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Resilience Capacity and Food Security: Is There a Relationship Between Household Resilience Profiles and Food Security Outcomes?

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Abstract

Resilience thinking has gained prominence in research and policy debates in food security analysis. This article aims to estimate the effect of household resilience capacity on food security outcomes. The manuscript uses the Cambodia Living Standard Measurement – Plus Survey 2019-2020. The measurement of resilience capacity is done through Resilience Index Measurement and Analysis – II by FAO. In the RIMA approach, the manuscript also applies Latent Profile Analysis (LPA) to cluster households, categorizing homogenous resilience levels through “Low Resilient,” “Medium Resilient,” and “High Resilient” profiles. In the estimation strategy, the current study proposes a step-by-step analytical approach for using the propensity score matching (PSM) techniques with LPA to draw causal effects of resilience profiles on dietary diversity and food expenditure per capita. The findings generally confirm that “Medium Resilient” and “High Resilient” households have positive effects on food security outcomes compared to those labelled as “Low Resilient” households.

Keywords: Resilience capacity, food security, latent profile analysis, propensity score matching, average treatment effect

JEL: Q18, Q13, O20, C01

Introduction

Dynamics in climate change, political instability, economic exacerbation, and social issues are major threats to food security status (Kavallari, Fellmann, and Gay 2014, Ilboudo Nébié, Ba, and Giannini 2021, Akter and Basher 2014). In this circumstance, the challenge puts the concept of resilience at the forefront of the research campaign to mediate the negative consequences of shocks on food security outcomes. Therefore, the concept of resilience has already become a strategic orientation to implement intervention programs to build resilience in households and communities. However, the proliferation of approaches to conceptualize resilience towards food security creates challenges, making policy communications and development programmes less effective. In this case, the content and qualities of resilience measurement towards food security requires the flexibility across the setting, populations, and contexts (Constas, d’Errico, and Pietrelli 2022), still having a need for the improvement in resilience measurements for better policy recommendations (Upton, Constenla-Villoslada, and Barrett 2022). Moreover, a pertinent approach is needed to explain whether strengthening resilience is a desirable policy outcome in all circumstance due to the existence of trade-off (Béné et al. 2016, Béné et al. 2014).

Resilience is a multifaceted concept having different elements to explain the condition of the community, household, or individual. Although the term resilience comes from engineering and ecological science (Walker et al. 2006, Holling and systematics 1973, Walker et al. 2004), the most prominent definitions define resilience as “... *the ability of countries, communities and households to manage change, by maintaining transforming living standards in the face of shocks or stresses-such as earthquake, drought or violent conflict-without compromising their long-term prospects*” (DFID 2011). Another definition by Serfilippi and Ramnath (2018) confirms resilience as “... *the capacity of people, communities, or systems to prepare for and to react to stressors and shocks in ways that limit vulnerability and promote sustainability*”. This definition reflects on the components of resilience which was proposed by the Resilience Measurement – Technical

Working Group (RW-TWG).¹ For example, the definition of the resilience towards development outcomes, particularly food security conditions, implies that resilience is based on multi scale and multi capacity components describing household capacity from the livelihood to respond to and recover from shocks in a way that shock should not have long-lasting negative consequences on food security outcomes (Constas, Frankenberger, and Hoddinott 2014, d'Errico et al. 2016).

The measurement and operationalization of resilience are necessary for obtaining robust and evidence-based solutions for policy recommendations. In this case, FAO is at the forefront of communicating different frameworks for strengthening the measurement of resilience to food insecurity. One of the most prominent frameworks is related to Resilience Index Measurement and Analysis (RIMA) pronouncedly using a quantitative approach to establish a relationship between resilience and food security outcomes (FAO 2024). The ubiquity of the RIMA approach for the measurement of resilience is explained by two main reasons: (i) it allows the estimate of the Resilience Capacity Index (RCI) through different pillars (determinants), and (ii) it explains the relationship between RCI and food security outcomes (FAO 2016). Although some authors corroborated the measurement of resilience and confirmed that there are foundational determinants of resilience such as absorptive capacity, adaptive capacity, and transformative capacity (Folke 2006, Béné et al. 2012, Carpenter, Westley, and Turner 2005), Ansah, Gardebroek, and Ihle (2019) found that the RIMA methodology has become one of the foundational approaches to assess causality between resilience and household food security. In the measurement, Alinovi, Mane, and Romano (2008) are one of the first contributors defining resilience as household capacity measured through Access to Basic Services (ABS), Assets (AST), Access to Public Services (APS), Income and Food Access (IFA), Stability (S), and Adaptive Capacity (AC).

¹ The Resilience Measurement Technical Working Group (RM-TWG) was established by the Expert Consultation on Resilience Measurement for Food Security in FAO to create a mechanism for the conceptualization of resilience and its measurement towards development outcomes.

The surge occurring in the discussion about the connection between household resilience and food security has already been studied by different scholars (Béné et al. 2016, Fan, Pandya-Lorch, and Yosef 2014, Smith and Frankenberger 2018, Upton, Cissé, and Barrett 2016, Pelletier et al. 2016). However, the causal claims showing the effect of resilience on food security outcomes is very limited (Ansah, Gardebroek, and Ihle 2019, Conostas 2023). By using the RIMA approach, this empirical lacuna has been fulfilled with an Instrumental Variable (IV) approach. For example, d'Errico and Pietrelli (2017) used a two-stage least square regression (2SLS) to detect a causal relationship between RCI and child nutritional outcomes. In the same way, Egamberdiev et al. (2023) drew a causal relationship between RCI and food security outcomes, where there were both static and dynamic natures of food conditions in the model. Without utilizing IV, more fervent attempts to establish the causal relationship are implemented. Perhaps other conspicuous contributions are based on more dynamic nature of the relationship (Murendo, Kairezi, and Mazvimavi 2020, Sunday et al. 2022). There are also plausible explanations for the effect of resilience on food security outcomes by providing a more comprehensive analysis (d'Errico et al. 2019). However, substantive research on causal inferences needs to be carried out to establish more concrete policy designs and intervention programs.

Objective

In the context of low-income or developing countries, a viable proposition to strengthen household resilience is to define a threshold showing household probabilities of failing into worsened states of resilience (Barrett and Conostas 2014). For example, d'Errico et al. (2019) could identify resilience thresholds by defining clusters entailing a regime shift in the effects of temperature anomalies. From another perspective, Upton, Constenla-Villoslada, and Barrett (2022) used conditional probability thresholds to define resilient and non-resilient households. Similarly, other scholars tried to define resilience topologies by using different measures to categorize household resilience (Asmamaw, Mereta, and Ambelu 2019, Otchere and Handa 2022, Nahid et al. 2021, d'Errico and Di Giuseppe 2016). However, clustering household resilience levels using Latent

Profile Analysis (LPA) allows for an understanding heterogeneity in a population. In this case, the existing literature has not systematically analysed the heterogeneity by identifying households with similar resilience characteristics. Since robust resilience measurement still exists (Jones and d'Errico 2019, Upton, Constenla-Villoslada, and Barrett 2022), the method proposed to measure resilience through LPA may contribute to the existing literature.

In the operationalization, the study aims to define a relationship between household resilience and food security outcomes. As for outcome variables, the current study used two food security variables: *food consumption expenditure per capita* and *dietary diversity* in the household. Many scholars manifest food insecurity resilience in a complex multidimensional nature, albeit this is the most prominent way to construct resilience. This study measured the household resilience capacity index through a multidimensional, latent, and index-based nature. In order to measure resilience, this manuscript used Resilience Index Measurement and Analysis—II, in which Resilience Capacity Index (RCI) is measured through Access to Basic Services (ABS), Assets (AST), Adaptive Capacity (AC) and Social Safety Nets (SSN) pillars (FAO 2016).

The objective is accordingly accomplished through the following research questions:

1. What are the latent profiles that characterize household resilience capacity?
2. What are the effects of the latent profiles for household resilience on household food security outcomes?

A major limitation in the literature is related to building causal pathways between household resilience and food security outcomes (Ansah, Gardebroek, and Ihle 2019). In the methodology, this manuscript proposes an approach for the causal inference by integrating the Latent Class (LC) analysis into the Propensity Score (PS) approach, which is likely to improve the recent methodology for establishing a more decisive conclusion for the role of resilience through the LP method. Although this integration does not fully claim causal inferences, the methodology used in this manuscript tries to reduce selection bias.

Data and Methodology

Data

The data is based on the Cambodia Living Standards Measurement-Plus (LSMS +) Survey 2019-2020. The data is helpful in analysing the availability and quality of economic opportunities and welfare in low-and middle-income countries (WB 2021). The LSMS + program aimed to conduct interviews with the adult household members from different parts of the country; therefore, the data is nationally-representative survey. The scope of the survey was to cover socio-economic aspects of the household, particularly focusing on agriculture, livestock, migration, and food security topics.

The data is essential for food security analysis because Cambodia is heavily exposed to the consequences of climate change (WB 2023), while many households and communities suffer from the inability to withstand shocks due to low resilience levels (Nop 2022). Although the improvement of resilience to climate change and disaster risks is the central pillar of the country(Pereira and Shaw 2022, Natarajan, Brickell, and Parsons 2019, Work et al. 2019), 15% of people are under-nourished or 32% of children under 5 are stunted (WFP 2023). In addition, other non-climate-related problems make the country more vulnerable (Hunsberger, Work, and Herre 2018). It shows that Cambodia needs to sustain the improvement of resilience towards food insecurity in the face of climate change.

Latent Class Analysis

The LC methodology, initially introduced by Andersen (1982), has already been extended due to its applications for obtaining maximum likelihood estimates. Therefore, the LC methodology has already become one of social and behavioural science's most frequently applied analyses. In addition to this, LC analysis has many advantages over traditional cluster techniques because it is considered a probabilistic type of non-hierarchical cluster analysis (e.g. the K-means methods for clustering technique) (Vermunt and Magidson 2004). Another significant advantage of LC

analysis is explained by its application in dealing with the problem of unobserved heterogeneity. Without any previous knowledge, the LC analysis is useful for defining homogenous classes within the heterogeneous population. The LC analysis is implemented by having two major components: the measurement and structural components (Bakk 2023). In the measurement component, item response probabilities distinguishing latent classes show the probability that the observed variables belong to the latent classes (Collins and Lanza 2009). This step defines the number of latent classes that should be labelled according to the response probabilities of each observed item. Different conceptual advantages exist for estimating the measurement model without including covariates (Nylund-Gibson et al. 2014). The latent class membership is regressed with the auxiliary variables in the second component (Vermunt 2010).

In contrast, LC studies help define underlying population subgroups (i.e., latent classes or profiles) through the patterns of behaviour or conditions obtained from different observable variables. Since LC analysis deals with the problem of unobserved heterogeneity based on individual differences, the method is embedded in a person-centered approach. On the other hand, a traditional variable-centered approach deals with quantifying the study variables. Therefore, LC representing a subgroup of individuals with similar characteristics through their response patterns is likely to represent a homogenous population. Under the finite mixture modelling, LC in development research has already been extended including categorical and continuous indicators through Latent Class Analysis (LCA) and Latent Profile Analysis (LPA), respectively (Lanza and Cooper 2016). One more prominent tool for the extension of the LC model is the availability to include observed covariates to predict latent class membership (Dayton and Macready 2002, Vermunt 2010, Bakk, Oberski, and Vermunt 2016, Bray, Lanza, and Tan 2015, Lanza, Tan, and Bray 2013). This extension is crucial to understanding the composition of classes, allowing us to characterize unobserved latent phenomena. One major problem of LC is that causality cannot be inferred about the relationship between covariates and obtained latent classes. Another major complication is due to the multidimensional and latent nature of the variable.

Precisely, RCI, being a latent, multidimensional, and index-based variable, may provide extra complications, such as the problem of heterogeneity in addition to the problem of endogeneity to analyse the effect of resilience on food security outcomes.

As for the implementation of LC analysis, the manuscript constructed ABS, AST, AC, and SSN pillars to cluster households categorizing homogenous resilience levels (Figures A1-A8 in Appendix). Before running LPA analysis, each pillar was measured through observable variables provided in Table-A1 in Appendix. For data suitability analysis, Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, Bartlett's test of sphericity, and determinant of R-matrix are included (Jackson 2005, Acock 2013). All reliability findings are available in Table-A2 of Appendix. The varimax rotation technique decreased the distance between factor loadings (Kaiser 1958). The factor scoring is based on the Bartlett scoring method proposed by Bartlett (1937). Moreover, a min-max scaling method is applied to transform factor scores into a standardized index (d'Errico, Romano, and Pietrelli 2018, Lascano Galarza 2020).

Latent and Propensity Score Matching

In randomized controlled trials, as one of the most prominent analyses of causal claims, participants are randomized into treatment and control groups. In this case, estimating Average Treatment Effect (ATE) explains the differences in the outcome adjusted for covariates (Greenland, Pearl, and Robins 1999). In social science, randomization into treatment and control groups is not always possible, requiring further identifiability conditions of the ATE (Hernán and Robins 2006). In this case, observed confounders might be included in a regression module to estimate the conditional treatment effect. In addition to this, there are other available techniques estimating marginal treatment effects on the observational data in which direct matching (Rosenbaum 1999), propensity score matching (Austin 2011) and inverse propensity weighting (Imbens 2000) are widely used. By creating an artificial sample as if it is generated from a randomized controlled trial, the researcher is able to balance the treatment and control groups on

the confounders (Lanza, Moore, and Butera 2013). In the presence of observational data rather than randomized ones, an assignment into treatment vs. control groups should be based on specific characteristics because the characteristics over both the treatment and control groups are not consistent. Therefore, PS is one of the options to remove selection bias in observational study. In social science, the PS method has already been extended to multiple and continuous treatments (Imbens 2000). This extension is helpful when not all the effects are based on a binary treatment condition.

One existing problem in comparing food security outcomes between latent profiles is the existence of unbalanced latent profiles. It is assumed that latent profiles are likely to change the food security outcomes in both profiles. Therefore, there should be an attempt to decrease the bias from an imbalance between the profiles. In this case, we believe the propensity score matching is one of the most prominent ways to balance covariates among the groups (in the literature, the groups are referred to as treated and controlled groups) (Rubin 1973) in which the balancing is realized through the matching with the propensity scores (Rosenbaum and Rubin 1983). The method has been improved by designing PS approaches with multiple treatment effects (Imbens 2000). By integrating LC with PS models, it is possible to decrease the bias on the treatment effect due to the problem of heterogeneity (Kim and Steiner 2015). By solving the problem of imbalanced nature of the observed covariates, the researcher is likely to face with another difficulty in including the latent variable in matching. An unobserved nature of the latent variable explains this problem.

Latent Profile Model

In this step, LPA was performed to divide household resilience into homogenous clusters. As for model fit and selection information provided in Table-1, the fit information selected the 3 – class model because AIC and BIC indicate the best fit without having a convergence in the 4 – class model. The information provided with Entropy also indicates that 3 – model is better than 2 – class outcome.

Table-1: Fit information of latent profile models

| No. | LL | df | AIC | BIC | Entropy |
|------------|-----------|-----------|------------|------------|----------------|
| 1 | 2173.667 | 8 | -4331.334 | -4289.006 | |
| 2 | 3162.851 | 13 | -6299.702 | -6230.92 | 0.647 |
| 3 | 3229.417 | 18 | -6422.835 | -6327.597 | 0.667 |

LL log-likelihood, *df* number of free parameters, *AIC* Akaike information criterion, *BIC* Bayesian information criterion.

Posterior probabilities from the models are provided in Figure-1. According to parameter estimates, Profile 1 (0.18 prevalence) is evident with its low probabilities of ABS, AC, and SSN pillars characterizing less resilient households. This profile is named as “Low Resilient” household due to having the lowest posterior probabilities in three pillars. Profile 2 (0.47 prevalence) has the highest probabilities of SSN and second highest ABS and AST pillars. Therefore, this profile is labelled a “Medium Resilient” household. Although Profile 3 (0.35 prevalence) has the lowest probability of AST pillar, it has relatively high probabilities of ABS, SSN, and particularly AC. This profile is, accordingly, labelled “High Resilient” household.

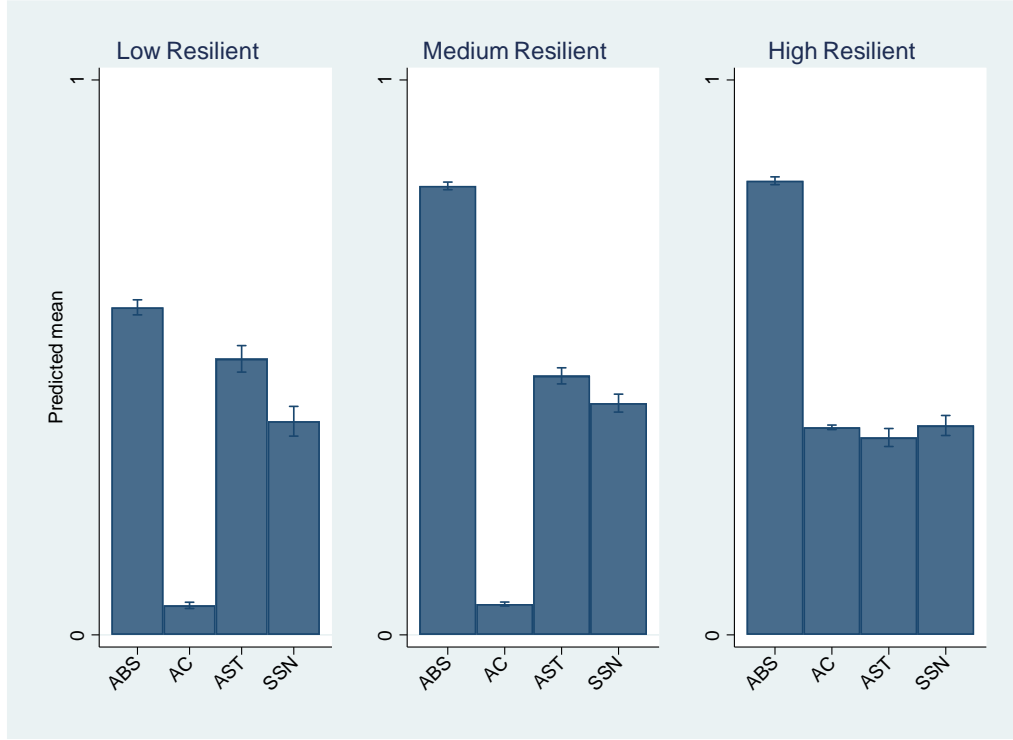


Fig.1 Latent Profiles for Household Resilience

Having more than one profile allows us to apply multinomial exposures in the PS approach proposed by Imbens (2000). Accordingly, Bray et al. (2019) recommend including causal questions through

1. estimating the causal effects of a membership versus another membership of the profile,
2. estimating the causal effects of a profile membership compared to other profiles, and
3. estimating pairwise comparisons between profiles.

In our context, the manuscript proposes to establish the ATEs by comparing “Low Resilient” households to both “Medium Resilient” and “High Resilient” households.

Calculating Propensity Scores

The estimation of propensity score for household h , $\hat{\pi}_h$, is based on the model for selecting an exposure group. It is generally measured using logistic regression because the score is the probability that households have exposure in the presence of confounders.

In this case, a household's propensity score is measured by its predicted probability of membership in the profile to which it belongs (Bray et al. 2019). For the binary estimation, an exposure T is obtained from the logistic regression because the membership in the exposed group is expressed by $T=1$ compared to one not exposed or $T=0$. In the regression, an exposure is predicted by the vector of confounders or x_h ; therefore, the propensity score as the predicted probability of profile membership is conditional on the cofounders. Accordingly, the estimated propensity score which is $\widehat{\pi}_h = P(T = 1|x_h)$ for the exposed group or $\widehat{\pi}_h = P(T = 0|x_h)$ for those not exposed defines the ATE. As for the probability $(P(T = 1|x_h))$, the logistic regression with potential confounders $(1, \dots, p)$ is obtained from the following equation:

$$P(T = 1|x_h) = \frac{\exp(\beta_0 + \beta_1 x_{h1} + \beta_2 x_{h2} + \dots + \beta_p x_{hp})}{1 + \exp(\beta_0 + \beta_1 x_{h1} + \beta_2 x_{h2} + \dots + \beta_p x_{hp})} \quad 1$$

where $(T = 0|x_h) = 1 - P(T = 1|x_h)$.

If the exposure is not dummy but multinomial variable with $(1, \dots, n_T)$, multinomial logistic regression is preferred. By taking the same probability of membership to the group, household's propensity score is found from the following equation:

$$\widehat{\pi}_h = P(T = T_h|x_h) = \sum_{t=1}^{n_T} (P(T = t|x_h)I\{T_h = t\}) \quad 2$$

where $I\{T_h = t\}$ is equal to 1 and 0 otherwise. As for multinomial logistic regression, the probability $P(T = t|x_h)$ is obtained:

$$P(T = 1|x_h) = \frac{\exp(\beta_{0t} + \beta_{1t} x_{h1} + \beta_{2t} x_{h2} + \dots + \beta_{pt} x_{hp})}{\sum_{t'=1}^{n_T} \exp(\beta_{0t'} + \beta_{1t'} x_{h1} + \beta_{2t'} x_{h2} + \dots + \beta_{pt'} x_{hp})} \quad 3$$

By applying the technique for the propensity score with the latent profile (Leite et al. 2021, Bray et al. 2019), the propensity score of a latent profile $\widehat{\pi}_h$ is defined by the posterior probability of membership in class t $P(T = t|u_h)$ with the covariates x_h and latent profile indicator u_h . Accordingly, a generalized propensity score for latent profile exposure is defined as:

$$\widehat{\pi}_h = \sum_{t=1}^{n^T} P(T = t|\mathbf{x}_h)P(T = t|\mathbf{x}_h, \mathbf{u}_h)$$

In equation – 4, each household experiences only one $\widehat{\pi}_h$ representing the sum of probabilities of profile membership in the exposure groups. The profile membership is obtained from the posterior probabilities of membership.

In this stage, receiving “treatment” corresponds to the level of resilience in the household defined by LPA. An extension of finite mixture models made it possible to claim a causal inference in LPA. Since causality is not inferred from the relationship between covariates and latent class membership, findings support conducting PSM in LPA to draw causal inference (Lanza, Coffman, and Xu 2013, Khodamoradi et al. 2023, Butera, Lanza, and Coffman 2014). In this case, the proposal is to apply the three-step approach (Asparouhov and Muthén 2014, Vermunt 2010) by integrating the PSM, particularly the regression adjustment method, in the third step. In a nutshell, latent profiles are performed, which are defined without any covariates on the unweighted data. Based on the posterior class membership probabilities, the memberships of households are determined. The last stage is to define the class membership probabilities of certain profiles assigned to treatment vs. to the control group. This manuscript used two multivalued effect estimators with regression methods. In this case, estimators were obtained by applying the inverse probability weighted regression adjustment (IPWRA). The reason behind using IPWRA is that the obtained estimators are called “doubly robust” (Cattaneo 2010, Cattaneo, Drukker, and Holland 2013, Wooldridge 2010). For robustness analysis, the manuscript provides findings from the regression adjustment (RA) estimators, allowing multivalued treatment in the estimation (Linden et al. 2016).

Results

Assess Overlap and Balance

After obtaining the propensity score for each observation, it is important to analyse whether there is an overlap in the scores between the exposure groups (Garrido et al. 2014). Figure-2 shows the overlap of propensity scores across “Low Resilient”, “Medium Resilient”, and “High Resilient” profiles. In this case, the figure indicates that the extent of overlap is satisfactory. In other words, the range of propensity scores for the households in one exposure group mostly corresponds to the remaining two exposure groups.

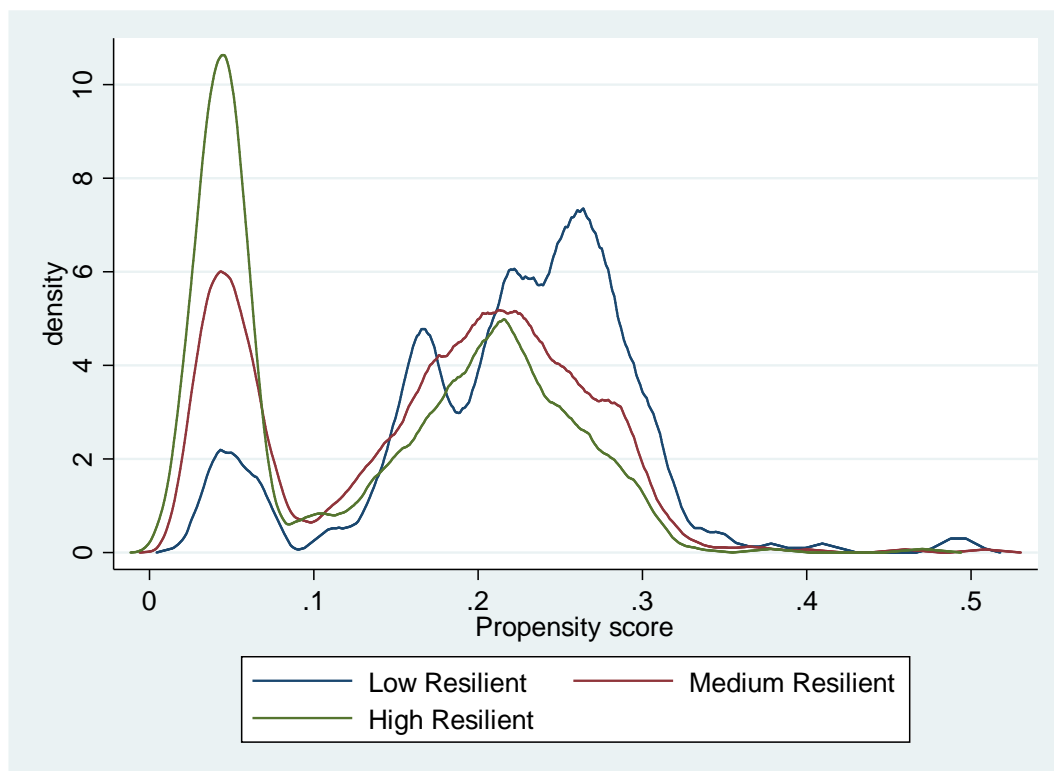


Fig.2 Distribution of propensity scores

Causal estimates should also check another inference technique based on the balance of the confounders for the treatment and control group (Austin 2011). A covariant balance analysis shows that all covariates for the latent profiles were balanced. Summary statistics are available in Table-A3 in Appendix. A conclusion is based on the standardized mean differences (SDM) which should

be smaller than 0.25, and variance ratio, which should be close to 1 (Lanza, Moore, and Butera 2013). With almost all confounders in Table-2, the balance is achieved.

Table-2: Balance table for standardized differences and variance ratio

| | Medium Resilient | | High Resilient | |
|------------------|-------------------------|-----------------------|-----------------------|-----------------|
| | Standardized | Variance ratio | Standardized | Variance |
| | differences | | differences | ratio |
| Head age | 0.232 | 0.850 | -0.011 | 0.791 |
| Female head | 0.102 | 1.009 | 0.010 | 1.014 |
| Head married | -0.013 | 1.027 | -0.020 | 1.033 |
| Rural | -0.518 | 1.002 | -0.001 | 1.001 |
| Elderly | 0.173 | 1.002 | 0.009 | 1.009 |
| Farming activity | -0.116 | 0.980 | 0.051 | 0.975 |
| (last 12 months) | | | | |

Multivalued treatment effects

Table-3 provides the impact of household resilience on food security outcomes. As for the level of significance, all outcomes are statistically significant. Moving from “Low Resilient” to “Medium Resilient” household results in an increase in dietary diversity of 0.004. Looking at the ATE as a percentage, an increase the dietary diversity score is by 0.4% when households are labelled as “Medium Resilient” compared to the households characterised as “Low Resilient”. Compared to “Low Resilient” households, “Medium Resilient” households experience higher dietary diversity by 0.006 than the average 0.939 diversity index. Notably, an increase in dietary diversity by 0.06% is explained by moving from “Low Resilient” to “Medium Resilient” status.

These findings are consistent with studies analysing a causal relationship between RCI and dietary diversity (Egamberdiev et al. 2023, Murendo, Kairezi, and Mazvimavi 2020).

Table-3: Average treatment effects of resilience profiles on dietary diversity and food expenditure per capita

| | | IPWRA | | RA | |
|----|----------------|--------------|-----------|--------------|-----------|
| | | ATE | ATE% | ATE | ATE% |
| DD | | | | | |
| | Medium | 0.004* | 0.400* | 0.005* | 0.573* |
| | Resilient | (0.002) | (0.002) | (0.002) | (0.003) |
| | High Resilient | 0.006** | 0.600** | 0.007** | 0.764** |
| | | (0.002) | (0.003) | (0.003) | (0.003) |
| FE | | | | | |
| | Medium | 12250.770*** | 37.100*** | 12752.730*** | 39.290*** |
| | Resilient | (1977.473) | (0.075) | (1999.484) | (0.078) |
| | High Resilient | 25882.520 | 78.437*** | 26614.840*** | 81.999*** |
| | | (2446.349) | (0.102) | (2486.089) | (0.107) |
| N | | 1494 | 1499 | 1494 | 1499 |

Note. *p < 0.10; **p < 0.05; ***P < 0.001; Standard errors in parentheses; DD: Dietary Diversity;

FE: Food Expenditure per capita.

The results in Table-3 also show that moving from “Low Resilient” to “High Resilient” status in the household increases per capita food expenditure by 12250 Cambodian riel when the average consumption expenditure is around 32997 Cambodian riels. In other words, the average expenditure increases by more than 37% if households are “High Resilient” compared to those “Low Resilient”. Food expenditure per capita also increases by 25882 Cambodian riel when profile changes from “Low Resilient” to “High Resilient”. With respect to changes as a percentage, the

expenditure increases by more than 78% at this change to the “High Resilient” condition. For comparison and a robustness check, the manuscript presents both ATE and ATE as a percentage by RA estimator. The results reveal that both average treatment effects and percentage changes in ATEs provide similar results. Some authors support this by concluding causal claims between RCI and food consumption (Sunday et al. 2023, Egamberdiev et al. 2023). Therefore, as some authors mentioned, climate-resilient strategies are one of the main alternatives to improve the food security condition in Cambodia (Tacconi et al. 2023, Bairagi, Mishra, and Durand-Morat 2020).

Conclusion

Enhancing household resilience capacity is crucially important in ensuring food security in a developing country like Cambodia. The current study employed cross-sectional data obtained from the LSMS Survey in 2019. The study has applied a range of econometric methods to analyse the effect of resilience on food security outcomes. Since one of the main challenges to identifying causal mechanisms is explained by the issue of confounding bias, constructing treatment effects in observational data is particularly important. This paper provides one of the first empirical illustrations of integrating latent analysis with the propensity score approach in resilience study. Applied LPA approach in this manuscript allowed to glean insights into resilience analysis by defining resilience topologies for the households. In this case, the manuscript could define households through “More Resilient,” “Resilient,” and “Low Resilient” profiles. Therefore, it was possible to explain household resilience by homogenous subgroups which are mixed (Jason and Glenwick 2016). This person-centered mixture modelling approach to categorise households into homogenous classes may eventually help to develop intervention programs targeting less resilient households. In the next stage, the manuscript integrated LPA with PS methods. A plausible explanation for such integration is that it is impossible to experience households that are not absolutely resilient. In addition, the resilience of the households suffers from the heterogeneity problem. Therefore, the current study methodology fits within an emerging knowledge basis of how to use LC methodology for causal inferences.

The results from the context of Cambodia indicate that more resilient households are likely to have better outcomes in the context of food security. It supports the argument that the intervention programs should target strengthening household resilience to maintain or enhance both food consumption and dietary diversity. The findings suggest that building or strengthening resilience should enhance ABS, AST, AC, and SSN because these pillars determine household resilience towards food insecurity. Therefore, policies leveraging the improvement of food

security conditions in Cambodia should promote the strengthening of the pillars together, ensuring improved household resilience capacity.

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Appendix

Table-A1: Observable variables used for pillars

| Pillar | Variable | Mean | St.Dev | Min | Max |
|---------------------------------|--|--------|--------|-----|------|
| Access to Basic Services | | | | | |
| (ABS) | | | | | |
| | Available toilet facility | 0.756 | 0.429 | 0 | 1 |
| | Available energy | 0.416 | 0.493 | 0 | 1 |
| | Household floor area | 53.717 | 44.204 | 6 | 720 |
| | Number of rooms available in the dwelling unit | 1.455 | 1.729 | 0 | 48 |
| Assets (AST) | | | | | |
| | Tropical Livestock Unit (TLU) | 0.281 | 0.529 | 0 | 2.62 |
| | Agricultural land | 0.591 | 0.491 | 0 | 1 |
| | Secondary agricultural activity | 0.085 | 0.279 | 0 | 1 |
| | Current account | 0.052 | 0.223 | 0 | 1 |
| | Saving account | 0.158 | 0.364 | 0 | 1 |
| Adaptive Capacity (AC) | | | | | |
| | Running farm business | 0.341 | 0.474 | 0 | 1 |
| | Migrant number | 2.408 | 1.047 | 1 | 8 |
| | Higher education | 0.094 | 0.292 | 0 | 1 |

| | | | | |
|-----------------------------|-------|-------|---|---|
| Employed family members | 1.155 | 1.160 | 0 | 8 |
| Entrepreneurship activities | 0.474 | 0.770 | 0 | 8 |

Social Safety Nets (SSN)

| | | | | |
|-------------------------|-------|-------|---|---|
| Annual leave | 0.196 | 0.397 | 0 | 1 |
| Paid maternity | 0.231 | 0.421 | 0 | 1 |
| Paid medical assistance | 0.197 | 0.398 | 0 | 1 |
| Paid health insurance | 0.223 | 0.416 | 0 | 1 |
| Pension | 0.079 | 0.270 | 0 | 1 |
| Subsidies | 0.205 | 0.403 | 0 | 1 |
| Transport subsidies | 0.174 | 0.379 | 0 | 1 |
| Other benefits | 0.111 | 0.314 | 0 | 1 |

Table-A2: Factorability analysis

| Index | Component | Cumulative Variance | |
|-----------------------------|------------------|--------------------------------|-------------|
| ABS | | | |
| | 1 | 0.412 | |
| | 2 | 0.667 | |
| Bartlett Test | | | 446.988*** |
| KMO | | | 0.599 |
| determinant of R- matrix | | | 0.744 |
| AST | | | |
| | 1 | 0.471 | |
| Bartlett Test | | | 194.375*** |
| KMO | | | 0.563 |
| determinant of R- matrix | | | 0.879 |
| AC | | | |
| | 1 | 0.391 | |
| | 2 | 0.681 | |
| Bartlett Test | | | 1912.545*** |
| KMO | | | 0.553 |
| determinant of R- matrix | | | 0.271 |
| SSN | | | |
| | 1 | 0.391 | |
| | 2 | 0.681 | |
| Bartlett Test | | | 5140.029*** |
| KMO | | | 0.879 |
| determinant of R- matrix | | | 0.033 |

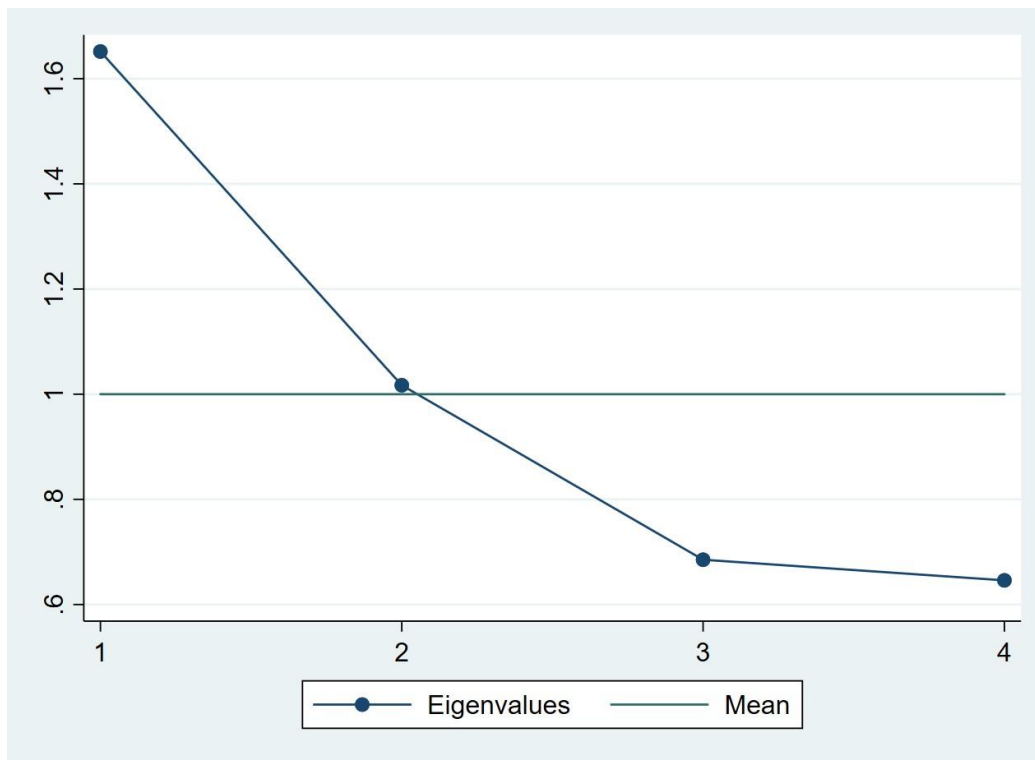


Fig.A1 Eigenvalues for ABS

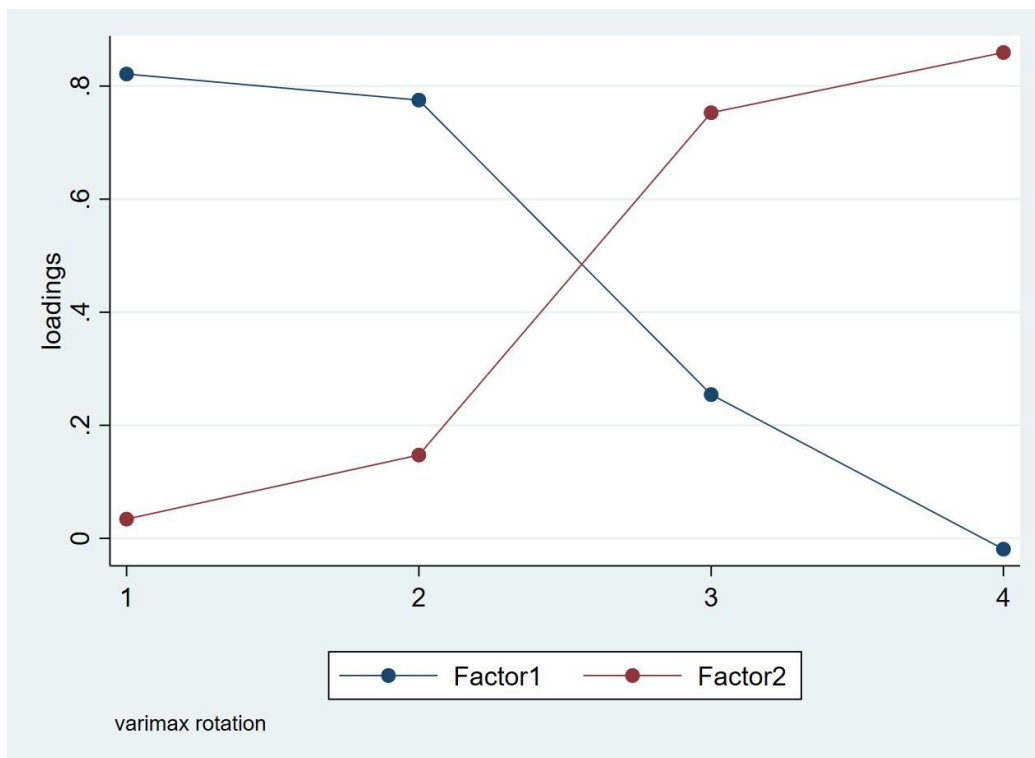


Fig.A2 Factor loadings in ABS

Note: 1- Available toilet facility; 2- Available energy; 3-Household floor area; 4-Number of rooms available in the dwelling unit

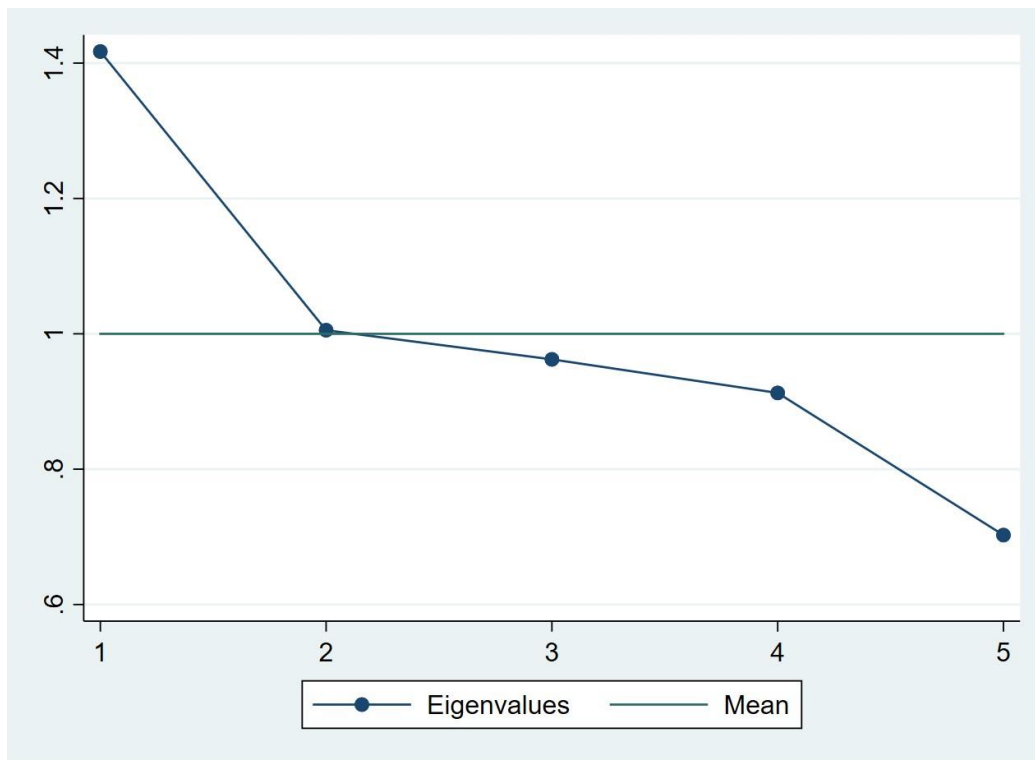


Fig.A3 Eigenvalues for AST

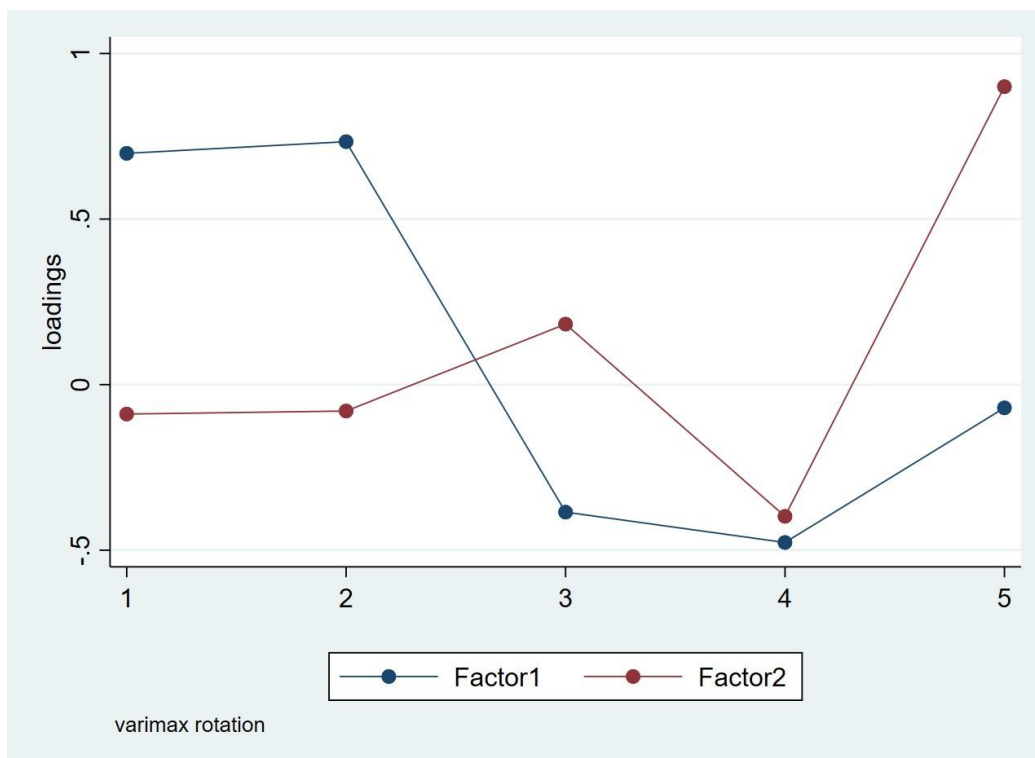


Fig.A4 Factor loadings in AST

Note: 1- TLU; 2- Agricultural land; 3-Secondary agricultural activity; 4-Current account; 5-Saving account

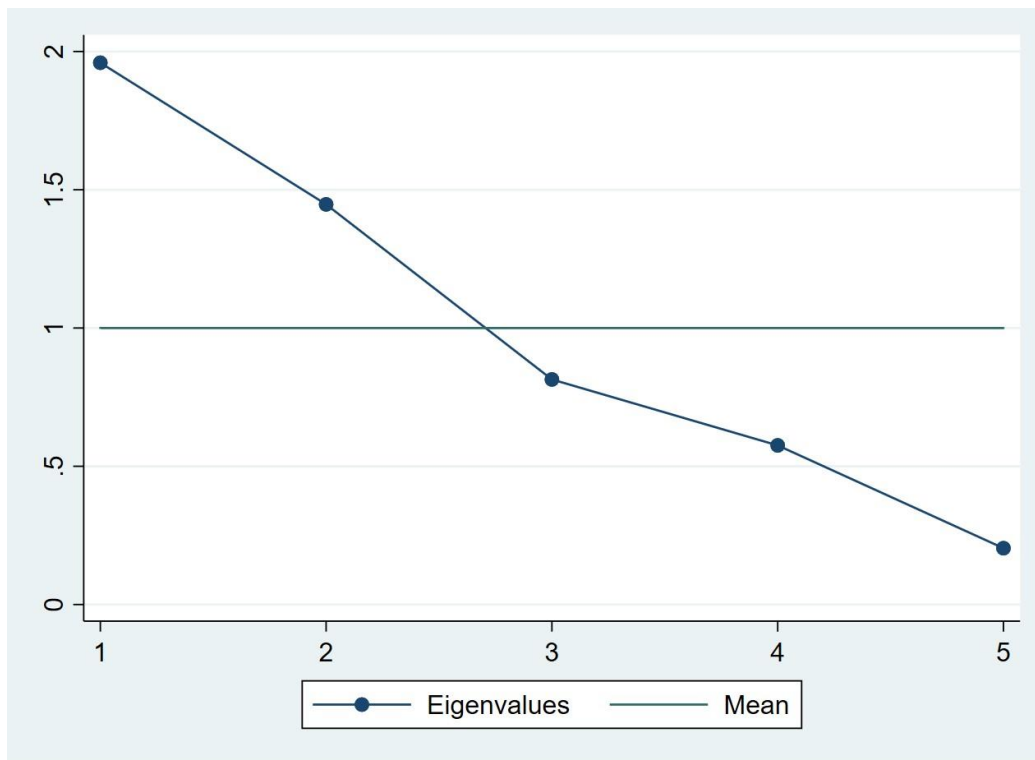


Fig.A5 Eigenvalues for AC

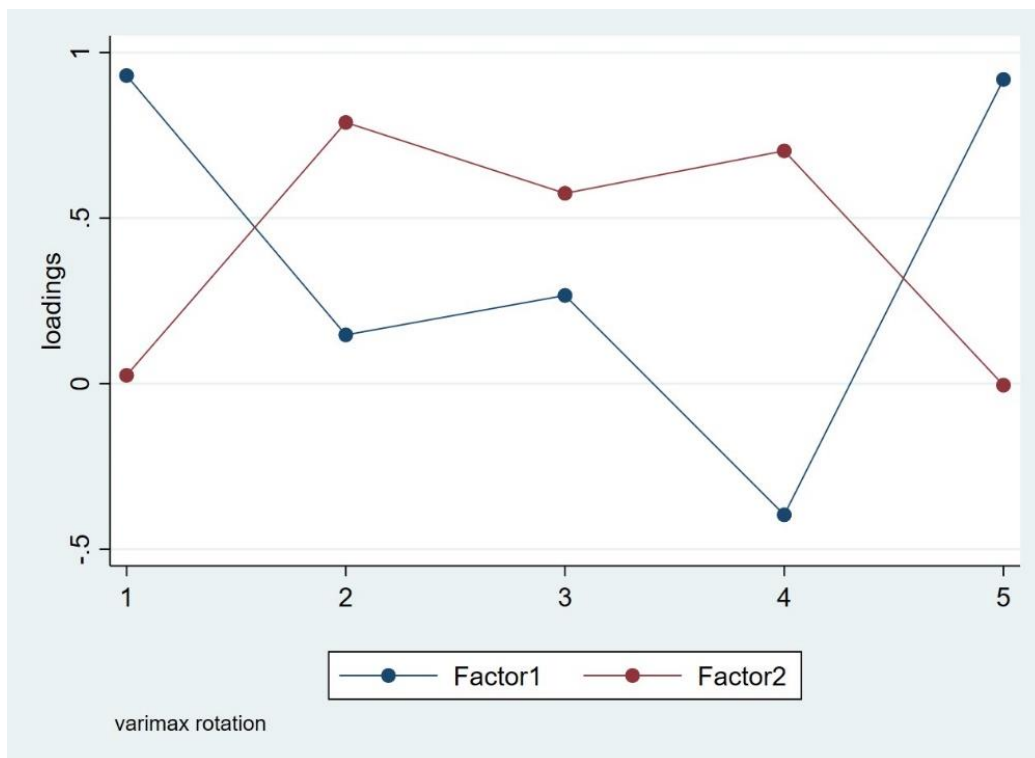


Fig.A6 Factor loadings in AC

Note: 1- Running farm business; 2- Migrant number; 3- Higher education; 4- Employed family members; 5- Entrepreneurship activities

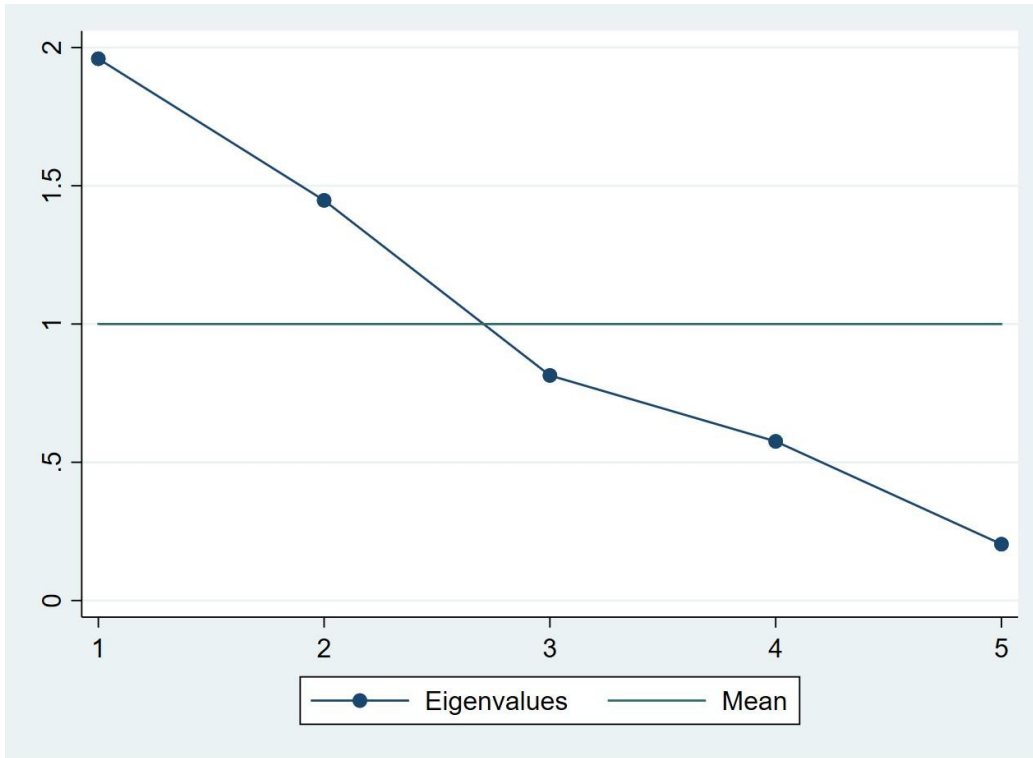


Fig.A7 Eigenvalues for SSN

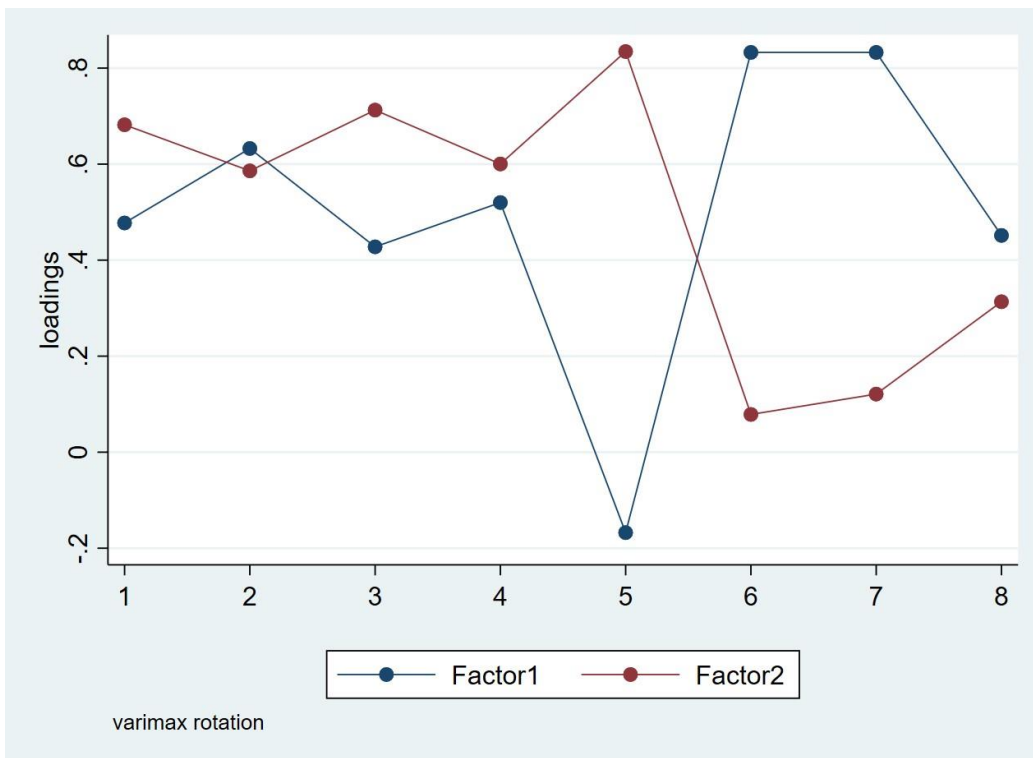


Fig.A8 Factor loadings in SSN

Note: 1-Annual leave; 2-Paid maternity; 3-Paid medical assistance; 4-Paid health insurance; 5-Pension; 6-Subsidies; 7-Transport subsidies; 8-Other benefits

Table-A3: Summary Statistics

| Variable | Definition | Pooled sample | | Low Resilient | | Medium Resilient | | High Resilient | | Diff. (p-value) |
|----------|---|---------------|----------|---------------|----------|------------------|----------|----------------|----------|-----------------|
| | | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. | |
| Age | Age of household head | 52.013 | 14.253 | 49.104 | 14.471 | 52.638 | 14.526 | 52.535 | 13.567 | 0.236 |
| Female | Female household head | 0.207 | 0.405 | 0.167 | 0.374 | 0.205 | 0.404 | 0.228 | 0.420 | 0.132 |
| Married | Married household head | 0.809 | 0.392 | 0.816 | 0.387 | 0.807 | 0.394 | 0.808 | 0.393 | 0.950 |
| Rural | Household in rural area | 0.698 | 0.459 | 0.916 | 0.277 | 0.723 | 0.447 | 0.568 | 0.495 | 0.000 |
| Elderly | Availability of old age person in household | 0.273 | 0.445 | 0.214 | 0.411 | 0.298 | 0.456 | 0.271 | 0.445 | 0.052 |

| | | | | | | | | | | |
|-----------------------|---|-------|-------|----------|----------|----------|----------|----------|----------|-------|
| Farming | Farm activities in household for last 12 months | 0.617 | 0.486 | 0.729 | 0.445 | 0.672 | 0.469 | 0.499 | 0.500 | 0.000 |
| Dietary Diversity | Household dietary diversity index (Simpson index) | 0.944 | 0.050 | 0.937 | 0.026 | 0.943 | 0.056 | 0.947 | 0.050 | 0.000 |
| Food Expenditure | Household food expenditure per capita | | | 31276.02 | 21185.79 | 44361.89 | 31192.67 | 64170.36 | 52698.34 | 0.000 |
| Number of observation | | 1519 | | 251 | | 702 | | 566 | | |