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# Resilience capacity, food consumption and socio-economic status in Zimbabwe

## Advanced policy-focused poverty analysis in Zimbabwe

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# Introduction

Climatic, natural, health and economic shocks are ravaging the world and are on the increase (d'Errico and Di Giuseppe, 2018; Muricho et al., 2019). Shocks such as health pandemics, drought, cyclones, floods, food price spikes and conflicts can have far reaching and negative consequences on individuals, households and communities, affecting their health, income, food consumption, nutrition, and may subsequently manifest widespread death and poverty (Béné et al., 2016a; d'Errico and Di Giuseppe, 2018). Resilience, which refers to the ability of individuals, households and communities to withstand shocks and maintain welfare (Smith and Frankenberger, 2018), has gained tremendous attention in recent literature (Béné et al., 2016b; Béné et al., 2017; d'Errico et al., 2018; Smith and Frankenberger, 2018; Ado et al., 2019). There is a growing body of evidence, demonstrating that resilience capacities improve household welfare in the presence of shocks (d'Errico and Pietrelli, 2017; d'Errico et al., 2018; Smith and Frankenberger, 2018). d'Errico et al. (2018) highlighted that resilience capacity reduced food insecurity in the presence of shocks in Uganda and Tanzania. In another study conducted in Mali, d'Errico and Pietrelli (2017) found that higher resilience capacity was associated with lower probability of child malnutrition.

Recently, a number of international organizations (e.g. FAO, UNDP, WFP), Non-Governmental Organizations (e.g. Care International, Oxfam, Mercy Corps) and donors (e.g. EU, DFID, USAID) have now started supporting resilience building interventions to improve household welfare and reduce dependency syndrome (Béné et al., 2016b; Béné et al., 2017; d'Errico and Di Giuseppe, 2018). Zimbabwe is an interesting case study, given that from 2015 onwards, DFID, EU and WFP have started implementing rural and urban resilience projects to improve household and community welfare (UNDP, 2019).

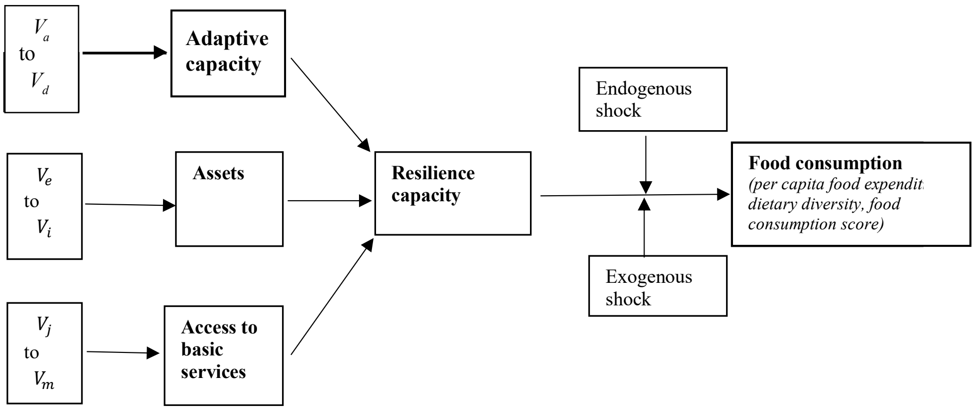
Despite the increased attention to resilience, the link between resilience capacity and household food consumption has not been fully and extensively analysed in the context of Zimbabwe. Resilience capacities are expected to have different welfare effects depending on household socio-economic status, gender, and education of main decision maker among others. Yet, the heterogeneous effects of resilience capacity on food consumption have not been fully analysed and understood. This article addresses the above identified research gaps and contributes to literature in many ways. We analysed the role of resilience capacity as well as individual resilience capacity pillars on food consumption in Zimbabwe. One of the important policy questions is whether resilience capacities and their influence on food consumption differ by household socio-economic status. Hence, we investigated the heterogenous effects of resilience capacity and pillars on food consumption of different socio-economic classes of households. The study findings aim to provide important policy insights on how government and development partners can build household resilience capacities and how to effectively target resilience building interventions in the country.

## Conceptual framework

Resilience is complex and multi-dimensional. Approaches to measure it have relied on objective and subjective methods (Béné et al., 2016b; Ansah et al., 2019; Jones and d'Errico, 2019). One of the objective approaches conceptually views resilience as composed of assets, capital and opportunities (Ansah et al., 2019). Based on these, households with better assets, capital and opportunities are assumed to be resilient compared to their less endowed counterparts. d'Errico and Pietrelli (2017) in their study in Mali, used the objective technique and measured resilience capacity using the three capacities, namely: adaptive capacity (AC), assets (AST) and access to basic services (ABS). More recently, authors have expanded this conceptual framework and treated households as decision making units by defining resilience as composed of three capacities: absorptive, adaptive and transformative capacities (Smith and Frankenberger, 2018; Ansah et al., 2019). Furthermore, the subjective approach relies on external observation or self-assessed judgements to compute a subjectively self-evaluated resilience score (Jones and d'Errico, 2019). Similar to the objective approach, this subjective approach considers resilience to be composed of resilience-related capacities. About nine validated resilience-related capacities and capitals are used and respondents are asked to rate their levels of agreement ranging from strongly agree to strongly disagree (Jones and d'Errico, 2019).

Although resilience can be measured using various approaches, in this article we rely on the conceptual framework utilized by d'Errico and Pietrelli (2017) as discussed above. Our choice is primarily driven by the available variables in the PICES dataset and their applicability to the country context. Figure 1 shows the conceptual framework analysing the link between resilience and food consumption. Resilience is vital for enhancing food consumption and reduction of hunger. It protects and smooth food consumption in the face of shocks and helps individuals and households adapt to changing conditions (d'Errico et al., 2018; Jones and d'Errico, 2019). There is, therefore, need to build and strengthen resilience capacities at the individual, household, and community levels. These capacities include adaptive capacity, assets and access to basic services (d'Errico and Pietrelli, 2017; Ado et al., 2019; Ansah et al., 2019). Adaptive capacity refers to household ability to adapt to changing environment as well as respond to shocks (Smith and Frankenberger, 2018; Ado et al., 2019). For example, diversification of crop, livestock and income sources enhance household adaptive capacity and may decrease the negative effects of a shock on a household (d'Errico and Di Giuseppe, 2018).

***Figure 1. Conceptual framework analysing association between resilience and food consumption. V refers to the variables used to compute the respective capacity.***




Assets are used to cope with shocks and stress. Productive and non-productive assets can be used by households to increase income and smooth consumption during shock periods and are an important ingredient of resilience (Hoddinott, 2006). During shock periods, households might sell assets and protect consumption or they can reduce their consumption and preserve their assets (d'Errico and Di Giuseppe, 2018). Access to basic services improves household resilience by providing important public services that facilitate the household to withstand shocks (Ado et al., 2019). For example, good transport and communication infrastructure reduces transaction costs, improves access to markets and facilitates the faster delivery of farm produce to consumers (Okoye et al., 2016), thereby enhancing food consumption. When these resilience capacities are strengthened and maintained, households will be able to better protect critical investments, food security will be improved and sustained even in the face of recurrent shocks and stresses.

# Methodology

### *Study area*

In order, to understand resilience in the context of Zimbabwe it is important to provide a brief overview of the natural or agro-ecological regions of the country. Each natural region is described in terms of rainfall patterns, crops grown and type of agricultural practices (Musiyiwa et al., 2017). Zimbabwe has five natural regions, which are distinguished by annual rainfall, temperature, agricultural productive potential of the soils, and vegetation. Intensity of farming activities varies across these natural regions (Musiyiwa et al., 2017; ZIMSTAT, 2019). Region one (specialized and diversified intensive farming) receives more than 1000 mm of rainfall per annum. The main agricultural activities include forestry, fruit production and intensive livestock rearing. It covers 7 000 km2 (less than 2 percent of total area of Zimbabwe). Region two (intensive farming) receives between 750-1000 mm of rainfall per annum. It specializes in crop farming and intensive livestock rearing and covers 58 600 km2 (15 percent of total area) (Musiyiwa et al., 2017). Region three (semi-intensive farming) receives between 650-800 mm of rainfall per annum and specializes in livestock rearing, fodder, and cash crops (Musiyiwa et al., 2017). It has marginal production of maize, tobacco, and cotton and covers 72 900 km2 (19 percent of total area). Region four (extensive farming) receives 450-650 mm of rainfall per annum. It specializes in extensive livestock breeding and the cultivation of drought-resistant crops. It covers 147 800 km2 (38 percent of total area). Finally, Region five (semi-extensive farming) receives low and erratic rainfall (below 450mm per annum) which are not suitable even drought-resistant crops. It specializes in extensive cattle and game ranching and covers 104 400 km2 (27 percent of total area) (Musiyiwa et al., 2017; ZIMSTAT, 2019).

## Data

The data used for this article is drawn from the Agricultural Productivity Module (APM) which formed a sub-sample of the Zimbabwe Poverty, Income, Consumption and Expenditure Survey (PICES) of 2017. The APM was collected by Zimbabwe National Statistics Agency in collaboration with Ministry of Agriculture, with funding and technical assistance from the World Bank (ZIMSTAT, 2018, 2019). The PICES utilized a stratified two-stage sampling design and combined random systematic sampling with Probability Proportional to Size to collect information from 32,256 households in all the administrative districts of Zimbabwe. To select the APM sub-sample a two-stage sample design was used. The first stage involved the selection of Enumeration areas (EAs) from the PICES EAs that were in the March, April, and May 2017 sample. The EAs were selected using the Probability Proportional to Size (PPS) sampling method. The measure of size was the number of households enumerated during the 2012 population census. The second stage involved the selection of households from a sample of PICES households using random systematic sampling method. The sample design strategy allowed for representativeness at national level as well as different farming systems. The households were selected using random systematic sampling from EAs in APM Survey. A sample of 8 households per EA was selected from Communal Lands and Resettlement Areas and a census of all PICES households (i.e. 14 households) was taken for EAs in the A1 Farms and the Small-Scale Commercial Farms (SSCF). A reserve of four extra households was selected per EA for replacement purposes. The APM consisted of two interview rounds, post planting and post harvesting. The first round took place after planting during March-May 2017 while the second round took place from September to November 2017. A total of 2552 households from 280 EAs were sampled for the APM survey and these consisted of rural smallholder households engaged in agricultural activities (ZIMSTAT, 2019). Finally, 2282 households from 8 provinces with full information on demographics, food security, assets and agriculture production were used in this article as shown in Table 1.

***Table 1. Total sample used for analysis***

| Province | Total |
|---|---|
| Manicaland | 296 |
| Mashonaland Central | 290 |
| Mashonaland East | 323 |
| Mashonaland West | 296 |
| Matebeleland North | 256 |
| Matebeleland South | 266 |
| Midlands | 252 |
| Masvingo | 303 |
| Total sample | 2282 |

## Measurements

In this section, we show how the resilience pillars and resilience were measured. The choice of variables used to compute each resilience pillar was guided by literature (d'Errico and Pietrelli, 2017; d'Errico et al., 2018; Smith and Frankenberger, 2018; Ado et al., 2019) and the availability of the variables in the dataset.

*Adaptive capacity (AC)*
The variables used included household head education and whether head is employed and earns a wage income. Education and wage earner were measured as a dummy variable of having secondary education and above and whether head is employed respectively. The number of crops grown (ranged from 0 to 13). The number of animals was converted into tropical livestock units (TLU). Conversion factors used were cow, oxen and heifers was 0.7, calves, 0.25, donkey 0.5, sheep/goat, pig, and all chicken/rabbits with 0.1, 0.2 and 0.01, respectively (Maass et al., 2012; Arslan et al., 2015). The TLU ranged from 0 to 40.24 and higher TLU is associated with high livestock numbers and diversification. Principal component analysis was used to construct the household AC index.

*Assets (AST)*
The assets included arable land owned by household in hectares, number of rooms, ownership of mouldboard plough, ox drawn cart and wheelbarrow. The plough, cart and wheelbarrow ownership are binary variables equated to 1 if household owned these and 0 otherwise. The variables are used to compute an AST index using principal component analysis. Households with a high AST index are expected to be more resilient.

*Access to basic services (ABS)*

The variables used to compute ABS index included dummy variables of whether household has access to electricity, any member with a mobile phone and has a hygienic toilet facility. The hygienic facility included a flush toilet. The fourth variable was number of extension topics or subjects that the household was trained on by extension staff using different training methods. A household that have received training on a wider range of agricultural topics is assumed to be more knowledgeable and better able to adopt resilience building interventions.

*Resilience capacity index (RCI)*

The variables used to compute the resilience capacity index included the three above computed indices of resilience pillars: AST, AC and ABS. Principal component analysis was used to compute the AST, AC, ABS and RC indices. More recently authors have used this approach (Smith and Frankenberger, 2018; Ado et al., 2019). An index having a Kaiser-Meyer-Olkin (KMO) statistic greater than or equal to 0.5 are retained. KMO is a measure of sampling adequacy, and values greater than 0.5 indicate that principal component analysis is appropriate (Field, 2013). A positive and significant Bartlett test for sphericity also show that principal component analysis is appropriate (Field, 2013). The first factor with an eigenvalue equal to or greater than 1 is assumed to be our measure of underlying latent variable (Vyas and Kumaranayake, 2006; Field, 2013; Ado et al., 2019). A higher index means that the household has a higher capacity for that specific index.

*Shock*

Drought is the common shock affecting food security of most households in Zimbabwe. Respondents were asked during the survey whether drought affected their food availability, and this was coded yes or no.

*Food consumption*

Household dietary diversity (HDDS): is computed using consumption of twelve food groups (cereals, roots and tubers, nuts and pulses, vegetables, meat and meat products, fish, eggs, fruit, milk and milk products, fats and oil, sugar, spices and condiments) over the past 7 days (Swindale and Ohri-Vachaspati, 2004; Swindale and Bilinsky, 2006; Koppmair et al., 2016; Murendo et al., 2018).

Food Consumption Score (FCS): The food consumption score (FCS) is computed as a composite score based on dietary diversity, food frequency, and relative nutritional importance of different food groups (Kennedy et al., 2010). The FCS is computed using the frequency of consumption of different food groups consumed by a household during the past 7 days before the survey. The assigned weights for each food group are based on energy, protein, and micronutrient densities of each food group. The consumption frequency of eleven food groups except condiments is multiplied by a group assigned nutrient weight, and the resulting values are summed to obtain the FCS (Kennedy et al., 2010).

*Socio-economic status*

Socio-economic status (SES) is commonly measured by either education, income, wealth, or occupational status (Turrell et al., 2003). SES is used to determine a household's social standing and is broken into different categories (e.g., poorest, poor, average, rich and richest) to describe the level a household may fall into (Turrell et al., 2003). Turrell et al. (2003) used separate indicators of occupation, education, and household income to measure socio-economic inequalities on dietary patterns. In this study, we used per capita consumption expenditure to compute five socio-economic quintiles to group households into different poverty profiles. The average per capita consumption expenditures were US$20.92 for poorest income group (quintile 1), US$29.97 for poor income group (quintile 2), US$40.31 for moderate income group (quintile 3), US$56.02 for rich income group (quintile 4) and US$118.28 for richest income group (quintile 5).

## Estimation strategy

Here, we analysed the association between household resilience capacity and food consumption. The relationship between resilience capacity and food consumption accounting for drought shock is expected to be positive, specifically: a higher RCI is expected to improve food consumption. In addition, covariate shocks may affect food consumption (d'Errico and Pietrelli, 2017; d'Errico et al., 2018; Smith and Frankenberger, 2018). The relationship between resilience and household food consumption is estimated through the following regression model:

$$F_i = \alpha + \beta RCI_i + \boldsymbol{\gamma X}_i + \delta S_i + \theta RCI_i S_i + \varepsilon_i$$

where F is the food consumption outcome variable (HDDS and FCS) for household i ; RCI is the resilience capacity index for household i; □ is a vector of other individual and household characteristics; S is the shock variable; ε is the usual error term and α are household fixed-effects. The other characteristics that are included in the model as independent variables are: gender of household head, household size and whether household resides in low rainfall area. To capture agro-ecological variation across households, a dummy variable of low rainfall area that equals one if the household is in natural regions 4 and 5 and zero in natural regions 1, 2 and 3 was used. It is expected that households in lower-rainfall areas are less likely to have higher farm production diversity and productivity and hence lower food consumption than households in higher-rainfall areas. The interaction term between the RCI and the shock variable is included in the model to capture the marginal effect of the RCI on food consumption as the shock intensity increases.

*Regression model estimators*

Our outcome variables are household dietary diversity and food consumption score. These variables are treated as count variables (Sibhatu et al., 2015; Murendo et al., 2018), and are not normally distributed. Count data models are best estimated using poisson regression (Cameron and Trivedi, 2010). Poisson regression assumes equidispersion meaning the mean and variance of the dependent variable are assumed to be equal. Overdispersion, where the conditional variance is greater than the conditional mean is common in many practical applications and using poisson can lead to incorrect standard errors. The ideal approach is to use a goodness of fit test to see if the null hypothesis of equidispersion cannot be rejected to warrant the use of poisson regression (Cameron and Trivedi, 2010). For all household dietary diversity and food consumption score models, the goodness-of-fit chi-squared tests were statistically significant, indicating that the poisson models do not fit reasonably well. Given this, the negative binomial regression which is suitable for over-dispersed data is used for estimating all models (Wooldridge, 2010). The estimated coefficients in negative binomial regression model are interpreted as semi-elasticities, that is a coefficient estimate states by what percentage the outcome variable changes when the explanatory variable changes by one unit (Cameron and Trivedi, 2010; Wooldridge, 2010).

The forgoing notwithstanding, it is important to highlight some of the limitations of this study. Resilience is complex and multidimensional concept whose measurement rely on computation of latent variables based on data reduction techniques. The variables used to proxy this concept have both long and shorter effect periods together and this complicates the inferential analysis. In addition, the food consumption and shock indicators are based on recall and are not immune to the associated recall bias. The study used cross section data which fails to account for seasonality in food consumption.

# Results and discussion

*Descriptive analysis*

The AC, AST, ABS and RCI indices were computed using principal component analysis. The factor loadings for each variable and measures of sampling adequacy are shown in Table 2. The KMO measures of sampling adequacy are greater than 0.5 and the Bartlett tests for sphericity are significant indicating that principal component analysis is appropriate (Field, 2013). The first factors with eigen values greater than one was retained and assumed to measure each index (Field, 2013; Ado et al., 2019).

***Table 2. Factor loadings of variables used to construct resilience pillars and resilience index and model fit***

| Resilience item | Variable | Factor loading | Mean |
|---|---|---|---|
| **Adaptive** | Education (1= head secondary school & above) | 0.12 | 43.8 |
| | Employed (1=head employed) | - 0.16 | 9.8 |
| | Crop diversity (number) | 0.71 | 3.6 |
| | Tropical Livestock Unit | 0.70 | 2.77 |
| | KMO | | 0.51 |
| | Bartlett test: | | 171*** |
| | Eigen value of first component | | 1.19 |
| | Variance of first component | | 29.79% |
| **Assets** | Area (ha) | 0.28 | 2.1 |
| | Rooms (number) | 0.46 | 3.5 |
| | Mould board plough (1=own) | 0.52 | 46.5 |
| | Ox cart (1=own) | 0.51 | 27.6 |
| | Wheelbarrow (1=own) | 0.41 | 30.5 |
| | KMO | | 0.73 |
| | Bartlett test: | | 1617*** |
| | Eigen value of first component | | 2.16 |
| | Variance of first component | | 43.22% |
| **Access to basic services** | Electricity (1=Have electricity) | 0.55 | 49.6 |
| | Mobile phone (1=own) | 0.57 | 40.1 |
| | Toilet (1= hygienic; flush, improved latrine) | 0.46 | 48.3 |
| | Number of extension topics received | 0.40 | 3.0 |
| | KMO | | 0.58 |
| | Bartlett test: | | 215*** |
| | Eigen value of first component | | 1.38 |
| | Variance of first component | | 34.49% |
| **RCI** | AC (Adaptive capacity) | 0.58 | |
| | AST (Assets) | 0.65 | |
| | ABS (Access to basic services) | 0.49 | |
| | KMO | | 0.56 |
| | Bartlett test: | | 941*** |
| | Eigen value of first component | | 1.70 |
| | Variance of first component | | 56.77% |

Results in Table 3 show the descriptive statistics of outcome variables and resilience indices for full sample and differentiated by gender. The gender comparisons are computed using independent sampled t-test. Male headed households had higher dietary diversification, food consumption and resilience compared to their female counterparts, indicating female disadvantages in food consumption and resilience capacity. Interventions that help to build resilience capacities and improve food consumption should be inclusive and include female headed households.

***Table 3. Descriptive statistics for full sample and by gender of household head***

| | Full sample | Min | Max | Male | Female | Differences |
|---|---|---|---|---|---|---|
| HDDS | 5.93 | 1 | 12 | 6.01 | 5.81 | -0.20*** |
| FCS | 23.41 | 1 | 126 | 23.86 | 22.93 | -0.93 |
| RCI | 0 | -2.66 | 4.72 | 0.11 | -0.16 | -0.27*** |
| Adaptive capacity | 0 | -2.26 | 5.61 | 0.05 | -0.07 | -0.12** |
| Assets | 0 | -1.95 | 7.46 | 0.09 | -0.13 | -0.22*** |
| Access to basic services | 0 | -2.26 | 2.84 | 0.10 | -0.15 | -0.25*** |
| Drought | 39.20 | 0 | 1 | 0.38 | 0.41 | 3.0 |
| Household size | 4.88 | 1 | 10 | 5.08 | 4.42 | -0.66*** |
| Low rainfall area | 49.0 | 0 | 1 | 46.0 | 0.54.0 | 8.0*** |
| Observations | 2228 | | | 1388 | 840 | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. Independent samples t-test used to compute differences.

We categorized household into dietary diversity tertiles. Since, there are no universal cut-offs for categorizing households according to their household dietary diversity score, we followed Pauzé et al. (2016) and divided the sample into HDDS tertiles, which are classified as: low (0–5), moderate (6–7) and high (8–10) dietary diversity. Figure 2 shows the proportion of households who have low, moderate, and high dietary diversity by socio-economic class. Results show that poorer households (quintile 1 and 2) had a higher proportion of households with low dietary diversity compared to other classes. As expected, richer income groups (quintile 4 and 5) had higher proportions of households with high dietary diversity. About 18.4% and 28.2% of the households were categorized as having high dietary diversity in quintile 4 and 5, respectively, and thus higher dietary diversity was confined to richer households. About 57.9% and 43.3% of households in the poor income groups, quintile 1 and 2 respectively had low dietary diversity. Therefore, the government, private sector and development agencies should promote nutrition-sensitive interventions to improve dietary diversity in the country, with special focus given to the poorer households.

***Figure 2. Proportion of households who have low, moderate, and high dietary diversity by socio-economic class***

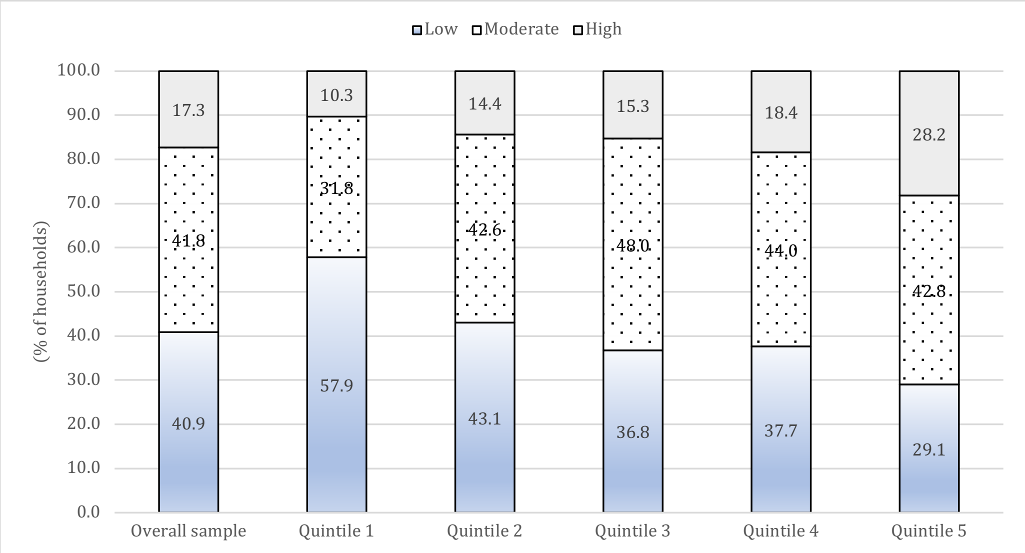



Figure 3 shows the proportion of households who have poor, borderline, and acceptable food consumption by socio-economic class. The thresholds used to determine household food consumption categories were classified as follows: 0-21 (poor), 21.5-35 (borderline) and greater than 35 for the acceptable food consumption category (Kennedy et al., 2010). It was noted that a higher proportion of households (around 57%) had poor food consumption in the overall sample. These results highlight that the greater proportion of sampled households were food insecure. Additionally, the results of the socio-economic classes, shows that poorer income groups (quintile 1 and 2) had a higher proportion of households with poor food consumption compared to other classes. Relatively richer income groups (quintile 4 and 5) had higher proportions of households with acceptable food consumption. About 27.4% and 32.7% of the households in quintile 4 and 5 had acceptable food consumption, respectively. In order to determine food insecurity, we combined poor and borderline food consumption. Our findings show that 88.4% and 67.3% of households in the poorest and richest quintile respectively, were food insecure. These results are plausible, given the widespread El'nino in 2016/17 season which adversely affected agricultural productivity in Zimbabwe and the greater parts of Southern Africa. Therefore, programmes and policy interventions to improve food security should be promoted across all the socio-economic classes. For example, promoting resilience building and nutrition sensitive agricultural programmes such as home gardens, aquaculture and small livestock production that have been documented as promising interventions to address nutrition (Ruel et al., 2018).

***Figure 3. Proportion of households who have poor, borderline, and acceptable food consumption by socio-economic class***

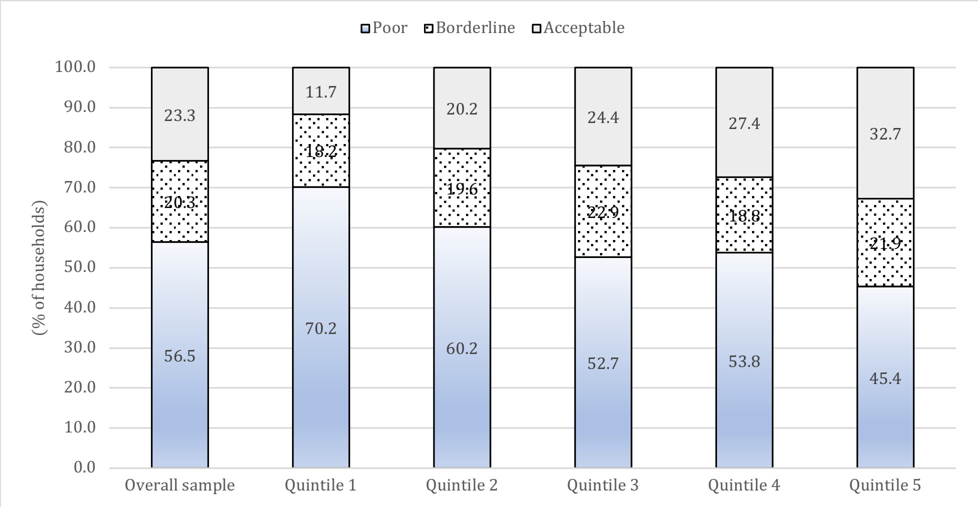
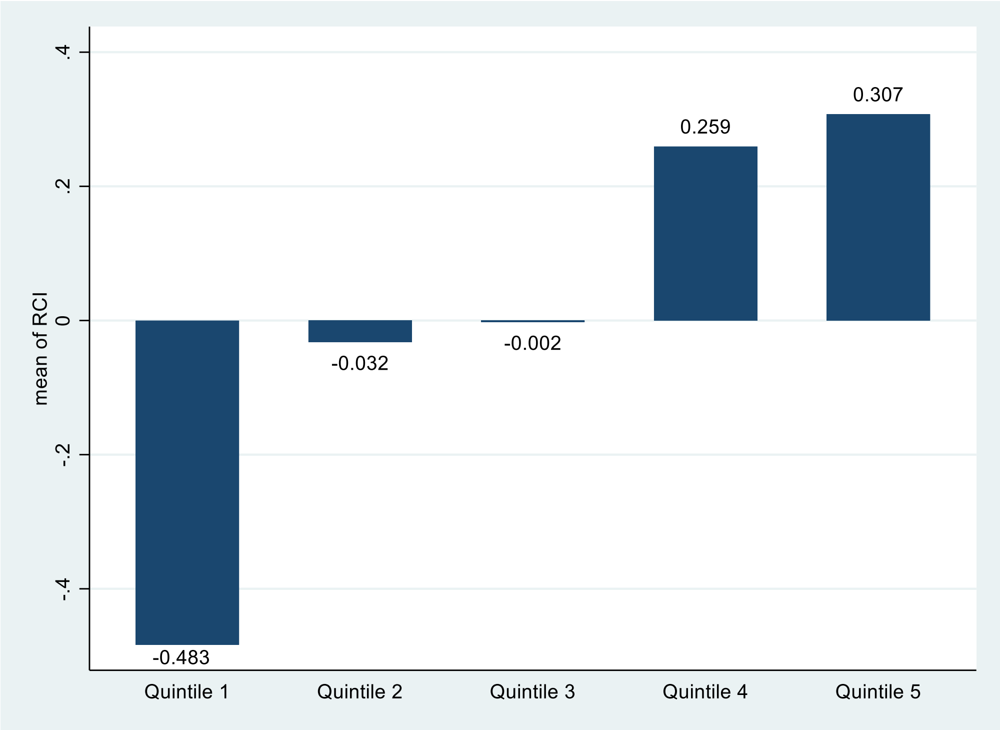



Figure 4 present results of the mean resilience index by socio-economic class. It was shown that the mean resilience capacity index was -0.483 for poorest households, -0.002 for those in quintile 3, and 0.307 for those in the richest category (quintile 5). These results show that richer households have higher resilience capacity compared to poor households. Therefore, resilience building interventions should deliberately target the poor households in the first, second and third quintiles in the country.

***Figure 4. Mean resilience capacity by socio-economic class***




## Econometric analysis

*Role of resilience capacity on household dietary diversity*

The results in Table 4 show the role of resilience capacity on household dietary diversity while controlling for drought shock. In model 1, we estimated the relationship between drought and HDDS without introducing resilience indicators. Study results show that drought reduced the number of food groups consumed by 12.4%. Taken into context, these results are plausible given the El'nino induced drought of 2016/17 season was severe and characterised by widespread crop failure with negative ramifications on food consumption in the whole country. Hence, investments in climate proofing strategies, for example irrigation, water harvesting and climate change mitigation measures and smart agricultural practices by government and development agencies are needed in the smallholder farming communities.

In the second model, we included the resilience variables in our regression analysis. Results show that resilience capacity is positively associated with household dietary diversity. As shown earlier, the estimated coefficients for negative binomial regression can be interpreted as semi-elasticities (Cameron and Trivedi, 2010). A one-index point increase in RCI is associated with an increase in the number of food groups consumed by 7.6%. Our analysis confirms the importance of promoting resilience building interventions for improving food consumption in rural areas of Zimbabwe. A couple of recent studies found similar results that resilience capacity is positively associated with food consumption (d'Errico and Pietrelli, 2017; d'Errico et al., 2018; Smith and Frankenberger, 2018). After the introduction of resilience variables, the impact of drought on household dietary diversity drops by from 12.4% to 8.2%. This result is quite interesting, and the 4.2% reduction emphasises the crucial role of resilience capacity in smoothing household food consumption during drought periods. The results also show that household size reduced food consumption. An additional member in the household was associated with a decrease in the number of food groups consumed by 0.6%. Residence in low rainfall areas is associated with 4.8% decrease in the number of food groups consumed by the household. Our results show that drought and residence in low rainfall areas is associated with lower food consumption. There is need for interventions that enhance water availability and access in low rainfall areas and during drought periods. The government and development agencies need to invest in resilience building interventions, for example irrigation infrastructure, soil and water harvesting technologies, crop and livestock diversification, drought tolerant crops and livestock breeds in low rainfall areas to boost agricultural productivity and subsequently food consumption.

***Table 4. Role of resilience capacity on household dietary diversity***

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. |
| Drought | -0.124*** | 0.015 | -0.082*** | 0.014 |
| Gender | 0.023 | 0.015 | 0.010 | 0.014 |
| Household size | 0.007** | 0.003 | -0.006* | 0.003 |
| Low rainfall area | -0.034** | 0.014 | -0.048*** | 0.013 |
| RCI | | | 0.076*** | 0.006 |
| RCI*drought | | | 0.007 | 0.010 |
| Constant | 1.813*** | 0.019 | 1.867*** | 0.018 |
| Observations | 2228 | | 2228 | |
| Loglikelihood | -4.06e+05*** | | -4.00e+05*** | |
| Deviance goodness-of-fit | 92854*** | | 81874*** | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. RCI mean resilience capacity index.

*Role of resilience capacity on household dietary diversity by socio-economic status*

Results in Table 5 show the influence of resilience capacity on household dietary diversity by socio-economic status. The relationship between the resilience capacity index and HDDS is positive and statistically significant across all the socio-economic classes. A one-index point increase in RCI is associated with a 12.5% and 3.5% increase in the number of food groups consumed by the poorest (Quintile 1) and richest (Quintile 5) households respectively. The effect size of resilience capacity tends to be more pronounced among poorer household demonstrating socio-economic gradient on the effects of resilience capacity. The negative effects of low rainfall tend to be more pronounced among the poorest and poor households. Investments in irrigation infrastructure and climate smart agricultural practices should target poor households and those in low rainfall area as they are more vulnerable. The policy implication is that resilience and nutrition building interventions should prioritize targeting of poorer households and those residing in low rainfall areas.

***Table 5. Role of resilience capacity on household dietary diversity by socio-economic status***

| | Poorest | | Poor | | Moderate | | Rich | | Richest | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. |
| RCI | 0.125*** | 0.022 | 0.080*** | 0.016 | 0.084*** | 0.013 | 0.045*** | 0.014 | 0.035*** | 0.010 |
| Drought | -0.109*** | 0.035 | -0.050* | 0.030 | -0.039 | 0.026 | -0.110*** | 0.034 | -0.087*** | 0.031 |
| RCI*drought | -0.060* | 0.031 | -0.014 | 0.025 | 0.015 | 0.020 | -0.001 | 0.023 | 0.046*** | 0.017 |
| Gender | 0.010 | 0.035 | 0.013 | 0.031 | -0.023 | 0.027 | -0.004 | 0.029 | 0.045 | 0.029 |
| Household size | -0.009 | 0.008 | -0.002 | 0.008 | -0.007 | 0.007 | 0.014* | 0.008 | 0.022*** | 0.008 |
| Low rainfall area | -0.074** | 0.033 | -0.089*** | 0.029 | -0.029 | 0.026 | -0.064** | 0.029 | -0.041 | 0.030 |
| Constant | 1.859*** | 0.062 | 1.840*** | 0.048 | 1.875*** | 0.041 | 1.817*** | 0.038 | 1.815*** | 0.032 |
| Observations | 446 | | 446 | | 446 | | 446 | | 444 | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. RCI mean resilience capacity index.

*The association between resilience capacity pillars and household dietary diversity*

In this subsection, we estimated the same equation as in (1) above, with "resilience capacity index" replaced by indices of its three pillars – AC, Assets and ABS. We analysed separately the individual roles of the three pillars of resilience capacities on household dietary diversity and the results are shown in Table 6. Results in model 2 show that after the introduction of resilience capacity pillars, the detrimental effect of drought is reduced from 12.4% (model 1) to 7.8% in model 2, further confirming the cushioning effects of resilience capacity pillars. We proceed and interpret results in model 2. AC, Assets and ABS are positively associated with household dietary diversity in the study area. A one-index point increase in adaptive capacity, assets and access to basic services is associated with an increase in the number of food groups consumed by 3.4%, 2% and 6.6% respectively.

Overall, our results confirm that all the three resilience pillars: AC, AST and ABS are important for food consumption in the country. Hence, households with higher adaptive capacity, asset endowments, and better access to basic services have improved food consumption compared to those with lower adaptive capacities, assets, and poor access to basic services in the same communities. Our findings are supported by recent empirical evidence. For example, Smith and Frankenberger (2018) found that assets and access to services improved food security among households in Bangladesh. With regards to access to basic services, our findings are in tandem with Shively (2017) who found that health and transport infrastructure buffer the negative effects of rainfall shortages on child nutrition in Nepal and Uganda. Furthermore, the interaction between AC and drought is positive and significant in the dietary diversity model. This could suggest that AC smooth consumption during drought periods. For example, a household with higher adaptive capacity (measured by education, employed, crop and livestock diversity) is likely to be more resilient to drought shocks that threaten food security through consumption smoothing (i.e., selling livestock to maintain current level of consumption). This further emphasize the importance of adaptive capacity for food consumption and resonates with studies highlighting food consumption smoothing (Hoddinott, 2006; Ansah et al., 2019).

***Table 6. Association between resilience capacity pillars and household dietary diversity***

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. |
| Drought | -0.124*** | 0.015 | -0.078*** | 0.014 |
| Gender | 0.023 | 0.015 | 0.008 | 0.013 |
| Household size | 0.007** | 0.003 | -0.005 | 0.003 |
| Low rainfall area | -0.034** | 0.014 | -0.041*** | 0.013 |
| AC | | | 0.034*** | 0.008 |
| Asset | | | 0.020*** | 0.006 |
| ABS | | | 0.066*** | 0.008 |
| AC*drought | | | 0.038*** | 0.013 |
| Asset*drought | | | -0.011 | 0.011 |
| ABS*drought | | | -0.017 | 0.012 |
| Constant | 1.813*** | 0.019 | 1.857*** | 0.018 |
| Observations | 2228 | | 2228 | |
| Loglikelihood | -4.06e+05*** | | -3.99e+05*** | |
| Deviance goodness-of-fit | 92854*** | | 80138*** | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. AC and ABS mean adaptive capacity, and access to basic services respectively.

*Role of resilience pillars on household dietary diversity by socio-economic status*

Table 7 show the influence of resilience pillars on household dietary diversity differentiated by household socio-economic status. Adaptive capacity increases dietary diversity by 6.4% and 6% among poor (Quintile 2) and moderate (Quintile 3) households respectively. Assets positively increased household dietary diversity among the poorest households only. A one-index point increase in assets is associated with 6.1% increase in the number of food groups by poorest households. This may indicate that poorer households rely on assets for smoothing consumption during drought periods. However, as drought intensifies the effect of asset for consumption smoothing tends to disappear as shown by the negative interaction term between asset and drought. Therefore, interventions that prevent distress sale of assets by poorer households during drought are needed. The relationship between access to basic services and household dietary diversity is positive and statistically significant across all the socio-economic classes. For example, a one-index point increase in ABS is associated with an increase in the number of food groups consumed by 8% and 6.4% among the poorest (Quintile 1) and richest (Quintile 5) households respectively. Overall results show that the three resilience capacity pillars are important for household dietary diversity, but the effects vary depending on socio-economic class. The magnitude of the coefficients tends to be higher among poorer households compared to the non-poor.

***Table 7. Role of resilience pillars on household dietary diversity by socio-economic status***

| | Poorest | | Poor | | Moderate | | Rich | | Richest | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. |
| AC | 0.033 | 0.030 | 0.064*** | 0.018 | 0.060*** | 0.012 | 0.020 | 0.017 | 0.009 | 0.014 |
| Asset | 0.061*** | 0.018 | 0.006 | 0.015 | 0.012 | 0.014 | 0.017 | 0.012 | 0.000 | 0.012 |
| ABS | 0.080*** | 0.022 | 0.055*** | 0.018 | 0.057*** | 0.017 | 0.037** | 0.018 | 0.064*** | 0.014 |
| Drought | -0.113*** | 0.034 | -0.053* | 0.030 | -0.028 | 0.026 | -0.109*** | 0.034 | -0.067** | 0.031 |
| AC*drought | 0.030 | 0.044 | 0.031 | 0.031 | 0.006 | 0.021 | 0.037 | 0.032 | 0.036 | 0.024 |
| Asset*drought | -0.061** | 0.026 | -0.003 | 0.026 | -0.003 | 0.021 | -0.024 | 0.024 | 0.021 | 0.019 |
| ABS*drought | -0.039 | 0.030 | -0.046* | 0.028 | 0.024 | 0.026 | -0.002 | 0.028 | -0.008 | 0.023 |
| Gender | 0.012 | 0.033 | 0.011 | 0.030 | -0.028 | 0.027 | -0.005 | 0.029 | 0.036 | 0.028 |
| Household size | -0.008 | 0.009 | 0.003 | 0.008 | -0.005 | 0.007 | 0.013 | 0.008 | 0.020*** | 0.007 |
| Low rainfall area | -0.066** | 0.033 | -0.083*** | 0.030 | -0.036 | 0.026 | -0.060** | 0.030 | -0.028 | 0.029 |
| Constant | 1.852*** | 0.063 | 1.805*** | 0.049 | 1.867*** | 0.041 | 1.818*** | 0.038 | 1.803*** | 0.031 |
| Observations | 446 | | 446 | | 446 | | 446 | | 444 | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. AC and ABS mean adaptive capacity, and access to basic services respectively.

## Robustness checks

The objective of this study is to better understand the role of resilience capacity on food consumption. Nevertheless, there are several other indicators, beyond dietary diversity that are used to measure food consumption. To examine this further, we re-estimated the models by using food consumption score as the dependent variable. The finding that resilience capacity tends to increase food consumption also holds with this alternative specification (Table A1). Results in Table A2 show that resilience capacity positively increases food consumption across all socio-economic classes, except the quintile 5. A one-index point increase in RCI is associated with an increase in food consumption score by 40.9% and 14.2% among the poorest (Quintile 1) and rich (Quintile 4) households respectively. AC, Assets and ABS are positively associated with food consumption score (Table A3). Results show that resilience pillars are important for food consumption score, but the effects vary depending on socio-economic class. As discussed earlier, the magnitude of the coefficients tends to be higher among poorer households compared to the non-poor (Table A4). The findings are largely in line with those discussed in the main results above. Hence, the results do not seem to be driven by the way food consumption is measured. We interpret this as evidence that resilience capacity is crucial for food consumption and that interventions to improve resilience and food consumptions should deliberately target poorer households in the country.

## Conclusion

Using a survey of 2282 rural households this study analyzed the role of resilience capacity as well as individual resilience capacity pillars on food consumption in Zimbabwe. In addition, we investigated whether resilience capacities and their influence on food consumption differ by socio-economic status of the household. The negative binomial regression which is suitable for over-dispersed data was used for estimation. The descriptive results show that male headed households had higher dietary diversification, food consumption and resilience capacity compared to their female counterparts.

The econometric study findings show that drought reduced food consumption. However, the inclusion of resilience variables reduced the negative effects of drought on food consumption. Hence resilience capacity is important in smoothing household food consumption during drought periods. With regards to three resilience pillars, the study findings highlight that adaptive capacity, assets and access to basic services are associated with improved household food consumption while reducing negative effects of drought. Households residing in low rainfall areas had reduced food consumption compared.

Resilience capacity improved food consumption across all the socio-economic classes. However, the magnitude of the effects is higher among poorer compared non-poor households. Turning to the resilience capacity pillars, results show that adaptive capacity increased food consumption among households in quintiles 2 and 3 while assets positively improved food consumption among the poorest households only. Access to basic services improved household food consumption across all the socio-economic classes. Overall, study findings show that resilience capacity pillars improved food consumption, but the effects vary depending on socio-economic class and the effect sizes tend to be higher among poorer households.

## Policy Implications

Four important policy implications emerge from the findings of this analysis. First, descriptive statistics highlighted that female headed households had lower resilience capacity and food consumption compared to male headed households. It is well acknowledged that female headed households in developing countries, face huge constraints in terms of access and control of land, productive and financial resources that are crucial for nutrition security (Malapit et al., 2015). Therefore, interventions that deliberately focus on building resilience capacities and improving women empowerment and inclusiveness with regards to access to and control over productive resources should be promoted as they have the potential to improve household nutrition security (Malapit et al., 2015).

Second, drought reduced food consumption. In addition, households residing in low rainfall areas have lower food consumption. Hence, government, policymakers, program implementers, and international development partners need to promote investments in irrigation infrastructure and climate smart agricultural practices to cushion household food consumption from negative effects of drought and low rainfall. Examples of climate smart agricultural practices include drought tolerant crops and varieties, drought tolerant livestock breeds, soil, and water conservation technologies.

Third, resilience building interventions (such as promoting crop and livestock diversification, home vegetable gardens, small livestock production, and aquaculture) are particularly important and should be promoted by the government and development agencies to boost food consumption and maintain the environment. Ruel et al. (2018) also highlight that these interventions are quite promising in addressing underlying determinants of malnutrition. These should be complemented with interventions that improve human capital development, extension, road, and telecommunication infrastructure.

Fourth, resilience building interventions should be promoted across all socio-economic classes of households. The effects of resilience capacity on food consumption tend to be higher among poorer households relative to the non-poor. Resilience building interventions need to be inclusive of poorer and marginalized societies. Hence, government and development agencies should deliberately target poorer households and those residing in low rainfall areas and focus on improving their resilience capacities and food consumption.

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## Disclosure statement

The authors declare that there are no competing interests for this article.

## Ethics and consent

This study is based on a publicly available data set. The data are publicly available with all identifier information removed. The data were collected after the appropriate ethical approvals had been granted, and there was no special ethical issue to address. However, permission to use the data set was obtained from ZIMSTAT.

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# ANNEX

## Robustness checks using food consumption score as the dependent variable

***Table A1. Role of resilience capacity on household food consumption score***

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. |
| Drought | -0.436*** | 0.049 | -0.308*** | 0.049 |
| Gender | 0.011 | 0.048 | -0.043 | 0.047 |
| Household size | 0.027** | 0.012 | -0.014 | 0.011 |
| Low rainfall area | -0.055 | 0.048 | -0.115** | 0.046 |
| RCI | | | 0.223*** | 0.022 |
| RCI*drought | | | 0.059 | 0.037 |
| Lnalpha | -0.279*** | 0.027 | -0.380*** | 0.028 |
| Constant | 3.241*** | 0.066 | 3.411*** | 0.063 |
| Observations | 2226 | | 2226 | |
| Loglikelihood | -8.29e+05*** | | -8.18e+05*** | |
| Deviance goodness-of-fit | 3510674*** | | 3137699*** | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. RCI mean resilience capacity index.

***Table A2. Role of resilience capacity on household food consumption score by socio-economic status***

| | Poorest | | Poor | | Moderate | | Rich | | Richest | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. |
| RCI | 0.409*** | 0.062 | 0.314*** | 0.057 | 0.234*** | 0.046 | 0.142*** | 0.053 | 0.054 | 0.034 |
| Drought | -0.249* | 0.133 | -0.178* | 0.100 | -0.233** | 0.092 | -0.369*** | 0.112 | -0.496*** | 0.104 |
| RCI*drought | -0.193* | 0.115 | -0.080 | 0.084 | 0.103* | 0.062 | 0.025 | 0.095 | 0.262*** | 0.058 |
| Gender | 0.043 | 0.115 | -0.163 | 0.106 | -0.065 | 0.090 | -0.133 | 0.103 | 0.101 | 0.089 |
| Household size | -0.029 | 0.032 | -0.021 | 0.028 | -0.022 | 0.024 | 0.041 | 0.030 | 0.076*** | 0.023 |
| Low rainfall area | -0.108 | 0.110 | -0.277*** | 0.102 | -0.156* | 0.089 | -0.165 | 0.101 | -0.042 | 0.087 |
| Lnalpha | -0.346*** | 0.062 | -0.382*** | 0.062 | -0.509*** | 0.074 | -0.345*** | 0.054 | -0.559*** | 0.074 |
| Constant | 3.213*** | 0.237 | 3.484*** | 0.180 | 3.483*** | 0.148 | 3.338*** | 0.143 | 3.192*** | 0.098 |
| Observations | 446 | | 445 | | 446 | | 446 | | 443 | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. RCI mean resilience capacity index.

***Table A3. Association between resilience capacity pillars and food consumption score***

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. |
| Drought | -0.436*** | 0.049 | -0.293*** | 0.049 |
| Gender | 0.011 | 0.048 | -0.051 | 0.047 |
| Household size | 0.027** | 0.012 | -0.013 | 0.011 |
| Low rainfall area | -0.055 | 0.048 | -0.101** | 0.047 |
| AC | | | 0.110*** | 0.025 |
| Asset | | | 0.055** | 0.023 |
| ABS | | | 0.193*** | 0.024 |
| AC*drought | | | 0.088* | 0.047 |
| Asset*drought | | | 0.019 | 0.037 |
| ABS*drought | | | -0.048 | 0.040 |
| lnalpha | -0.279*** | 0.027 | -0.393*** | 0.029 |
| Constant | 3.241*** | 0.066 | 3.383*** | 0.065 |
| Observations | 2226 | | 2226 | |
| Loglikelihood | -8.29e+05*** | | -8.16e+05*** | |
| Deviance goodness-of-fit | 3510674*** | | 3087650*** | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. AC and ABS mean adaptive capacity and access to basic services respectively.

***Table A4. Role of resilience pillars on food consumption score by socio-economic status***

| | Poorest | | Poor | | Moderate | | Rich | | Richest | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. | Coef | Std. err. |
| AC | 0.145* | 0.087 | 0.309*** | 0.065 | 0.184*** | 0.037 | 0.073 | 0.055 | 0.008 | 0.043 |
| Asset | 0.164*** | 0.059 | 0.028 | 0.051 | 0.056 | 0.045 | 0.059 | 0.046 | -0.048 | 0.036 |
| ABS | 0.271*** | 0.059 | 0.183*** | 0.059 | 0.093* | 0.053 | 0.076 | 0.056 | 0.231*** | 0.043 |
| Drought | -0.259** | 0.131 | -0.177* | 0.100 | -0.204** | 0.093 | -0.377*** | 0.112 | -0.401*** | 0.106 |
| AC*drought | 0.033 | 0.138 | -0.063 | 0.111 | -0.056 | 0.076 | 0.109 | 0.113 | 0.173* | 0.089 |
| Asset*drought | -0.139 | 0.101 | 0.024 | 0.079 | 0.076 | 0.071 | -0.060 | 0.090 | 0.155** | 0.063 |
| ABS*drought | -0.153 | 0.104 | -0.128 | 0.089 | 0.126 | 0.077 | 0.013 | 0.092 | -0.056 | 0.078 |
| Gender | 0.060 | 0.111 | -0.172* | 0.104 | -0.073 | 0.089 | -0.130 | 0.103 | 0.048 | 0.090 |
| Household size | -0.024 | 0.034 | -0.003 | 0.028 | -0.015 | 0.025 | 0.039 | 0.029 | 0.067*** | 0.023 |
| Low rainfall area | -0.075 | 0.106 | -0.261** | 0.107 | -0.169* | 0.091 | -0.174* | 0.105 | 0.004 | 0.088 |
| Lnalpha | -0.363*** | 0.062 | -0.405*** | 0.063 | -0.520*** | 0.074 | -0.349*** | 0.055 | -0.618*** | 0.077 |
| Constant | 3.165*** | 0.241 | 3.357*** | 0.180 | 3.457*** | 0.149 | 3.342*** | 0.138 | 3.136*** | 0.098 |
| Observations | 446 | | 445 | | 446 | | 446 | | 443 | |

*, **, ***. Statistically significant at the 10%, 5%, and 1% level, respectively. AC and ABS mean adaptive capacity and access to basic services respectively.

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