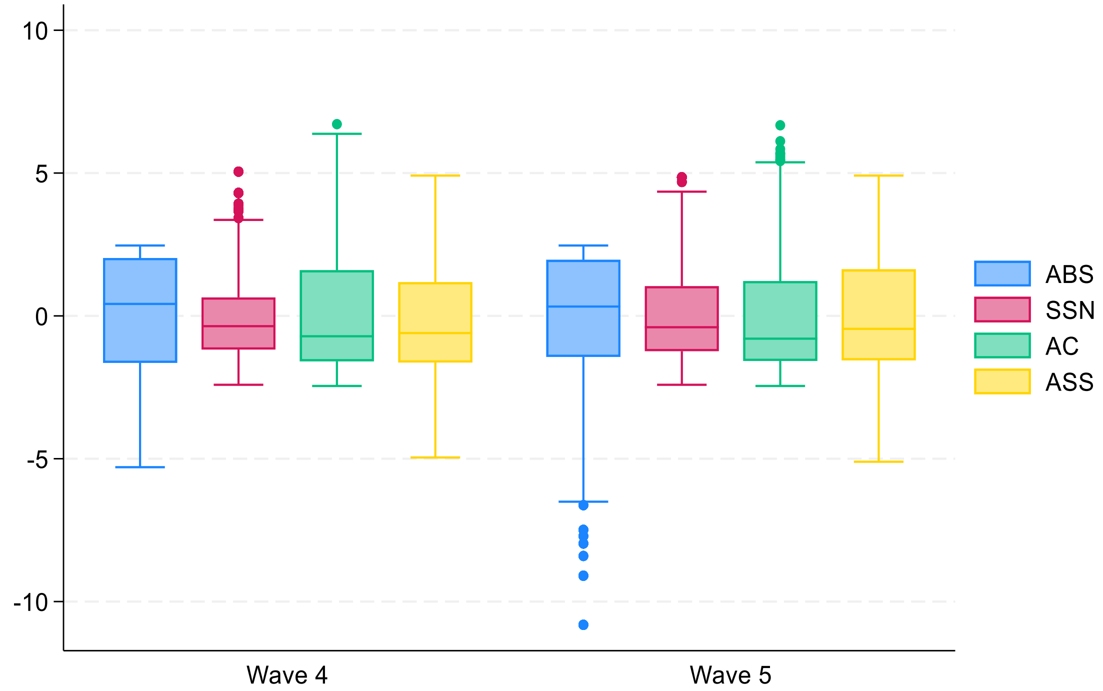

Figure A 2: Boxplots of Pillar Indicators by Wave

Weighted boxplots showing median, IQR, and outliers for all indicators, highlighting shifts between 2018/19 and 2021/22.

Appendix B

Appendix Tables

2.1. Appendix B.I Model selection

Here we document (i) why each main estimator is appropriate for the scale/distribution of each food-security outcome, and (ii) how alternative specifications in Tables B.1–B.5 test sensitivity to functional form, survey design, and identification (between-household vs within-household/panel variation; contemporaneous vs lagged resilience). Across outcomes, the guiding principles are:
(a) match the estimator to the outcome type (bounded shares, counts, ordinal categories), and
(b) verify that the substantive conclusions are not driven by one modeling choice (weights vs FE; pooled vs panel; levels vs changes; one-part vs two-part).

Table B. 1: Summary of outcome scale, main model, and robustness estimators

Outcome	Dimension	Scale / distribution	Main specification	Key robustness checks
FES [0,1]	Access (economic)	Bounded share (0–1) heteroskedasticity likely	HH & Year FE linear	First-difference (Δ) SVY; PPML HH FE; fractional logit SVY
HDCI) (1-3)	Utilization	Ordinal categories	SVY ordered logit	CRE/Mundlak panel ordered logit; SVY ordered logit with lagged RCI
HDDS (1-12)	Utilization	Count, over-dispersion possible	SVY Poisson	SVY NB; lagged RCI; Mundlak/CRE panel count model
FIES (0–8)	Access (experiential)	Count with many zeros, over-dispersion	SVY Negative Binomial	SVY Poisson; PPML HH FE + Year FE; two parts (any vs positive part)
HHS (0–9)	Access (extreme)	Zero-heavy count, right-skew	SVY Negative Binomial	SVY Poisson; PPML HH FE + Year FE; logit any hunger; hurdle positive part

2.2. Appendix B.II. Robustness and sensitivity checks

2.2.1. Food Expenditure Share (FES): "economic access / budget pressure"

— **Outcome scale.**

FES is a bounded share (0–1). Because shares commonly exhibit heteroskedasticity and may be sensitive to functional form, results are checked under both linear and fractional-response frameworks.

— **Main specification** (Column 1: Household & Year FE linear).

The benchmark model includes household and year fixed effects to (i) absorb time-invariant household heterogeneity, (ii) net out common time shocks, and (iii) provide interpretable marginal effects for shocks and shock × RCI terms.

— **Interpretation notes.**

FES can reflect vulnerability and/or coping reallocations; emphasis is placed on consistency of signs and inference across estimators rather than comparing magnitudes across different links.

— **Robustness checks.**

- Column (2): First difference (Δ) SVY. Uses within-household change between waves to test sensitivity to levels vs changes and reduce concerns about time-invariant differences.
- Column (3): PPML with HH FE. A robustness estimator for mean effects under heteroskedasticity, providing a nonlinear pseudo-likelihood check.

Table B. 1: Main and Robustness checks models for FES

Variable	**(1) HH & Year FE**	**(2) 1st difference (Δ) SVY**	**(3) PPML FE**
RCI	-0.018* (0.011)	-0.019 (0.017)	-0.021 (0.013)
Health shock=1	-0.001 (0.007)	0.006 (0.008)	-0.001 (0.010)
Job loss=1	-0.032* (0.017)	-0.032 (0.021)	-0.044* (0.024)
Drought shock=1	0.005 (0.014)	-0.030** (0.012)	0.007 (0.018)
Rain shock=1	0.004 (0.014)	-0.010 (0.009)	0.004 (0.018)
Output price deflation=1	-0.019 (0.028)	0.017 (0.023)	-0.024 (0.038)
Food price inflation=1	-0.008 (0.007)	-0.009 (0.007)	-0.010 (0.009)
Input price inflation=1	-0.006 (0.010)	-0.009 (0.010)	-0.007 (0.014)
Livestock death=1	-0.025 (0.023)	-0.021** (0.008)	-0.032 (0.031)
Political shock=1	-0.033*** (0.012)	-0.026** (0.012)	-0.044*** (0.016)
Health shock × RCI	-0.004 (0.007)	-0.029 (0.025)	-0.005 (0.009)
Job loss × RCI	-0.024 (0.020)	0.011 (0.057)	-0.036 (0.027)
Drought × RCI	0.032*** (0.012)	0.013 (0.036)	0.039** (0.016)
Rain shock × RCI	0.012 (0.014)	-0.000 (0.029)	0.014 (0.018)
Output price deflation × RCI	-0.015 (0.024)	-0.066 (0.086)	-0.020 (0.032)
Food price inflation × RCI	0.001 (0.006)	0.008 (0.018)	0.001 (0.008)
Input price inflation × RCI	0.002 (0.009)	-0.007 (0.020)	0.003 (0.012)
Livestock death × RCI	-0.007 (0.020)	0.032 (0.031)	-0.011 (0.026)
Political shock × RCI	-0.011 (0.011)	-0.039 (0.035)	-0.017 (0.014)
Dependency	0.007 (0.014)	0.004 (0.018)	0.009 (0.017)
Age of HH head	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Sex of HH head (Male)	0.007 (0.011)	—	0.009 (0.013)
Wave 5 (2021/22)	—	—	—
Constant	0.820*** (0.017)	0.012* (0.007)	-0.190*** (0.02)

****Note:*** Standard errors in parentheses. Stars: * p<0.10, ** p<0.05, *** p<0.01. *Column (2) is the first difference model (Δ) between Wave 4 and Wave 5; the shock regressors are Δ shocks taking values −1, 0, +1 (disappearance / no change / new shock). Columns (1), (3), and (4) use shock levels (0/1).*

2.2.2. Household Daily Calory Intake (HDCI): “consumption adequacy/utilization”

Outcome scale: HDCI is ordinal; models must respect category ordering.

Main specification (Column 1: SVY ordered logit): Selected to match the ordinal outcome and provide design-consistent inference under the complex survey design, while allowing shock × RCI moderation.

Robustness checks.

- Column (2): CRE/Mundlak panel ordered logit. Exploits the two-wave structure and adds household means of time-varying regressors to address correlation between unobserved time-invariant heterogeneity and covariates. This tests whether the main moderation patterns persist when separating with in- and between-household components.
- Column (3): SVY ordered logit with lagged RCI. Uses predetermined resilience (t–1) as a sensitivity check against simultaneity. Because lagging may change effective identification and does not include year FE in the same way, it is interpreted as a robust check rather than a replacement.

Interpretation notes: Ordered-logit coefficients depend on category coding; results should be summarized using predicted probabilities (shifts across categories) rather than raw coefficient signs alone.

Table B. 2: Main and Robustness checks models for HDCI

Variable	(1) SVY ologit	(2) CRE (Mundlak) xtologit	Mundlak Mean	(3) SVY ologit (lag RCI)
RCI	-0.225*** (0.068)	0.040 (0.213)	-0.319 (0.22)	-0.127 (0.124)
Health shock=1	0.105 (0.098)	0.169 (0.128)	-0.154 (0.19)	0.149 (0.157)
Job loss=1	-0.056 (0.402)	-0.125 (0.456)	-0.226 (0.89)	0.455 (0.383)
Drought shock=1	-0.544* (0.277)	-0.097 (0.234)	-0.532** (0.26)	-0.719** (0.278)
Excess Rain =1	0.185 (0.193)	0.278 (0.245)	-0.059 (0.29)	0.263 (0.226)
Output price deflation=1	0.099 (0.380)	-1.052** (0.506)	2.303*** (0.82)	-0.097 (0.354)
Food price inflation=1	-0.085 (0.113)	0.068 (0.135)	-0.190 (0.21)	-0.210 (0.138)
Input price inflation=1	0.336** (0.138)	-0.129 (0.189)	1.036*** (0.27)	0.215 (0.155)
Livestock death=1	0.138 (0.431)	0.122 (0.333)	-0.094 (0.33)	-0.102 (0.433)
Political shock=1	-0.013 (0.184)	-0.052 (0.229)	-0.083 (0.37)	-0.070 (0.222)
Health shock × RCI	0.048 (0.111)	0.086 (0.107)		0.042 (0.138)
Job loss × RCI	-0.989* (0.574)	-1.156** (0.452)		-0.590 (0.507)
Drought × RCI	-0.166 (0.244)	-0.006 (0.194)		-0.334 (0.289)
Excess shock × RCI	-0.152 (0.202)	-0.018 (0.221)		-0.157 (0.204)
Output price fall × RCI	-0.110 (0.392)	-0.370 (0.323)		-0.198 (0.308)
Food price inflation × RCI	0.054 (0.108)	0.119 (0.093)		-0.001 (0.141)
Input price inflation × RCI	0.176 (0.167)	0.218 (0.140)		0.023 (0.183)
Livestock death × RCI	0.420 (0.356)	0.369 (0.296)		0.299 (0.362)
Political shock × RCI	0.070 (0.188)	-0.044 (0.177)		0.132 (0.227)
Wave 5 (2021/22)	-0.327** (0.127)	-0.312*** (0.087)		—
Age of HH head	-0.008*** (0.003)	-0.009*** (0.003)		-0.010** (0.004)
Male	-0.328*** (0.091)	-0.410*** (0.104)		-0.356*** (0.12)
cut1	—	-2.270*** (0.184)		—
cut2	—	-1.285*** (0.178)		—
sigma²_u	—	1.127*** (0.180)		—
Number of observations	9,698	9,698		9,698
Number of Households				

Notes: *Standard errors in ( ). Stars: * p<0.10, ** p<0.05, *** p<0.01. Lag-RCI model estimated on Wave 5 subpopulation (Wave==5), so Year FE is not included and may imply different effective identifying variation and sample restrictions. CRE/Mundlak includes household-mean controls to address correlation between unobserved heterogeneity and covariates.*

2.2.3. Household Dietary Diversity Score (HDDS): "quality/utilization"

Outcome scale. HDDS is a count outcome with limited range (1-12); mild over-dispersion is common.

Main specification (Column 1: SVY Poisson). Chosen because it is appropriate for counts and supports survey-weighted inference aligned with population parameters and no over dispersion.

Robustness checks.

- Column (2): Mundlak/CRE panel count model. Adds household-mean controls to address time-invariant heterogeneity correlated with shocks/resilience. Because survey-weighting is not always available for panel count implementations, this is treated as a sign/stability robustness check rather than a population-inference benchmark.
- Column (3): Lagged RCI. Replaces contemporaneous RCI with t–1 RCI to reduce simultaneity concerns.

Table B. 3: Main and Robustness checks models for HDDS

Variable	(1) POI _HDDS_SVY	(2) HDDS_ MUNDLAK	Mundlak Mean	(3) Poslag RCI_HDDS
RCI /RCI_lag	0.103*** (0.006)	0.035*** (0.013)	0.099*** (0.01)	0.080*** (0.013)
Health shock = 1	0.002 (0.013)	0.007 (0.007)	0.003 (0.01)	0.017 (0.017)
Job loss = 1	0.082*** (0.029)	0.029 (0.030)	0.014 (0.05)	0.085** (0.039)
Drought shock = 1	-0.018 (0.028)	0.047*** (0.013)	-0.009 (0.02)	0.006 (0.025)
Excess Rain = 1	0.012 (0.019)	0.031** (0.014)	-0.033 (0.02)	0.002 (0.021)
Output price deflation = 1	0.031 (0.042)	-0.050* (0.030)	0.062 (0.04)	0.016 (0.055)
Food prices inflation = 1	-0.017 (0.013)	0.025*** (0.007)	-0.051*** (0.01)	-0.023* (0.014)
Input price inflation = 1	0.009 (0.017)	-0.000 (0.010)	0.035** (0.02)	0.011 (0.017)
Livestock death = 1	0.007 (0.029)	0.025 (0.020)	-0.036* (0.02)	0.046 (0.047)
Political shock = 1	-0.016 (0.017)	-0.026** (0.013)	0.002 (0.012)	-0.006 (0.018)
Health shock × RCI	0.022* (0.012)	0.014** (0.006)		0.040*** (0.015)
Job loss × RCI	-0.021 (0.043)	-0.012 (0.026)		-0.013 (0.054)
Drought × RCI	-0.041* (0.023)	-0.000 (0.011)		0.013 (0.019)
Excess Rain × RCI	0.002 (0.023)	0.009 (0.011)		-0.012 (0.022)
Output price deflation × RCI	-0.006 (0.037)	-0.033 (0.022)		-0.044 (0.048)
Price inflation × RCI	0.003 (0.012)	-0.014*** (0.005)		0.017 (0.015)
Input price inflation × RCI	-0.053*** (0.017)	-0.031*** (0.007)		-0.043*** (0.015)
Livestock death × RCI	-0.013 (0.025)	-0.010 (0.017)		0.013 (0.042)
Political shock × RCI	0.015 (0.018)	-0.008 (0.011)		0.022 (0.020)
Wave =5 (2021/22)	0.091*** (0.015)	0.088*** (0.005)		—
Household head Age	-0.000 (0.000)	-0.001*** (0.000)		0.001 (0.000)
Household head Sex (=male)	0.036*** (0.010)	0.044*** (0.005)		0.045*** (0.013)
Rural (Urban=2)		-0.042*** (0.010)		
Constant	1.915*** (0.021)	1.977*** (0.011)		1.966*** (0.025)
lnalpha	—	-20.665*** (0.138)		—
N	9,637	9,637		4,831

*Notes: Standard errors in parentheses. Stars: * p<0.10, ** p<0.05, *** p<0.01. Lagged-RCI models use t–1 resilience and may imply different effective identifying variation and sample restrictions.*

2.2.4. Food Insecurity Experience Scale (FIES): "experiential access"

Outcome scale. FIES is count (0–8) with many zeros and over-dispersion, motivating negative binomial and complementary two-part approaches.
Main specification (Column 1:). It handles over-dispersion while preserving survey design for correct inference, including for shock × RCI terms.
Robustness checks.

- Column (2): SVY Poisson. Tests distributional sensitivity (Poisson vs NB).
- Column (3): PPML HH FE + Year FE. Stricter within-household identification check focuses on changes within the same household over time.
- Column (4): Logit for any food insecurity (FIES>0). Extensive margin: entry into food insecurity.
- Column (5): Positive-part model for severity among FIES>0. Intensive margin: severity conditional on being food insecure.

Interpretation notes. The two parts hurdle distinguishes shock effect of the likelihood of becoming food-insecure & severity once insecurity occurs.

Table B. 4: Main and Robustness checks models for FIES

Variable	(1) SVY_NB	(2) POI_ FIES_SVY	(3) PPML _FE	(4) LOGIT_ FIES_ANY	(5) POI_ FIES_POS
RCI	-0.160** (0.063)	-0.163*** (0.058)	-0.004 (0.139)	-0.223*** (0.079)	-0.032 (0.038)
Health shock = 1	0.254*** (0.053)	0.226*** (0.049)	0.104 (0.075)	0.453*** (0.099)	0.073* (0.039)
Job loss = 1	0.397** (0.182)	0.301 (0.195)	0.210 (0.281)	0.867 (0.568)	0.037 (0.106)
Drought shock = 1	0.274** (0.122)	0.261** (0.104)	-0.004 (0.148)	0.316 (0.241)	0.151*** (0.052)
Excess Rain = 1	0.286** (0.125)	0.207* (0.105)	0.112 (0.146)	0.493* (0.252)	0.085 (0.076)
Output price deflation = 1	0.335 (0.221)	0.417** (0.203)	0.076 (0.310)	0.274 (0.446)	0.384** (0.157)
Food prices inflation = 1	0.346*** (0.069)	0.306*** (0.069)	0.185*** (0.071)	0.583*** (0.145)	0.081** (0.038)
Input price increase = 1	-0.033 (0.085)	0.010 (0.079)	0.145 (0.109)	-0.133 (0.165)	0.037 (0.044)
Livestock death = 1	0.138 (0.149)	0.129 (0.138)	0.022 (0.217)	0.223 (0.369)	0.055 (0.093)
Political shock = 1	0.030 (0.126)	-0.015 (0.134)	0.377*** (0.129)	0.229 (0.272)	-0.098 (0.066)
Health shock × RCI	-0.083 (0.057)	-0.063 (0.050)	-0.247*** (0.076)	-0.232** (0.099)	0.008 (0.040)
Job loss × RCI	0.299 (0.209)	0.256 (0.185)	1.140*** (0.344)	1.238** (0.501)	-0.148 (0.129)
Drought × RCI	0.020 (0.109)	0.028 (0.081)	0.036 (0.148)	-0.066 (0.224)	0.021 (0.050)
Excess Rain × RCI	0.101 (0.132)	0.042 (0.099)	-0.024 (0.156)	0.113 (0.277)	0.028 (0.069)
Output price fall × RCI	-0.125 (0.202)	-0.008 (0.128)	0.119 (0.252)	-0.754 (0.509)	0.112 (0.090)
Food Price inflation × RCI	0.013 (0.078)	0.063 (0.063)	0.068 (0.068)	0.001 (0.154)	-0.006 (0.035)
Input price inflation × RCI	0.016 (0.088)	-0.022 (0.072)	-0.034 (0.108)	-0.188 (0.232)	0.039 (0.036)
Livestock death × RCI	-0.035 (0.118)	-0.038 (0.096)	-0.362* (0.197)	0.020 (0.297)	-0.063 (0.064)
Political shock × RCI	0.197** (0.099)	0.164 (0.107)	0.551*** (0.149)	0.126 (0.209)	0.107 (0.067)
Wave=5 (2021/22)	0.805*** (0.077)	0.767*** (0.071)		1.197*** (0.142)	0.224*** (0.035)
Household head Age	-0.002* (0.001)	-0.003* (0.001)	0.001 (0.004)	-0.005 (0.004)	-0.001 (0.001)
Household head Sex (=male)	-0.297*** (0.058)	-0.262*** (0.051)	-0.332** (0.158)	-0.387*** (0.107)	-0.127*** (0.030)
Constant	0.207** (0.092)	0.238*** (0.088)	1.319*** (0.240)	-0.547*** (0.168)	1.251*** (0.055)
lnalpha	0.313*** (0.081)				-4.500*** (1.021)
N	9698	9698	6684	9698	4377

2.2.5. Household Hunger Scale (HHS): “extreme access failure”

Outcome scale. zero-heavy, right-skewed count (0–9), so it is important to check both standard count and models that separate onset vs severity.

Main specification (Column 1: SVY Negative Binomial). It allows over-dispersion & preserve survey design in estimation.

Robustness checks.

- Column (2): SVY Poisson. Distributional sensitivity check.
- Column (3): PPML HH FE + Year FE. Within-household identification checks emphasizing time variation.
- Column (4): Logit for any hunger (HHS>0). Extensive margin.
- Column (5): Hurdle positive-part model (HHS|HHS>0). Intensive margin among those already hungry.

In the two-part hurdle results help distinguish shifts in households into hunger/insecurity versus worsening severity among those already affected.

Table B. 5: Main and Robustness checks models for HHS

Variable	*(1) SVY NB (Main)*	*(2) SVY Poisson*	*(3) PPML HH FE + Year FE*	*(4) SVY Logit: Any HHS*	*(5) HHS HURDLE POS*
RCI_std	-0.118 (0.122)	-0.143 (0.110)	-0.119 (0.222)	-0.128 (0.133)	-0.022 (0.041)
Health shock=1	0.301*** (0.112)	0.231** (0.115)	0.432*** (0.123)	0.361*** (0.122)	0.005 (0.080)
Job loss=1	0.474 (0.327)	0.337 (0.321)	-0.384 (0.311)	0.803 (0.489)	-0.084 (0.183)
Drought shock=1	0.603** (0.236)	0.580*** (0.196)	0.415* (0.234)	0.854** (0.333)	0.067 (0.151)
Excess Rain =1	0.408 (0.279)	0.261 (0.204)	-0.180 (0.256)	0.417 (0.287)	0.064 (0.131)
Output price deflation =1	0.627* (0.327)	0.745*** (0.275)	0.281 (0.438)	1.051 (0.657)	0.198 (0.159)
Food price inflation =1	0.389*** (0.128)	0.335** (0.129)	0.338*** (0.121)	0.391*** (0.147)	0.074 (0.076)
Input price inflation =1	-0.185 (0.173)	-0.065 (0.154)	0.101 (0.191)	-0.013 (0.181)	-0.069 (0.121)
Livestock death=1	0.130 (0.261)	0.044 (0.227)	0.287 (0.368)	0.310 (0.367)	-0.159 (0.173)
Political shock=1	-0.196 (0.238)	-0.217 (0.240)	0.136 (0.191)	-0.348 (0.333)	-0.027 (0.082)
Health shock × RCI	-0.101 (0.141)	-0.044 (0.116)	-0.097 (0.132)	-0.081 (0.138)	0.001 (0.079)
Job loss × RCI	0.464 (0.458)	0.492 (0.352)	1.056** (0.439)	0.276 (0.613)	0.289 (0.227)
Drought shock × RCI	0.026 (0.253)	0.012 (0.171)	-0.029 (0.249)	0.003 (0.278)	-0.028 (0.159)
Excess Rain × RCI	0.122 (0.269)	0.012 (0.139)	-0.354 (0.250)	0.124 (0.266)	-0.019 (0.091)
Output price inflation × RCI	-0.033 (0.274)	0.162 (0.177)	0.025 (0.371)	-0.236 (0.449)	0.155 (0.174)
Food price inflation × RCI	0.012 (0.123)	0.046 (0.103)	0.295** (0.123)	-0.052 (0.143)	0.048 (0.061)
Input price inflation × RCI	-0.118 (0.137)	-0.103 (0.108)	-0.211 (0.206)	-0.187 (0.172)	0.024 (0.108)
Livestock death × RCI	0.044 (0.237)	-0.060 (0.196)	-0.349 (0.348)	0.236 (0.325)	-0.214 (0.163)
Political shock × RCI	0.295 (0.251)	0.273 (0.254)	0.214 (0.203)	0.265 (0.364)	0.093 (0.092)
Wave 5 (2021/22)	1.613*** (0.136)	1.574*** (0.134)	1.176*** (0.078)	1.626*** (0.150)	0.290*** (0.065)
Household head Age	-0.001 (0.002)	-0.002 (0.002)	0.016** (0.006)	-0.004 (0.004)	0.001 (0.002)
Household head Sex (=male)	-0.464*** (0.104)	-0.455*** (0.112)	-0.109 (0.208)	-0.482*** (0.153)	-0.140* (0.074)
Constant	-1.853*** (0.154)	-1.785*** (0.168)	-1.418*** (0.351)	-2.361*** (0.226)	0.665*** (0.115)
lnalpha	1.108*** (0.125)				-3.034*** (0.750)
Observations	9,698	9,698	3,058	9,698	1,689

2.3. Summary

Across Tables B.2–B.6, the robustness suite shows that key relationships between resilience capacity, shocks, and food-security outcomes are not artifacts of a single estimator, functional-form assumption, or reliance on between-household comparisons. Results are evaluated for consistency across survey-weighted population models, panel/within-household identification checks, and lagged-resilience sensitivity specifications, with additional two-part/hurdle models clarifying whether effects operate primarily through onset versus severity for zero-heavy food insecurity measures.

Stability interpretation across outcomes: Stability is assessed indirectly through (i) wave effects capturing the shift in the food-security environment between 2018/19 and 2021/22, and (ii) sensitivity of outcomes to shocks and shock × RCI interactions. Stability is most credibly tested using within-household estimators (first-difference models and PPML HH FE) and two-part/hurdle models (onset vs severity).

Appendix C

Table C. 1: Regression outcomes for rural and urban households for the food security outcomes

	FES Rural b/se	FES Urban b/se	HDCI Rural b/se	HDCI Urban b/se	HDDS Rural b/se	HDDS Urban b/se	FIES Rural b/se	FIES Urban b/se	HHS Rural b/se	HHS Urban b/se
main										
Health shock=1	0.002	0.002	0.094	0.140	-0.016	0.020	0.284***	0.157*	0.213	0.193
	(0.01)	(0.01)	(0.12)	(0.14)	(0.01)	(0.02)	(0.04)	(0.08)	(0.15)	(0.15)
Job loss=1	-0.006	-0.037	2.390***	-0.957	0.170**	0.036	-0.040	0.611***	-0.644	0.709
	(0.02)	(0.03)	(0.72)	(0.69)	(0.07)	(0.03)	(0.24)	(0.22)	(0.44)	(0.55)
Drought=1	-0.034***	0.015	-0.166	-0.714**	0.059**	0.025	0.203*	0.123	0.573**	0.325
	(0.01)	(0.03)	(0.23)	(0.35)	(0.03)	(0.02)	(0.10)	(0.11)	(0.23)	(0.26)
Excess Rain=1	-0.006	-0.008	0.298	0.195	-0.008	-0.003	0.164	0.060	0.254	0.075
	(0.01)	(0.02)	(0.24)	(0.27)	(0.02)	(0.02)	(0.10)	(0.15)	(0.19)	(0.28)
Food Price Deflation=1	-0.001	-0.019	0.141	-0.517	0.019	0.013	0.359**	0.044	0.308	0.604
	(0.02)	(0.04)	(0.51)	(0.49)	(0.04)	(0.06)	(0.14)	(0.30)	(0.25)	(0.43)
Food price Inflation=1	-0.013*	-0.009	-0.154	-0.115	-0.016	-0.023	0.224***	0.464***	0.226*	0.663***
	(0.01)	(0.01)	(0.15)	(0.16)	(0.02)	(0.01)	(0.07)	(0.12)	(0.13)	(0.23)
Input price Inflation=1	-0.007	-0.004	0.021	0.560**	0.019	0.008	0.141	-0.121	0.203	-0.489**
	(0.01)	(0.02)	(0.19)	(0.24)	(0.02)	(0.03)	(0.09)	(0.13)	(0.13)	(0.22)
Livestock Death=1	-0.011	-0.128**	-0.100	-0.139	0.027	0.008	0.121	0.247	-0.075	0.048
	(0.01)	(0.06)	(0.19)	(0.83)	(0.02)	(0.07)	(0.09)	(0.18)	(0.15)	(0.45)
Political Shock=1	-0.026**	-0.024	-0.153	-0.010	-0.013	-0.033*	-0.279*	0.376**	-0.632**	0.456
	(0.01)	(0.02)	(0.26)	(0.20)	(0.03)	(0.02)	(0.16)	(0.15)	(0.30)	(0.32)
	(0.01)	(0.02)								
Age of HH head	-0.000	-0.001	-0.008**	-0.010***	-0.001	-0.001	-0.002	-0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	0.002	0.017	-0.505***	-0.151	0.005	0.012	-0.177***	-0.228***	-0.441***	-0.215
	(0.01)	(0.02)	(0.13)	(0.12)	(0.01)	(0.01)	(0.06)	(0.07)	(0.15)	(0.14)
RCI/ Centered			0.263***	-0.084	0.097***	0.112***	-0.205***	-0.489***	-0.126	-0.684***
			(0.09)	(0.09)	(0.01)	(0.01)	(0.07)	(0.07)	(0.15)	(0.13)
Health shock=1 # RCI/ centered	0.005	-0.004	-0.122	0.243	0.001	0.041**	0.046	-0.044	0.128	-0.176
	(0.01)	(0.01)	(0.10)	(0.15)	(0.01)	(0.02)	(0.06)	(0.06)	(0.13)	(0.11)

Job loss=1 # RCI	-0.008	0.015	-2.305**	-0.394	-0.130*	-0.032	0.073	0.288*	0.634	0.275
	(0.03)	(0.02)	(1.00)	(0.48)	(0.07)	(0.03)	(0.28)	(0.17)	(0.53)	(0.38)
Drought=1 # RCI	-0.023**	-0.016	0.027	-0.025	-0.057**	-0.009	0.134	0.265**	0.198	0.363
	(0.01)	(0.02)	(0.14)	(0.30)	(0.02)	(0.02)	(0.09)	(0.12)	(0.13)	(0.24)
Excess Rain=1 # RCI	-0.002	-0.001	0.183	-0.336	0.035**	-0.065***	0.050	-0.140	0.023	-0.132
	(0.01)	(0.02)	(0.30)	(0.22)	(0.01)	(0.02)	(0.11)	(0.11)	(0.14)	(0.24)
Food Price Deflation=1 # RCI	-0.056*	-0.044	0.102	0.091	-0.020	0.091***	0.296***	0.213	0.609***	0.831*
	(0.03)	(0.03)	(0.32)	(0.44)	(0.04)	(0.03)	(0.11)	(0.26)	(0.18)	(0.46)
Food price Inflation=1 # RCI	0.032***	-0.024**	0.196	-0.015	0.008	-0.020	0.024	0.157*	-0.131	0.069
	(0.01)	(0.01)	(0.13)	(0.15)	(0.02)	(0.01)	(0.06)	(0.09)	(0.10)	(0.15)
Input price Inflation=1 # RCI	0.011	-0.003	-0.042	-0.745***	-0.011	-0.042*	-0.055	-0.021	-0.126	-0.151
	(0.01)	(0.02)	(0.15)	(0.28)	(0.02)	(0.02)	(0.08)	(0.10)	(0.12)	(0.16)
Livestock Death=1 # RCI	-0.009	-0.092**	-0.038	0.283	-0.031	-0.011	-0.037	0.008	-0.141	-0.257
	(0.01)	(0.04)	(0.17)	(0.55)	(0.02)	(0.05)	(0.08)	(0.21)	(0.12)	(0.33)
Political Shock=1 # RCI	-0.003	0.009	0.237	0.078	0.004	0.003	-0.009	0.182	-0.219	0.323
			(0.20)	(0.19)	(0.02)	(0.03)	(0.10)	(0.12)	(0.22)	(0.20)
Age of HH head	-0.000	-0.001	-0.008**	-0.010***	-0.001	-0.001	-0.002	-0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	0.002	0.017	-0.505***	-0.151	0.005	0.012	-0.177***	-0.228***	-0.441***	-0.215
	(0.01)	(0.02)	(0.13)	(0.12)	(0.01)	(0.01)	(0.06)	(0.07)	(0.15)	(0.14)
Wave 5 (2021/22)			-0.506***	-0.121	0.101***	0.047***	0.807***	0.785***	1.795***	1.314***
			(0.16)	(0.17)	(0.02)	(0.02)	(0.08)	(0.12)	(0.19)	(0.19)
Constant	0.870***	0.746***			1.818***	2.048***	0.287***	-0.060	-1.911***	-2.105***
	(0.02)	(0.04)			(0.03)	(0.02)	(0.10)	(0.13)	(0.27)	(0.24)
cut1			-2.355***	-1.719***						
			(0.24)	(0.25)						
cut2			-1.517***	-0.851***						
			(0.21)	(0.24)						
Observations	4424	5154	4424	5154	4424	5154	4424	5154	4424	5154