J. ISSAAS Vol. 31, No. 2:1-22 (2025)

HOUSEHOLD RESILIENCE AND IMPACT OF UNEMPLOYMENT, CLIMATE, AND PRICE SHOCKS ON FOOD SECURITY: EMPIRICAL EVIDENCE FROM THE PHILIPPINES

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(Received: March 24, 2025; Accepted: June 26, 2025)

ABSTRACT

Given the recent global shocks, it has become increasingly relevant to enhance resilience to food insecurity to cushion households amidst its adverse impacts and allow them to at least maintain their current level of food security. Using the 2003 to 2009 panel data from the Philippines, this paper explored the direct and indirect impacts of unemployment, climatological, and price shocks on real per capita food expenditure and household dietary diversity through its impacts on household resilience. Utilizing the Resilience Index Measurement and Analysis II (RIMA-II) and Two-Stage Least Squares (2SLS) approaches, it was found that shocks may have multiplier negative effects on future food security outcomes. However, a higher level of household resilience significantly improves future food expenditure, although it does not necessarily translate into a higher current level of household dietary diversity. Household resilience is also a significant factor for recovery from the loss induced by shocks in real per capita food expenditure and dietary diversity. Overall, it was found that strengthening household resilience, especially its most relevant pillars such as the use of basic services, social safety net, and adaptive capacity, is crucial in improving the long-term household food security status of Filipino households.

Key words: 2SLS, dietary diversity**,** food expenditure

INTRODUCTION

In the continuing fight against poverty, numerous studies have been conducted to characterize the vulnerable populations to reduce their risk of falling into poverty (ex-ante studies) (Bayudan-Dacuycuy and Lim 2013; Mina and Imai 2017; Ouadika 2020) and to assess which anti-poverty programs have been effective (ex-post studies) (Davis et al. 2005; Do et al. 2013). However, given the recent shocks in the economy (i.e., COVID-19 pandemic, rising oil prices, etc.), it has also become necessary to improve the resilience of the vulnerable households amidst these shocks. This is important because while uplifting the economic conditions of the vulnerable groups usually takes time, at the very least, their condition should not worsen even amid stressors, or the adverse impacts should not be long-lasting.

Food insecurity is one of the faces of poverty that is especially exacerbated in times of crisis. Between 2019 and 2020, there was a sharp increase in the incidence of food insecurity from 25 to 29 percent under the shadow of the COVID-19 pandemic, and the figures remain almost unchanged even after three years, with 2.33 billion people in the world experiencing moderate or severe food insecurity (FAO et al. 2024) making it harder to achieve the zero hunger target by 2030. Sociodemographic factors and asset ownership influence both the recurrent and episodic food insecurity of smallholder farmers, highlighting the need for policies and programs that will improve food security and resilience to extreme weather shocks (Alpizar et al. 2020). This was also supported by a previous study, which pointed out that the major reasons why rural households are vulnerable are the neglect to food security and food system management, and sustainability and resiliency (Nahid et al. 2021). An attempt to address this call is to examine how household resilience capacity affects food security outcomes.

This study sought to assess how household resilience affects food security outcomes amidst shocks, specifically unemployment, extreme rainfall and temperature, and price shocks, in the Philippine context, and to determine the separate impact of these shocks on household resilience and food security outcomes. While a growing number of studies have reviewed the link between household resilience and food security outcomes in the presence of shocks (Ansah et al. 2019; D'Errico et al. 2018; Haile et al. 2022), to the authors' knowledge, this paper is among the few to study household resilience as a causal pathway to food security which implies formulating policies that can address short-term and long-term food insecurity. Most studies measured resilience as an indicator of food security, making it difficult to differentiate the two concepts (Ansah et al. 2019). By studying household resilience as a pathway to food security, this paper addresses the gap in the existing literature and provides substantiation on the possible synergies and trade-offs that may exist between the two concepts in the presence of shocks. Further, using evidence from the Philippines, this paper also offers a perspective from Southeast Asia, as African perspectives dominate the existing literature. The Philippines had the second highest prevalence of food insecurity in Southeastern Asia (about 45%) next to Cambodia (51% prevalence) (FAO et al. 2024) and has topped the World Risk Index due to its frequent exposure to natural calamities and high vulnerability (Bündnis Entwicklung Hilft/ IFHV 2023) in 2023. By understanding the dimensions of household resilience of Filipino households, the results of this study also provide inputs to policymakers in identifying priority areas to focus on to increase households' resilience to shocks and indirectly resolve food insecurity problems.

MATERIALS AND METHODS

Data. The household-level panel data from the merged triennial Family Income and Expenditure Survey (FIES) and quarterly Labor Force Survey (LFS) conducted by the Philippine Statistics Authority (PSA) covering the periods: 2003, 2006, and 2009 were used. While more recent FIES datasets are available (i.e., 2012, 2015, and 2018), the respondents covered in the more recent rounds are different at each round as the PSA employed a repeated cross-sectional survey from 2012 onwards, in contrast to the panel survey employed from 2003 to 2009. Nevertheless, the experience of the households in response to the shocks that occurred from 2003 to 2009 may provide important insight into how household resilience can influence food security outcomes and how it can act as a pathway to achieve long-term food security. It is important to note that during the periods of 2003 to 2009, the Philippines has experienced extreme weather events (four El Niño and three La Niña episodes) that brought devastating typhoons, extreme flooding, and prolonged droughts; 2007/2008 global financial crisis which has also surged up rice prices; and other macroeconomic shocks (Mina and Imai 2017). These shock occurrences were presumed to have affected the resilience of the households and their food security status. Around this time, poverty and food and nutrition insecurities were already critical problems in the Philippines, citing both adults and children suffering from its consequences (Angeles-Agdeppa 2002; Fernandez-San Valentin and Berja Jr. 2012).

The 2003-2006-2009 panel dataset comprised a total of 6,253 households but after data cleaning, 6,251 households were retained in the sample. The FIES contains annual information on the households' socio-economic characteristics, detailed sources of income and expenditure, asset ownership, private transfers, and other household characteristics. On the other hand, LFS provides detailed information on the employment status of the members of the households. This includes information on whether a member of the household has experienced unemployment during the survey period.

The food security indicators that were used in the analysis were the annual per capita food expenditure (an indirect measure of food caloric intake) and the household dietary diversity index measured using Simpson-index (SI) (also known as Berry-index) that was calculated from FIES datasets using the formula:

$$SI=1-\sum_{i=1}^{n} p_i^2 \qquad (1)$$

Where p_i is the proportion of consumed calories (in terms of value) of the i^{th} food group in a sample of n food groups (Drescher et al. 2007; D'Errico et al. 2018; Nithya and Bhavani 2016).

Although household dietary diversity score (HDDS) is the more common measure of household dietary diversity used in developing countries like the Philippines, SI was used in the analysis since it does not only measure the quality of food intake but also reflects the distribution of the food types consumed by the household (Verger et al. 2021). However, SI does not increase if the distribution of food consumed moves in favor of healthier food types, which might be desired from a nutritional perspective (Drescher et al. 2007). The SI ranges from zero to one, with one indicating maximum diversity in the household's food basket.

The per capita food expenditure was deflated using the average core consumer price index (CPI) of June and December of the survey periods (obtained from the PSA database) to capture the real per capita food expenditure (the average core CPI in June and December 2003 was 67.9; the average core CPI in June and December 2006 was 79.2; the average core CPI in June and December 2009 was 89.8; and the base year is 2012). The average core CPI of June and December were used as deflators since FIES surveys are conducted twice per round. The first visit was July, covering the first six months (January to June), and the following visit was January of the succeeding year, covering the latter six months of the year (July to December). The prevailing market prices during the survey period were used by PSA in the computations of household expenditures, so the core CPIs in June and December were used for better accuracy of the estimates. However, since the expenditures were based on households' recall, measurement errors may still exist. Further, real per capita food expenditure may fall short as a proxy of caloric food intake since it captures both the quantity and quality of food intake.

As for the shock variables, the covariate shocks that were included in the study were climatological shocks, such as extreme rainfall and temperature and price shocks. The climatological shocks were represented by dummy variables equal to one if there were recorded extreme values on rainfall and temperature at the local weather satellite stations. Rainfall and temperature shocks were tested for correlation using pairwise correlation to check whether they are highly correlated. Based on the pairwise correlation, rainfall and temperature shocks that occurred in 2003 were not highly correlated (correlation = 0.031, significant at 5% alpha) and thus, were both included in the models. Price shocks were represented by dummy variables equal to one if their values deviate by two standard deviations from the historical average. Inflation was measured using the provincial CPIs. These variables were presumed to have direct impacts on household income, especially since some of the population being studied belongs to the agricultural sector, known to be vulnerable to weather, fuel, and food price shocks (Mina and Imai 2017). The data on climatological extremes were obtained from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) and the price shocks were obtained from PSA website. These data were matched to each household using the Philippine Standard Geographic Code (PSGC), which is the standard classification and coding used in the Philippines for geographical-political subdivisions, that can be found in the merged FIES-LFS datasets. Note that while the geo-locations of the households were available in the datasets, climate shock dummies were limited to provincial-level variation since not all the cities/municipalities in the Philippines have their own weather satellite stations. The idiosyncratic shock that was considered in the analysis was the self-reported experience of unemployment of members of the household. Further, the household's distance to the nearest bank was estimated using Google Maps. Households' locations and addresses of all banks in the Philippines obtained from the *Bangko Sentral ng Pilipinas'* (BSP) website were pinned on Google Maps to calculate the shortest distance. A summary of the variables used in the analysis is shown in Table 1.

Table 1. Description of the variables used in the analysis

Variable	Definition/Notes
Log of real per capita food expenditure	log of real per capita annual food expenditure including those received as gifts and produced for own consumption; taken for the years 2003, 2006, and 2006
Change in per capita food expenditure between 2003 and 2006	difference of real per capita food expenditure in 2003 and 2006 (in PhP100)
Change in per capita food expenditure between 2006 and 2009	difference of real per capita food expenditure in 2006 and 2009 ((in PhP100); restricted sample (only those who experienced a loss in real per capita food expenditure in between 2003 and 2006 were included)
HH dietary diversity	measured in terms of Simpson Index (SI); values range from 0 to 1 where 1 indicates highest level of dietary diversity and 0 indicates no diversity in diet; taken for the years 2003, 2006, and 2009
Change in HH dietary diversity between 2003 and 2006	difference of SI between 2003 and 2006
Change in HH dietary diversity between 2006 and 2009	difference of SI between 2006 and 2009; restricted sample (only those who experienced a loss in household dietary diversity between 2003 and 2006 were included)
UBS components	
Infrastructural index	index used to indicate dwelling condition of the household; combines five dummies each of them equal to 1 for having a roof and walls made of strong material (galvanized, iron, al, tile, concrete, brick, stone, asbestos), toilet, water supply, and electricity. The index was created using factor analysis (FA) and indicates better dwelling conditions for higher value.
Transportation and communication	household expenditures for transportation and communication (in PhP)
Education	household expenditures for education services (in PhP)
Medical care	household medical care expenditure (in PhP)
Clothing	household clothing expenditures (in PhP)
AST components	
Wealth index	Index used to proxy the richness of the household; higher values are assumed for households with greater non-productive asset position; created using FA by combining dummy variables assuming value of 1 or 0 to indicate whether the household has specific non-productive assets such as radio, TV, VTR, stereo, refrigerator, washing machine, airconditioner, sala, dining, car, phone, microwave, oven, motorcycle, and own or owner-like possession of house and lot.
Interest earned	measured in PhP
Dividend	dividends from investment (measured in PhP)
Profit from stocks	profit from sales of stocks, etc. (measured in PhP)

Variable	Definition/Notes
Winning from gamblings	net winnings from gambling, etc. (measured in PhP)
Savings/business equity	measured in terms of withdrawal from Savings/Business equity (in PhP)
Backpay and proceeds from insurance	measured in PhP
Other receipts (excl. Loans and withdrawals)	measured in PhP
Inheritance	measured in PhP
Rental value of house	measured in PhP
SSN components	
Cash receipts/support from abroad	measured in PhP
Cash receipts/support from domestic source	measured in PhP
Total received as gifts	measured in PhP
Pension and retirement benefits	measured in PhP
Loans from other families	measured in PhP
AC components	
Income diversification index	index generated using FA with dummies for income from (1) wages/salary from agricultural activity, (2) wage/salary from non-agricultural activity, (3) crop farming and gardening, (4) livestock and poultry raising, (5) fishing, (6) forestry and hunting, (7) transfers, (8) other income sources, etc
Household head job/business indicator	dummy =1 if the head of the household has job/business
No children in the family	dummy =1 for household with no children family members (<15 years old)
Household head education	dummy = 1 if at least high school graduate
Number of family members employed for pay	count of family members employed
Income earners' share	count of family members employed for pay/profit divided by household size
Savings indicator	dummy variable =1 if with savings
Wife employment	dummy variable =1 if wife is employed
RCI	estimated using MIMIC; at time t = 2003
RCI2	estimated using SEM; at time t = 2003
Female household head	dummy =1 if the head of the household is female
Age of household head	in years
Agricultural HH indicator	dummy = 1 if the household is primarily engaged in agricultural sector
Urban/rural	dummy =1 if the household is residing in urban area
Household size	average family size for 1st and 2nd visit for 2003

Variable	Definition/Notes
Shocks (in 2003)	
Experienced unemployment	dummy =1 if any member of the family experienced unemployment
Weather shocks	provincial level variations
Temperature	dummy = 1 if the province where the household resides experienced extreme temperature as reported by PAG-ASA weather satellite stations
Rainfall	dummy = 1 if the province where the household resides experienced extreme rainfall (greatest amount of rainfall) as reported by PAG-ASA weather satellite stations
Price shock	Price shock was represented by dummy variable equal to 1 if annual consumer price index (CPI) (used to measure inflation) deviates by two standard deviations from historical average (1994-2002); provincial level variation
Distance to nearest bank	Measured in kilometers

Resilience estimation. In measuring resilience, the authors employed the Food and Agriculture Organization (FAO) Resilience Index Measurement and Analysis II (RIMA-II) approach which has the advantage of providing an adequate estimate of household resilience to food insecurity since it properly linked resilience capacity index (RCI) with household food security by jointly estimating RCI by its causes, pillars, and food security indicators (Bruck et al. 2018). Based on FAO's analytical framework, the fundamental pillars of resilience are: (1) access to basic services (ABS), (2) assets (AST), (3) social safety nets (SSN), (4) sensitivity (exposure to risk), and (5) adaptive capacity (AC); in the RIMA-II approach, the sensitivity pillar is considered exogenous and is included in the regression analysis to assess the real impact of the shocks on resilience capacity. However, some modifications were done in this study (Fig. 1). Use of basic services (UBS) instead of ABS was used as one of the pillars of resilience since the observed variables used to measure this dimension were in expenditure terms, which capture both the quality and quantity of service.

While there are other approaches in measuring resilience, the FAO RIMA-II approach dominates the literature and has been advocated (Ansah et al. 2019; Haile et al. 2022). The RIMA-II approach involves a two-stage procedure. The first step identifies the attributes that contribute to household resilience (those that constitute the pillars mentioned earlier) based on the observed variables using Factor Analysis (FA) (Fig. 1).

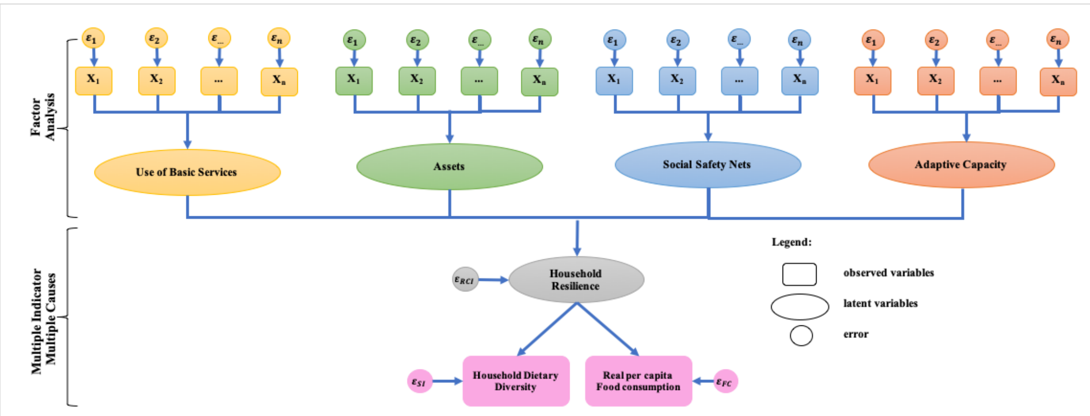


Figure 1. Analytical framework of RIMA-II approach
Note. Adapted from D'Errico et al. (2018)

By employing FA, a set of observed variables that are closely correlated is reduced into a single variable that may well proxy the pillar of resilience, which is a latent variable. The number of factors that was selected for each pillar has a minimum eigenvalue of one.

After which, a Multiple Indicators Multiple Causes (MIMIC) model was constructed to specify the relationships between resilience (unobserved latent variable), food security indicators (outcome indicators), and pillars (a set of attributes). The MIMIC model simultaneously estimates the measurement equation (2) and the structural equation (3). However, this was only used as a descriptive tool to establish the relationship between resilience and its components and subsequent regression analysis was used for the causal inference since there is a risk of endogeneity when the latent construct (RCI) and the outcome of interest are jointly determined or when the RCI is correlated with the error term (D'Errico et al. 2018; FAO 2016).

$$\begin{bmatrix} \text{Household dietary diversity} \\ \text{Real per capita food expenditure} \end{bmatrix} = [\Lambda_1, \Lambda_2] \text{ x } [\text{RCI}] + [\varepsilon_1, \varepsilon_2] \quad (2)$$

$$\text{RCI} = \beta_1 \text{UBS} + \beta_2 \text{AST} + \beta_3 \text{SSN} + \beta_4 \text{AC} + \varepsilon_3 \quad (3)$$

The RCI was standardized through a Min-Max scaling transformation as proposed by FAO (2016) and D'Errico et al. (2018) using the formula:

$$\text{RCI}_h^* = \frac{(\text{RCI}_h - \text{RCI}_{min})}{(\text{RCI}_{max} - \text{RCI}_{min})} \text{ x } 100 \quad (4)$$

Where h represents the h^{th} household.

Household resilience and food security. To assess how household resilience affects future food security outcomes, a multiple regression model was estimated where the dependent variable, the change in food security (FS) outcome (i.e., change in real per capita food expenditure or dietary diversity index) between 2003 and 2006 (change in $FS_{2003,\,2006}$), was regressed with the RCI and a vector of time-variant household characteristics **X** in 2003 and time-invariant household characteristics **Z**. The linear form and not the log of the outcome variable was used for the change in real per capita food expenditure since the log form excludes the negative changes in real per capita food expenditure in the sample. Shock variables were also included in the analysis to capture their marginal effects on the change in FS outcome. The interaction of RCI and shock variables was also included to capture the marginal effect of the RCI on the future food security status of households impacted by the shocks. Mathematically, the estimated equation is expressed as:

$$\text{change in } FS_{2003,2006} = \alpha + \beta_1 RCI_{h,2003} + \beta_2 \mathbf{S}_{h,2003} + \beta_3 RCI_{h,2003} \text{ x } \mathbf{S}_{h,2003} + \beta_4 \mathbf{X}_{h,2003} + \beta_5 \mathbf{Z}_{2003} + \varepsilon \quad (5)$$

Where **S** is a vector of the shocks that affected the household between 2003 and 2006, $\boldsymbol{\beta}$s are the coefficients of the variables, α is the constant, and ε is the error term. The effect of the lagged resilience capacity estimate ($RCI_{h,2003}$) to the change in food security status of the households between 2006 and 2009 was also examined to check whether the current level of RCI influences long-term food security outcomes and speed of recovery as shown in equation (6). For this part, the sample was restricted to those who experienced a loss in food security outcomes between 2003 and 2006.

$$\text{change in } FS_{2006,2009} = \alpha + \beta_1 RCI_{h,2003} + \beta_2 \mathbf{S}_{h,2003} + \beta_3 RCI_{h,2003} \text{ x } \mathbf{S}_{h,2003} + \beta_4 \mathbf{X}_{h,2003} + \beta_5 \mathbf{Z}_h + \varepsilon \quad (6)$$

Impact of shocks to food security outcomes through household resilience. To determine the separate impact of shocks on household resilience and food security outcomes and understand the dynamics of how shocks affect food security outcomes through household resilience, a two-stage least square (2SLS) regression was employed. An instrumental variable (IV) was used to address endogeneity issues between household resilience and food security since reverse causality may exist between the two wherein a more resilient household tends to be more food secure as it can adapt/adjust well to shocks and stressors. The household's distance to nearest bank was used as an IV for this purpose. Without directly affecting the household's food security, distance to the bank may improve the household's resilience by providing better access to credit and savings. Some caveat still remains, though, with regard to the exclusion restriction since banks are normally located strategically in commercial areas and areas with economic potential. Further, unobservable omitted variables (i.e., abilities of household) and measurement errors may also exist regarding the measure of household resilience capacity itself.

Using the pillars of resilience estimated through FA, Structural Equation Modelling (SEM) was employed to aggregate the resilience indicators and predict the latent variable, RCI. SEM is preferred than FA in this part because it allows correlation among residual errors, which is most likely the case when there is a high probability of intra-dimension correlation (D'Errico and Pietrelli 2017). Since measuring the latent variable, RCI, requires a formative measurement model (not the usual reflective measurement model) given that RCI is caused by the observed variables, one of the formative indicators, UBS, was fixed to have a loading of 1.0 and the error variance for the composite latent variable, RCI, was fixed at 0 (Acock 2013).

In the first stage of 2SLS, the RCI that was estimated using SEM was used as the dependent variable and was regressed with the shock variables ($\mathbf{S}_{h,2003}$), the instrument distance to nearest bank_h, and control variables ($\mathbf{X}_{h,2003}$, $\mathbf{Z}_h$):

$$RCI_{h,2003} = \alpha + \beta_1 \text{distance to nearest bank}_h + \beta_2 \mathbf{S}_{h,2003} + \beta_3 \mathbf{X}_{h,2003} + \beta_4 \mathbf{Z}_h + \varepsilon \quad (8)$$

In the second stage, the estimated $\widehat{RCI}_{h,2003}$ from equation (8) was used as an independent variable to estimate FS outcomes:

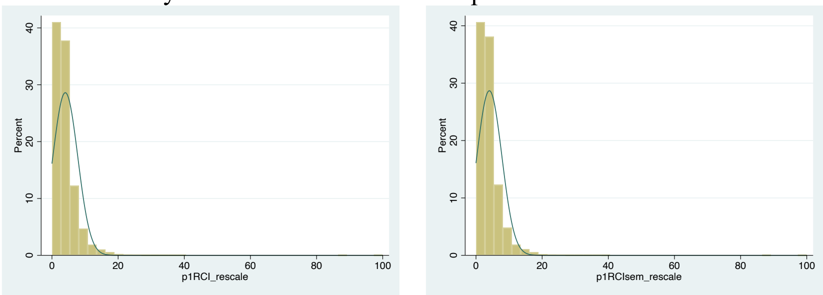
$$FS_{h,2003} = \alpha + \beta_1 \widehat{RCI}_{h,\,2003} + \beta_2 \mathbf{S}_{h,2003} + \beta_3 \mathbf{X}_{h,2003} + \beta_4 \mathbf{Z}_h + \varepsilon \quad (9)$$

The validity of the IV used in the model was tested using the Montiel Olea-Pflueger (MOP) Effective First-Stage F-statistics. However, only the relevance condition was tested since the model is exactly identified (a good IV must satisfy both the relevance and exogeneity conditions, but the latter cannot be tested in this study).

Robustness checks. To determine whether the results are robust, the same models were employed as above using different time periods. For instance, RCI in 2006 was estimated using MIMIC and multiple regression models were ran using the change in real per capita food expenditure and SI between 2006 and 2009 as outcome variables and same regressors measured in 2006 to check for the robustness of models (3) and (7) in Tables 4 and 5. Similarly, RCI in 2006 was estimated using SEM and a 2SLS model was ran using log of real per capita food expenditure and SI in 2006 as outcome variables and the same regressors measured in 2006 to check for the robustness of models (9) to (11) in Table 6. However, due to lack of available data, the robustness of models (4) and (8), which were used to measure the long-term influence of household resilience on food security outcomes, cannot be checked. Further, in estimating RCI in 2006, the total number of household members who are of working age (those aged 15 to 59 years old) was added as one of the observed variables in the AC pillar in order to generate a factor with a minimum eigenvalue of one.

RESULTS AND DISCUSSION

Household resilience. While Filipinos are anecdotally known for being resilient or being able to withstand or recover quickly from natural calamities, when measured, it was found that they generally have low level of household resilience (Fig. 2). From a maximum scale of 100, the mean RCI of households in 2003 was only around four. Less than one percent has a resilience index of more than 50.



(a) RCI (b) RCI2

Figure 2. Histogram of RCI across households, 2003

Among the four pillars, MIMIC estimates show that the UBS pillar contributed the most to their household resilience (Table 2). Transportation and communication, clothing, and education are among the most relevant variables in the UBS pillar (Table 3). This means that better access to these basic services largely contributes to improving the resilience of Filipino households. SSN and AC pillars also have a statistically significant contribution to the RCI estimates, although in relatively lower magnitudes. For SSN, cash receipts/support from abroad contribute substantially to enhancing the resilience of the Filipino households. Remittances from abroad allow them to recover easily from shocks. However, it is important to note that heavy reliance on remittances from abroad make them more vulnerable to global shocks since these global shocks affect real values of remittances.

Table 2. Coefficients of structural and measurement components of the Multiple Indicators Multiple Causes (MIMIC) model of Resilience Capacity Index (RCI)

Structural component		
Use of basic services (UBS)	0.267	***
	(0.073)	
Assets (AST)	0.181	
	(0.116)	
Social safety nets (SSN)	0.017	***
	(0.004)	
Adaptive capacity (AC)	0.124	***
	(0.016)	
Measurement component		
Per capita food expenditure[(a)]	1.000	
Dietary diversity (in terms of SI)	0.049	***
	(0.002)	

Goodness-of-fit statistics	
Standardized root mean squared residual (SRMR)	0.003
Coefficient of determination (CD)	0.437
Observations	6,042

Notes:
(a) Since the estimated RCI is not anchored to any scale of measurement as it is inherently observed, the coefficient of real per capita food expenditure loading (Λ_1) was set to one, implying that one standard deviation increase in RCI corresponds to one standard deviation increase in real per capita food expenditure (D'Errico et al. 2018; FAO 2016).
(b) In parenthesis are the standard errors; ***p<0.01

Table 3. Household resilience structure: absolute correlation of variables by pillar

UBS	
Infrastructural index	0.4277
Transportation and communication*	0.8698
Education*	0.7038
Medical care	0.3059
Clothing	0.8507
AST	
Wealth index*	0.6079
Interest earned*	0.6125
Dividend	0.2264
Profit from stocks*	0.6617
Winning from gambling	0.0333
Savings/business equity	0.2658
Backpay and proceeds from insurance	0.036
Other receipts (excl. loans and withdrawals)	0.1605
Inheritance	0.0171
Rental value of house*	0.8037
SSN	
Cash receipts/support from abroad*	0.8958
Cash receipts/support from domestic sources	0.1822
Total received as gifts	0.4071
Pension and retirement benefits	0.3352
Loans from other families	0.1473
AC	
Income diversification index	-0.2181
HH job/business indicator	0.0472
No children in the family (<15 years old)	0.0359

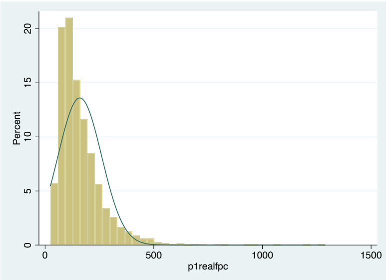
HH education (= 1 if at least HS grad)	0.1644
Number of family members employed for pay*	0.8391
Income earners' share*	0.7383
Savings indicator	0.2558
Wife employment*	0.6336

Note:
(a) The most relevant variables by pillar are denoted by asterisk (*).

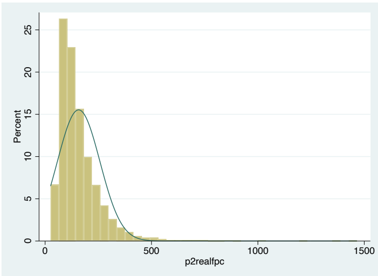
Ironically, income diversification index has a negative correlation with AC. It could be explained by the fact that some economic activities have negative correlations with each other (i.e., transportation and fishing, crop gardening and manufacturing, forestry and wholesale and retail, etc.).

Meanwhile for AC, the number of family members employed for pay, income earners' share, and wife's employment are the most important variables. A greater number of employed household members allows households to adapt well and better cope with shocks.

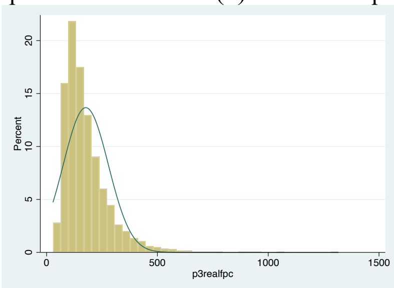
Food security status. In terms of food security status, there are generally lower levels of real per capita food expenditure across households across the three-year period but generally higher levels of dietary diversity (Figs. 3 and 4). With a maximum value of one, the mean SI of households in 2003 is 0.753. However, the mean values of SI declined to 0.718 from 2003 to 2009. This somewhat shows that while real per capita food expenditure is generally low, Filipino households maintain a generally diverse diet. To check whether SI similarly captures the dietary diversity condition of the household, the HDDS of the households in the sample was also computed using the formula: HDDS = sum of food groups consumed (INDDEX Project 2018). Using HDDS, with a maximum score of seven, the mean HDDS of households in 2003 is 6.89, 6.90 in 2006, and 6.91 in 2009, indicating high diversity in the diet.



(a) Annual real per capita food expenditure in 2003

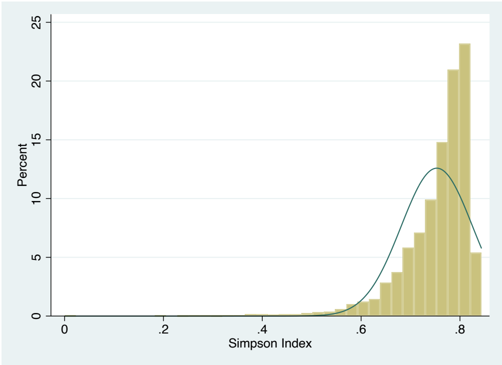


(b) Annual real per capita food expenditure in 2006

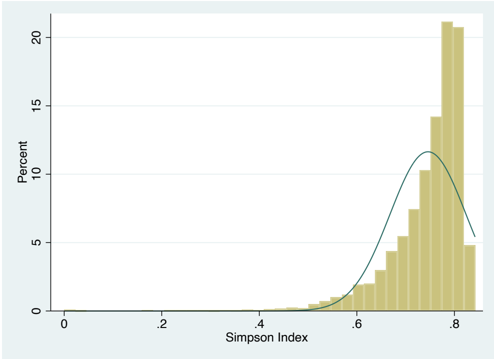


(c) Annual real per capita food expenditure in 2009

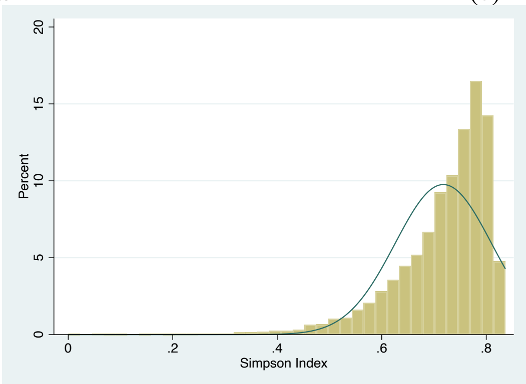
Figure 3. Distribution of annual real per capita food expenditure (in hundred PhP) in 2003, 2006, and 2009



(a) 2003 SI



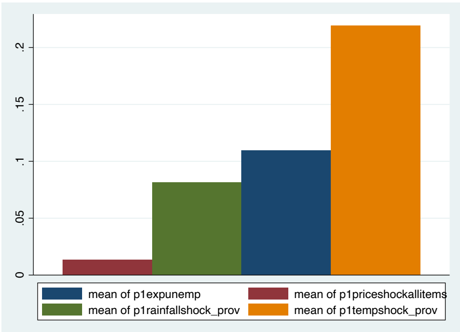
(b) 2006 SI



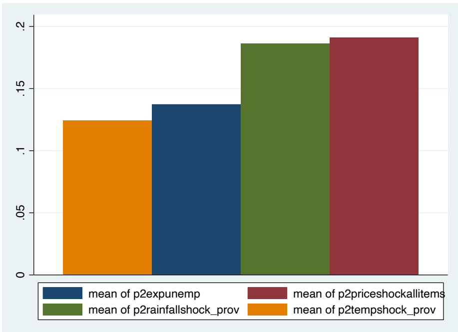
(c) 2009 SI

Figure 4. Household dietary diversity (measured in terms of SI) in 2003, 2006, and 2009

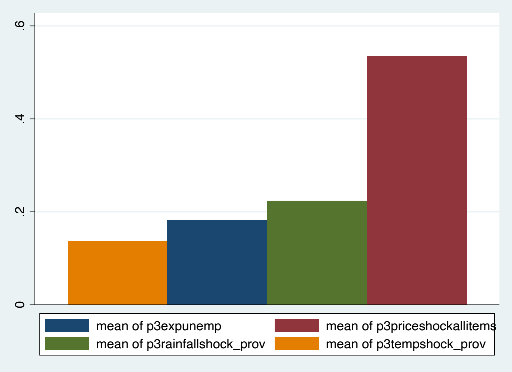
Exposure to shocks. Shocks ultimately affect household's food security status. The idea is that when households experience a shock at time *t*, they become more vulnerable at present and depending on how fast they recover, their future welfare may also be reduced. Based on the data, the most common shock experienced by households in 2003 was extreme temperature, followed by experienced unemployment of a family member (Fig. 5). Price shocks were the least experienced by the households during this period. However, this was reversed in 2006 and 2009. In 2006 and 2009, price shock became the most common shock experienced by the households and a higher number of households were exposed to this shock which may be due to the global financial crisis around this time.



(a) mean exposure to various shocks in 2003



(b) mean exposure to various shocks in 2006



(c) mean exposure to various shocks in 2009

Figure 5. Mean household exposure to various shocks in 2003, 2006, and 2009

Empirical results. Tables 4 and 5 show empirical evidence on the effect of household resilience to future food security outcomes. Models (1) and (5) show how current level of household resilience affects future short-term food security outcomes without controlling for the shock variables and their interaction with the resilience estimate; models (2) and (6) control for the shock variables; models (3) and (7) control for the shocks and include its interaction term with the resilience estimate to assess whether higher household resilience dampens the impact of the shock on future short-term food security outcomes; and models (4) and (8) determine whether current level of household resilience affects long-term food security outcomes and whether it is a significant factor for recovery. Further, models (4) and (8) assess whether shocks have lagged and long-term impacts on food security outcomes. Models (1) to (3) in Table 4 and models (5) to (7) in Table 5 include all the samples in the dataset while models (4) and (8) restrict the sample to those who experienced a loss in food security outcomes between 2003 and 2006.

Table 4. Relating changes in real per capita food expenditure and household resilience (FAO-RIMA II approach)

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
VARIABLES	**Difference in real per capita food expenditure b/w 2003 and 2006**	**Difference in real per capita food expenditure b/w 2003 and 2006**	**Difference in real per capita food expenditure b/w 2003 and 2006**	**Difference in real per capita food expenditure b/w 2006 and 2009 (*Recovery indicator*)**
RCI	4.667***	4.639***	5.537***	4.059***
	(0.724)	(0.722)	(0.787)	(0.950)
Log of real per capita food expenditure in 2003	-87.01***	-87.00***	-87.71***	
	(3.555)	(3.545)	(3.387)	
Experienced unemployment		-0.527	3.844	-12.43
		(3.181)	(5.097)	(12.48)
Temperature shock		-0.834	6.644	0.888
		(2.608)	(4.583)	(6.436)
Rainfall shock		3.137	12.38	-16.23**
		(4.308)	(8.308)	(7.878)

VARIABLES	Model (1) Difference in real per capita food expenditure b/w 2003 and 2006	Model (2) Difference in real per capita food expenditure b/w 2003 and 2006	Model (3) Difference in real per capita food expenditure b/w 2003 and 2006	Model (4) Difference in real per capita food expenditure b/w 2006 and 2009 (*Recovery indicator*)
Price shock		-21.33**	-19.25	54.17***
		(8.504)	(11.84)	(12.63)
Experienced unemployment x RCI			-0.888	1.838
			(1.165)	(3.004)
Temperature shock x RCI			-1.731	-0.595
			(1.184)	(1.459)
Rainfall shock x RCI			-2.464	-0.485
			(2.271)	(1.705)
Price shock x RCI			-0.612	-11.04***
			(3.126)	(3.796)
Log of real per capita food expenditure in 2006				-37.94***
				(5.009)
Constant	827.2***	825.4***	829.5***	404.8***
	(34.36)	(34.47)	(33.09)	(47.59)
F-statistics				
(a) Shocks = 0		1.73	2.62	6.51
		(p< 0.14)	(p< 0.033)	(p<0.000)
(b) Shocks x RCI = 0			1.53	2.22
			(p<0.191)	(p<0.064)
Controlling for HH characteristics	Yes	Yes	Yes	Yes
Controlling for regional variations	Yes	Yes	Yes	Yes
Observations	6,104	6,104	6,104	3,042
R-squared	0.177	0.177	0.180	0.067

Notes:

(a) In parentheses are the robust standard errors; *** p<0.01, ** p<0.05, * p<0.1
(b) All models were tested for multicollinearity (mean variance inflation factor < 10).
(c) Except for the log of real per capita food expenditure in 2006, all the regressors are at time t=2003.

Table 5. Relating changes in household dietary diversity (SI) and household resilience (FAO-RIMA II approach)

Variables	Model (5) Difference in SI b/w 2003 and 2006	Model (6) Difference in SI b/w 2003 and 2006	Model (7) Difference in SI b/w 2003 and 2006	Model (8) Difference in SI b/w time 2006 and 2009 (*Recovery indicator*)
RCI	0.00317***	0.00318***	0.00366***	0.00341***
	(0.000361)	(0.000373)	(0.000326)	(0.000521)
SI in 2003	-0.689***	-0.689***	-0.692***	

Variables	Model (5) Difference in SI b/w 2003 and 2006	Model (6) Difference in SI b/w 2003 and 2006	Model (7) Difference in SI b/w 2003 and 2006	Model (8) Difference in SI b/w time 2006 and 2009 (*Recovery indicator*)
	(0.0234)	(0.0232)	(0.0230)	
Experienced unemployment		0.00488*	0.0104***	0.00883
		(0.00266)	(0.00396)	(0.00703)
Temperature shock		0.00858***	0.0128***	-0.00739
		(0.00243)	(0.00341)	(0.00606)
Rainfall shock		-0.000690	-0.00499	-0.00567
		(0.00407)	(0.00595)	(0.00787)
Price shock		-0.0170**	-0.0522***	-0.0251*
		(0.00796)	(0.0166)	(0.0137)
Experienced unemployment x RCI			-0.00116**	-0.000651
			(0.000519)	(0.000938)
Temperature shock x RCI			-0.000980**	0.00171*
			(0.000442)	(0.000891)
Rainfall shock x RCI			0.00107	0.00242**
			(0.000853)	(0.00118)
Price shock x RCI			0.0116***	-0.000105
			(0.00433)	(0.00464)
SI in 2006				-0.620***
				(0.0370)
Constant	0.538***	0.538***	0.538***	0.462***
	(0.0191)	(0.0192)	(0.0191)	(0.0314)
F-statistics				
(a) Shocks = 0		5.51 (p<0.000)	8.74 (p<0.000)	1.72 (p<0.144)
(b) Shocks x RCI = 0			5.25 (p<0.000)	2.21 (p< 0.065)
Controlling for HH characteristics	Yes	Yes	Yes	Yes
Controlling for regional variations	Yes	Yes	Yes	Yes
Observations	6,103	6,103	6,103	3,310
R-squared	0.313	0.316	0.318	0.315

Notes:

(a) In parentheses are the robust standard errors; *** p<0.01, ** p<0.05, * p<0.1
(b) All models were tested for multicollinearity (mean variance inflation factor < 10).
(c) Except for the SI in 2006, all the regressors are at time t=2003.

Empirically, regression results show that higher household resilience significantly improves future food security status. An improvement in household resilience significantly increases future real per capita food expenditure by around PhP554 (see Model 3 in Table 4; Model 3 is the preferred model since it controlled for the shock and interaction of shock and resilience bias), equivalent to about six percent of the annual per capita food threshold in the Philippines in 2006 (PSA 2016), and future household dietary diversity (Table 5). The results are consistent in all the models in terms of the signs of the coefficients and the significance level.

Restricting the sample to those who experienced a decline in real per capita food expenditure and household dietary diversity, models (4) and (8) in Tables 4 and 5 show that the lagged RCI (RCI in 2003) is a significant factor for recovery. This also implies that the current level of household resilience can influence even longer than two periods of food security status (long-term food security). Based on model (4), those who experienced a decline in their real per capita food expenditure between time 2003 and 2006 were able to recover about PhP406 in their real per capita food expenditure per unit increase in their level of household resilience, holding other factors constant.

Current level of dietary diversity and real per capita food expenditure also significantly affect future food security outcomes (Tables 4 and 5). However, the signs of their coefficients are negative. According to D'Errico et al. (2018), this may reflect the fact that a household with higher initial levels of food security may lessen its food intake without having to compromise its survival; whereas those with lower initial levels of food security cannot decrease much of its food intake since it may put their survival at risk. The results are also robust based on the robustness checks.

Impact of shocks on food security outcomes. Looking at the impact of shocks, it was found that in terms of real per capita food expenditure, the impact of covariate shocks on real per capita food expenditure was not immediate but lagged. The coefficients of the rainfall and price shocks that occurred in 2003 are not significant in models (2) and (3) but are significant in model (4) (Table 4). The lagged impact of rainfall shock in 2003 on the change in real per capita food expenditure between 2006 and 2009 was negative, indicating that those who experienced this shock in 2003 and experienced a reduction in their real per capita food expenditure between 2003 and 2006 have even worsened food security outcome in the succeeding period (Model 4). The negative impact of rainfall shock in 2003 translates to a reduction of about PhP1,623 in annual real per capita food expenditure between 2006 and 2009 (equivalent to 14% of the annual per capita food threshold in 2009; annual per capita food threshold in 2009 = PhP11,780 (PSA 2016)).

In addition, the price shock in 2003 also has a lagged impact on the change in real per capita food expenditure between 2006 and 2009. However, its coefficient is positive, that is, an increase of about PhP5,417 in annual real per capita food expenditure between time 2006 and 2009 for those who experienced this shock in 2003 and experienced a reduction in real per capita food expenditure between 2003 and 2006 (Model 4). Nevertheless, this might just reflect their attempt to recover the loss incurred in real per capita food expenditure from the price shock experienced in the previous period (this is equivalent to about 46% of the annual per capita food threshold in 2009). When interacting with the lagged RCI, the sign of its coefficient became negative, which could be because households with higher RCI tend to cope up better in the presence of shocks, so the cost of recovery is lower.

In terms of household dietary diversity, it was found that both idiosyncratic shock and covariate shocks have a significant impact to future household dietary diversity but only in the short term (see Model 7; Model 7 is the preferred model since it controlled for the shock and interaction of shock and resilience bias). Contrary to expectation, the direction of the impact of the unemployment of a family member is positive. There could be several possible explanations. First, it could be that those who have experienced the shock in 2003 may have recovered already in 2006—implying that the effect of this shock to household's dietary diversity is short-lived. Second, the unemployment of a family member may just be a temporary unemployment. And third, the unemployed family member may be the one who is in-charge with the food preparation (i.e., wife) which might explain why the sign of the interaction term of the shock and RCI estimate is negative (Model 7). That is, reduced adaptive capacity but better dietary diversity since the unemployed family member has more time to prepare for the food of the household.

As for the climatic shocks, its impact to household dietary diversity is significant in the short-term (Models 6 and 7) and in the long-term when interacted with the lagged RCI estimate (Model 8). However, the signs of the coefficients of the impact of the shock in the short term vary. Aggarwal (2021) noted that higher consumption should be interpreted as a 'cost of adaptation' rather than an improvement in living standards if it is a response to climatic shocks (i.e., an increase in food consumption due to heat stress). Also, when the climatic shocks interacted with the RCI estimate, the sign of the coefficient became negative (Model 7). The result is robust based on the robustness checks. If the increase in dietary diversity is interpreted as a 'cost of adaptation', the negative sign of the interaction term of the climatic shock and RCI estimate would mean that a higher level of household resilience reduces the cost of adaptation. In the long term, however, the lagged interaction term of the climatic shock and RCI estimate have positive signs which may indicate that those who experienced climatic shocks in 2003 and suffered a dietary diversity loss between 2003 and 2006 may have recovered between 2006 and 2009 due to their higher resilience capacity (Model 8).

With regard to price shock, it was found that its impact on household dietary diversity is only short. Its coefficient and the coefficient of its interaction term with RCI estimate are significant in model (7) but not in model (8) based on the joint hypothesis test. The price shock per se has a negative impact on household dietary diversity but when interacted with RCI estimate, the sign of its coefficient became positive. This might be indicative of the fact that higher level of household resilience allows the household to adapt better in the presence of a shock (if not speeds up their recovery). The impact of price shock on household dietary diversity is relatively high in magnitude (in absolute terms) compared to the impact of the other shocks.

Expounding resilience as a pathway to food security. The first-stage regression of the 2SLS model (Table 6) shows that price shock has a large impact (in absolute terms) on household resilience. The direction of its impact may be negative when the increase in prices of services decreases their use of basic services such as transportation and communication, clothing, education, and medical care but may also be positive (in the robustness check, the coefficient of the price shock is 0.743 and is significant at 1% alpha) when the increase in cost of goods and services stimulates them to expand their social networks (which is also another dimension of household resilience) to better cope up with the price shock (i.e., borrowing resources from neighbors who are not much affected of the shock/friends/distant relatives, resource-sharing/pooling, etc.). However, it is unclear whether idiosyncratic shock and climatic shocks have a significant impact on household resilience per se since the results are not robust based on the robustness checks. However, the lagged impact of rainfall shock in 2003 on the future real per capita food expenditure between 2006 and 2009 may indicate that rainfall shock impacts future real per capita food expenditure through household resilience (Model 4 in Table 4).

Table 6. Impact of shocks to food security outcome through household resilience (2SLS models)

	First-stage regression	**2SLS**	**2SLS**
VARIABLES	**Model (9) RCI2 in 2003**	**Model (10) Log of real per capita food expenditure in 2003**	**Model (11) SI in 2003**
Distance to nearest bank	-0.00340*** (0.000598)		
$\widehat{RCI}2$		0.173*** (0.0260)	-0.0216*** (0.00783)

	First-stage regression	2SLS	2SLS
Experienced unemployment	-0.103	-0.00148	-0.00360
	(0.216)	(0.0329)	(0.00587)
Temperature shock	-0.234*	0.0199	-0.0106**
	(0.133)	(0.0215)	(0.00445)
Rainfall shock	-0.526***	0.0166	-0.00781
	(0.195)	(0.0327)	(0.00736)
Price shock	-1.491***	0.131**	-0.0638***
	(0.314)	(0.0656)	(0.0168)
Constant	2.095***	9.615***	0.841***
	(0.290)	(0.0689)	(0.0186)
F-statistics			
Shocks = 0	8.42	4.26	15.68
	(p<0.000)	(p<0.372)	(p<0.004)
Controlling for HH characteristics	Yes	Yes	Yes
Controlling for regional variations	Yes	Yes	Yes
Observations	6,222	6,222	6,221
R-squared	0.216	0.201	

Notes:
(a) In parentheses are the robust standard errors; *** p<0.01, ** p<0.05, * p<0.1
(b) Testing for instrument validity, the first-stage F-statistic = 84.66 is greater than the rule of thumb (10). Further, using MOP Effective First-Stage F-statistics, the models are acceptable when there could be 10% bias in estimated coefficients in the worst-case scenario. MOP Effective F-statistics of models (10) and (11) is 32.262.
(c) All the regressors are at time t=2003.

Further, even after removing the impact of the shocks on RCI itself, it was found that RCI still has a significant impact on current food security outcomes, which is in line with the recent study of Egamberdiev et al. (2023). However, the direction of its impact varies depending on the outcome variable. For the log of current real per capita food expenditure, its impact is positive as expected. Current real per capita food expenditure is expected to increase by 17.3 percent with an improvement in the level of household resilience (Model 10). In contrast, the opposite is true for the current household dietary diversity, implying that improving household resilience tends to worsen household dietary diversity in the very short term (Model 11). The reason could be that in an attempt of the household to be more resilient amidst shocks, household dietary diversity may be sacrificed in the very short-term (although a higher current level of household resilience translates to better future household dietary diversity as discussed in the earlier section of this paper). This is also supported by D'Souza and Jolliffe (2016) wherein they noted that as a response to price shocks or negative shocks, households face some trade-offs to cope up in the short-term—rather than reducing calories, they adjust the type/composition of foods they ate (especially those whose caloric intake is already at the least). The result is robust based on the robustness checks.

Resilience as a pathway, it was found that price shock affects real per capita food expenditure only indirectly through household resilience as shown in models (9) and (11) (Table 6). In model (11), price shock negatively affects household resilience but do not have direct significant impact on current log of real per capita food expenditure based on the joint hypothesis test (Model 10). This might explain why its impact on the future real per capita food expenditure is lagged, as discussed in the earlier section of this paper. The results are robust based on the robustness checks.

With regard to dietary diversity, it is not clear on whether climatic shocks have indirect impact (through household resilience) on household dietary diversity since the result is not robust based on the robustness checks, but it does have a direct impact (i.e., temperature shock in Model 11). Further, it is not certain on whether price shock directly affects dietary diversity directly since the result is not robust based on the robustness checks although its indirect impact through household resilience is clear based on 2SLS models (Model 9). If climatic and price shocks are found to have both direct and indirect impacts on household dietary diversity through household resilience, the impacts of these shocks may have multiplier effects on the households' future dietary diversity.
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In terms of idiosyncratic shock, it is not clear on whether this type of shock affects household dietary diversity directly, indirectly, or both since the result is not robust based on the 2SLS models (i.e., in Table 6, the coefficients of experienced unemployment are not significant in models (9) to (11) but in the robustness checks, its coefficient is significant in the first-stage regression and in the 2SLS model using SI as the outcome variable). However, since it was found in the earlier section of this paper that the experienced unemployment shock has a significant impact on future short-term household dietary diversity, it may be that the difference in the results is due to the difference in the timing of the occurrence of the shock and the time of the survey.

CONCLUSION, POLICY IMPLICATIONS, AND RECOMMENDATIONS

The evidence suggests that improving the current level of household resilience improves future food security outcomes both in terms of real per capita food expenditure and household dietary diversity, and facilitates the recovery of the households who suffered losses in real per capita expenditure and dietary diversity.

However, while higher current level of household resilience improves current real per capita food expenditure, this does not necessarily translate to higher current household dietary diversity. Although the possibility of endogeneity issues may have also affected the results of the study, this could also reflect how households cope up in the short-term to negative shocks—they might sacrifice short-term diet diversity in response to the shocks. This kind of short-term coping mechanism may have long-term consequences on the household's health and human capital development, especially on households who are already suffering from mineral and vitamin deficiencies—further reductions in nutrition may be detrimental or may lead to malnutrition. Hence, it may be important for the government or other institutions involved to educate households on cheaper food alternatives that do not sacrifice diversity in the type of diet.

Understanding resilience as a pathway to food security, it was found that shocks may affect food security outcomes directly, indirectly, or both. When shocks affect both household resilience and food security outcomes, the impact of the shocks can have some sort of multiplier effects to future food security status. Without providing some system that could mitigate the negative impact of shocks to household resilience and/or interventions that could increase household resilience, the state of food security of the household in the future may be much worsened due to the negative multiplier effects, which could further trap vulnerable and poor households to poverty. Government institutions aiming to improve household resilience may prioritize the enhancement of the most relevant pillars (UBS, SSN, and AC) to make the greatest impact. For the UBS pillar, this would mean focusing on improving the quality and access to basic services on transportation and communication, education, and clothing. There might also be a need to improve other SSN factors, such as their access to/availment of pension and retirement benefits so that households will not be heavily reliant on remittances from abroad. Improving savings behavior of households may also improve the structure of their AC pillar and may cushion the households from temporary unemployment or job loss.

Aside from reducing the negative impact of shocks and enhancing household resilience, reducing household's vulnerability to climatic shocks (i.e., by promoting adaption of climate change adaptive technologies) may also be necessary as well as providing mechanism to stabilize prices/reduce price volatility especially food price as it has a relatively large magnitude of impact (in absolute terms). This is especially critical among the rural and agricultural households who are mostly affected by covariate shocks such as climatic shocks and price shocks.

In contrast, some shocks (i.e., experienced unemployment on household dietary diversity) are found to have short-term impacts that do not significantly affect long-term future food security outcomes. Shocks may also have lagged impacts to future food security outcomes because their impacts are indirectly through household resilience (i.e., price shocks on real per capita food expenditure). In addition, we found that some shocks (i.e., price shocks) may enable households to build capacities and expand social networks which improve their household resilience rather than worsening it. However, it is still noteworthy to further understand the coping mechanisms of households and formulate policies that take into consideration households' behavior amidst shocks since households may face trade-offs not only in short-term dietary diversity but also in other non-food activities (i.e., increasing school dropouts and rising child labor, increasing debt, etc.) which could perpetuate intergenerational transmission of poverty.

Nevertheless, the complexities of the direct and indirect effects and the short-term and lasting effects of shocks to food security outcomes make this study more relevant in formulating policies that aim to address short-term and long-term food insecurity.

ACKNOWLEDGMENT

The authors would like to thank the government offices of PSA and PAG-ASA for providing the necessary data needed for the analysis, Prof. Yoko Kijima of GRIPS for the valuable feedback that enhanced the credibility of this research output, and the following people for their guidance: Ricxie Maddawin, Aika Maddawin, and Laarni Revilla. This study is the master's thesis of the main author and was financially supported by the Asian Development Bank-Japan Scholarship Program (ADB-JSP) and UPLB.

REFERENCES CITED

Acock A.C. 2013. Discovering structural equation modeling using Stata. Texas: Stata Press.

Aggarwal R. 2021. Impacts of climate shocks on household consumption and inequality in India. Environment and Development Economics. 26(5-6): 488-511. doi:10.1017/S1355770X20000388

Alpizar F., M. Saborio-Rodriguez, R. Martinez-Rodriguez, B. Viguera, R. Vignola, T. Capitan, and C.A. Harvey. 2020. Determinants of food insecurity among smallholder farmer households in Central America: Recurrent versus extreme weather-driven events. Regional Environmental Change. 20: 22. https://doi.org/10.1007/s10113-020-01592-y

Angeles-Agdeppa I. 2002. Food and nutrition security and poverty alleviation in the Philippines. Asia Pacific Journal of Clinical Nutrition. 11: S335-S340. https://doi-org.grips.idm.oclc.org/10.1046/j.1440-6047.11.s13.1_11_s1.x

Ansah I.K., C. Gardebroek, and R. Ihle. 2019. Resilience and household food security: A review of concepts, methodological approaches and empirical evidence. Food Security. 11:1187–1203. https://doi.org/10.1007/s12571-019-00968-1

Bayudan-Dacuycuy C. and J.A. Lim. 2013. Chronic and transient poverty and vulnerability to poverty in the Philippines: Evidence using a Simple Spells Approach." Soc Indic Res. 118:389-413. DOI 10.1007/s11205-013-0409-5

Bruck T., M. D'errico, and R. Pietrelli. 2018. The effects of violent conflict on household resilience and food security: Evidence from the 2014 Gaza conflict. World Development. 119: 203–223. https://doi.org/10.1016/j.worlddev.2018.05.008

Bündnis Entwicklung HILFT/ IFHV. 2023. World risk report 2023. Berlin: Bündnis Entwicklung Hilft.

Davis, B., H. Sudhanshu, M.R. Arranz, M. Stampini, and P. Winters. 2005. An impact evaluation of agricultural subsidies on human capital development and poverty reduction: Evidence from Rural Mexico. Working Paper: OVE/WP-03/05. https://publications.iadb.org/publications/english/document/An-Impact-Evaluation-of-Agricultural-Subsidies-on-Human-Capital-Development-and-Poverty-Reduction-Evidence-from-Rural-Mexico.pdf

D'Errico M., D. Romano, and R. Pietrelli. 2018. Household resilience to food Insecurity: Evidence from Tanzania and Uganda. Food Security. 10:1033–1054. https://doi.org/10.1007/s12571-018-0820-5

D'Errico, M. and R. Pietrelli. 2017. Resilience and child malnutrition in Mali. Food Security. 9: 355-370. DOI 10.1007/s12571-017-0652-8

Do, T.T, H.C. Le, V.C. Nguyen, H.T. Nguyen, T.T. Phung, and D.T. Phung. 2013. Impact assessment of poverty reduction programs of Ho Chi Minh City in Vietnam. MPRA Paper 52876, University Library of Munich, Germany. https://mpra.ub.uni-muenchen.de/52876/

Drescher, L.S., S. Thiele, and G.B. Mensink. 2007. A new index to measure healthy food diversity better reflects a healthy diet than traditional measures. The Journal of Nutrition. 137(3):647-51. doi: 10.1093/jn/137.3.647

D'Souza, A. and D. Jolliffe. 2016. Coping with food price shocks in Afghanistan. In Food Price Volatility and Its Implications for Food Security and Policy, edited by M. Kalkuhl, J. von Braun, and M. Torero. Springer, Cham. https://doi.org/10.1007/978-3-319-28201-5_21

Egamberdiev, B., I. Bobojonov, L. Kuhn, and T. Glauben. 2023. Household resilience capacity and food security: Evidence from Kyrgyzstan. Food Security. 15: 967-988. https://doi.org/10.1007/s12571-023-01369-1

FAO, IFAD, UNICEF, WFP and WHO. 2024. The state of food security and nutrition in the world 2024. Financing to end hunger, food insecurity and malnutrition in all its forms. Rome, FAO. https://doi.org/10.4060/cd1254en

FAO [Food and Agriculture Organization]. 2016. RIMA-II (Resilience Index Measurement and Analysis-II). Food and Agriculture Organization. https://www.fsinplatform.org/sites/default/files/resources/files/a-i5665e.pdf

Fernandez-San Valentin, C. and J.G. Berja Jr. 2012. Philippine food and nutrition security atlas. World Food Programme. https://documents.wfp.org/stellent/groups/public/documents/ena/wfp246455.pdf

Haile, D., A. Seyoum, and A. Azmeraw. 2022. Food and nutrition security impacts of resilience capacity: Evidence from rural Ethiopia. Journal of Agriculture and Food Research. 8: 100305. https://doi.org/10.1016/j.jafr.2022.100305

INDDEX Project. 2018. Data4Diets: Building blocks for diet-related food security analysis. Tufts University, Boston, MA. https://inddex.nutrition.tufts.edu/data4diets. Accessed on 18 July 2022.

Mina, C.D. and K.S. Imai. 2017. Estimation of vulnerability to poverty using a multilevel longitudinal model: Evidence from the Philippines. The Journal of Development Studies. 53:12, 2118-2144, DOI: 10.1080/00220388.2016.1265942

Nahid, N., F. Lashgarara, S.J. Farajolah Hosseini, S.M. Mirdamadi, and K. Rezaei-Moghaddam. 2021. Determining the resilience of rural households to food insecurity during drought conditions in Fars Province, Iran. Sustainability. 13: 8384. https://doi.org/10.3390/ su13158384

Nithya, D.J. and R.V. Bhavani. 2016. Do dietary diversity indices reflect the nutritional status of school aged children? The Indian Journal of Nutrition and Dietetics. 53(4): 405-416. 10.21048/ijnd.2016.53.4.8399.

Ouadika, S.B. 2020. Health shocks and vulnerability to poverty in Congo." Humanities and Social Sciences Communications. 7:182. https://doi.org/10.1057/s41599-020-00674-w

PSA [Philippine Statistics Authority]. 2016. Annual per capita food threshold, subsistence incidence and magnitude of subsistence poor population, by region and province: 1991, 2006, 2009, 2012 and 2015. https://psa.gov.ph/poverty-press-releases/nid/63819

Verger, E.O., A. Le Port, A. Borderon, G. Bourbon, M. Moursi, M. Savy, F. Mariotti, and Y. Martin-Prevel. 2021. Dietary diversity indicators and their associations with dietary adequacy and health outcomes: A systematic scoping review. Advances in Nutrition. 12(5):1659-1672. doi: 10.1093/advances/nmab009.

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