



Household resilience capacity and food security: evidence from Kyrgyzstan

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Received: 15 June 2022 / Accepted: 25 March 2023 / Published online: 8 May 2023
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Abstract

Commonly, resilience against external shocks is treated as a household or community capacity. Resiliency against food insecurity is of particular importance for rural household under the impression of recent price surges and supply chain disruptions. The aim of this paper is to analyze the effect of household resilience capacity on food security outcomes in Kyrgyzstan, using individual, household and community datasets of the “Life in Kyrgyzstan” panel survey for several waves from 2011 to 2016. Firstly, a resilience capacity index to food insecurity was estimated through key determinants or pillars under the Resilience Index Measurement and Analysis (RIMA) II methodology, while latent analysis was used to classify shocks. The effect of resilience capacity on food security outcomes was estimated along an instrumental variable approach. Our results suggest that resilience capacity serves to improve food security status and decrease the proneness of households to suffering from food insecurity in the presence of shocks. Furthermore, the interaction between resilience capacity and shocks was included to explain whether the negative effect of the shocks is weakened by resilience. The findings confirm that resilience capacity is able to mitigate the adverse effects of shocks on food security outcomes; moreover, it is sufficient to resist a decline in food security. Following the large contributions of social safety nets and adaptive capacity to the resilience capacity index, policy efforts should be focused on increasing income generating capacity, networking, migration, and education level of households to strengthen resilience to food insecurity.

Keywords Resilience · Food security · Latent class · Central Asia

1 Introduction

Political conflict, global climate change and socio-economic shocks confronted 155 million people worldwide with acute food insecurity in 2020 (UN, 2021). In light of the increasing frequency of climate-related shocks, but also systemic events like the recent COVID epidemic and related economic and

political upheavals, the ability to absorb and compensate for shocks has become of the utmost importance for maintaining a sustainable food system. Food systems exhibit various potential and interlinked vulnerabilities to climate shocks in particular, including food insecurity and social welfare loss among consumers, environmental degradation and disruptions of food system activities (Ericksen, 2008). In order to decrease food system vulnerabilities, various programs are aimed at introducing more consistent response mechanisms, including the FAO’s Food and Nutrition Security Resilience Program (FAO, 2020), Country Strategic Plans or Food Assistance for Assets of the World Food Program (WFP, 2021a, b), the UNDP’s Global Commission for Adaptation (UNDP, 2020) and the Food System Resilience Program (World Bank, 2021).

Response mechanisms to shocks are commonly summarized under the term resilience. Within the United Nations’ Sustainable Development Goals (SDGs), resilience is defined as, “*the ability to prevent disasters and crises as well as to anticipate, absorb, accommodate or recover from*

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them in a timely, efficient and sustainable manner” (FAO, 2021). Socioeconomic research has long established a strong connection between resilience and long-term economic development (Beauchamp et al., 2021; Fan et al., 2014), supporting the understanding of resilience as a development goal (Barrett & Conostas, 2014). More recent work defines resilience as the capacity to deal with ongoing exposure to risks (Conostas et al., 2014). Correspondingly, development studies explain resilience as the capacity of economic agents to cope with different types of shocks (Alfani et al., 2015; Béné et al., 2015). As a strategy, Pasteur (2011) has advanced the definition of resilience to, “the ability to absorb, cope with and recover from the effects of hazards and to adapt to longer term changes in a timely and efficient manner without undermining food security or wellbeing”.

Resilience capacity from the perspective of farm households touches three vulnerability dimensions of the farm system at the same time, namely food insecurity, food system activities, and social welfare among producers. By building resilience capacity, farm households may endure shocks and stresses without suffering from a long-lasting deterioration of their production and livelihoods, thus maintaining their food system activities and securing regional food security. We therefore argue that the ability to maintain a sufficient food supply under severe shock events is both a strong indicator of a proactive response of farm households to shock events as well as a decisive factor in the prevention of ripple-down effects from the micro-perspective of producers into food systems at the macro level. In order to explore the relationship between resilience and food security, this paper broadens one of the existing food insecurity resilience conceptualizations, taking the case of Kyrgyzstan. With a population of 6.7 million people, Kyrgyzstan is located in the north-east of Central Asia (NSC, 2022). Kyrgyzstan is one of the few Low-Income Food-Deficit (LIFD) and Landlocked Developing countries (LLDC) where more than 60% of the population live in rural areas (FAO, 2018b, 2022; UN, 2022). Furthermore, Kyrgyz regions are characterized by the hazard of the country’s geographical isolation and climate vulnerability in Central Asia, showing the significance of studying resilience in the country (Xenarios et al., 2019). While Kyrgyzstan has introduced various action plans (Burkitbayeva et al., 2020) and investment programs (Bhutta et al., 2020) for food security and nutritional development, a large part of the population is still on the brink of food insecurity and malnutrition (WFP, 2020). This problem is compounded by poor adaptive capacity, inadequate transport infrastructure, limited access to basic health or sanitary facilities and low social protections (FAO, 2019a). Therefore, designing food security and nutritional interventions or policies may not be enough unless there are extra commitments to build or strengthen household and community resilience to

shocks. This further requires an understanding of the structural dimensions of resilience and their dynamics towards food insecurity. In this respect, it is of interest for us to analyze the relationship between household resilience and food security by adopting a multidimensional approach that contributes more effectively to resilience policy programs in Kyrgyzstan.

In order to analyze the connection between resilience and food security, we utilize a longitudinal multi-topic survey with 3,000 households in the Kyrgyz countryside from the “Life in Kyrgyzstan” (LiK) study. The LiK includes detailed information on individual, household and community levels, covering topics on household demographics, assets, expenditure, migration, agriculture, shocks, networking, well-being and others (Research Data Center of IZA, 2016). Supplying multi-dimensional and high-frequency panel data, the LiK study enables us to analyze resilience trajectories and food security dynamics by integrating individual, household and community modules over several waves from 2011, 2012, 2013 and 2016.

In order operationalize resilience capacity as a latent intermediate outcome of different capacity building dimensions in the household, we require a multi-stage approach (Alinovi et al., 2010b). For this paper, we chose the Resilience Index Measurement Analysis II (RIMA-II) to measure resilience capacity to food insecurity in the presence of shocks (Ansah et al., 2019; FAO, 2016). In contrast to its predecessor RIMA-I, RIMA-II treats resilience as household capacity (Ansah et al., 2019). According to this methodology, food security is the result of activating resilience in the face of shocks.

Overall, this paper provides several contributions to the exiting literature. Firstly, a growing body of literature looking into the relationship between resilience and food security points out the necessities to differentiate between endogenous and exogenous shocks (Brück et al., 2019; d’Errico et al., 2018; Lascano Galarza, 2020; Murendo et al., 2020). We follow this suggestion by conceptually analyzing the relationship between resilience capacity and food security in the presence of shock clusters that are categorized by Latent Class Analysis (LCA) under distinct characteristics of observable variables (Collier & Leite, 2017). A second contribution of this paper is related to the analysis of resilience along a dynamic perspective, as recommended by the FAO (2016). Since very few studies have applied resilience in a dynamic context, the applicability of resilience as measured by the RIMA approach remains unconfirmed (d’Errico & Di Giuseppe, 2016; d’Errico et al., 2021).

In this paper, household resilience estimated at time t_0 is regressed on food security outcomes t_1 . In order to capture resilience to food insecurity, we include the following food security outcomes: (a) static food security outcomes at t_1 and (b) food security loss between t_0 and t_1 . Furthermore,

some interaction terms between the RCI and shock variables are introduced in order to understand the shock-mediating role of resilience. In this regard, we expect that the resilience capacity of the household acts as a mediator, ensuring food security outcomes are not adversely affected. In order to deal with the problem of endogeneity regarding the link between the RCI and food security outcomes, we apply an Instrumental Variable (IV) approach to estimate the causal effects of household resilience on food security.

The remaining part of the paper is structured as follows: Sect. 2 provides a literature review on resilience and its relationship with food security outcomes; Sect. 3 includes a data description, measurements and the model; Sect. 4 presents empirical findings on the relationship between resilience and food security outcomes, and Sect. 5 contains concluding remarks.

2 Literature review

Resilience as a concept was earlier described in ecological literature. Some scholars successfully defined resilience as a system persistence that has the ability to absorb changes without shifting into an alternate regime (Holling, 1973; Tilman & Downing, 1994), particularly in the case of decreasing variability (Pimm, 1984; Schulze, 1996). Indeed, a resilient system is expected to absorb disturbances in which there should not be any change in maintaining the functions of the system. However, not shifting into alternative states is a misnomer in complex social-ecological systems; therefore, other scholars have proposed resilience as both adaptation and transformation (Folke, 2006; Walker et al., 2004, 2006). In this case, adaptability refers to the extent of managing the system, while transformability is the ability to create a new system. In environmental and socio-economic systems, the nature of resilience has been explained by stimulus and responses to shocks (Levin et al., 1998), and later characterized by absorption, adaption and transformation dimensions (Béné, 2013; Béné et al., 2012; Nelson et al., 2007; Walker et al., 2004). Such a dimensional approach allows for the integration of capacities such as the ability of households or communities to deal with shocks, making resilience an intermediate outcome for socio-economic studies.

In recent years, various papers have undertaken an application of the concept of resilience to a development context, for instance with respect to rural development (Salvia & Quaranta, 2017; Schouten et al., 2012; Scott, 2013), sustainable livelihoods (Quandt, 2018; Sok & Yu, 2015; Thulstrup, 2015), well-being (Beauchamp et al., 2021; Walsh & Hallegatte, 2020) and food security (Fan et al., 2014; FAO, 2021). One of the first contributions applying the resilience concept to food insecurity assumed that households not merely absorb shocks but react by using available response mechanisms and capacities (Alinovi

et al., 2010b). In food security analysis, resilience is commonly understood as an unobservable or latent household capacity explaining how to withstand different types of socio-economic, climatic and other types of shocks (d'Errico et al., 2018).

The quantification of resilience entails several conceptual and operational challenges (Béné et al., 2016a, b). Conceptually, the estimation of resilience should be based on principles proposing resilience as a latent and multidimensional capacity index (d'Errico et al., 2016). In theory, resilience *capacity* is described as a shock mediator that helps to put the household in a better position to improve food security or recover from any food security loss (Constas et al., 2014). In this case, shocks can be typified as both widely experienced (i.e. exogenous) or suffered from by an individual (i.e. endogenous) (Choularton et al., 2015). This condition is one of the fundamental precursors to operationalize resilience as a capacity (d'Errico et al., 2016). Empirically, the resilience index is constructed as a *latent* variable, since it is not observable per se (Alinovi, d'errico, et al., 2010). Although there is no congruent structure of resilience capacities, it should represent different aspects of household livelihoods (Crookston et al., 2018). Therefore, another important foundation of measurement is related to its *multidimensionality* (FAO, 2016).

As a composite index, the resilience index of households includes stability, social safety nets, access to public services, assets, income and food access and also an adaptive capacity (Alinovi et al., 2010b). This conceptual framework treats resilience as latent and multidimensional, showing the ability of households to maintain their wellbeing in the face of shocks. This methodology was later operationalized into the so-called RIMA-I model. However, the RIMA-I framework has two shortages in its modelling, by not treating resilience as a capacity index and food security as one of the indicators of resilience (Ansah et al., 2019). Later, RIMA-II was developed, treating resilience as capacity and food security as outcome variables. One of the most promising proposals to measure the Resilience Capacity Index (RCI) integrates four pillars: Access to Basic Services (ABS), Assets (AST), Social Safety Nets (SSN) and Adaptive Capacity (AC) (FAO, 2016). According to RIMA-II, the framework assumes that a change in Y outcome between t_0 and t_1 (e.g. food security) can be observed due to the occurrence of different types of shocks.

The relationship between resilience and food security outcomes is most studied in the RIMA-II framework (Brück et al., 2019; Chiwaula et al., 2022; Ciani & Romano, 2014; Haile et al., 2022; Otchere & Handa, 2022), particularly where dynamic (d'Errico & Di Giuseppe, 2016) and cross-country analysis (d'Errico et al., 2021; d'Errico et al., 2018; Sibrian et al., 2021) have provided promising results. By considering a fundamental problem in causal relationships between resilience and food security or nutritional outcomes,

d'Errico and Pietrelli (2017) used the IV approach in their identification strategies. Their findings confirmed a causal relationship indicating a negative effect of the RCI on the probability of having malnourished children and the number of malnourished children in the household. Moreover, some authors conceptualized the relationship between resilience and food security in the presence of dynamic changes of food security (d'Errico et al., 2018; Haile et al., 2022). More precisely, the RCI is modelled in the outcomes of both food security loss and food security recovery. This gives a clear understanding of how resilient households are able to bounce back to a previous food security condition. Another paper by Murendo et al. (2020) has added a contribution to the RIMA-II approach in which authors conceptualized the association between the RCI and pillars with diet diversity and a food consumption score. In the estimation strategy, a lagged RCI variable is taken into the model to deal with reverse causality. By providing extra evidence to explain a mediating role of resilience, the framework is further formalized through the interactions between the RCI and different types of shocks. Acknowledging its mediating role, findings have confirmed the effectiveness of the RCI in dealing with shocks on food security outcomes (d'Errico et al., 2018; Haile et al., 2022; Murendo et al., 2020; Ouoba & Sawadogo, 2022; Sunday et al., 2022). Generally, the empirical analyses mostly confirm a positive relationship between resilience and food security. However, there are still avenues for empirical investigations providing further robust scientific evidence.

3 Methodology and data

3.1 Data

The LIK is a multi-topic longitudinal survey collected from both households and individuals in Kyrgyzstan. The survey was conducted as part of the research project “Economic Transformation, Household Behavior and Well-Being in Central Asia: The case of Kyrgyzstan”, which was undertaken by the German Institute for Economic Research (DIW Berlin) in collaboration with the Humboldt-University of Berlin, the Center for Social and Economic Research (CASE-Kyrgyzstan) and the American University of Central Asia (Brück et al., 2014). Being nationally and regionally representative, the survey includes five waves (2010, 2011, 2012, 2013 and 2016) from seven Kyrgyz regions (oblasts) as well as the cities of Bishkek and Osh, with the same 3,000 households with 8,000 individuals being tracked over the waves (Research Data Center of IZA, 2016). To be consistent in the selection of variables in the construction of the RCI, the initial waves are excluded from the analysis. We construct variables for the four resilience pillars (ABS, AST,

AC and SSN) for 2013 and, for food security outcomes, we mostly use the 2016 wave to make further inferential analysis between the RCI in t_0 and food security outcomes in t_1 .

After dropping observations with insufficient information to generate the RCI and outcome variables, we ended up with a final sample of 2,530 households (Appendix, Table 6). In most cases, the household heads were male, although more than 25% of the families were headed by females, most likely due to high occurrences of (seasonal) labor migration among the rural male population. The average age of household heads was 54 years, and more than 60% of the household heads were married. The average household size was 5 family members. More than 60% of households were located in rural areas. Since there is a noticeable heterogeneity of resilience levels among regions of Kyrgyzstan (FAO, 2019a), we grouped 9 oblasts (provinces) into 3 main regions: Bishkek and the Northwest, Issyk-Kul and the Tian-Shan, and Fergana Valley. The analysis of microdata confirmed that the accessibility indicators generally coincide with the three mentioned regional differences (Blankespoor, 2013). Correspondingly, more than 40% of communities in the sample belonged to Fergana Valley, while around 34% and 12% of communities represented Bishkek and the Northwest as well as Issyk-Kul and the Tian-Shan regions, respectively.

3.2 Measures

3.2.1 Resilience capacity—RIMA-II

Methodologically, RIMA-II is based on a two-stage measurement analysis including Factor Analysis (FA) and Multiple Indicators and Multiple Causes (MIMIC) (FAO, 2016). Four resilience pillars, namely ABS, AST, SSN and AC, are constructed by factor analysis (Alinovi et al., 2010b).

For the construction of the RCI along the RIMA-II methodology, we followed the existing literature and applied Principal Component Analysis (PCA) (Ado et al., 2019; Atara et al., 2020; Gambo Boukary et al., 2016; Lascano Galarza, 2020). By defining the principal components, which are linear combinations of variables explaining a large proportion of variance in the dataset, this method allows for the number of variables to be reduced (Rabe-Hesketh & Everitt, 2003). For a list of underlying variables used to construct the four pillars, we refer to Table S1 in the Supplementary. To compute factor scores, we used the weighted sum method proposed by Bartlett (Bartlett, 1937). By avoiding the risks of multicollinearity, the Bartlett method produces relatively unbiased estimations of true factor scores (Hershberger, 2005). In the final step, the four pillars were turned into a composite index representing the resilience capacity index (RCI) of a household:

$$RCI = f(ABS, AST, SSN, AC) \quad (1)$$

Here, the RCI of a household is a function of the four pillars ABS, AST, SSN and AC. To generate a standardized index, the Min–Max scaling transformation was applied. A similar scaling technique was used to obtain standardized RCI indexes (d'Errico et al., 2018; Lascano Galarza, 2020).

$$RCI^* = (RCI - RCI_{min}) / (RCI_{max} - RCI_{min}) \times 100 \quad (2)$$

Before constructing pillar indices and the RCI, we applied the *Bartlett Test of Sphericity* to detect factorability, which tests for whether the variables are orthogonal (Tobias & Carlson, 1969). For measuring sampling adequacy, the *KMO (Kaiser–Meyer–Olkin)* statistic was used (Kaiser, 1974). In our study, we used a *KMO* value of 0.5 or above as a model selection criterion (Field, 2013). To check for multicollinearity, we applied a *Determinant of R-Matrix* or correlation coefficient matrix in the model, which should be greater than 0.00001 (Field, 2013). By applying a latent root criterion for component extraction in the factor analysis, we only considered factors with an eigenvalue bigger than 1.0 or the *Kaiser criterion* (Acock, 2013; Kaiser, 1960). In order to maximize the dispersion of factor loadings within each extracted factor, we applied a *Varimax Rotation* method (Kaiser, 1958).

Our choice of resilience capacity pillars is based on a literature review, household characteristics, data availability and statistical analysis (Supplementary, Table S2). In the following section, we introduce our four dimensions, or pillars, of resilience capacity, with the first being ABS, which describes the ability of households to activate resilience strategies based on access to basic services (FAO, 2016). In this paper, we included household characteristics that represent the quality of the conditions of the shared dwellings, along with distances to certain destinations. Moreover, this entails access to health and the household Infrastructure Index. The second pillar is AST, which is an important prerequisite for shock response (Alinovi, d'errico, et al., 2010). The effects of shock depend on the types of productive and non-productive assets as preferable proxies for income during and post shock-recovering phases. In this context, it is explicable on the basis that included variables to construct AST pillar represent both productive and non-productive of assets per capita. AC refers to the extent of household capacity to cope with and/or adapt to a new situation in which households are able to perform usual activities without long-lasting disturbances (Alinovi, d'errico, et al., 2010; FAO, 2016). An explanation may be that relatively more adaptive households are more capable at dealing with new environments without deteriorating the quality of usual performances (Gallopín, 2006; Lascano Galarza, 2020). Our paper includes diverse socio-economic contexts of adaptive

capacity believed to make households reconfigure without significant deterioration in their functioning. Because many households are located in rural areas, we included an Informal Networking Index and migration-related variables to characterize social capital and extra flexibility of the households in dealing with shocks. Finally, the pillar SSN represents a household's ability to access both formal and informal assistance from relatives and friends, international agencies, charities, non-governmental organizations and others (Alinovi, d'errico, et al., 2010). In this paper, we included cash or in-kind sources covering migration remittances, aids and allowances.

3.2.2 Food security

As food security indicators we used three variables, namely a household dietary diversity index, weekly food expenditures and the adequacy of fruit and vegetable consumption. In capturing both monetary and diet diversity aspects of food security, we are in line with previous approaches (Brück et al., 2019; d'Errico et al., 2018; FAO, 2016; Lascano Galarza, 2020). Household dietary diversity is frequently used in food security analysis (Hoddinott & Yohannes, 2002) for its ability to assess nutritional adequacy over a reference period (Smith & Subandoro, 2007). Household dietary diversity in this paper is measured by the Simpson Index (Simpson, 1949), which was initially developed for assessing biodiversity, although recently it has also found application in assessing nutritional diversity (Krivonos & Kuhn, 2019). The measure of food expenditure (Molledo et al., 2014) is weekly food expenditures spent on food items by the household, expressed in Kyrgyzstani Som (KGS). In order to analyze the nutritional aspects of food security, it is recommended to consider fruits and vegetables, which can provide an overview about vitamins and minerals for nutrient and density supply of calories (Molledo et al., 2014). Since the daily intake of fruits and vegetables in developing countries is relatively below the recommended level (Rekhy & McConchie, 2014), we used the adequacy of fruit and vegetable consumption in the household, which should be a minimum of 400 g/capita/day (INDDEX, 2018).

As was proposed by the RIMA-II approach, food security outcomes should reflect both static and dynamic perspectives, where we draw our conclusions on changes in food security outcomes between t_0 and t_1 . Therefore, to capture changes, we included (a) food security outcomes and (b) loss in food security outcomes (Appendix, Table 6). In 2016, the average dietary diversity (Simpson) score was 0.87. However, more than 66% of households suffered from a reduction in dietary diversity between the years 2013–2016. As for food expenditure, the average weekly amount was KGS 2035 in 2016, representing 28%

of affected households in the last 3 years. The adequacy of fruit and vegetable consumption was 391 g/capita/day, which was lower than the recommended level of 400 g/capita/day. The level of decrease of this adequacy over the last 3 years was more than 62%. Approaching resilience thinking in both static and dynamic nature of food security allows us to further explore the long-term effects of household resilience on food security outcomes.

3.2.3 Shocks

In this paper, another task is to identify and accurately enumerate homogenous shock classes. When it comes to household systems, there are generally two types of shocks, namely endogenous shocks that affect individuals or households, and exogenous shocks that affect groups of households or communities. To classify shocks, we applied LCA to generate categorical latent variables (Hagenaars & McCutcheon, 2002) through observed variables for detecting population heterogeneity (Lanza & Cooper, 2016). This allowed us to obtain similar groups representing homogenous households in terms of experienced shocks. In the dataset, shocks were measured by dummy variables indicating whether the household had faced a specific type of shock within the last twelve months. In this respect, we included five types of exogenous shocks and eight types of endogenous shocks for creating latent classes from the 2016 wave (Supplementary, Table S3). In order to model identified latent classes as covariates in the relationship between the RCI and food security outcomes, we applied a three-step approach (Collier & Leite, 2017; Vermunt, 2010; Vermunt & Magidson, 2021). First, we built a latent class model for a set of response items. Second, we assigned subjects to the classes based on posterior class membership probabilities. Third, we analyzed the association between class membership and external variables. The last step allowed us to use a regression analysis by taking the latent class variable in the regression analysis.

Since the latent class prevalence is the probability of class membership, we measured an individual’s posterior class-membership probabilities (Collins & Lanza, 2009; Hagenaars & McCutcheon, 2002):

$$P(Y = y) = \sum_{c=1}^C \gamma_c \prod_{j=1}^J \prod_{r_j=1}^{R_j} \rho_{J,r_j|c}^{I(y_j=r_j)} \tag{3}$$

where y_j represents element j of y response pattern. When the response to variable $j = r_j$, the indicator function $I(y_j = r_j)$ is equal to 1 and otherwise 0. Therefore, the probability of a vector response is regarded as the function of the probabilities of membership in each latent class and the probabilities of each response conditional on class membership

represented by γ' s and ρ' s, respectively. The vector of item-response probabilities of the variable for a particular latent class is always equal to 1 (Collins & Lanza, 2009):

$$\sum_{r_j=1}^{R_j} \rho_{j,r_j|c} = 1 \tag{4}$$

Taking into account the assumption of “local independence” or “conditional independence” of LCA, Eq. (4) indicates that the probability of a response (ρ) to each variable is conditioned on class membership only. Therefore, LCA is recognized as a probabilistic approach in which each observed respondent belongs to only one class that is defined as mutually exclusive (Collins & Lanza, 2009). In order to assess the fit of the LC models, we applied Akaike’s Information Criterion (AIC) (Akaike, 1987), the Bayesian Information Criterion (BIC) (Schwarz, 1978), and entropy based criteria (Larose et al., 2016), since they are widely applied for comparing models by considering their balance between fit and parsimony (Collins & Lanza, 2009; Tein et al., 2013).

3.3 Estimation model

The problem of endogeneity between the RCI and food security outcomes has already been mentioned in previous publications (Ansah et al., 2019; Murendo et al., 2020). We addressed this issue by using the IV approach. In order to incorporate community-related variables, we used the LIK community dataset from the 2011 wave. Taking country contexts and the available literature into account, we used *the distance to the nearest country border from the community* as a valid instrument. The distance variable is re-scaled with the Min–Max technique, in which the value of 100 indicates the maximum distance in km. Discussions on the RCI and food security outcomes include the improvement of cross-border coordination, collaboration and information sharing to increase household resilience capacity for those who depend on seasonal migration in search of alternative income sources (FAO, 2019b). Accordingly, the level of the RCI is highly varied depending on the location, explained by certain characteristics such as conflict, economic prosperity, trade activities and education levels. Moreover, recent literature findings cogently explain the roles of trade facilitation across borders (Bonuedi et al., 2020), which certainly makes inroads into strengthening the resilience to withstand different types of shocks (Şlusarciuc, 2017). For example, a border trade based on transit bazaars between Kyrgyzstan and other countries plays an important role (Steenberg, 2016), and a bazaar-centered informal economy manifests its significance in Kyrgyz economy (Karrar, 2019). Taking into account that countries undergoing development are often prone to external shocks (Ryan, 2012), Kyrgyzstan

highly depends on border relationships, strongly reflected on natural resources (Toktomushev, 2017). This is particularly important for countries depending on agriculture, since a close border relationship is one of the key positions in strengthening household resilience (Ambrosino et al., 2018). In this respect, a *regional cross-border approach* by analyzing cross-border livelihoods illuminates the ways to measure the resilience in food security perspectives (FAO, 2018a).

As we propose, the RCI should have a positive relationship with food security outcomes. At the same time, it should protect from the negative impacts of shocks on food security. Accordingly, we used the RCI in 2013 to analyze its relationship with the static nature of food security outcomes in 2016 and food security loss from 2013 to 2016 for dynamic changes. In order to understand whether the RCI mediates the relationship between shocks and food security outcomes, we separately looked at the relationship between RCI*Shock and food security outcomes in further models.

As has been mentioned, both food security outcomes and loss were measured by dietary diversity, weekly food expenditures and the adequacy of fruit and vegetable consumption. We also included a corresponding lagged dependent variable calculated from the 2012 and 2013 waves to capture the effects of its past status (Vaitla et al., 2020; Wilkins, 2018). Therefore, our models indicate that both static and dynamic outcomes are the function of past food security levels. Since we have both continuous and binary outcomes, the relationship using IV is estimated through two-stage least squares (2SLS) and a Probit model with continuous endogenous regressors (IV Probit). The model can be written in reduced form:

$$y_h^* = \mathbf{y}_h \beta_1 + x_{1h} \beta_2 + u_h \quad (5)$$

$$y_h = x_{1h} \prod_I + x_{2h} \prod_2 + v_h \quad (6)$$

where $h = 1, \dots, N$, y_h^* is the dependent and \mathbf{y}_h is the endogenous variable for h th observation. Both x_{1h} and x_{2h} collectively represent the instruments while x_{2h} is the excluded exogenous regressor (instrument). For binary outcomes, we observe:

$$y_h = \begin{cases} 0 & y_h^* \leq 0 \\ 1 & y_h^* > 0 \end{cases} \quad (7)$$

by assumption, $(u_h, v_h) \sim N(\mathbf{0}, \Sigma)$, implying joint normal distribution.

To check for endogeneity, we applied a *Wald test of exogeneity* (Wooldridge, 2010), indicating RCI or RCI*Shock is fully exogenous. Since the RCI is still endogenous, the interaction variable representing the RCI and shocks may

provide inconsistent results in the presence of endogeneity. To obtain consistent estimators of interaction terms in this situation, we incorporated additional instrumental variables by interacting the existing instrument, which is *the distance to the nearest country border*, with exogenous shock variables (Aghion et al., 2005; Ebbes et al., 2022; Kim et al., 2011; Nizalova & Murtazashvili, 2016). In order to include a valid instrument representing excluded exogenous variables in the model, there should be a statistically significant correlation with the endogenous regressor but not with the error term (Cameron & Trivedi, 2009). Therefore, we implemented the first-stage regression to analyze whether the instrumental variable is a predictor of RCI or RCI*Shock interactions. The results suggest a negative and statistically significant association between the border distance and RCI or RCI*Shock terms. Moreover, we implemented *Anderson-Rubin (AR)* (Finlay & Magnusson, 2009) and *Cragg-Donald statistics* (Cragg & Donald, 1993) to check the strength of our instruments; the test results show that the selected instruments are strong enough (Appendix, Tables 7, 8). After obtaining fitted values of the RCI by using selected instrumental variable and covariates from the 2013 wave in the first stage, we also used them as exogenous variables for robustness checking together with covariates from 2016 in the second-stage regression. The standard errors of fitted values of the RCI are obtained via bootstrapping (Supplementary, Table S4-S6). In this way, it is still possible to obtain unbiased estimates of both intercepts and slopes (Grace, 2021), particularly with bootstrapping the standard errors (Cameron & Trivedi, 2009).

4 Results

4.1 Latent class analysis

Until the best model was achieved in Table 1, we selected a two-class solution for exogenous shocks. Due to non-convergence in the third class for endogenous shocks, we were still able to distinguish between homogenous shock classes depending on a two-class model.

Overall statistics of exogenous shock indicate that flood, cold weather and drought were the major shock events experienced by households in 2016. As for latent classes of exogenous shock, the existence of all types of shocks is significantly low in the first class (Supplementary, Fig. S1). In other words, there is a low conditional probability of shocks happening. Therefore, we labeled the first class "*Low Shock*" latent class. As for the predicted probability of class memberships, the "*Low Shock*" class represents about 78%. Correspondingly, we named the second class "*High Shock*", because the above-mentioned three corresponding shock events are very much above the mean in the predicted scale. This class represents the remaining 22% of the sample.

Table 1 Model fit statistics

	Model	N	LL (model)	df	AIC	BIC	Entropy
Exogenous Shock	Class-1	2518	-4811.967	5	9633.935	9663.091	
	Class-2	2518	-4223.693	11	8469.387	8533.53	0.522
	Class-3	2518	-4128.983	17	8291.966	8391.096	0.278
Endogenous Shock	Class-1	2518	-4179.886	8	8375.772	8422.422	
	Class-2	2518	-3899.158	17	7832.317	7931.447	0.487

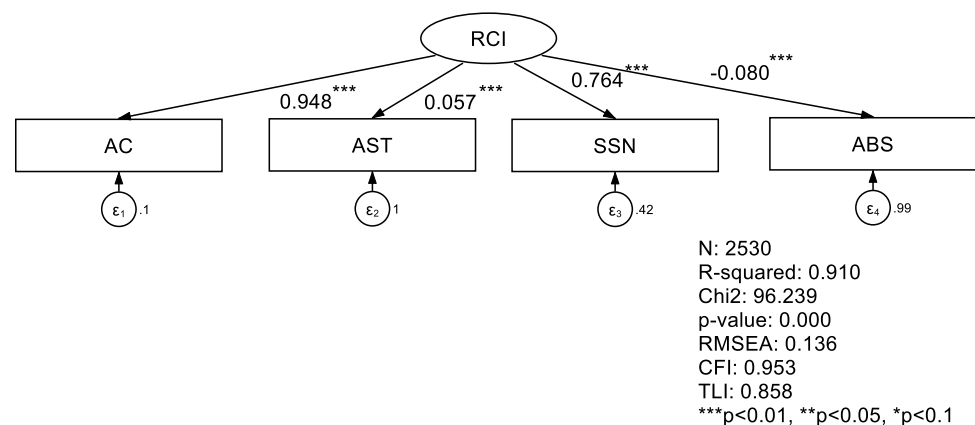
With respect to endogenous shocks in Class-1, disease in crops and livestock as well as water insufficiency were commonly experienced shock events in 2016. Looking at the latent class analysis, the probabilities of almost all types of shocks in Class-1 are below the median (Supplementary, Fig. S2). Therefore, we labeled Class-1 “*Low Shock*” and Class-2 “*High Shock*” latent classes. Class memberships represent around 19% and 81% for “*Low Shock*” and “*High Shock*” classes, respectively.

4.2 SEM analysis

In order to understand the explanatory power of the pillars and their correlations to resilience, we used Structural Equation Modelling (SEM) for a descriptive purpose only. One advantage of this method is that the latent variable (RCI in our case) is linearly correlated with underlying factors (the pillars in our case) (Acock, 2013). Our findings, both the unstandardized with reference to AC and the standardized without any reference group, indicate that all pillars except ABS are positively correlated with the RCI (Supplementary, Table S7). As it is recommended, the highest value of the coefficient of AC was taken as a reference group (Acock, 2013). The findings indicate that SSN and AC are the most contributing pillars for building stronger food security resilience. The PCA results are also very consistent with our SEM findings, where one can observe higher explanatory weights of both AC and SSN in Factor-1 (Supplementary, Fig. S3).

Figure 1 illustrates that the AC pillar is one of the most significantly contributing factors, which is in line with other findings (Ado et al., 2019; Brück et al., 2019; d’Errico & Pietrelli, 2017; d’Errico et al., 2018). The finding of the Factor-1 of the AC, the RCI is inextricably intertwined with migration (Supplementary, Fig. S4). For example, both variables representing migration share for the last 12 months and the consecutive five years manifest alternative income sources. In practice, migration and alternative income sources contribute significantly to the resilience of households in Central Asian countries (Marat, 2009). In many cases, unrecorded channels in rural areas, which may determine informal social networks, are not easily integrated into the construction of the RCI (FAO, 2016). In this case, we tried to capture unofficial social networks in AC by recognizing the possibility of different forms of networking by constructing the Informal Networking Index. This index indicates household abilities to respond to shocks with financial and non-financial aids through informal networking possibilities. Correspondingly, it elicits information about generating additional income through informal channels, which indicates that the AC of resilience strongly depends on the existence of informal networks.

As SSN is the second most relevant pillar for the RCI, the importance of it in resilience capacity has been acknowledged in particular for poor population strata (Alinovi, d’errico, et al., 2010). For example, SSN was found to be the second most contributing factor of the RCI for Tanzania

Fig. 1 SEM of RCI

and Uganda (d'Errico et al., 2018). For the measurement, SSN represents different types of safety nets (Alinovi et al., 2010b), where support from friends or relatives (Ado et al., 2019), cash assistance (Brück et al., 2019) and state support (Lascano Galarza, 2020) can be precursors of the household resilience capacity in the struggle with the adverse effects of shocks. Looking at the factor loadings for SSN, money transfers from abroad and the number of times where money from migrants working abroad is received have relatively higher loadings in Factor-1, indicating the significance of migration for resilience (Supplementary, Fig. S5). Accordingly, both

Factor-2 and Factor-3 represent mostly money aid obtained from other forms, pensions, and allowances in Kyrgyzstan.

AST, where productive assets are mainly in Factor-1 and non-productive assets in Factor-2 (Supplementary, Fig. S6), represents the significance of building or strengthening resilience. Similar to our findings, other authors have also found that AST is the most relevant pillar for the RCI, as in the case of Malian households (d'Errico & Pietrelli, 2017; Lascano Galarza, 2020).

Since capacity dimensions or pillars may behave differently depending on the situation (Constas et al., 2014), a

Table 2 OLS and 2SLS models of food security outcomes

	Dietary Diversity (DD)		Food Expenditure (FE)		Adeq.Fruits and Vegetables (AFV)	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
RCI	0.000 (0.000)	0.004*** (0.001)	-0.337 (1.413)	68.242*** (22.683)	0.290 (0.378)	11.368** (5.007)
DD_2013	-0.014 (0.034)	0.013 (0.048)				
FE_2013			0.343*** (0.030)	0.267*** (0.050)		
AFV_2013					0.018 (0.022)	0.021 (0.027)
Age HH head	0.001** (0.000)	-0.002 (0.001)	10.541 (10.482)	-48.490** (24.628)	12.491*** (2.813)	1.971 (5.786)
Sq. Age HH head	-0.000** (0.000)	0.000 (0.000)	-0.054 (0.092)	0.431** (0.208)	-0.100*** (0.024)	-0.013 (0.048)
Female head	0.007 (0.004)	0.010 (0.006)	-25.729 (70.406)	-20.304 (101.533)	11.048 (19.180)	18.962 (22.935)
Head married	0.011** (0.004)	0.020*** (0.007)	108.203 (71.882)	225.795** (110.648)	9.973 (15.525)	34.348 (25.542)
HH size	0.003** (0.001)	-0.000 (0.002)	168.594*** (28.933)	121.314*** (44.531)	-114.486*** (7.586)	-125.726*** (10.291)
Sq. HH size	-0.000* (0.000)	-0.000 (0.000)	-9.377*** (2.032)	-7.720** (2.980)	4.930*** (0.543)	5.347*** (0.668)
Rural	-0.008*** (0.002)	-0.013*** (0.004)	-404.628*** (46.415)	-521.139*** (77.150)	-5.178 (12.146)	-19.480 (15.726)
Exogenous shock	0.005* (0.003)	-0.001 (0.005)	-31.801 (51.848)	-162.149* (86.213)	25.258* (13.929)	3.821 (19.076)
Endogenous shock	0.013*** (0.004)	0.010* (0.005)	181.261*** (61.571)	146.133 (89.530)	56.983*** (16.591)	50.471*** (19.816)
Issyk-Kul and the Tian-Shan	-0.026*** (0.004)	-0.018*** (0.006)	-435.411*** (65.263)	-329.166*** (100.403)	-53.163*** (17.573)	-32.772 (22.698)
Fergana Valley	-0.008** (0.004)	-0.035*** (0.010)	-53.515 (49.785)	-519.856*** (169.563)	68.696*** (13.417)	-5.516 (36.983)
Constant	0.836*** (0.036)	0.878*** (0.052)	782.656*** (295.893)	1818.541*** (546.322)	392.649*** (80.344)	572.031*** (124.622)
Observations	2138	2138	2169	2169	2169	2129
R-squared	0.041		0.192		0.235	
Cragg-Donald Statistics		16.781		17.536		17.021

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$. A base class for both exogenous and endogenous shocks is "Low Shock" class. Standard errors in parentheses. The excluded regional dummy is Bishkek and the Northwest

negative relationship between ABS and the RCI might be expected. In our context, households living far from main facilities or lower ABS may experience higher levels of migration, informal networking, or others indicated in AC. This observation about synergies between pillars or capacities of resilience is consistent with discussions stating that improving one capacity may shape the level of another capacity of resilience (Béné et al., 2012). Since the obtained factors in ABS (Supplementary, Fig. S7) represent the access to infrastructure, basic services and health, ABS still can be regarded as a good proxy for the quality of the RCI.

4.3 Household resilience capacity and food security

A positive relationship between the RCI in 2013 and food security outcomes in 2016 (Table 2) indicates that a higher RCI is meant to increase outcomes by 0.004 on average in dietary diversity (Column-2), KGS 68.242 in food expenditure (Column-4) and 11.368 g/capita/day in the adequacy of fruit and vegetable consumption (Column-6). The relationship between shocks and food security outcomes is rather complex. By taking “*Low Shock*” as the base, the “*High Shock*” latent class for exogenous shock is negative

Table 3 2SLS model of food security outcomes (mitigating effect of RCI).

	Dietary Diversity (DD)		Food Expenditure (FE)		Adeq.Fruits and Vegetables (AFV)	
RCI*Exog. Shock	0.002*** (0.000)		44.208*** (15.395)		8.435** (3.577)	
RCI*Endog. Shock		0.003*** (0.001)		47.487*** (15.421)		8.929** (3.601)
DD_2013	-0.012 (0.045)	0.006 (0.047)				
FE_2013			0.280*** (0.047)	0.277*** (0.046)		
AFV_2013					0.021 (0.027)	0.025 (0.027)
Age HH head	-0.001 (0.001)	-0.001 (0.001)	-36.633* (21.660)	-36.385* (20.656)	2.941 (5.334)	3.025 (5.119)
Sq. Age HH head	0.000 (0.000)	0.000 (0.000)	0.333* (0.778)	0.330* (0.175)	-0.021 (0.045)	-0.022 (0.043)
Female head	0.009 (0.006)	0.010* (0.006)	-23.484 (96.259)	-14.802 (95.057)	16.772 (23.031)	20.772 (22.912)
Head married	0.016** (0.006)	0.018*** (0.006)	172.008* (100.656)	190.527* (100.498)	25.277 (24.248)	30.507 (24.484)
HH size	0.001 (0.002)	0.001 (0.002)	148.905*** (40.110)	151.869*** (39.380)	-121.097*** (9.507)	-120.491*** (9.267)
Sq. HH size	-0.000 (0.000)	-0.000 (0.000)	-9.166*** (2.778)	-9.325*** (2.741)	5.081*** (0.651)	5.061*** (0.641)
Rural	-0.010*** (0.003)	-0.013*** (0.004)	-457.673*** (65.954)	-509.058*** (71.055)	-10.827 (14.710)	-20.125 (15.556)
Exogenous shock	-0.054** (0.022)	-0.001 (0.005)	-1027.163*** (353.573)	-148.463* (79.373)	-165.668** (82.890)	2.354 (18.902)
Endogenous shock	0.009 (0.005)	-0.050** (0.021)	124.817 (86.423)	-806.323** (331.255)	43.853** (20.591)	-130.179* (78.040)
Issyk-Kul and the Tian-Shan	-0.016** (0.006)	-0.019*** (0.006)	-283.656*** (103.568)	-354.404*** (91.806)	-21.764 (24.955)	-34.868 (22.007)
Fergana Valley	-0.027*** (0.008)	-0.030*** (0.008)	-400.148*** (137.258)	-425.999*** (137.101)	6.626 (31.376)	2.928 (31.403)
Constant	0.892*** (0.052)	0.877*** (0.050)	1710.613*** (515.834)	1681.491*** (492.737)	574.214*** (124.039)	563.713*** (117.926)
Observations	2138	2138	2169	2169	2129	2129
Cragg-Donald Statistics	17.275	19.951	17.347	20.418	17.232	20.108

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$. A base class for both exogenous and endogenous shocks is “*Low Shock*” class. Standard errors in parentheses. The excluded regional dummy is Bishkek and the Northwest.

with the outcome of food expenditure (Column-4) while the endogenous “*High Shock*” class is significantly positive with both dietary diversity and adequacy outcomes. This result seems to be consistent with previous studies, finding a positive relationship between certain types of shocks and food security outcomes (Brück et al., 2019; d’Errico et al., 2018), which might be due to activating food coping strategies in the short period of time (Lascano Galarza, 2020; Murendo et al., 2021). In the current context, strong family attachments in Kyrgyz households can,

not surprisingly, enable them to use unofficial networking channels when faced with endogenous shocks. A study by Wossen et al. (2016) confirmed that households are able to smooth consumption by activating informal networks of social capital. A significant and positive coefficient of the lagged dependent variable in Column-4 indicates that food expenditure is a function of its past level. Ansah et al. (2019) have indicated that more food-secured households might be expected to adopt strategies or institutional mechanisms easily in achieving better food security outcomes.

Table 4 Marginal effects of Probit and IV Probit models of food security loss

	Dietary Diversity (DD)		Food Expenditure (FE)		Adeq.Fruits and Vegetables (AFV)	
	(1) Probit	(2) IV Probit	(3) Probit	(4) IV Probit	(5) Probit	(6) IV Probit
RCI	-0.000 (0.000)	-0.060* (0.032)	0.000 (0.000)	-0.034*** (0.011)	-0.000 (0.000)	-0.010 (0.009)
DD_2013 loss	-0.272*** (0.019)	-0.209*** (0.058)				
FE_2013 loss			-0.208*** (0.020)	-0.231*** (0.031)		
AFV_2013 loss					-0.248*** (0.020)	-0.251*** (0.022)
Age HH head	0.002 (0.005)	0.060* (0.033)	0.003 (0.005)	0.037*** (0.013)	-0.008 (0.005)	0.001 (0.010)
Sq.Age HH head	-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000 (0.000)
Female head	-0.037 (0.034)	-0.087 (0.079)	-0.023 (0.033)	-0.052 (0.051)	-0.019 (0.035)	-0.027 (0.037)
Head married	-0.045 (0.035)	-0.178* (0.104)	-0.039 (0.034)	-0.119** (0.058)	-0.027 (0.035)	-0.049 (0.042)
HH size	-0.023* (0.013)	0.042 (0.045)	0.023*** (0.013)	0.058** (0.023)	0.049*** (0.013)	0.059*** (0.017)
Sq. HH size	0.001 (0.000)	-0.001 (0.002)	-0.000 (0.000)	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)
Rural	0.013*** (0.022)	0.114 (0.073)	0.031 (0.021)	0.079** (0.036)	0.082*** (0.022)	0.096*** (0.027)
Exogenous shock	-0.038 (0.025)	0.076 (0.075)	-0.081** (0.022)	0.018 (0.042)	-0.060** (0.026)	-0.041 (0.032)
Endogenous shock	-0.118*** (0.031)	-0.061 (0.074)	-0.021 (0.028)	0.003 (0.045)	-0.019 (0.030)	-0.011 (0.032)
Issyk-Kul and the Tian-Shan	0.019 (0.032)	-0.088 (0.089)	0.107*** (0.029)	0.040 (0.050)	0.040 (0.033)	0.021 (0.039)
Fergana Valley	-0.098*** (0.023)	0.303 (0.221)	0.007 (0.023)	0.239*** (0.084)	-0.148*** (0.024)	-0.083 (0.067)
Observations	2086	2086	2086	2086	2077	2077
Pseudo R-squared	0.093		0.029		0.095	
Cragg-Donald Statistics		16.497		17.731		17.297
Wald-test of exogeneity		11.65		19.70		1.19
p-value		0.000		0.000		0.274
AR		4.48		18.16		1.34
p-value		0.034		0.000		0.247

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$. A base class for both exogenous and endogenous shocks is “*Low Shock*” class. Standard errors in parentheses. The excluded regional dummy is Bishkek and the Northwest

A negative and significant relationship of rural households with dietary diversity (Column-2) and food expenditure (Column-4) was detected. As expected, the size of a household is positively associated with food expenditure in Column-4, compared to negative outcomes of the adequacy rate in Column-6. Households with a married head are likely to have better outcomes in dietary diversity and food expenditure, as presented in Column-2 and Column-4, respectively. There is a negative relationship between the age of the household head and food expenditure outcome.

The direction of this relationship changes in the squared coefficient, indicating a nonlinear effect of age.

Moreover, a more comprehensive estimation is included, where each shock class was interacted with the RCI for each outcome model (Table 3). Accordingly, the relationship between RCI*Exogenous or RCI*Endogenous shocks and food security outcomes provides robust results. More precisely, the sign and magnitude of effects are similar to those models with the absence of interaction terms, indicating the role of resilience in smoothing shocks. In this case, the

Table 5 Marginal effects of IV Probit model of food security loss (mitigating effect of RCI)

	Dietary Diversity (DD)		Food Expenditure (FE)		Adeq.Fruits and Vegetables (AFV)	
RCI*Exog Shock	-0.048*		-0.019***		-0.011	-0.010
	(0.267)		(0.006)		(0.007)	(0.007)
RCI*Endog Shock		-0.049*		-0.021***		
		(0.027)		(0.007)		
DD_2013 loss	-0.216***	-0.225***				
	(0.061)	(0.056)				
FE_2013 loss			-0.232***	-0.233***		
			(0.028)	(0.028)		
AFV_2013 loss					-0.248***	-0.247***
					(0.023)	(0.022)
Age HH head	0.060*	0.057*	0.027**	0.027***	0.004	0.002
	(0.034)	(0.033)	(0.010)	(0.010)	(0.011)	(0.010)
Sq. Age HH head	-0.000*	-0.000*	-0.000***	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female head	-0.080	-0.098	-0.041	-0.050	-0.028	-0.032
	(0.086)	(0.085)	(0.045)	(0.046)	(0.039)	(0.039)
Head married	-0.135	-0.164	-0.080*	-0.095*	-0.046	-0.051
	(0.098)	(0.103)	(0.048)	(0.049)	(0.042)	(0.043)
HH size	0.019	0.017	0.038**	0.038**	0.057***	0.056***
	(0.040)	(0.038)	(0.018)	(0.018)	(0.016)	(0.016)
Sq. HH size	0.000	0.000	-0.000	-0.000	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Rural	0.071	0.118	0.048*	0.071**	0.090***	0.100***
	(0.063)	(0.078)	(0.029)	(0.031)	(0.026)	(0.028)
Exogenous shock	0.372***	0.087	0.362***	-0.029	0.172	-0.0333
	(0.010)	(0.082)	(0.137)	(0.036)	(0.142)	(0.034)
Endogenous shock	-0.014	0.336***	0.012	0.445***	0.001	0.185
	(0.091)	(0.014)	(0.042)	(0.128)	(0.036)	(0.039)
Issyk-Kul and the Tian-Shan	-0.167	-0.085	0.028	0.057	-0.001	0.018
	(0.128)	(0.093)	(0.048)	(0.043)	(0.047)	(0.039)
Fergana Valley	0.271	0.280	0.159***	0.175***	-0.069	-0.072
	(0.212)	(0.222)	(0.061)	(0.063)	(0.065)	(0.066)
Observations	2086	2086	2086	2086	2077	2077
Cragg-Donald Statistics	16.893	19.962	17.992	21.264	17.531	20.463
Wald-test of exogeneity	12.39	10.87	14.99	15.99	2.29	1.93
p-value	0.000	0.001	0.000	0.000	0.130	0.165
AR	4.13	3.72	14.87	15.28	2.22	1.98
p-value	0.042	0.053	0.000	0.000	0.136	0.159

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$. A base class for both exogenous and endogenous shocks is "Low Shock" class. Standard errors in parentheses. The excluded regional dummy is Bishkek and the Northwest

findings are consistent with other conclusions confirming a weakened effect of the shocks by the RCI (d'Errico et al., 2018; Haile et al., 2022; Murendo et al., 2020; Ouoba & Sawadogo, 2022; Smith & Frankenberger, 2018). Moreover, it can be observed that shocks are negatively associated, with a majority of relationships being statistically significant.

Looking at the relationship between the RCI and food security loss outcomes in Table 4, a higher RCI is likely to decrease the probability of food security loss. In Column-2, a one-point higher change in the RCI shows a decreased probability of diet diversity by an average of 0.060. As for the relationship between the RCI and loss in food expenditure, we observe a similar relationship, with a lower magnitude of effect. More precisely, a point increase in the RCI decreases the probability of loss by an average of 0.034 in Column-4. The sign of the relationship between the RCI and loss in adequacy of fruits and vegetables does not change, but the marginal effect is not statistically significant (Column-6). Households experiencing a loss in the past are likely to recover it in the future, since the coefficients of all lagged dependent variables are negative. This might be due to activating resilience (d'Errico et al., 2018; Haile et al., 2022) or non-food coping strategies in the past (Lascano Galarza, 2020). A positive relationship between rural communities and loss in food security outcomes is also confirmed, out of which the coefficient of food expenditure loss is statistically significant. As for other controlling variables, both the age of the household head and the size of household increase the probability of loss in major cases. To some extent, the direction of this relationship changes in the squared measures of age, indicating potentially nonlinear effects of age. A household with a married head is also stable at decreasing the loss in dietary diversity (Column-2) and food expenditure (Column-4).

Moreover, it is expected that the interaction terms between the RCI and shocks should have a negative relationship with loss. Although findings in the probability of fruit and vegetable consumption adequacy loss are not statistically significant, the interaction terms have negative effects on the loss probability of dietary diversity and food expenditure (Table 5). As for the shocks, the “*High Shock*” latent class for both exogenous and endogenous shocks is significantly positive with dietary diversity and food expenditure outcomes. This could indicate that household resilience has a protective effect on loss as exogenous shocks intensify.

5 Discussion and conclusion

In this paper, we analyzed the effect of resilience capacity on food security status and its loss under exogenous and endogenous shock events along a dataset of LIK for Kyrgyz smallholders. In the first step, we constructed the

RCI through ABS, AST, AC and SSN pillars. The results call for interventions and policies to encourage especially SSN and AC in order to enhance the RCI. Access to transfers from migrants in Kyrgyz households represents one of the major contributors of SSN and AC pillars. In practice, migration and remittance are paramount for economic growth in Kyrgyzstan (Murzakulova, 2020); therefore, programs and institutional mechanisms to support efficient coordination of remittance income at the household level likely unlock the potentials of strengthening resilience to food insecurity. Households also become more adapted towards increasing resilience when they have opportunities to build informal networks, which is in accord with studies confirming a positive relationship between social capital and resilience (Anuradha et al., 2019; Béné et al., 2016a; Rayamajhee & Bohara, 2019; Wang et al., 2021). This implies that policies strengthening resilience should appreciate the functions of networking, since social capital is likely to serve as a substitute for physical assets. Related tangible factors such as allowances and savings are also particularly important to strengthen SSN and AC, respectively. Therefore, resilience interventions should consider existing and potential social assistance programs and financial systems in Kyrgyzstan. Similar to findings by d'Errico and Pietrelli (2017), education is found to be one of primary contributing factors to increase AC. It is expected that higher level of education significantly contributes to stabilize resilience in the presence of shocks, particularly under limited availability of safety nets. From another perspective, a potential synergy between productive and non-productive assets in AST is also essential for increasing resilience. A negative relationship between ABS and RCI implies that there should be more pertinent approaches by focusing on factors having relatively obvious and direct relationships with resilience.

In the second step, we applied LCA to identify unobserved homogeneous groups based on different types of shocks experienced by households over the twelve months of 2016. We found that the latent class representing “*High Shock*” for endogenous shocks is positively associated with food security outcomes, while the reverse is true for the case of exogenous shocks in connection with food expenditure. This finding might be explained by two arguments: Firstly, shocks are based on very subjective perspectives of the respondents, which have shown to be strongly influenced by individual risk attitudes and other personal characteristics. One of the cases reported by d'Errico et al. (2018) also concluded over-/under-estimation of self-reported shock perceptions for analyzing household resilience to food insecurity. Secondly, it is quite possible that households experiencing endogenous shocks might be able to activate short-term risk-coping strategies. This

finding further supports the idea that resilient households are likely to use coping strategies (Crookston et al., 2018) characterized by a set of capacities such as absorbing, adapting and transforming in the face of shocks and stressors (Constas et al., 2014). Exogenous shocks, in contrast, make risk coping a more difficult task, as they are likely to exhaust the financial resources of the whole social network and government resources alike. Such unpredictable exogenous shocks make coping mechanisms less effective in low-income transition economies (Kuhn & Bobojonov, 2021), especially for food insecurity (Alinovi et al., 2010b). Moreover, findings from applying interaction-terms confirm that both shocks frequently deteriorate food security conditions. They also increase the loss of dietary diversity and food expenditure. Correspondingly, interventions primarily should consider how different types of shocks affect the condition of food security for designing a resilience approach. Such recognition certainly improves the effectiveness of resilience based interventions to development outcomes (Choularton et al., 2015).

In the last stage, we established a causal relationship between the RCI and food security outcomes. To control for potential endogeneity, we employed the IV approach, instrumenting the distance to the nearest country border from the community for the RCI. Our results suggest that the household resilience capacity serves to increase household dietary diversity, food expenditure and the adequacy of fruit and vegetable consumption or to decrease losses in dietary diversity and food expenditure. This message is consistent with conclusions indicating a positive relationship between the RCI and food security outcomes (d'Errico & Pietrelli, 2017; Murendo et al., 2020) and a negative relationship between the RCI and loss in dietary diversity and food expenditure (d'Errico et al., 2018; Haile et al., 2022). Policy and program interventions aiming to strengthen household resilience are likely to make some significant inroads into ensuring long-term food security in poor or developing countries. We further integrated our multiplicative effect models by including the interaction terms between the RCI and latent shock classes. In order to obtain consistent estimates for the interaction terms, we treated them as separate endogenous regressors with their own instrumental variables. The interaction terms between the RCI and shocks are consistent with our initial models built without the moderating role of resilience. Findings imply that the RCI is able to mediate the impact of shocks on food security outcomes, which is in line with other studies (Haile et al., 2022; Murendo et al., 2020; Ouoba & Sawadogo, 2022; Sunday et al., 2022). Particularly, the

results reveal that resilience has a role in mitigating the negative effects of both exogenous and endogenous shocks on all static food security outcomes. The results in dynamic findings also confirm the mitigating role of resilience on the impact of both types of shocks on the loss of dietary diversity and food expenditure. This supplementary finding reinforces our conclusion of the positive effect of the RCI on static food security conditions or its negative effect on losses of food security in the presence of shocks. By addressing shocks with resilience to food insecurity, households are able to achieve better outcomes by decreasing losses in food security, which is important for developing resilience-based policies.

Looking at other variables in the models, previous or lagged values of food security indicators are likely to predict future values, particularly when it comes to loss. A negative relationship between a previous and future probability of loss is probably due to activated coping strategies or household resilience. The age of the household head and the size of the household have a positive and significant relationship with suffering from food insecurity, which has similarly been found in other studies (d'Errico & Pietrelli, 2017; d'Errico et al., 2018). Concurrently, a further policy recommendation is related to strengthening the role of younger farmers or decision-makers in the household to contribute to the improvement of food security, for instance by strengthening agricultural education and providing targeted trainings. Since rural areas are subject to relatively higher vulnerability to food insecurity, policies building or strengthening food insecurity resilience should focus on targeting rural populations. The low resilience of rural populations can be explained by pronounced rural–urban gaps in income or public services, but also by the systemic character of production shocks in agricultural, usually affecting not a single household but the whole regions and communities. Concrete measures could be the formation of larger social networks and institution based on collective actions in the more remote areas. By considering the remittance as one of the most consistent parts of income in Kyrgyzstan (FAO, 2019a), improving remittance channels by creating safe and accessible links to transfer in highly migrating rural areas is of particular significance in increasing resilience.

We acknowledge some limitations of this study. First of all, resilience research still lacks some concrete cut-off points to define whether the status of a household is resilient or not (Atara et al., 2020). The categorization of resilience dimensions is one step towards the differentiation between vulnerable and resilient households in the context

of food security outcomes (Nahid et al., 2021). Moreover, an understanding of the dynamic nature of resilience and its heterogeneity across different groups is important in order to differentiate livelihood strategies for household mechanisms (Alinovi, d'errico, et al., 2010; Atara et al., 2020). Finally, a measurement conceptualization for resilience is implemented through tangible indicators. In this paper, the majority of factors applied to construct the RCI is based on tangible assets. Further attempts to measure resilience

capacity may consider intangible assets such as perception, trust, gender roles and others, which will probably improve the operationalization techniques (Ansah et al., 2019). In order to link household resilience and food security, the resilience of local food systems should be considered as one of the influencing factors (Béné, 2020). Correspondingly, the results will certainly complement and extend related conclusions towards the role of household resilience to improve food security outcomes.

Appendix

Table 6 Summary statistics

	Mean	Std. Dev	Min	Max
RCI	17.610	15.133	0	100
Exogenous Shock	1.212	0.409	1	2
Endogenous Shock	1.135	0.342	1	2
Age HH head	54.029	13.377	21	90
Female head	0.252	0.434	0	1
Head married	0.615	0.488	0	1
HH size	5.253	2.537	1	17
Rural	0.612	0.487	0	1
Issyk-Kul and the Tian-Shan	0.122	0.328	0	1
Fergana Valley	0.442	0.496	0	1
Bishkek and the Northwest	0.337	0.472	0	1
Dietary Diversity in 2016. ^a	0.873	0.062	0.262	0.959
Food Expenditure in 2016	2035	1064.609	0	17,180.09
Adeq.Fruits and Vegetables in 2016	391.424	313.849	11.773	3892.857
Dietary Diversity in 2013	0.899	0.041	0.580	0.958
Food Expenditure in 2013	1504	774.646	110.769	12,282.31
Loss in Dietary Diversity (2013–2016)	0.668	0.470	0	1
Loss in Food Expenditure (2013–2016)	0.280	0.449	0	1
Loss in Adeq.Fruits and Vegetables (2013–2016)	0.624	0.484	0	1
Loss in Dietary Diversity (2012–2013)	0.274	0.446	0	1
Loss in Food Expenditure (2012–2013)	0.356	0.478	0	1
Loss in Adeq.Fruits and Vegetables (2012–2013)	0.651	0.476	0	1

^aIt is based on Simpson index. The value ranges from 0 to 1, where 1 represents the maximum value of diversity. The equation of Simpson index for diet diversity: $\text{Simpson index} = 1 - \sum_{h=1}^n p_h^2$, where p_h is the proportion of household consumptions in a sample of n food groups

Table 7 First-stage regression results

	RCI	RCI	RCI
Border distance	-0.123*** (0.030)	-0.126*** (0.030)	-0.124*** (0.030)
DD_2013	-5.352 (8.147)		
FE_2013		0.001** (0.000)	
AFV_2013			-0.000 (0.001)
Age HH head	0.964*** (0.159)	0.872*** (0.158)	0.963*** (0.159)
Sq.Age HH head	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)
Female head	-0.661 (1.087)	-0.068 (1.068)	-0.707 (1.096)
Head married	-2.140* (1.109)	-1.688 (1.090)	-2.169* (1.115)
HH size	1.057** (0.426)	0.710 (0.438)	1.051** (0.433)
Sq. HH size	-0.040 (0.030)	-0.026 (0.030)	-0.040 (0.031)
Rural	1.470** (0.692)	1.906*** (0.705)	1.480** (0.695)
Exogenous shock	1.873** (0.793)	1.857** (0.786)	1.889** (0.795)
Endogenous shock	0.700 (0.947)	0.590 (0.934)	0.671 (0.948)
Issyk-Kul and the Tian-Shan	-1.712* (1.005)	-1.337 (0.991)	-1.637 (1.005)
Fergana Valley	6.745*** (0.780)	6.995*** (0.742)	6.887*** (0.754)
Constant	-11.946 (8.555)	-15.570*** (4.481)	-16.670*** (4.583)
Observations	2138	2169	2129

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. A base class for both exogenous and endogenous shocks is “Low Shock” class. Standard errors in parentheses. The excluded regional dummy is Bishkek and the Northwest

Table 8 First-stage regression results (mitigating effect of RCI)

	RCI*Exog. Shock	RCI* Endog. Shock	RCI*Exog. Shock	RCI* Endog. Shock	RCI*Exog. Shock	RCI*Endog. Shock
Border	-0.127***	-0.124***	-0.127***	-0.125***	-0.127***	-0.125***
Distance*Shock	(0.030)	(0.027)	(0.030)	(0.027)	(0.030)	(0.027)
DD_2013	1.091	-5.269				
	(11.451)	(10.374)				
FE_2013			0.001**	0.001**		
			(0.000)	(0.000)		
AFV_2013					-0.000	-0.000
					(0.001)	(0.001)
Age HH head	1.173***	1.103***	1.074***	0.994***	1.181***	1.106***
	(0.223)	(0.202)	(0.222)	(0.201)	(0.224)	(0.203)
Sq.Age HH head	-0.009***	-0.009***	-0.008***	-0.008***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female head	-0.689	-1.045	-0.051	-0.225	-0.707	-1.111
	(1.528)	(1.385)	(1.501)	(1.363)	(1.541)	(1.396)
Head married	-1.853	-2.307	-1.375	-1.698	-1.829	-2.341
	(1.559)	(1.412)	(1.531)	(1.390)	(1.568)	(1.420)
HH size	0.887	0.791	0.465	0.381	0.862	0.757
	(0.599)	(0.543)	(0.616)	(0.559)	(0.609)	(0.551)
Sq. HH size	-0.023	-0.021	-0.007	-0.004	-0.022	-0.019
	(0.043)	(0.039)	(0.043)	(0.039)	(0.043)	(0.039)
Rural	0.946	1.910**	1.438	2.420***	0.949	1.928**
	(0.972)	(0.880)	(0.990)	(0.898)	(0.977)	(0.885)
Exogenous shock	22.890***	2.582**	22.694***	2.407**	22.897***	2.591**
	(1.116)	(1.010)	(1.104)	(1.002)	(1.119)	(1.013)
Endogenous shock	1.749	21.420***	1.417	21.194***	1.733	21.392***
	(1.331)	(1.209)	(1.313)	(1.195)	(1.334)	(1.211)
Issyk-Kul and the Tian-Shan	-3.613**	-1.998	-3.215**	-1.481	-3.589**	-1.905
	(1.411)	(1.279)	(1.313)	(1.263)	(1.412)	(1.279)
Fergana Valley	7.822***	7.666***	8.007***	8.025***	7.800***	7.802***
	(1.095)	(0.992)	(1.042)	(0.947)	(1.060)	(0.960)
Constant	-23.667**	-15.816	-21.444***	-19.349***	-22.686***	-20.219***
	(12.024)	(10.892)	(6.293)	(5.715)	(6.441)	(5.835)
Observations	2138	2138	2169	2169	2129	2129

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$. A base class for both exogenous and endogenous shocks is "Low Shock" class. Standard errors in parentheses. The excluded regional dummy is Bishkek and the Northwest

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s12571-023-01369-1>.

Acknowledgements The authors would like to thank the editor and two anonymous referees for providing helpful comments on an earlier version of the manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data Availability The Life in Kyrgyzstan data for 2010-2019 are available from the International Data Service Central of the Institute of Study of Labor: <https://datasets.iza.org/dataset/124/life-in-kyrgyzstan-panel-study-2013>.

Declarations

Conflict of interests The authors declare that they have no conflict of interests and/or competing interests.

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