The Effect of Monetary Losses Due to Weather Shocks on Food Security in Malawi: A Subjective Approach

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Abstract

This paper investigates the effect of extreme weather shocks on food security in Malawi for the period 2010-2016. The paper uses the household's subjective assessments of life satisfaction in four domains to quantify a monetary equivalent of the losses due to weather shocks. Then, the paper uses those estimates to investigate how the estimated income losses due to weather shocks affect food security. The main findings show that income losses associated with weather shocks are correlated with a worsening in the food security indicators. There are interesting differences across indicators. While the estimates for the Food Consumption Score and the Household Dietary Diversity are in the expected direction but not significant, the estimates for Reduced Coping Strategies Index are positive and strongly significant as one would have expected. I also argue that these findings have important policy applications to decrease food insecurity in the case of adverse shocks.

1 Introduction

This paper quantifies the extent to which monetary losses due to extreme weather conditions affect the food security of Malawian households. The empirical analysis first computes the monetary losses associated with extreme weather shocks and then explores the relationship between those losses and three commonly used food security indicators.

Malawi is one of the poorest countries in the world.[1] Its economy is heavily dependent on agriculture with approximately 90% of the population engaged in subsistence-level rain-fed agriculture either through food production or as hired farm labor.[2] The large-scale reliance on agriculture as the main source of income makes Malawian households highly vulnerable to extreme weather conditions such as drought and irregular rains.[3] Indeed, the slowdown in the GDP per capita growth in 2018 compared to the previous years is due to a reduction in the agricultural production caused mainly by long dry spells.

The increase in the recent years in the intensity and frequency of environmental hazards have often resulted in weak harvests.[4] Poor crop yields have significant long-term negative consequences on Malawian households'

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[1] Although as made significant economic progress in the past decade, the Gross Domestic Product per capita in Malawi was at 516.80 US dollars in 2018, equivalent to only 4% of the world's average. See World Bank (2019) for further discussion of the most recent figures and forecasts.

[2] See Darkoh et al. (2012).

[3] See Dercon (2006) for a discussion of the vulnerability of households engaged in subsistence-level agriculture.

[4] The incidence of extreme weather events is projected to worsen due to global warming and climate changes.

income, assets, food production, and consumption.[5] These negative effects are particularly strong for households who live in rural areas.[6] Magrath and Sukali (2009) point out that crop failures due to extreme weather conditions cause serious food shortage, hunger, and malnutrition.

Weather shocks are one of the many shocks that negatively affect household welfare in the least developed countries. An extensive literature has also investigated other types of shocks such as the death of a member of the family due to HIV, or conflicts or violence that have similar consequences to weather shocks.[7] This paper focuses on extreme weather shocks because they have the highest incidence on households, in terms of both frequency and magnitude.[8]

Previous research has shown that weather shocks affect several economic outcomes.[9] Marchetta et al. (2018) find a decline in schooling attendance as a consequence of weather shocks. Deschênes and Moretti (2009) and Deschênes and Greenstone (2011) document the relationship between weather and mortality rates. Beuermann et al. (2017) suggests that when expectant mothers are exposed to tropical storms and hurricanes, their children are more likely to show low birth weight and long-term physical development. Edoka et al. (2013) shows using Vietnamese data that weather shocks negatively affect child nutritional status. Last but not least, weather shocks also cause public health crises resulting from the outbreak of diseases, the disruption of safe drinkable water supply and sanitation (Watson et al., 2007).

The main focus of this paper is to investigate how monetary losses due to weather shocks are related to household welfare and vulnerability with a specific interest in food insecurity. The panel structure of the Integrated Household Panel Survey (IHPS) enables me to follow a representative sample of the population over the period spanning from 2010 to 2016. I investigate the changes in household food nutrition indicators such as the Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), and Reduced Coping Strategies Index (rCSI) after the occurrence of extreme weather shocks.

Many papers have studied the effect of weather conditions on food indicators. Jensen (2000) finds that child malnutrition in Côte d'Ivoire doubles in the presence of adverse weather conditions that damage the agricultural production. Demeke et al. (2011) analyzes the effect of rainfall shocks on Ethiopian rural households and finds that rainfall variability is an important determinant of households' food security. Skoufias et al. (2011) shows that although the income of rice farm households in Indonesia is negatively affected by low rainfalls, their food consumption remains unaltered at the expense of lower nonfood expenditures.

The first contribution of this paper to the literature is to compute monetary losses when information on losses associated with weather shocks are not collected in the surveys.[10] The implementation of this methodology broadens the set of research questions that can be investigated using survey data. To quantify the monetary value of shocks that worsen individual well-being, I use the methodology proposed in Ferrer-i-Carbonell and van Praag (2002), commonly used in Health Economics. I use the modules of subjective assessment of well-being from the Malawi IHPS to implement this methodology.[11] The methodology quantifies the monetary equivalent

[5]The literature refers to resilience as the situation in which short-term shocks have adverse long-term consequences. See Hoddinott (2014) for a detailed definition and importance of the concept.

[6]The Malawian poverty headcount rate was 51.5% in 2017 with peaks of over 65% in rural areas affected by weather shocks.

[7]See Baylies (2002) and Ingram et al. (2012).

[8]Dercon (2006) and Dercon et al. (2005) show that 47% of Ethiopian households hit by a shock report to be affected by extreme weather shocks. Cole et al. (2013) report that extreme weather events are the major source of adverse income shocks for 88% of rural Indian households.

[9]See Dell et al. (2014) for a literature review of the effects of weather shocks on the economic outcome and individual well-being.

[10]Most surveys do not collect information on losses related to shocks. The panel survey of South African households is an exception and reports the economic costs due to shocks. See Carter and Maluccio (2003) for further description of the data sources.

[11]The use of subjective assessment of well-being and shocks may present some potential shortcomings due to endogeneity bias in answering the questionnaires. Trærup and Mertz (2011) shows that there is a correspondence between households who reported weather

of the losses due to weather shocks by using the household's subjective assessments of life satisfaction in four domains.

An advantage of calculating the "income equivalent" based on changes in subjective well-being is that it accounts for costs of a different nature. For example, the members of a household that have been negatively affected by drought, in addition to having losses of livestock or crops, may also experience excessive nervousness, fear, apprehension, and worry for not having the resources to achieve the pre-shock well-being state. These mental health issues experienced due to the shock would be considered in the subjective well-being assessment approach. This methodology differs from the traditional ones that exclusively use the economic losses collected in the surveys, and that represents only a part of the worsening in welfare that individuals may face after the occurrence of negative shocks.

The estimated monetary losses are used to quantify the effect on food security after the occurrence of self-reported weather shocks. The paper provides suggestive evidence that monetary losses associated with weather shocks are correlated with a worsening of food security indicators. There are interesting differences across indicators. The estimates for the Food Consumption Score (FCS) and the Household Dietary Diversity Score (HDDS) are in the expected direction but not significant. The estimates for Reduced Coping Strategies Index (rCSI) are positive and strongly significant as one would have expected. The paper provides evidence that shows differences between calculated monetary losses using self-reported weather shocks information and objective measures, such as precipitation.

The findings of this paper fit into a broad policy debate. Policies that aim to decrease food insecurity in the case of adverse shocks have to aim to increase the household's resiliency and flexibility to adapt to new environments without compromising the household's food security. One possible policy intervention should aim to support the diversification of income sources for households engaged in subsistence-level rain-fed agriculture. An alternative policy intervention should aim to educate households in allocating income resources optimally, between good and adverse times.

This paper is structured as follows. Section 2 describes the data. Section 3 presents the empirical strategy. In Section 4, I present the main empirical findings and discuss the economic implications. Section 5 presents the results using objective weather shocks measures. Section 6 concludes.

2 Data

The primary dataset for this paper is the Malawi Integrated Household Panel Survey (IHPS). The IHPS was created to examine the trends in poverty, socioeconomic, and agricultural characteristics over time. The dataset consists of three waves of data collected in 2010, 2013, and 2016. The IHPS is part of the Living Standards Measurement (LSMS) - Integrated Surveys on Agriculture (ISA) project sponsored by the World Bank. The collection of the three waves occurred between March 2010 and March 2011, from April to October 2013, and between April 2016 and April 2017, for the first, second and third wave, respectively.[12]

The IHPS is composed of five sections: household, agriculture, fisheries, community, and individual-level. The five sections are split into 90 modules. For the scope of this analysis, I have merged 21 modules plus

shocks and the observed variability in climate conditions. These results suggest that households do not misreport.

[12]With respect to the second wave, some residual tracking operations were implemented in November and December 2013. This residual tracking accounted for cases difficult to track such as individuals who changed their residency between the baseline 2010 and the second round interview in 2013.

the geographic information.[13] For comparability purposes, I have harmonized the data in order to generate standardized variables that are comparable across the waves. The harmonization has generated around 1053 variables that have the same name and the same codification across the three waves.[14]

The sample used in this study includes 6,407 "tracking-eligible" individuals based on the 2016 IHPS. "Tracking-eligible" individuals are defined as the individuals who were interviewed in all three waves. Due to budget cuts and an increasing number of households to be tracked as a consequence of new family formation, the sample size of individuals interviewed in 2016 is significantly smaller than the one in the two previous rounds. Precisely, in 2016 only 102 Enumeration Areas (EAs) were included out of the 204 EAs surveyed in the 2010 baseline survey.[15] The final sample includes 19,221 time-individual observations grouped in 6,407 individuals and in 1,513 households that match the number reported in the methodological documentation released by the World Bank.

The stratification of households in the survey design enables the IHPS to be representative at national, urban, and rural areas. In addition to the complex survey design, the accurate representativeness of the population is achieved by weighting all sample variables by the panel weights. The methodology used to calculate the IHPS panel weights is described in Himelein (2013).

I have constructed three measures of food security that I use as a dependent variable in the regression analysis. The first measure, Food Consumption Score (FCS), is a composite score that captures dietary diversity, food frequency, and relative nutritional importance of different food groups. This measure is a proxy of the caloric intake and diet quality at the level of the household. I have used information on food groups from the survey module G3 and I have summed the weighted consumption frequencies of each group to create a composite indicator.[16] The higher the FCS, the more diversified is the household food consumption.

The second measure, the Household Dietary Diversity Score (HDDS), proxies the quality of a diet in terms of diversity in food consumption. I have computed, for each household, the number of food categories the household has consumed in the one-week prior to the survey.[17] As for the FCS, the higher the HDDS, the more diversified household food consumption.

The last measure is the Reduced Coping Strategies Index (rCSI). This indicator is designed to capture the quantity or sufficiency of consumption. The indicator is constructed by using a series of questions about how households manage to cope with a shortfall in food for consumption. The survey responses to these questions are used to construct a weighted score across the household coping strategies in the survey.[18] The higher the

[13] The modules merged for the project are: Module A: Households Identification, Module B: Household Roster, Module C: Education, Module D: Health, Module F: Housing, Module G1: Food consumption over the past week, Module G2: Food Consumption over the past week (10 food groups), Module G3: Food Consumption over the past week (children), Module H: Food Security, Module H: Food Security, Modulo I1: Households Other Non-Food Expenditures Over Past Week (For Annual Non-Food Expenditures: Other Non-Food), Modulo I2: Households Other Non-Food Expenditures Over Past Month (For Annual Non-Food Expenditures: Other Non-Food), Modulo J: Households Non-Food Expenditures Over Past Three Months (For Annual Non-Food Expenditures: Other Non-Food),Modulo K: Households Non-Food Expenditures Over Past 12 Months (For Annual Non-Food Expenditures: Other Non-Food), Module L: Durable goods, Module P: Other Income, Module R: Social Safety Nets, Module T: Subjective Assessment of Well-Being, Module U: Shocks and Coping Strategies, Module V: Child Anthropometry, Module W: Deaths in households, Module CB: Roster Of Informants, Module CG: Changes, Module CH: Community Needs, Actions and Achievements, Module CI: Communal Resource Management, and Module CJ: Communal Organization

[14] For example, in the survey of 2010 the question referred to the shocks asked if the households were affected negatively by droughts or irregular rains in the last 12 months, while in the rounds of 2013 and 2016, the same question was divided in two, one for droughts and one for irregular rains. Therefore, to make the last two waves comparable with the baseline, I aggregated the two questions by generating a dummy that takes the value of one if the household was affected by droughts or irregular rains.

[15] For further details about the composition of the sample between and within the waves, see World Bank (2017).

[16] I have used the standard weights in the literature proposed by the World Food Programme (WFP). Those weights are reported in Table A1 in the Appendix.

[17] The indicator is constructed using the seven food categories defined by the International Food Policy Research Institute (IFPRI). See Smith and Subandoro (2007) for further description of the categories and the methodology.

[18] In the Malawian IHPS, there are five questions about coping strategies with a food shortfall. Those strategies are described in

rCSI, the worse is the food security condition of the household because it means that the household needs to apply more or more drastic coping strategies to accommodate the food shortfall.

3 Methodology

The empirical strategy I use consists of two steps. In the first step, I estimate the monetary loss due to extreme weather conditions. The estimation of the subjective cost follows an approach similar to the one proposed by Ferrer-i-Carbonell and van Praag (2002). This methodology estimates the *equivalent income* changes that would be necessary to modify the individual satisfaction in an equal amount as an extreme weather event would do.

In the second step, I use the estimated income losses to quantify the effect on the three food security indicators presented in the previous section.

3.1 Estimation of the Monetary Loss due to Weather Shocks

In order to estimate the *income equivalent* associated with extreme weather conditions, the general satisfaction (GS) is defined as a function of a set of domains of satisfaction (DS). Specifically,

$$GS = GS(DS_1, ..., DS_4) \tag{1}$$

where the four domains of satisfaction included in the Malawian surveys are: Food Satisfaction (FS), Housing Satisfaction (HS), Clothing Satisfaction (CS), and Health Satisfaction (HeaS). For simplicity, I will assume in the remainder of the paper that there exists a linear relationship between the domains of satisfaction and the general satisfaction.

The latent satisfaction variable DS_j for each domain j is assumed to be a function of income y, other individual observable characteristics x, and a stochastic component υ that captures the random component in the individual satisfaction:

$$DS_j = DS_j(y, x; \upsilon) \qquad j = 1, ..., J \tag{2}$$

For simplicity, I assume a linear functional relationship between the covariates and the domains of satisfaction. It follows that the latent model equation can be written as:

$$DS_j = a_j + b_j' X + \upsilon_j \qquad \forall j = 1, ..., J \tag{3}$$

where $X = [y, x]$ is a vector containing all observable covariates.

The first challenge I face in the empirical analysis is that the domains of satisfaction are ordinal variables.[19] That implies that the spacing between two subsequent values of an ordinal variable may not be the same across the levels of that variable. I address this problem by cardinalizing the domains of satisfaction in order to make the spacing between categories consistent and to enable their use in regression analysis. I follow the so-called "probit-adapted OLS" (POLS) approach to cardinalize the domain satisfaction variables. The POLS approach is computationally easier than the ordered probit model traditionally used in the econometric literature on cardinalization.[20] As showed by Stewart (1983) and more recently by Ferrer-i-Carbonell and van Praag (2007),

section 4.1. I use the severity weights proposed in Maxwell et al. (2003). The weights are reported in Table A2 in the Appendix.

[19]The scale of the possible answers to the satisfaction questions differs across domains. FS, HS, CS, and HeaS are ranked in ascending order from 1 to 3. GS is ranked in ascending order from 1 to 6. For further details about the survey, the reader may refer to National Statistical Office - Malawi Government (2012).

[20]See Maddala (1983) for further discussion of the topics.

the two approaches yield to equivalent results.

The POLS approach works as follows: I assume the real axis is partitioned into k intervals where k is the number of available categories in each satisfaction question. Each interval is defined as $I_i = (\mu_{i-1}, \mu_i)$ with $-\infty < \mu_0 < ... < \mu_k < \infty$. This formulation implies that a respondent belongs to the category i in the survey if and only if $DS \in I_i$. I do not observe directly the latent variable DS, but rather I observe the variable $\ddot{DS}$ that takes only one of the k discrete values that represent the alternative categories. The variable $\ddot{DS}$ is thought as the conditional expectation of being in an interval

$$\ddot{DS} = E\Big[DS \mid DS \in I_i\Big] = E\Big[DS \mid \mu_{i-1} < DS < \mu_i\Big] \tag{4}$$

The true latent variable DS is assumed to be the sum of its conditional expectation that is observable and a idiosyncratic rounding-off error η. The error accounts for the fact we can only observe the interval in which the true satisfaction falls in. Mathematically,

$$DS_j = \ddot{DS}_j + \eta_j \qquad \forall j = 1, ..., J \tag{5}$$

Plugging the linear functional relationship derived from Equation 3 into the previous result, I obtain the following expression:

$$\ddot{DS}_j = a_j + b_j' X + \varepsilon_j \tag{6}$$

where $\varepsilon_j = \upsilon_j - \eta_j$ is the difference between two noise terms.

Empirically, I estimate the following specification that is derived from Equation 6:

$$\ddot{DS}_{jnt} = C_t + \beta_j' X_{nt} + \alpha_j' \bar{X}_n + \delta_j s_{jnt} + \varepsilon_{jnt} \qquad \forall j = 1, ..., J \tag{7}$$

where $\ddot{DS}_{jnt}$ is the satisfaction in domain j for household n at time t; C_t are the time fixed effects; X_{nt} is a set of standard control variables; $\bar{X}_n$ is the average of the control variables over the sample period; s_{jnt} is a dummy variable that takes the value of 1 if the individual has faced a weather shock in period t, and ε_{jnt} is the idiosyncratic error term. Although the error terms may be correlated across domains, the OLS estimator yields to consistent estimates for the separate domain equations.

Turning back to Equation 1 and by assuming the existence of a linear relationship, I estimate the effect of domains of satisfaction on the general satisfaction accordingly to the following empirical specification:

$$GS_{nt} = \gamma' \hat{DS}_{nt} + \nu' \overline{\hat{DS}}_n + \lambda \hat{Z}_n + \epsilon_{nt} \tag{8}$$

where $\hat{DS}_{nt}$ is a matrix that contains the predicted values from Equation 7 for all four domains for household n at time t; $\overline{\hat{DS}}_n$ is a matrix that includes the averages over the sample period of the predicted values of the domain satisfaction; and $\hat{Z}_n$ is an auxiliary variable that captures elements that influence both the general and domains of satisfaction, for example, personality traits. If such factor existed and was omitted from the regression analysis, it would be included in the error terms of both general and domains of satisfaction. As a consequence, the explanatory variables would be correlated among them and with the error term ϵ_{nt}. The omission of this latent variable would cause an endogeneity bias and would invalidate the empirical estimates.

To account for the potential endogeneity bias, I construct a proxy for the latent variable by using the estimates from Equation 7. As the latent variable is omitted from the regression specifications for the domains of satisfaction, it is part of the residuals. Following Ferrer-i-Carbonell and van Praag (2002), I construct $\hat{Z}_n$ as the first principal component of the covariance matrix of the residuals computed from the domain satisfaction regressions.

Finally, I use the estimates from the Equations 7 and 8 to calculate the *income equivalent* associated with extreme weather events. To compensate in terms of money for the weather shocks, we need to calculate the effect of income changes on general satisfaction and the welfare loss associated with the extreme weather conditions.

Let's first start with the computation of the effect of income changes on general satisfaction. As income appears as an explanatory variable in each domain of satisfaction, there are several channels through which an income change affects the general satisfaction. The indirect effect of income changes associated with a domain j can be quantified as the product between the effect of the income change on the domain satisfaction and the effect of the domain satisfaction on the general satisfaction. Using the previous estimates, the effect of a change in income, $\Delta \ln y$, on general satisfaction through the domain satisfaction j is equal to

$$(\beta_{jy} + \alpha_{jy}) * (\gamma_j + \nu_j) \tag{9}$$

where β_{jy} and α_{jy} are the estimates from Equation 7 for log income and the average of log income, respectively. γ_j and ν_j are the estimates from Equation 8 for the "shock" and the "level" effects of the domain j on the general satisfaction, respectively.

The overall effect on the general satisfaction caused by a change in income, $\Delta \ln y$, is calculated as the sum of all indirect domain satisfaction effects, basically it is the sum of all products from Equation 9:

$$\sum_{j=1}^{J} (\beta_{jy} + \alpha_{jy}) * (\gamma_j + \nu_j) = \sum_{j=1}^{J} a_j b_j \tag{10}$$

Let's now move to the calculation of the welfare loss associated with the extreme weather conditions. An extreme weather condition significantly affects satisfaction in several domains. For instance, long periods of drought may cause health diseases leading to a worsening of individual health satisfaction. On the other hand, extreme weather conditions impact their respective income and food satisfaction in a way that cannot be ignored. The effect on the welfare of a weather shock for each domain satisfaction is computed using the estimates from Equation 7 and 8 as the product between the effect of each domain satisfaction on the general satisfaction and the estimate of the weather shock dummy on domain satisfaction:

$$(\gamma_j + \nu_j)\delta_j \tag{11}$$

and it follows that the overall effect from all domains of satisfaction is equal to the sum over all domains:

$$\sum_{j=1}^{J} (\gamma_j + \nu_j)\delta_j = \sum_{j=1}^{J} b_j \delta_j \tag{12}$$

As result, the "income equivalent" for extreme weather shocks is derived by equating the overall effect on the general satisfaction caused by a change in income and the overall welfare loss associated with the extreme weather conditions:

$$IE = 1 - \exp\left\{ \frac{\sum_{j=1}^{J} b_j \delta_j}{\sum_{j=1}^{J} a_j b_j} \right\} \tag{13}$$

The income equivalent is computed as in percentage terms. I calculate the loss for the household hit by a weather shock as the product between the income equivalent in percentage terms and the household income level. That implies households with higher income will face higher losses in absolute terms after the occurrence of weather shocks. As a cautionary note, although the magnitude of the income losses is computed as a share of the household's income level, there is not a linear relationship between the household's income and income losses. That is the case because households that do not face the shock experience zero income losses. As there is no perfect linearity between income and income losses, the use of the estimated losses in the regressions against food security indicators does not necessarily generate equivalent estimates to the ones that would be obtained by using the household income as a regressor directly.

3.2 Quantification of the Effect on Food Security

The estimated losses due to weather shocks are used in the second stage to investigate whether short-term income losses due to extreme weather correspond to observable changes in the food security of Malawian households. As income losses in absolute terms vary at a households-time level, I exploit this variation to identify the effect of the weather shock on food security outcomes.

The first challenge in implementing this empirical analysis is that households who do not experience any weather shock have income losses equal to zero. The high frequency of zeros is a common problem in empirical works based on survey data. The log transformation is not suitable for my application because the zero loss observations would be dropped from my sample. In my empirical analysis, I will follow the transformation recently proposed by Ravallion (2017). This transformation consists of a hybrid of the hyperbolic sine and its inverse that generates a concave log-like transformation.[21] Mathematically, a variable ω is transformed as it follows:

$$h(\omega) = I \sinh(\omega) + (1 - I) \sinh^{-1}(\omega) - \ln 2 \tag{14}$$

where I is a indicator function that takes value of one if $\omega \leq 0$, sinh is the hyperbolic sine function, and $\sinh^{-1}$ is the inverse of the hyperbolic sine function. Ravallion (2017) shows that a regression of $h(\cdot)$ on $h(\cdot)$ has the same interpretation as a log-log regression. In other words, we can interpret the estimate of a $h(\cdot)$ on $h(\cdot)$ regression as elasticity.

As a benchmark, I begin with the following empirical specification:

$$y_{nct} = \beta' L_{nct} + \nu_t + \varepsilon_{nct} \tag{15}$$

where y_{nct} is the hybrid transformation of one of the indicators of food security $\{FCS, HDDS, RCSI\}$ for household n at time t living in the community c, L_{nct} is the hybrid transformation of income loss in absolute terms experienced by the household after the occurrence of a weather shock, ν_t absorbs the heterogeneity across

[21] Ravallion (2017) argues that the hybrid transformation is preferable because it is concave over the entire real line domain. The inverse hyperbolic sine transformation may not be concave in some areas of the domain.

the survey rounds, and ε_{nct} is the error term.

In the specification 15, there is a possibility of omitted variable bias from community characteristics that may influence both income losses and nutritional habits. I address this concern by including a vector of additional covariates X at the community level that capture observable heterogeneity across communities, which are defined as enumeration areas. These community variables control for the availability of resources in the community, the exposure to shocks, and the interaction among members. The second empirical specification that I test is as follows:

$$y_{nct} = \beta' L_{nct} + \delta' X_{ct} + \nu_t + \varepsilon_{nct} \tag{16}$$

Still, specification 16 does not capture the full heterogeneity. There is likely heterogeneity across households within a community. This heterogeneity may bias the estimation results. To control for this heterogeneity, I estimate the specification 17:

$$y_{nct} = \beta' L_{nct} + \delta' X_{ct} + \gamma' Z_{nct} + \nu_t + \varepsilon_{nct} \tag{17}$$

in which I include, in addition to the previous controls, a set of standard household controls, Z_{nct} such as the size of the household divided by adults and children, and maximum level of education attained by the head of the household. In all regressions, I cluster the standard errors at the enumeration areas.[22] The choice of the clustering level is motivated by survey sampling design reasons. The sampled data are collected from the Malawian population using enumeration area clustered sampling.

There remains a possibility of unobservable factors that may bias these estimates. Thus, in drawing causal inference from these estimates, one should be cautious. Despite this caveat, I reckon the results to be useful and informative because they enable us to understand better the difference in responses across food security indicators and the possible motivations behind the results.

4 Results

This section is structured in three subsections. In the first sub-section, I report the descriptive statistics about the population. In the second sub-section, I estimate the household income losses associated with weather shocks. Finally, in the last sub-section, I present the effect of income losses due to weather shocks on food security indicators.

4.1 Descriptive Statistics

Table 1 reports the incidence of the five most frequent shocks that Malawian households have experienced in each survey wave.[23] The survey design records the occurrence of different negative shocks in the last twelve months before the survey period. Households may be hit by multiple shocks in the same survey period. Furthermore, there is a high positive correlation between some of the shocks; for example, extreme weather conditions damage the crops and may lead to high prices for food. As a consequence, the shares reported in Table 1 are not expected to sum to one.

Results in Table 1 are ordered by the frequency observed in the 2010 wave. The main finding is that weather shocks have a high incidence among Malawian households. In the 2010 and 2016 survey periods, weather shocks

[22] See Abadie et al. (2017) for a discussion of the reasons for the use of clustered errors.

[23] The remain sixteen types of shocks have a much lower incidence on Malawian households and they are not reported in Table 1.

Table 1: Shocks Incidence

	Survey Round		
	2010	2013	2016
Weather Shock: Drought/Irregular Rains	0.373	0.516	0.774
Unusually High Costs of Agricultural Inputs	0.260	0.685	0.541
Unusually High Prices for Food	0.247	0.829	0.701
Unusually Low Prices for Agricultural Output	0.126	0.315	0.203
Serious Illness or Accident of Household Member	0.126	0.180	0.180

are ranked as the most frequent and severe shock that Malawian households have experienced. These shares imply that 560, 772, and 1165 households out of 1513 have experienced the consequences of extreme weather conditions in 2010, 2013, and 2016 surveys, respectively. As already mentioned above, the share of households affected by weather shocks may be underestimated due to the fact that other shocks may be consequences of weather shocks. These figures justify the choice of investigating the consequences of weather shocks on Malawian households' welfare.

Table 2 reports descriptive statistics about the characteristics of the population of interest. All statistics reported in Table 2 are weighted to make them representative of the Malawian population. The average size of the Malawian households is approximately five members with an equal share of adults and children defined as family members younger than 15 years old. The average age of the household head between the 2010 and 2016 surveys has increased from 41 to 46. This result joint with the constant household size across survey waves implies that the composition of households has not changed substantially across waves.

The monthly total household expenditures in 2011 US dollars show significant high volatility across the three survey periods and within each wave. The expenditure ranges from \$389 in 2010 to \$507 in 2016 with a peak of \$729 in 2013. Part of this variation across waves captures changes in the macroeconomic conditions that affect household consumption. The calculations of the standard deviation highlight large differences in expenditure across households within each survey wave. In the most recent round of the survey, we observe a decline in the volatility relative to the two previous rounds.

Households are concentrated in rural areas and live in relatively small isolated communities. Less than one-third of the households, roughly 25%, report living in urban areas. This finding is consistent with the average distance between the household dwelling, and the nearest major road is of about 7.5 kilometers.[24] The average distance between the household dwelling and the nearest population center, defined as an urban agglomeration with at least 20,000 inhabitants, is of over 28 kilometers. These findings emphasize the scarcity of jobs not related to agriculture and the dependence on crops and livestock as a means of support.

Households have very low educational attainment. For about 70% of the population, primary school completion is the highest educational qualification that the most educated member of the household has achieved. This corresponds to 8 years of school attainment. Less than 5% of the sample has a level of education higher

[24] A a major road is defined as a road classified as a primary or secondary network. According to the Malawian government statistics, these roads account for 42% of entire Malawi's designated public road network.

Table 2: Descriptive Statistics: Households Characteristics

	Survey Round					
	2010		2013		2016	
	Mean	SD	Mean	SD	Mean	SD
	Panel A: Continuous Characteristics					
Education (max # years)	8.29	4.21	8.66	4.10	8.68	3.95
Age Head (# years)	41.86	15.56	44.25	15.08	46.86	14.80
Number of children	2.28	1.67	2.48	1.70	2.33	1.68
Number of adults	2.57	1.23	2.82	1.34	2.85	1.42
Monthly Expenditure (US$ 2011)	389.29	2197.34	729.85	5827.71	507.93	783.16
Less preferred food consumption (# days)	0.79	1.56	1.32	2.09	1.92	2.23
Limited food portion (# days)	0.61	1.48	0.88	1.70	1.40	2.06
Skipped Meals (# days)	0.43	1.19	0.62	1.42	1.35	2.05
Restricted adult food consumption (# days)	0.20	0.83	0.23	0.74	0.54	1.28
Food Borrowing (# days)	0.20	0.66	0.36	0.90	0.52	1.21
Distance to nearest road (Km)	7.58	9.26	7.67	9.36	7.78	9.44
Distance to nearest population center (Km)	27.74	19.73	28.48	20.02	28.50	19.85
Number of Clothes Changes	6.98	13.94	6.02	3.84	8.45	9.81
	Panel B: Binary Characteristics					
Male Head	0.79		0.77		0.73	
Urban Area	0.27		0.26		0.25	
Cellphone Ownership	0.45		0.51		0.59	
At least one illness/injury (past 2 weeks)	0.59		0.58		0.74	
Wall Improvement	0.47		0.55		0.63	
Roof Improvement	0.41		0.46		0.58	
Floor Improvement	0.33		0.34		0.35	
Waterpipe Improvement	0.16		0.17		0.18	
Sleep in Bed and Mattress	0.31		0.33		0.33	
	Panel C: Food Security Indicators					
Food Consumption Score (FCS)	68.14	16.18	70.35	16.28	62.73	17.98
Household Dietary Diversity Score (HDDS)	6.16	0.99	6.22	0.94	5.89	1.08
Reduced Coping Strategies Index (rCSI)	3.07	6.14	4.62	7.09	8.12	9.68

than secondary school that corresponds to 14 years of school attainment. The correlation between the level of education of the head of the household, who are usually men, and the level of education of the most educated member of the household is 81%. There is a disparity in educational attainment between women and men, with women completing fewer years of schooling than men.

The figures from Table 2 show a clear trend in increasing difficulties in meeting basic nutritional needs. The days per week in which households have to limit the food portion or to skip meals due to food scarcity have increased from less than one day in 2010 to more than one in 2016. An even more marked trend is observed for the consumption of less preferred and less expensive food, from less than one day per week in 2010 to about two days per week in 2016. Similar patterns, although less significant in magnitude, are also observed for the increase in food borrowing from friends and relatives and the restriction in adult food consumption.[25]

The statistics reported in panel C of Table 2 refer to the nutritional status and food security of Malawian households. All three indicators show a worsening in the food security indicators in the last survey round. The Food Consumption Score (FCS) and the Household Dietary Diversity Score (HDDS) in 2016 take the lowest levels relative to the two previous rounds. That implies a decrease in dietary diversity in the last round compared to the two previous survey periods. On the other hand, the Reduced Coping Strategies Index (rCSI) has gone up from 2010 to 2016. This finding implies that households rely more strongly on a coping strategy to guarantee a sufficient level of food consumption.

The three food indicators capture different aspects of food security and nutrition status. The relatively small correlations among these measures confirm these differences. The correlation between the FCS and the HDDS is around 0.56, while the correlation between these two measures and the rCSI is equal to -0.26.

Table 3 report the shares of households by domain satisfaction levels. In all domains, 95% of the households assess their condition to be just adequate or below. The high concentration of responses in the two lowest categories signals a general dissatisfaction of households with the economic and living conditions.

Table 3: Share Households by Domain Satisfaction Levels

	Levels of Domain Satisfaction		
	Less than adequate (Level 1)	Just adequate (Level 2)	More than adequate (Level 3)
Food	0.44	0.50	0.06
Housing	0.47	0.48	0.05
Clothing	0.60	0.37	0.03
Health	0.39	0.56	0.05

The variation of satisfaction across waves, not shown in the paper, highlights an important fact. While the shares by category are very similar between the 2010 and 2013 surveys, there is a worsening in satisfaction in the 2016 wave. The share of households that assess their well-being to be less than adequate has increased by around 20%. This worsening is spread across all domains of satisfaction. One possible explanation for this result is the deterioration of the macroeconomic indicators. Another possible explanation is the higher incidence of

[25]The responses to these questions are used to construct the Reduced Coping Strategies Index (rCSI).

shocks, particularly weather shocks, experienced in the last round. As already noted in Table 1, the share of households that report the occurrence of shocks has risen significantly in the 2016 round relative to the two previous ones. Botha et al. (2018) document that Malawi has faced successive and compounding climatic shocks such as the worst flood in 50 years in 2015 and the strongest El Niño phenomenon in 35 years in 2016, which left 39% of the population in need of food assistance.

The descriptive statistics presented in this sub-section seem to support the story that an increase in frequency and severity of extreme weather conditions have negative consequences on individual's well-being and their nutritional status and food security.

4.2 Monetary Value of Losses due to Weather Shocks

Table 4 shows the results for the domains of satisfaction from the regression specification 7.[26] The estimates capture the common sense. As expected, the results emphasize a significant negative effect of weather shocks on all domains of satisfaction. Not surprisingly, weather shocks are associated with a very large decline in the Food domain satisfaction. Indeed, as the majority of the Malawian households engage in subsistence-level rain-fed agriculture, weather shocks have massive consequences on the availability of food and goods of primary need.

Table 4: Domains of Satisfaction Results

	Domains of Satisfaction			
	(1) Food	(2) Housing	(3) Clothing	(4) Health
Weather Shock	-0.099***	-0.108***	-0.063***	-0.047**
	(0.026)	(0.026)	(0.022)	(0.022)
HH Expenditure	0.036**	0.020	0.006	-0.000
	(0.016)	(0.017)	(0.015)	(0.016)
Mean HH Expenditure	0.155***	0.071**	0.094***	0.030
	(0.023)	(0.028)	(0.022)	(0.025)
Observations	4,363	4,365	4,344	4,363
R^2	0.252	0.130	0.217	0.074
Time FE	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

The remaining two rows of Table 4 report the estimates for the dependence of domains of satisfaction on income. As the IHPS does not collect information about income, I proxy the household income using the level of expenditure. The domains of satisfaction depend on income in two ways. The first dependency, reported in the second row of Table 4, is through the current income. These estimates measure the current income shock effect on satisfaction. The second dependency is through the mean household income. This second effect resembles Friedman's permanent income hypothesis. The estimates show a positive and strongly significant relationship between the mean income and the satisfaction in all domains but health. Interestingly, the current household expenditure has no significant effects on satisfaction except for the Food domain. Food consumption, different

[26] The estimates for the household controls are omitted from Table 4. Those estimates are all in the expected direction, and most of them are statistically significant at the standard significance levels.

from the other dimensions of satisfactions, is more sensitive to income shocks. Thus, it is reasonable that there is a stronger relationship between current levels of expenditure and Food satisfaction rather than other domains.

The results from Table 4 are used to compute the monetary value of a weather shock as explained in Sub-section 3.1. The first row of Table 6 shows the computation of the level effect of income on the different domains of satisfaction. These effects have been computed as the sum of the estimates for the current and the mean income effects. For example, the coefficient 0.191 for the Food domain of satisfaction in Table 6 is calculated as the summation of 0.036 and 0.155 that correspond to the coefficients taken from Table 4 of HH Expenditure and the Mean of HH Expenditure, respectively. Similar calculations are performed for the other domains of satisfaction.

Table 5 reports the estimates from equation 8. These estimates highlight the relationship between the domains of satisfaction and the general satisfaction. The first block includes the shock effect of domain satisfaction on general satisfaction, while the second block shows the mean effects. The estimates highlight the positive significant relationship between the domains of satisfaction and the general satisfaction. Furthermore, the domains of satisfaction have quite high power in explaining the general satisfaction; indeed, the R^2 is 40%.

Table 5: General Satisfaction Results

Shock Effect		*Mean Effect*	
Food	0.417***	Food	-0.023
	(0.141)		(0.167)
Housing	0.267**	Housing	0.029
	(0.121)		(0.183)
Clothing	0.866***	Clothing	0.832***
	(0.116)		(0.164)
Health	0.371	Health	0.112
	(0.358)		(0.408)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

The coefficients of the shock effects for all domains but health are strongly significant. On the other hand, most coefficients of the mean effect are nonsignificant. Only the estimate for the clothing domain is positive and significant. These findings suggest that individuals assess their general satisfaction based on the current level rather than the mean effect.[27]

The estimates from Table 5 are used to construct the effect of domain satisfaction on general satisfaction accordingly to the methodology explained in in Sub-section 3.1. These effects are reported in the second row of Table 6. For example, in the case of the Food domain satisfaction, the coefficient (0.394) is the result of the summation of the coefficients of the shock effect (0.417) and the mean effect (-0.023) for the Food domain from Table 5.

The remaining rows of Table 6 report intermediate calculations to compute the income equivalent associated with losses due to the occurrence of weather shock. The third row of Table 6 shows the welfare effect of each domain of satisfaction. For instance, the welfare effects for the Food domain satisfaction is calculated as the

[27]The Z variable, not reported in the table, captures elements that influence both the general and domains of satisfaction such personality traits and results to be positive and strongly significant at the 1% significance level.

Table 6: DS - Expenditure Multipliers

	Domain Satisfaction			
	(1) Food	(2) Housing	(3) Clothing	(4) Health
Expenditure Effect on DS	0.191	0.092	0.100	0.029
DS Effect on GS	0.394	0.296	1.698	0.483
Welfare Effect	-0.136	-0.112	-0.373	-0.079
Income Equivalent	0.503			

product between the coefficient of the weather shock dummy from the Food satisfaction regression (-0.099) and Food domain satisfaction's effect on the General domain (0.394) divided by the sum of the product effects of the expenditure on the domains of satisfaction time effect of domains of satisfaction on general satisfaction (0.191*0.394 + 0.092*0.296 + 0.100*1.698 + 0.029*0.483 = 0.286). Finally, by summing the welfare effects by domain of satisfaction and then by applying the transformation in Equation 13, I obtain that the income equivalent is 0.503.

The estimate of the income equivalent implies that when a household faces a weather shock, it needs to be compensated by 50% of its income to make it returning to the level of well-being that it had before the occurrence of the shock. In terms of money loss, when a household with average income (540USD in 2011 PPP) experiences a weather shock, the estimates indicate that its equivalent income loss is equal to $270. This finding is in the range of the estimates of previous literature. For instance, Ferrer-i-Carbonell and van Praag (2002) estimate income reductions for health shocks that range from 20% to 47%.

Households with higher income face a higher loss in absolute terms due to a weather shock. I compute the household income loss by multiplying the household income by the percentage income equivalent factor estimated in this sub-section. The estimates of the losses are used to investigate the impact of weather shocks on food security indicators.

4.3 Food Security Results

Table 7 summarizes the results from the regression models presented in the sub-section 3.2 for the three indicators of food security $\{FCS, HDDS, RCSI\}$. In order to interpret the estimates as percentage effects, I use the transformation proposed by Ravallion (2017) that consists of a hybrid hyperbolic sine and its inverse explained in detail in sub-section 3.2. I apply this transformation to both the food security indicators (dependent variable) and income losses (independent variable).

The results provide suggestive evidence that income losses associated with weather shocks are correlated with a worsening of the food security indicators. There are interesting differences in the findings across food indicators. The estimates for Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS) have both negative signs across the different specifications. That means households experience a deterioration in the quality and diet diversity and in the quantity of food consumed. Although the effect is in the expected direction, in most specifications, the estimates turn to be nonsignificant at any standard level. This finding signals households do not change their dietary habits substantially.

Table 7: Regression Results: Food Security Indicators

	Food Security Indicator								
	FCS			HDDS			rCSI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income Loss due to Weather Shocks	-0.005*	-0.004	-0.001	-0.001	0.000	0.002	0.047***	0.035**	0.024*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.015)	(0.016)	(0.015)
Observations	4,459	4,036	3,931	4,459	4,036	3,931	4,458	4,035	3,930
R^2	0.051	0.076	0.146	0.021	0.036	0.100	0.071	0.088	0.121
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Community controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Household controls	No	No	Yes	No	No	Yes	No	No	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Several reasons may explain the statistically non-significant effect on the dietary composition. First, households negatively affected by weather shocks may maintain their food consumption unaltered at the expense of a significantly lower expenditure in non-necessity goods. This explanation is consistent with previous research. In this context, Skoufias et al. (2011) shows a decline in non-food expenditures rather than in food consumption. The further investigation of this channel remains an important avenue for future research to better understand the effects of weather shocks on household well-being.

A second possible explanation for the results in FCS and HDDS is that the pass-through from weather shocks to nutritional restrictions is mitigated by the help from relatives, friends, and community members. If informal social protection networks were well-diffused, one could not observe a statistically strong deterioration in nutrition outcomes, even in the occurrence of negatively large income shocks. This consideration is related to the estimates for Reduced Coping Strategies Index (rCSI) that show a different story.

The estimates of the rCSI are positive and statistically significant at the 5% significance level, except in the last column of Table 7 in which the level is 10%. As expected, the estimates are positive. That implies that the occurrence of weather shocks is correlated with a higher number of days in which households have to develop coping strategies to overcome the lack of food availability. These findings emphasize an increase in food insecurity to satisfy basic nutritional needs. One percent decrease in income due to weather shocks is associated with an increase in food insecurity that, according to the specifications, ranges between 0.05% and 0.03%.

One relevant coping strategy that households adopt is to borrow food from friends and relatives. Under this scenario, one would observe, as the previous estimates show, a positive correlation between the income losses and the rCSI, but a not too strong negative relationship between the losses and the other indicators of food security.

To further investigate the importance of food borrowing and informal networks, I study the fraction of households that rely on food borrowing. More than 21% of the households borrow food from friends or relatives at least once a week when a weather shock occurs. Furthermore, there is an increase of over 8% in the share of households who rely on borrowing when hit by a weather shock. This figure highlights the importance of the informal social protection network in mitigating the negative effects of income shocks.

5 Income Losses using Objective Measures

In this subsection, I replicate the main results using precipitation levels, instead of the self-reported information, to determine the weather shocks and calculate the income losses associated with it. This section aims to identify the differences between the results using self-reported weather shocks information and objective criteria.

5.1 Extreme Weather and Food Security indicators

Table 8 and Table 9 show that the estimates of the relationship between food security indicators and weather shocks are in the same direction, either using the *self-reported weather shocks* or the *observed weather shocks*, respectively.

Table 8 shows the direct relationship between the *self-reported weather shock* and the food security indicators. This approach differs from Table 7, which shows the indirect effect of income losses due to weather shocks on food security indicators. Although the direct and indirect effects are of different natures, the effect's direction is consistent in both Table 7 and Table 8, where income loses due to weather shocks, and weather shocks are negatively associated with FCS and HDDS and positively associated with rCSI.

Table 8: Regression Results: Effect of Droughts (self-reported) on Food Security Indicators

	Food Security Indicator								
	FCS			HDDS			rCSI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
During the last 12 months, household affected by droughts	-0.063***	-0.058***	-0.025*	-0.035***	-0.027***	-0.007	0.365***	0.302***	0.173**
	(0.014)	(0.015)	(0.013)	(0.011)	(0.010)	(0.008)	(0.080)	(0.086)	(0.077)
Observations	4,539	4,106	3,949	4,539	4,106	3,949	4,538	4,105	3,948
R^2	0.059	0.082	0.208	0.026	0.039	0.153	0.078	0.094	0.166
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Community controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Household controls	No	No	Yes	No	No	Yes	No	No	Yes

Table 9 indicates the association between the *observed weather shock* and the Food Security Indicators. Using data from Matsuura and Willmott (2009), the observed weather shock is calculated using the monthly total precipitation data interpolated to a 0.5 by 0.5 degree grid resolution (centered on 0.25 degree) for one year prior to the survey to make it equivalent to the self-reported measure based on the question: "During the last 12 months, was your household affected negatively by any of the following [shock]?"[28] . The results show a negative relationship between the observed weather shocks and the FCS and HDDS indicators, consistent with other studies that emphasize that the short term weather shocks' effect is the reduction of the calorie intake Gitz et al. (2016), which is related to the two food security indicators[29]. The negative relationship between the observed weather shock and the rCSI indicator The recall of this indicator is only seven days. may be explained because this measure is affected by seasonality and may not reflect the current conditions if these conditions changed after the last data collection.

5.2 Monetary Loss based on Precipitation

Table 10 shows the effect of the income losses due to observed weather shocks (based on precipitation) on Food Security indicators. By using the precipitation to calculate the indirect effect of weather shock (income losses) on Food

[28]Drought is defined based on precipitation. To take into account, the variation across the period analyzed, I calculate the average precipitation in the three years prior to the survey 2009, 2012, and 2015. Then, drought is defined as the region with precipitation under the average of precipitation in the period of analysis.

[29]Gitz et al. (2016) indicates that in Malawi, a drought shock of 1 degree more than the upper confidence interval of the comfort zone implies a drop in overall consumption per capita by about 19.9 percent and food caloric intake by about 38.7.

Table 9: Regression Results: Effect of Droughts (observed) on Food Security Indicators

	Food Security Indicator								
	FCS			HDDS			rCSI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Droughts based on precipitation	-0.041*	-0.025	-0.013	-0.041***	-0.033**	-0.025**	-0.145	-0.288***	-0.319***
	(0.024)	(0.023)	(0.018)	(0.015)	(0.014)	(0.012)	(0.092)	(0.102)	(0.099)
Observations	4,537	4,104	3,949	4,537	4,104	3,949	4,536	4,103	3,948
R^2	0.052	0.075	0.207	0.030	0.041	0.157	0.066	0.093	0.173
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Community controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Household controls	No	No	Yes	No	No	Yes	No	No	Yes

Security indicators the effects are the opposite to the ones observed in table 7. The negative relationship between rCSI and income losses based on precipitation may be explained in part because the "hunger season" may have been milder in the year of the surveys, and the rCSI picks up the less-severe coping behaviors Maxwell et al. (2013). On the other hand, the positive relationship observed for FCS and HDDS, although nonsignificant in most of the cases, may be given because the precipitation of one lagged year is not negatively correlated with several satisfaction dimensions in the year of the survey, which are the main measures to calculate the income losses. Therefore, the income losses calculated with self-reported weather shocks are not comparable with the ones calculated using the observed measures.

Table 10: Regression Results: Food Security Indicators

	Food Security Indicator								
	FCS			HDDS			rCSI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income Loss due to Weather Shocks (Precipitation)	0.010*	0.013**	0.006	0.003	0.004	-0.000	-0.088***	-0.123***	-0.096***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.023)	(0.025)	(0.024)
Observations	4,532	4,099	3,944	4,532	4,099	3,944	4,531	4,098	3,943
R^2	0.052	0.080	0.208	0.020	0.036	0.153	0.075	0.106	0.176
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Community controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Household controls	No	No	Yes	No	No	Yes	No	No	Yes

6 Conclusion

This study shows the contribution of income loss, due to droughts or irregular rains, to household food insecurity. The reason behind the focus on weather shocks is because the majority of Malawian households have suffered the consequences caused by weather shocks.

I have estimated the monetary equivalent to losses due to weather shocks using people's subjective assessment of life satisfaction in four domains (Food, Housing, Clothing, and Health). The estimate of the income equivalent implies that when a household faces a weather shock, it needs to be compensated by 50% of its income to return to the pre-shock level of well-being.

I have used the estimated income losses to investigate how the estimated income losses due to weather shocks affect food security. The results show that estimated income losses due to weather shocks are, on the one hand, negatively correlated with the Food Consumption Score (FSC) and the Household Dietary Diversity Score (HDDS). On the other hand, there is a positive relationship between the estimated losses and the Reduced Coping Strategy Index (rCSI).

These results suggest that higher-income losses are associated with low quality and less diverse diet as well as with the presence of more unfavorable circumstances where the households have to apply strategies to safeguard the food security inside the household. It is worth to notice that households may also engage in alternative coping strategies such as precautionary saving, borrowing in the informal credit market, and social capital, not covered in this study, that contribute to minimizing the effect of negative shocks on dietary quality and diversity.

Although the estimations' direction is consistent when using self-reported or observed weather shock measures, the estimates of the income losses are sensitive to the indicator selected. Furthermore, the income losses calculated using either of the two measures are not comparable.

The findings of this paper fit into a broad policy debate. Policies that aim to decrease food insecurity in the case of adverse shocks have to aim to increase household's resiliency and flexibility to adapt to new environments without compromising the household's food security. Furthermore, policy design should be inclusive and pro-poor oriented. A positive change in the state of food insecurity will occur if the policies effectively reinforce the countries' economic resilience to safeguard food and nutrition in periods of economic slowdowns (Sofi, 2019).

One possible policy intervention should aim to support the diversification of income sources for households engaged in subsistence-level rain-fed agriculture. For example, as also suggested by Gao and Mills (2018), policies should support the diversification of economic activities into off-farm occupations in a way to ensure a minimum income also in the occurrence of negative weather shocks.

An alternative policy intervention should aim to educate households in allocating income resources optimally, between good and adverse times. Specifically, the policy should raise awareness on how to effectively use the limited income in adverse times. For instance, households should be taught about dietary practices under income restrictions in order to guarantee an adequate nutritional status.

There are three important avenues for further research that I aim to explore in the future. First, I will go beyond the analysis presented in this paper by investigating the most effective coping strategy and the interactions among them. I will explore how the food outcomes of households that engage in different coping mechanisms vary.

Second, as a complementary investigation to the one present in this study, I will explore how the results change by using an alternative measure of weather shock, such as the z-scores based on actual precipitation.

Third, households negatively affected by weather shocks may maintain their food consumption unaltered at the expense of a significantly lower expenditure in non-necessity goods. I plan to explore this channel by using the disaggregated food and non-food expenditures modules from the IHPS surveys.

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A Additional Tables

Table A1: Food Consumption Score Weights

Food group	Weight
Main staples, Cereals, Grains, Roots and Tubers	2
Legumes and Nuts	3
Vegetables	1
Fruits	1
Meat, Fish, and Eggs	4
Milk and other dairy products	4
Oils and Fat	0.5
Sugar	0.5
Condiments and Spices	0

Table A2: Reduced Coping Strategies Index Weights

Coping Strategy	Severity Weight
Rely on less preferred and less expensive foods?	1
Borrow food, or rely on help from a friend or relative?	2
Limit portion size at mealtimes?	1
Restrict consumption by adults in order for small children to eat?	2
Reduce number of meals eaten in a day?	2

Table A3: Proportion of Food Consumption Groups by Day

Food group	Proportion by Day							
	0	1	2	3	4	5	6	7
Main staples, Cereals, Grains, Roots and Tubers	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.94
Legumes and Nuts	0.34	0.18	0.16	0.11	0.07	0.03	0.02	0.10
Vegetables	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.94
Fruits	0.12	0.11	0.25	0.20	0.14	0.07	0.04	0.08
Meat, Fish, and Eggs	0.00	0.02	0.05	0.08	0.09	0.09	0.06	0.62
Milk and other dairy products	0.19	0.14	0.19	0.16	0.13	0.08	0.04	0.08
Oils and Fat	0.25	0.11	0.18	0.16	0.11	0.06	0.03	0.10
Sugar	0.23	0.06	0.06	0.06	0.05	0.04	0.03	0.48
Condiments and Spices	0.22	0.04	0.08	0.10	0.08	0.06	0.03	0.38