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How much do infrastructural investments mitigate impacts of seasonal shocks on food security?

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Abstract

Ending extreme hunger requires the interaction of both household and community level infrastructural investments. When communities and households are capital infrastructure constrained, the effects of extreme events such as droughts can fetter consumption growth and food security. This paper, assesses the impact of seasonal weather shocks on food security conditional on access to public physical infrastructure. The study uses fixed effects regression techniques on representative Malawian panel data collected between 2010 and 2016. The study uses three key indicators of food security namely food consumption expenditure shares, the Berry Index of dietary variety, and the Shannon Entropy Index. To measure idiosyncratic and covariate shocks, self-reported survey data and high-resolution station based standardized precipitation – evapotranspiration index were used. To measure infrastructure, survey data, triangulated with remote sensed night time lights, were used to construct an infrastructure index in a logistic regression framework. Results show that assuming minimal infrastructure a standard deviation deficit in the one to three-month interval drought reduces consumption by 26%. Assuming normal historical weather conditions, infrastructure improves economic access to food by 15%. Thus, conditional on infrastructure, the impacts of extreme weather events on food security are reduced by 54%.

Keywords: Food security, Dietary Diversity, Idiosyncratic and covariate shocks, infrastructure, Standardized Precipitation – Evapotranspiration Index, Night Time Lights

JEL codes: Q120, D130, D150

1. Introduction

We cannot end hunger if we ignore key complementary investments that enable resilience to economic disruptions. Investment in public infrastructure is significantly correlated with increased agricultural growth and positive welfare (Dorosh et al. 2012; Diao and Dorosh 2007; World Bank, 2018). Hard infrastructure may change allocation of economic resources such as food by altering internal terms of trade and changing the structure of uncertainty regarding production and factor allocation decisions in rural economies (Platteau 1996; World Bank 2018). Absence of infrastructure such as roads or markets increases transaction costs which may limit access to food by increasing prices. Taking this view, absence of infrastructure may be an implicit ad-valorem tax to economically isolated individuals (Renkow, Hallstrom, and Karanja 2004; Nissanke and Aryeetey 2017). A household lacking access to infrastructure may need to pay extra costs in time and resources to access markets making it less competitive and more inclined to be autarkic and self-sufficient.

Mechanisms explaining impacts of infrastructure on income distribution and hence food security are complex. Standard trade theory indicates that economic isolation is likely to lead to consumption bundles satisfying lower indifference curves and also lower production possibilities. Further, most produce that could lead to diversified diets elsewhere are spoiled due to lack of markets. Economic isolation could also lead to unsavoury terms of trade among poor farming households. Reducing economic isolation through infrastructure provisioning could enable trade, which could in turn reduce food spoilage, improve access and utilization by increasing consumption options.

While some literature argues the above position, using data from Madagascar, Minten and others (1999) contended that longer distances to roads were rather associated with lower consumer prices. Minten et al (1999) argued that longer distances are associated with higher economies of scale – making transportation of bulky commodities cheaper. This line of argument, however, only works when there is considerable connectivity as it may not make sense in the absence of critical infrastructure. In most parts of Africa, however, most bulky commodities are transported on foot, and by head load. This is not only unhealthy due to the strain goods put on the body but also unsafe and risky due to theft occurrences (Riverson, Carapetis, and others 1991; Barwell et al. 2019). Non-excludable physical infrastructure can, therefore, have positive welfare effects (Tilman, Dixit, and Levin 2019).

Noteworthy, Binswanger, Khandker, and Rosenzweig (1993; Donaldson 2018) argued that infrastructure is endogenous such that its placement is influenced by region and micro-climatic specific factors. In addition, Banerjee, Duflo, and Qian (2012; Guasch, Laffont, and Straub 2007; Boarnet 1997) reasoned that government and administrations might have their own preferences that might guide the politics of infrastructure delivery. For instance, In African agriculture, investments that are critical for increasing agricultural productivity and resilient livelihoods in the long-run are often not prioritized in favor of meeting immediate consumption needs of the populace and government recurrent expenditure. There is also general fear of recovery costs in engaging in infrastructural investments that would open up rural areas to new markets and increase economic activity (Raballand et al. 2011). Thus, any attempt to assess distributional and welfare effects of infrastructure must adequately account for endogeneity induced by administrators and governance frameworks.

Arezki and Sy (2016) reported that the African continent faces risky infrastructure deficiencies which make it suffer considerable diseconomies of scale. In the absence of proper infrastructure, effects of extreme events such as weather-related shocks and unusual price fluctuations in addition to household specific idiosyncratic shocks can impede agricultural growth and development. In fact, due to lack of connectivity, costs of service delivery range between 50 – 175% higher than anywhere in the world (African Development Bank 2014).

Although impacts of infrastructure provisioning and economic shocks on household welfare have been well documented, there is paucity of literature on the mitigating role of infrastructure to household and community level shocks. To illustrate, Frayne and McCordic (2015) using data from Malawi assessed the association of infrastructure and income on household food security using a lived poverty index (LPI) as a measure of infrastructure. However, the study did not explicitly discuss impacts of idiosyncratic and covariate shocks nor the interaction thereof. Besides, the study's use of a less known LPI as a measure of infrastructure without accounting for more important forms of infrastructure and endogeneity among its aggregated components renders the study's results weak.

Additionally, Herrmann and Grote (2015) found that income poverty among farm households that had access to out-grower irrigation schemes was less prevalent. Despite tackling effects of infrastructure on income poverty, the study did not assess effects of shocks nor the mitigating effects of infrastructure. In addition, Asfaw and Maggio (2018) found that weather shocks were severe among female headed households. Asfaw and Maggio (2018) measured shocks as deviations from the historical average without accurately accounting for crop output responses which directly link to food security outcomes. Such an omission could overestimate the actual impacts. To contribute to that inquiry, we use a more novel long-term Standardized Precipitation – Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería, and López-Moreno 2010; Kubik and Maurel 2016) drought index that adjusts for precipitation, potential evapotranspiration to determine whether an event was truly extreme at different monthly intervals. Kubik and Maurel (2016) have revealed that SPEI outperformed previous methodologies such as the one used by Asfaw and Maggio.

However, literature has shown that increased investment in infrastructure is significantly correlated with increased agricultural growth and positive welfare outcomes. While it is difficult to track actual financial disbursements, it is fairly easier and more objective to observe the actual outcome of the investments such as presence of electricity or roads. We can therefore use physical presence of public infrastructure as an objective indicator for investment and assess its effects on a range of welfare outcomes such as nutrition and food security (Donaldson 2018).

Malawi has a recent history of combined extreme weather and economic shocks, which due to its low infrastructural investment levels, have undermined its growth prospects (World Bank, 2018). For example, during the 2015/16 agricultural season, floods, due to extreme El Nino weather, displaced farming communities in southern Malawi making them unable to both produce and thereafter earn income for a living (Nation Publication 2017).

Further, the time period between 2010 and 2017 saw a shift in the country's macroeconomic policy from a fixed exchange rate regime to a market based floating policy (Pauw, Dorosh, and Mazunda 2013). Being a predominantly importing and consuming economy (Government of Malawi 2015), the successive currency depreciation eroded consumers' purchasing power albeit improving macroeconomic stability.

Further, weather shocks in neighbouring Tanzania lead to reduction in household incomes and later induced a 13% probability of migrating (Miguel 2005). Miguel (2005) also found that weather shocks such as droughts lead to increasing murder rates in Tanzania which indicates the severity that shocks have on people's livelihoods. Kudamatsu, Persson, and Strömberg (2012) found that droughts increased infant mortality in Africa. Their results indicated that infants were more likely to die if they were exposed to drought in utero and are born during hunger episodes. Noteworthy, McPeak, Doss, and Little (2011) found that perceptions of risks varied across different communities.

This paper, therefore, assesses the impact of household shocks on food security in Malawi conditional on infrastructural investments using food budget shares, Berry and Shannon indexes of dietary variety. Understanding endogenous placement of infrastructure among communities, we use instrumental variables in a fixed effects regression framework. Using three-wave panel data adds value to the growing literature, which has mostly relied upon cross-section data (Harttgen, Klasen, and Rischke 2015), small non-representative samples (Harttgen, Klasen, and others 2012) and computable general equilibrium (CGE) models (Pauw, Dorosh, and Mazunda 2013), by bringing evidence from three waves of nationally representative surveys with a simple, theoretically consistent and clearly identified methodology. The study also triangulates the self-reported drought incidence with high-resolution long-term gridded weather data at 0.5°×0.5° longitude-latitude grid cells. To further triangulate the survey data on access to infrastructure, we use remote sensed Night Time light data at the same grid level as the SPEI data. To the best of our knowledge, this study is the first to combine high-resolution data and micro data to assess the mitigating role of infrastructure on food and nutrition security during crises. Combining big data and representative, country level data enhances the precision and accuracy of impacts of shocks – which goes a long way to achieving evidence-based policy analysis.

We find that a standard deviation deficit in a one month to three-month interval SPEI, being inflationary in nature, raises the food budget shares by 26%, thereby limiting economic access to food. Dietary diversity responds negatively to a seasonal drought indicating that access to nutrient rich food is limited. In the midst of shocks, households that had 1% more access to infrastructure – measured as a combination of night-time radiance and self-reported accessibility – had 15% more economic access to food. We also found that households that had 1% more access to infrastructure were generally 68% more dietary diverse. The interaction between infrastructure access and seasonal shocks was negative for the food budget share and dietary diversity models. This suggests that the effects a seasonal drought or flood on economic access to food and dietary diversity is mitigated by the presence of supporting infrastructure.

The paper is structured as follows: Section 2 presents the methodology and data. In this section we describe a micro-economic theoretical framework on which our analysis is based. We use predictions from the theory to guide our econometric identification and estimation. Then we present sources of data and construction of key variables while getting insights from literature. In section 3 we present key results of impacts of seasonal shocks on household food security and impacts of community infrastructure on food security. In Section 4 we present a discussion of key results while in section 5 we provide a summary and conclusion.

2. Methodology

2.1. Theoretical framework

Public infrastructure could help cushion the household from the impacts of economic shocks by smoothing consumption. Following notation from Sadoulet and De Janvry (1995; Jacoby 2000; Liu and Henningsen 2016) with modifications, we assume that households in community (τ) maximize their utility

$$u = u(X, C, Z, M^h) \qquad 1$$

where $X = \{x_1, \dots, x_n\}$ is a set of home produced crops, $C = \{c_1, \dots, c_k\}$ is a set of imported commodities; and $Z = \{z_1, \dots, z_m\}$ is a set of other non-imported commodities and $M^h = \{m_1, \dots, m_k\}$ is a set of household specific characteristics.

Households engage in production of crops $Y = \{y_1, \dots, y_n\}$ using a well-behaved multi-input multi-output production technology that constrains utility. Thus, for a unit of output y_i the production function is

$$y_i = f(a_i, l_i, q_i, M^p) \qquad 2$$

where a_i is land; l_i is labour; $q_i = \{q_1, \dots, q_m\}$ is a vector of inputs such as fertilizer; and $M^p = \{m_1, \dots, m_k\}$ is a set of farm specific conditions including weather conditions represented by SPEI.

We define crop prices that the households in location τ face as $P^x = \{p_1^x, \dots, p_n^x\}$. Due to differences in infrastructure provisioning, e.g. some communities could have better roads, markets, electricity, among others, prices carry along transaction costs. For instance, let $\widetilde{p_i}^x = p_i^x - bh$ be the price the net producer household faces in the market after considering the cost *b* of traveling *h* hours to the market. Thus, if a household is a net buyer it will face a price of $\widetilde{p_i}^x = p_i^x + bh$. Further, input costs are also obtained with transaction costs, $\tilde{v} = v + bh$, where $v = \{v_1, \dots, v_m\}$ is a set of input prices; $\widetilde{w} = w + bh$ is the wage and $\tilde{r} = r + bh$ is the land rent (Jacoby 2000). Thus, a farm household facing infrastructure constraints will seek to maximize returns to its productive activities as follows

$$\rho(\widetilde{p_i}^x, \widetilde{w}, \tilde{v}, \tilde{r}) = \tilde{p}^x \cdot Y - \tilde{v} \cdot q_i - \widetilde{w} \cdot (l - T) - \tilde{r} \cdot a_i \qquad 3$$

which leads to a household budget constraint of the form

$$P^x \cdot X + P^c \cdot C + Z \leq \tilde{p}^x \cdot Y - \tilde{v} \cdot q_i - \widetilde{w} \cdot (l - T) - \tilde{r} \cdot a_i + E_i \qquad 4$$

where the price of commodity Z has been normalized to 1 and E_i is any exogenous income such as transfer payments or other income from off-farm businesses. Given first order conditions, we get a set of demand equations $X^* = \{x_1^*, \dots, x_n^*\}$; $C^* = \{c_1^*, \dots, c_m^*\}$ and $Z^* = \{z_1^*, \dots, z_n^*\}$ which are functions of prices $\widetilde{p_i}^x, \widetilde{p_i}^c, \rho(\widetilde{p_i}^x, \widetilde{w}, \tilde{v}, \tilde{r})$ and E (Sadoulet and De Janvry 1995). These demand equations give rise to the indirect utility function

$$\Psi\left(\widetilde{p_\iota}^{x*}, \widetilde{p_\iota}^{c*}, \rho(\widetilde{p_\iota}^{x*}, \widetilde{w}, \tilde{v}, \tilde{r})\right). \quad 5$$

Define Ω as a piece of infrastructure such as a road or market. Constructing a good road reduces economic isolation by reducing transaction costs. Let $\sigma^h(\Omega, h) = \rho^h(\widetilde{p_\iota}^{x}, \widetilde{w}, \tilde{v}, \tilde{r})$ be the income situation of the household after the infrastructure project in location $\tau = 1$. Thus, due to changes in transaction costs, profits, incomes and therefore demand for food commodity bundles may change while in a location without infrastructure $\tau = 0$ the may not (Jacoby 2000; Jacoby and Minten 2008).

In addition, we define $G(h, a)$ as the joint cumulative probability distribution function for distance from the market and the land endowments, we can define the social welfare function as

$$W(\Omega, h) = \int_a \int_0^{\overline{h}} \Psi\left(\widetilde{p_\iota}^{x*}, \widetilde{p_\iota}^{c*}, \rho^h(\widetilde{p_\iota}^{x*}, \widetilde{w}, \tilde{v}, \tilde{r})\right) dG(h, a). \quad 6$$

Differentiating the welfare function with respect to Ω gets

$$W_\Omega = \int_a \int_0^{h*} \Psi'\left(\widetilde{p_\iota}^{x*}, \widetilde{p_\iota}^{c*}, \rho_\Omega^{h'}(\widetilde{p_\iota}^{x*}, \widetilde{w}, \tilde{v}, \tilde{r})\right) dG(h, a). \quad 7$$

In this case, W_Ω measures the change in welfare with respect to the infrastructural endowment. On the other hand, if we differentiate the equation 13 with the M^p variable i.e.

$$W_{\Omega, M^p} = \int_a \int_0^{h*} \Psi''_{M^p}\left(\widetilde{p_\iota}^{x*}, \widetilde{p_\iota}^{c*}, \rho_{\Omega M^p}^{h''}(\widetilde{p_\iota}^{x*}, \widetilde{w}, \tilde{v}, \tilde{r})\right) dG(h, a) \gtrless 0 \quad 8$$

is the unknown mitigating role of infrastructure on impact of extreme weather events.

2.2. Estimation

Anand and Harris (1994; Deaton 2019) reported that food consumption indicators can be used to measure welfare changes. Thus, without losing much details, we assume that the indirect utility function can be adequately represented by food consumption behaviour at household level. We can econometrically estimate the food consumption expenditure adjusted for Engel's equivalence scales on the food budget share (*see* Deaton (2019 Ch. 4)) for household i in community j at time period t as

$$\ln W_{ijt} = \beta_{0ijt} + \beta_1 M_{ijt}^h + \beta_2 M_{jt}^p + \beta_3 S_{jt} \cdot \Omega_{jt} + \tau_j + t + e_{ijt} \quad 9$$

where $\ln W_{ijt}$ is the food budget share; dietary variety or a proxy index of consumption per person per day in year t; M_{ijt}^h is a vector of household level characteristics; M_{ijt}^p is a vector of agricultural characteristics; β_i are unknown parameters to be estimated; τ_j are community fixed effects; S_{jt} is a time specific vector of covariate and idiosyncratic shocks; Ω_{jt} is a vector of infrastructure endowments; e_{ijt} is an independent and identically distributed error term.

We also assume that $E(e_{ijt}|X_{ijt}, a_i) = 0$, $Var(e_{ijt}|X_{ijt}) = \sigma_e^2$, $\forall t \in T$ and $Cov(e_{ijt}, e_{ij}|X, a_i) = 0$ (Woodridge 2009). All things being equal, β_3 estimates the mitigating role of infrastructure on welfare measured as food security. In addition to the assumptions advanced in equation 9, one requirement for identifying causal effects is that the explanatory variable of interest i.e. infrastructure should not be correlated with the error term. That is, $cov(\text{infrastructure}, e = 0)$.

It has been widely reported, however, that infrastructure is often endogenously invested (Banerjee, Duflo, and Qian 2012; Guasch, Laffont, and Straub 2007; Boarnet 1997). For instance, in Africa following the wave of decentralization, most infrastructural developments have been devolved to local government authorities who are represented by local leaders (Bardhan and Mookherjee 2006). In view of Bardhan and Mookherjee (2006)'s observation that there are significant allocation distortions in delivery of public resources, infrastructure in developing countries such as Malawi depends on the political will of the constituency's member of parliament (MP), and the political party affiliation given geographic characteristics. Anecdotal evidence suggests that most opposition party members do not get large infrastructural projects and most projects are clustered around constituencies that belong to the ruling party.

Coupled with such elitist and partisan capture of infrastructural projects, Malawi follows a five-year political term before another election which brings a lot of pressure on politicians to seek re-election (Said and Singini 2014). Such pressure stifles well planned investments. Instead, politicians focus on projects that would appease their constituents to entice them for re-election. In such view, MPs that are not present for their constituents and who also do not belong to the ruling party might not have any infrastructure in their communities thereby risking losing the election. Our three waves of panel data fall within two extra-ordinary regime changes filled with dynamic partisan shifts in allocation of public infrastructural projects. In early 2012, the President Bingu wa Mutharika died midway through his second term. His death followed a regime change in which his estranged Vice President Joyce Banda broke away from the former President's party and formed her own. Some MPs moved to her new party while others remained behind. Projects that were allocated to some constituencies under Bingu stagnated and or were discontinued while for the newly formed party, new projects were initiated (Said and Singini 2014).

Given that infrastructure placement plays a huge role in connectivity and reduction of transaction costs (Donaldson 2018; Banerjee, Duflo, and Qian 2012), political affiliation of the MP and whether the MP comes from the same community (MPCM) – a key indicator of political will – are highly correlated. However, considering that our welfare indicator – food consumption expenditure adjusted for equivalence scales and the food budget share– is estimated from a seven day dietary recall, it is sufficient that we can use MPCM as an instrument to address infrastructure endogeneity. Clearly, whether an MP is from your community has something to do with whether you receive a road or a major project but it has little if nothing to do with whatever you ate the in the past seven days.

We subject MPCM to the Wald test to establish whether use of the instrument is warranted and also the Stock-Yogo test for weak instruments (Stock and Yogo 2002). Bun and Harrison (2019) recognized that weak instruments are a huge problem in most econometric work and advocate the use of identification by functional form and bootstrapping. Apart from our instrument passing the Stock-Yogo tests for all thresholds, we also bootstrap our results. We use the plm R statistical package (Croissant, Millo, and others 2008) using RStudio (RStudio Team 2019) to estimate instrumental variables in panel data form with fixed effects.

2.3. Data and descriptive statistics

Data used in this study came from three waves of Integrated Household Surveys (IHS3, IHSP and IHS4) of the National Statistics of Malawi (NSO). The surveys were conducted in 2010, 2013, and 2016 with support from the World Bank's Living Standards Measurement Survey and Integrated Surveys for Agriculture (LSMS-ISA) project. A stratified two-stage sample design was used for the IHS panel surveys and a sample size of 2,508 households was collected. The NSO reported that the surveys are representative at national level, rural/urban, regional and district-level.

2.3.1. Dependent variables considered

Food budget share: Using the consumption module of the IHS questionnaire, we computed quantities of food consumed per day per capita. The IHS questionnaire groups foods in categories of cereals, vegetables, meat etc. In each group, we calculated specific quantities of food consumed and how much the food costed. Assuming that the marginal cost of consuming food that was home produced was its market price, we converted the quantity of the food consumed at home by the median market price to get the value of food consumed. We then transformed the value of the food consumed by adjusting it for adult equivalence scales. For ease of interpretation, food consumption expenditure was transformed into food budget shares by dividing the food expenditure by the total household expenditure. Figure 1 summarizes results of the food budget. Although results are not significantly different across the regions (North, Center and South), results show a significant increase in the cost of food over the past six years. Generally, results show a two-third rise for a period of six years.

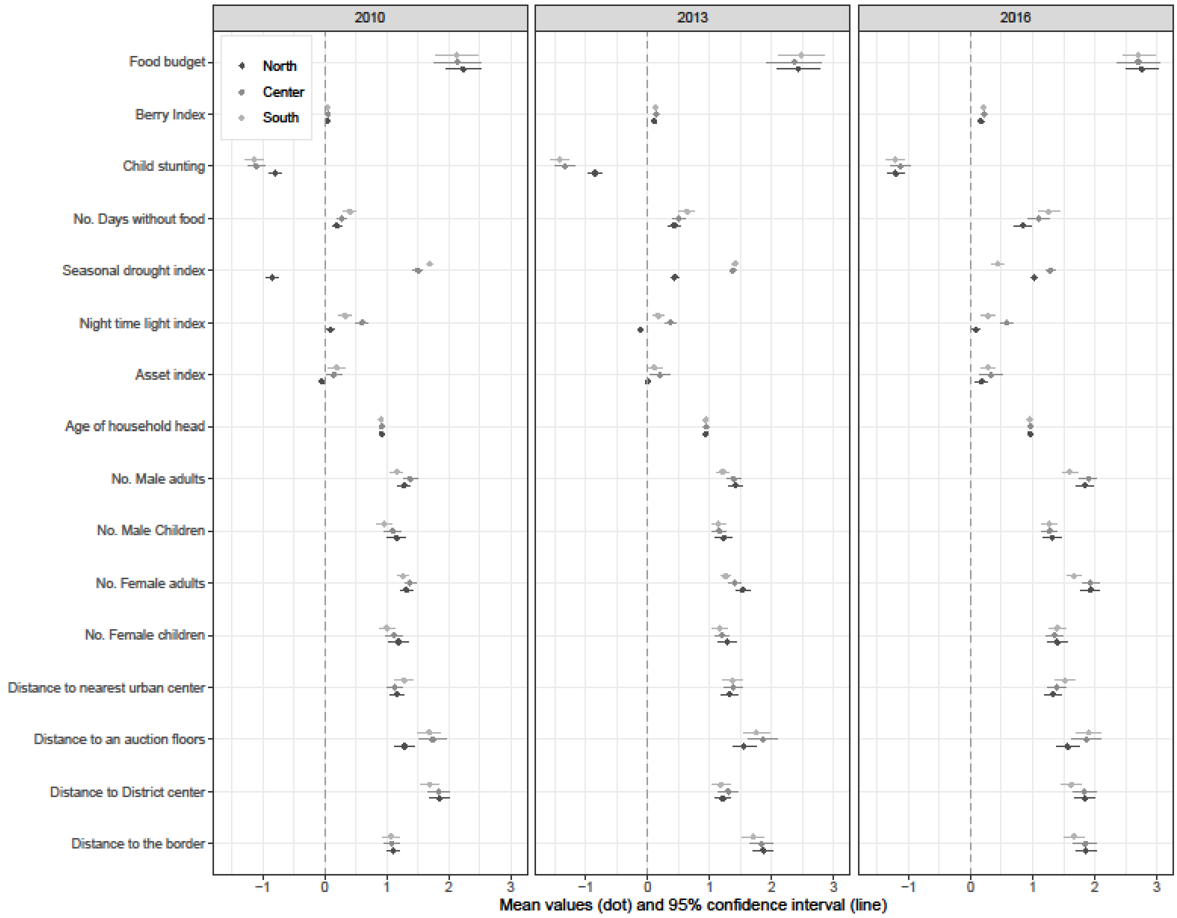

Figure 1 Descriptive statistics of variables used in the study.

Results are disaggregated by variable type, survey period and geographic region. This panel summarizes continuous variables beginning with dependent variables and explanatory variables used in later regression models. Age of the household head and food budget are in halved logarithms while all distances are in log transformed kilometres. A dot represents a mean of the variable *X* and the lines to the left and right of the dot represent the lower and upper 95% confidence intervals, respectively.

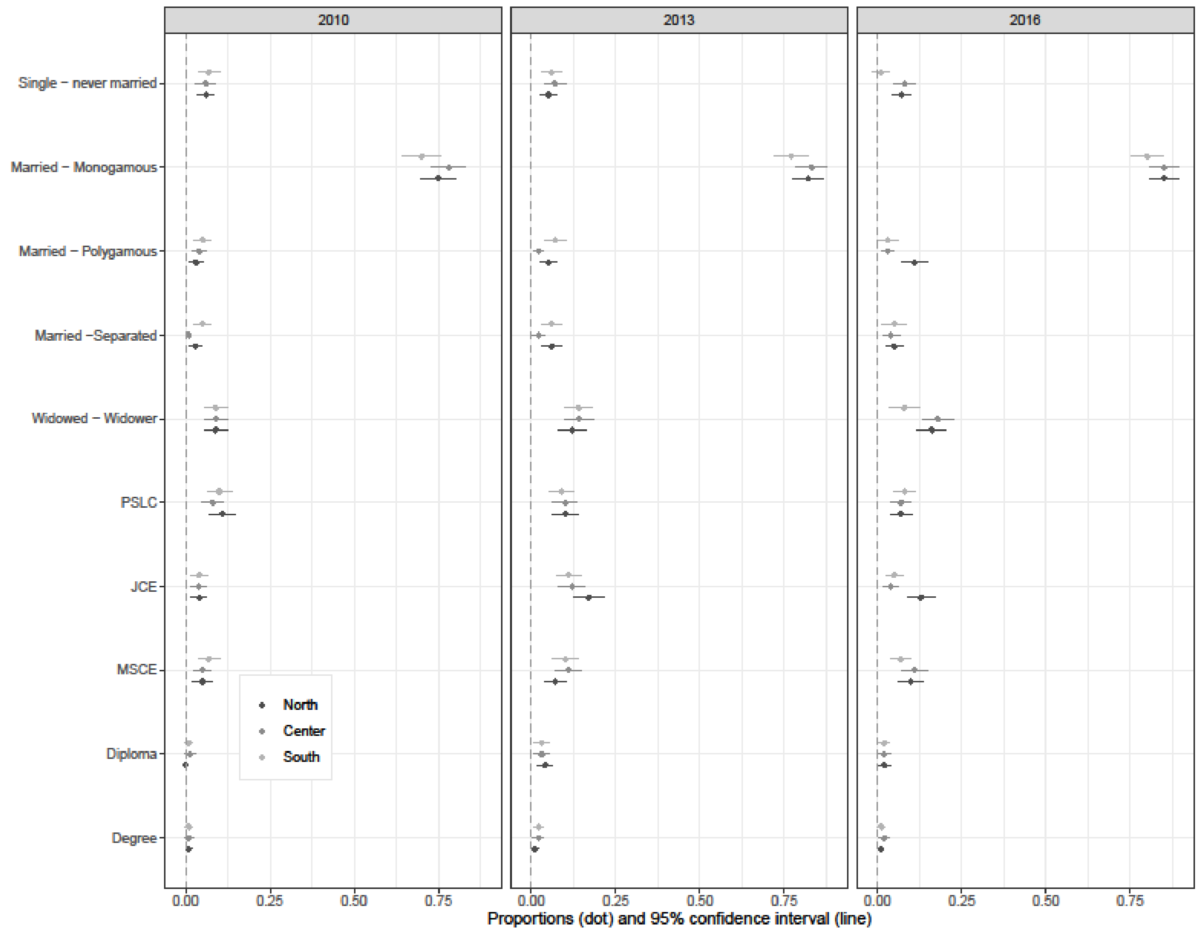

Figure 2 Summarizes categorical variables which are presented in proportions.

A dot represents a proportion of the dummy variable *X=1* otherwise *X=0* while the lines to the left and right of the dot represent the lower and upper 95% confidence intervals, respectively. A full detailed table is provided in Table 4.

Berry index of dietary variety: After calculating the quantities of food consumed, we also assessed dietary diversity by counting the total number of food commodities a household consumed in the last seven days. This roughly gives the household dietary diversity score. Then we calculated the share of each food item in the value of food consumed. We calculated the Berry-Index of dietary variety as $BI = 1 - \sum_i s_i^2$ where s_i is the share of the food consumed. A larger index means that the individual consumes a wide variety of foods (Drescher, Thiele, and Mensink 2007). Across all regions and years are quite low (less than 0.5). This shows that dietary diversity is very low across the country.

Shannon Entropy Index: To corroborate the Berry Index, we also computed the Shannon Entropy Index of dietary diversity. The Shannon Entropy Index is defined as $E = \sum_i^n s_i \log \frac{1}{s_i}$ where s_i is as defined above. Lower values of the entropy index imply lower dietary diversity while higher values reflect highly diversified diets (Liu, Shively, and Binkley 2014)

Child stunting: Using the anthropometric data from IHS data, we calculated child stunting following World Health Organization (2006) growth standards. While food expenditure per capita and dietary variety might be a good indicator for household food and nutrition security, the nutritional status of children through their height for age might reflect some dynamics of scarcity of food that have occurred at household level. We use Vidmar, Cole, and Pan (2013)'s zanthro Stata command to estimate stunting in children. This command generates z-scores which we can use for measuring stunting. The sample that uses stunting in children is much lower than the overall sample because we filtered the data to only those households that had under five children during the baseline. Results show high levels of child stunting as all height-for-age z-scores are less than 0.

Food security resilience index: Lastly in the consumption module of the household variable, a household was asked how many days they had to go without food or drastically reduced consumption with the past seven days. A count of the days was also used as an indicator of food insecurity. A natural logarithm of the variable was also considered as a dependent variable.

Other indicators considered were the nutrient disaggregation of commodities consumed using FAO's Food Composition Tables for Africa (Food Agriculture Organization 1968). These were used as a robustness check on how far reaching the effects of shocks and the mitigation of infrastructure can be.

Table 1 summarizes results of measures of association between indicators of food and nutrition security used in the study. The table is split into two parts to accurately measure the correlations. The first part in column 1 summarizes results of the sub-sample that contained households that had under five children. For this sub-sample, correlations with child stunting outcomes are most relevant. Column 2 summarizes results of the measures of association using the full sample but without including child stunting. Except for stunting outcomes, we use column 2 results.

Table 1 Associations between food security variables used in the study

VARIABLES	(1) Children sub-sample	(2) Full sample
mean(lnval)	9.026***	9.219***
	(0.128)	(0.051)
mean(berry)	0.625***	0.549***
	(0.026)	(0.009)
mean(haz06)	-0.305***	
	(0.076)	
mean(days_foins)	0.786***	0.736***
	(0.042)	(0.017)
var(lnval)	11.703***	11.430***
	(0.617)	(0.242)
var(berry)	0.501***	0.394***
	(0.026)	(0.008)
var(haz06)	4.106***	
	(0.217)	
var(days_foins)	1.288***	1.278***
	(0.068)	(0.027)
ρ(Budget, Berry)	0.501***	0.339***
	(0.092)	(0.032)
ρ(Budget, Stunting)	0.220***	
	(0.265)	
ρ(Budget, Days)	-0.068	-0.251***
	(0.145)	(0.057)
ρ(Berry, Stunting)	0.449***	
	(0.056)	
ρ(Berry, Days)	0.303***	0.218***
	(0.032)	(0.011)
ρ(Stunting, Days)	0.547***	
	(0.088)	
Observations	719	4,479

NOTE: Standard errors in parentheses
*Significantly different from zero at 90 percent confidence
**Significantly different from zero at 95 percent confidence
***Significantly different from zero at 99 percent confidence

Results generally show that indicators of food security are significantly associated with different directions and magnitudes. For example, the Berry index of dietary variety (BI) is 34% positively associated with the food consumption expenditure per capita. That is, higher food expenditures per capita are likely associated with increased economic access to a broad variety of food commodities. On one hand, it could mean that households that have more money also spend a lot on food. This might lead to better nutrition outcomes. Hence food budget could relate to other indicators through that channel. However, it could also mean that economic shocks such as extreme weather events lead to increased food budgets because food has now become more expensive. When food is more expensive, it becomes natural to diversify to other less desirable cheaper alternatives. Thus, there could be income and substitution effects at play such that it is important to control for other variables before making conclusions. Following the same narrative, in column 1, we note that stunting among under five children is highly associated with higher food budgets. That is, 1% increase in the food budget is associated with 22% increase in child stunting ($p < 0.01$). Understanding this association may help explain what is driving the direction of the effects of seasonal weather events on food security outcomes later. Similarly, household dietary diversity is also positively associated with child stunting (45%, $p < 0.01$). Although this appears unusual, under weather shocks, a diversification to other nutritionally inferior foods might not immediately translate to better nutrition outcomes for children. These results follow as a corollary to Bennett's law such that households that spend a large proportion of their budget on starchy foods, which have high calorific values, have limited economic access to other foods (Timmer and Falcon, 1983). The relationship between the number of days going hungry and stunting is intuitive. The finding that a unit increase in BI is associated with a 4% reduction in the number of days a household would either go completely without food or drastically reduce its food consumption is also consistent with the foregoing discussion.

Since the measures of food security are highly correlated, choice of a dependent variable used for assessing impact of shocks should be measured by its consistency with microeconomic theory. Thus, while the other indicators have been considered as robustness checks, food consumption expenditure share is our choice variable for discussion. We present the Berry, and Shannon Entropy Indexes as robustness checks for the main results and put the other dependent variables in the appendix.

2.3.2. A typology of self-reported household shocks

Table 2 summarizes 20 self-reported shocks in the study. We obtained the shocks from the household questionnaire and cross-checked them with the community questionnaire of the IHS. Results indicate varying occurrences of shocks during the baseline. Of note, Table 3 summarizes measures of association between shocks. The specific names of the shocks have been shortened to the first three letters of the names presented in Table 3 to save space. We corrected the relationships with a Bonferroni adjustment – a correction applied when multiple null hypotheses are being tested to reduce the probability of incorrectly rejecting the null hypothesis, due to a rare event, when in fact the null hypothesis is true. As shown some shocks show statistically significant correlations that have economic meanings at $p = 0.05$. For instance, high incidence of flooding is associated with a 22% increase in crop pests. Pests and diseases have a mutually reinforcing association with a magnitude of 35% while high agricultural input costs are associated with 16% and 15% increase in incidences of pests and diseases, respectively. Incidences of floods, pests and high input costs are associated with food price increases of 12%, 13% and 27%, respectively.

Occurrence of death of the household head is associated with a halt in earnings from salaried employment with a magnitude of 13%. Considering the large number of shocks reported in the study and how closely related some of the shocks are, we have a dimensionality problem. In order to reduce the number of highly related variables, we used Principal Component Analysis (PCA). PCA results (details not presented), using a minimum factor loading of 0.3, identified three key groups of shocks namely price related shocks labelled (a); extreme weather events (b); livestock and diseases (c) and household mixed distress events in Table 2. Thus, the analysis proceeds in assessing impacts of these four categories of shocks.

Table 2 Shocks used in the study

	Distress events (Shocks)	Percent
1	Drought/Irregular Rains	55.57^{b}
2	Floods/Landslides	5.52^{b}
3	Earthquakes	4.57
4	Unusually High Level of Crop Pests or Diseases	8.85^{c}
5	Unusually High Level of Livestock Diseases	8.18^{c}
6	Unusually Low Prices for Agricultural Output	34.45^{a}
7	Unusually High Costs of Agricultural Inputs	71.08^{a}
8	Unusually High Prices for Food	85.60^{a}
9	End of Regular Assistance/Aid/ Remittances	13.30
10	Reduction in the Earnings from Household	9.77^{a}
11	Household (Non-Agricultural) Business Failure	7.39^{d}
12	Reduction in the Earnings of Currently head	3.41^{d}
13	Loss of Employment of Previously Salaried employment	1.14^{d}
14	Serious Illness or Accident of Household	18.74^{d}
15	Birth in the Household	4.00^{d}
16	Death of Income Earner(s)	1.90
17	Death of Other Household Member(s)	7.14^{d}
18	Break-Up of Household	9.13^{d}
19	Theft of Money/Valuables/Assets/Agricultural output	5.61^{d}
20	Conflict/Violence	5.61

NOTE: Letters a,b,c refer to groups selected by Principal Component Analysis using varimax rotation.

Table 3 Pearson correlation coefficients between household shocks.

	DRO	FLO	EAR	PES	DIS	COS	FOO	AID	EAR	BUS	SAL	EMP	ILL	BIR	DEA	DEO	THE	CON
DRO	1																	
FLO	.074	1																
EAR	.021	.107	1															
PES	.063	.218*	.044	1														
DIS	.057	.110	.068	.347*	1													
COS	-.046	.073	-.006	.164*	.154*	1												
FOO	-.081	.121*	-.048	.130*	.082	.273*	1											
AID	-.055	.015	-.035	.058	.042	.062	.078	1										
EAR	-.057	.052	-.024	.083	.057	.024	.068	.027	1									
BUS	-.109	.006	-.039	.003	.048	-.050	.033	.007	.127	1								
SAL	-.064	.025	-.031	.027	-.018	-.002	.099	.065	.071	.014	1							
EMP	-.030	-.026	-.024	.030	.033	.025	.046	.041	.022	-.019	-.015	1						
ILL	-.042	.023	-.047	-.021	-.019	-.062	-.017	.018	-.029	.014	-.016	-.052	1					
BIR	-.013	-.007	.002	.005	.010	-.003	.001	-.032	.005	.020	.006	-.022	-.036	1				
DEA	-.002	.027	.003	.079	-.016	-.011	-.008	.067	.074	.056	.129*	-.015	.022	-.028	1			
DEO	-.094	.046	-.043	.031	-.015	-.069	-.064	.027	.014	-.006	.066	.005	.009	-.019	.097	1		
THE	-.115*	-.004	-.069	-.052	-.046	-.049	-.056	-.008	-.034	.021	.002	-.003	-.008	-.014	-.020	-.024	1	
CON	-.048	.013	-.014	.040	.033	-.025	-.011	.068	.010	.029	-.005	.013	.010	-.008	.057	.013	.009	1

NOTE: Pearson correlation coefficients after Bonferroni adjustment
*Significantly different from zero at 95 percent confidence
DRO =Drought/dry spells; FLO= Floods/Landslides; EAR= Earthquakes; PES=Crop Pests or Diseases; DIS = Livestock Diseases
COS=Costs of Agricultural Inputs; FOO=High Prices for Food; AID=End of Aid/ Remittances; EAR=Reduction in the Earnings;
BUS=Business Failure; SAL=Reduced earnings of head; EMP= Loss of Employment;ILL= Serious Illness; BIR=Birth in family
DEA=Death of head in family; DEO=Death of other family member; THE=Theft; CON= Conflict.

2.3.3. Seasonal drought and floods

The IHS data is geo-referenced. We therefore use the GPS coordinates from the survey and map them on a global Standardized Precipitation-Evapotranspiration Index, which provides near real-time data on drought conditions with a $0.5^{\circ} \times 0.5^{\circ}$, longitude by latitude spatial resolution and a monthly resolution of up to 48 months. The SPEI index uses Vicente-Serrano et al. (2010) method of calculating deviations from the mean water balance. Thus, the SPEI calculates drought condition by taking precipitation subtracting potential evapotranspiration. This method is better than other methods because it accounts for two important aspects of drought conditions namely rainfall and temperature conditions which are essential for crop production. Since the data collection covers the entire year, we use the December to March period as a measure of the rain season. Since the historical SPEI is standardized, with mean zero and standard deviation of one, positive values will refer to high precipitation while negative values will mean dry spells. In general, Malawi covers 16 full $0.5^{\circ} \times 0.5^{\circ}$ longitude by latitude spatial resolution (figure 3) which also cover its 8 agro-ecological zones which contain 21 meteorological Stations.

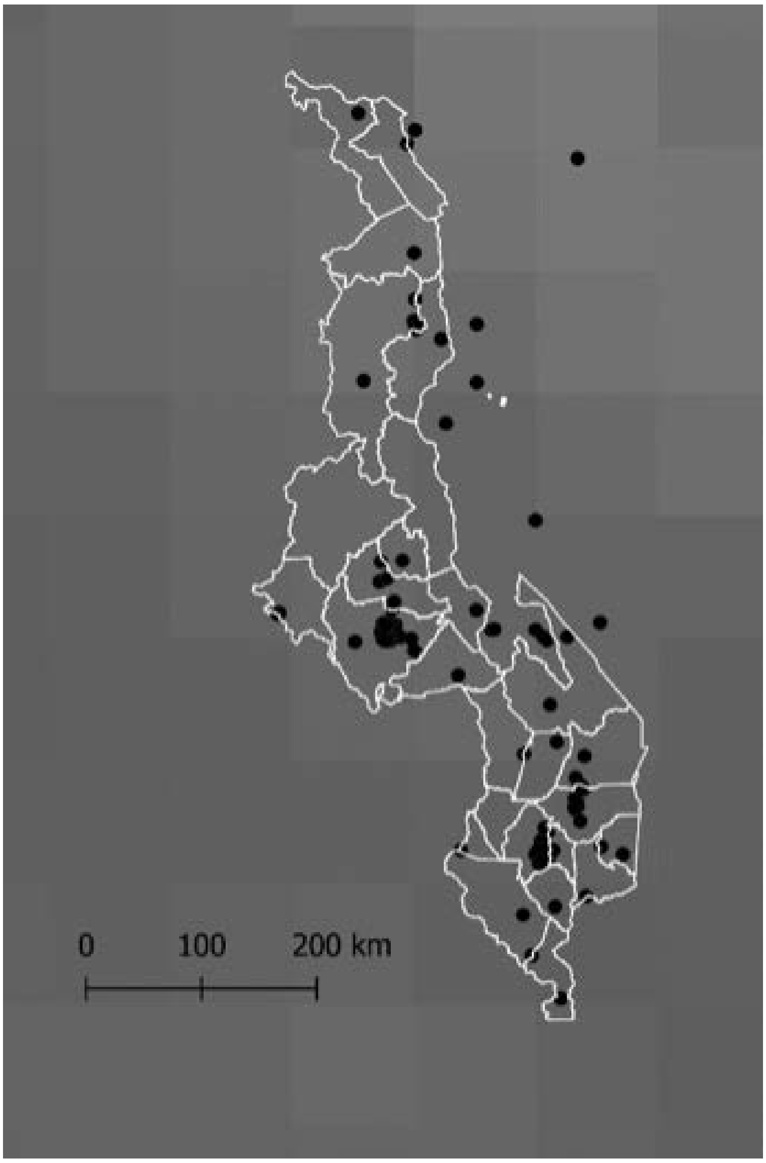

Figure 3 Map of Malawi showing $0.5° \times 0.5°$, longitude by latitude spatial resolution grid.

Noteworthy, every 4 grid cells approximately correspond to the country's agro-ecological zones. The dots are sampled geographical points.

With the exception of the northern region in IHS3, results presented in Figure 1 indicate that, as a country, Malawi experiences a sufficiently wetter agricultural season. This is evidenced by all mean seasonal drought index values lying to the right of the zero dotted line across all years. Few districts in the North experienced some dry spells during the 2010 and 2013 growing season. Importantly, results indicate that seasonal drought incidence varied widely across the country and over the three survey periods. F-test comparison of means (represented by an asterisk in Figure 1) shows that seasonal drought conditions were significantly different across the survey periods ($p < 0.01$) and also across the regions ($p < 0.01$).

2.3.4. *Community characteristics and infrastructure availability*

Community leaders and respondents at household level reported on whether the existence of different types and quality of infrastructure at household level. We constructed an indicator D based on the responses that they gave. For example, if a household reported that the community had electricity and was corroborated by the community leader, then $D = 1$. On the one extreme both would say that they had no electricity and D=0. Nevertheless, there were cases where both respondents gave contradicting information. In that case, we used Night Time Light (NTL) data – data gathered by US National Oceanic and Atmospheric Administration and NASA's polar orbiting satellites that cover the entire earth twice per day. Using near infra-red radiance, the data presents data points illuminated by electricity across the planet.

We standardized the radiance such that negative standard deviations would imply very low lights and positive standard deviations implying availability of light. Radiance greater than or equal to zero meant that the sample geographic point had light and if it was below zero, it did not. We augmented the self-reported data with NTL as follows: if $D = 1$ and radiance for the point was greater than or equal to zero, then we confirmed that $D = 1$. If the self-reported data was conflicting, we took the NTL indicator and assigned $D = 1$ if radiance was greater than or equal to 0. Compared to the rest of the world, Africa – especially Malawi – is not well illuminated, a sign that the continent has low infrastructure. Nevertheless, considering the radiance points within the longitude by latitude grid where Malawi is located and standardizing them can make a fair within country comparison. Using logit regression analysis with confounding factors that could affect infrastructure assignment were used as covariates at community level (Z_{ijt}). We determined the propensity score as $Pr[z] = Pr(D = 1|Z = z)$. Thus, we predicted propensity scores for infrastructure assignment using a logistic regression. Thus, the predicted propensity ranges between 0 and 1 such that being a probability, it can be read in percentages.

2.3.5. *Household characteristics*

Figure 1, panel A presents household and community characteristics. A general pattern shows that both household and community characteristics did not change much across the regions and also over the subsequent surveys.

Asset index: We calculated an asset index using principle component analysis by examining the availability at household level (Harttgen and Vollmer 2013). Using a varimax rotation procedure, we used the component that explained a lot of variation in the data. Results show no significant changes in the asset index the number of households with access to irrigation schemes (17%) between 2010 and 2013 but show a 21-percentage point increase in 2016. However, we notice regional variations within surveys across regions.

Age of the household head: The average age of the household head in the 2016 survey was 46. Although we find statistically significant ($p < 0.01$) results for equality of means, substantively, the ages do not differ much across the regions. Table 2 supplements Figure 1 and shows that, indeed, the age of the household head does not change much.

Table 4 Descriptive statistics of variables used in the study.

	2010/11 IHS3 data			2013 IHSP data			2016/17 IHS4 data		
	North	Center	South	North	Center	South	North	Center	South
Food budget	8.95	8.59	8.52	9.71	9.45	9.90	11.05	10.83	10.84
Berry Index	0.04	0.05	0.05	0.11	0.14	0.12	0.17	0.22	0.21
Child stunting	-0.79	-1.11	-1.14	-0.85	-0.91	-1.33	-1.26	-1.21	-1.09
No. Days without food	0.20	0.28	0.40	0.43	0.50	0.63	0.84	1.10	1.26
Seasonal drought index	-0.84	1.50	1.69	0.44	1.38	1.41	1.02	1.29	0.44
Night time light index	0.10	0.60	0.33	-0.12	0.37	0.17	0.09	0.59	0.28
Asset index	-0.05	0.15	0.20	0.00	0.20	0.11	0.18	0.33	0.28
Age of household head	3.67	3.66	3.62	3.75	3.77	3.73	3.83	3.85	3.81
No. Male adults	1.28	1.38	1.16	1.42	1.39	1.21	1.84	1.90	1.60
No. Male Children	1.16	1.10	0.96	1.23	1.16	1.14	1.32	1.27	1.27
No. Female adults	1.32	1.38	1.27	1.53	1.40	1.26	1.93	1.93	1.67
No. Female children	1.19	1.11	1.00	1.28	1.20	1.16	1.40	1.36	1.40
Pests & disease incidence	0.33	0.50	0.17	0.86	0.83	0.78	0.77	0.82	0.68
Single - never married	0.75	0.78	0.70	0.82	0.83	0.77	0.85	0.85	0.80
Married - Monogamous	0.06	0.06	0.07	0.05	0.07	0.06	0.07	0.08	0.01
Married - Polygamous	0.03	0.04	0.05	0.05	0.02	0.07	0.11	0.03	0.03
Married -Separated	0.03	0.01	0.05	0.06	0.02	0.06	0.05	0.04	0.05
Widowed - Widower	0.09	0.09	0.09	0.12	0.14	0.14	0.16	0.18	0.08
Distance to main road	0.60	0.41	0.58	0.71	0.54	0.83	0.73	0.57	0.92
Distance to nearest urban center	1.16	1.13	1.28	1.32	1.38	1.37	1.33	1.39	1.41
Distance to an auction floors	1.29	1.74	1.68	1.56	1.86	1.75	1.57	1.86	1.79
Distance to District center	1.85	1.84	1.69	1.21	1.30	1.18	1.84	1.83	1.72
Distance to the border	1.11	1.08	1.07	1.86	1.83	1.70	1.86	1.85	1.71

Number of male and female adults and children: Food security is a function of household composition and gender dynamics. Kennedy and Peters (1992) presents the oldest reference to gender food security linkage. The study argues that that households in which women have more discretionary power over expenditure decisions had better child and overall household nutrition outcomes. Kassie, Ndiritu, and Stage (2014) however found that female headed households had less food security outcomes. From a resource needs perspective, a household having more children requires a more nutritionally diverse food consumption bundle that a household that only has adults. Further, from an econometric perspective, an interaction of time variant and invariant characteristics makes evaluation of the gender inequality gap much easier to track. Results show that the distribution of the sexes is between one and two. A simple count shows that an average household has between two and five individuals regardless of sex.

Marital status: Panel B of figure 1 summarizes the marital status of the household. Continuing with the argument from Kennedy and Peters (1992) and Kassie, Ndiritu, and Stage (2014), the need to account for marital status follows naturally. Households for single individuals who have never married could have much lower food security requirements compared to households with married and more diverse compositions. Results summarized in figure 1 show that the majority of households were married and monogamous, accounting for about 75% of the sample observations in 2010. The number proportion increased to 83% in both 2013 and 2016 but with much variation across the regions. In a similar manner results for the other marital status categories also show similar patterns.

Distances to various places relative to the community: Distances to main economic hubs may be a good indicator of connectivity or isolation. An area further away from an economic hub may incur substantial transaction costs to access economic resources such as food (Dorosh et al. 2012; Pauw et al. 2011; Banerjee, Duflo, and Qian 2012).

3. Results

3.1. Proximate impacts of seasonal shocks on food security

In order to assess impacts of household shocks on food security, we implement a series of fixed effects regression models. Fixed effects models were consistently preferred to random effects models when we subjected the analysis to Hausman tests. Results of the Hausman tests are presented in the supplementary material. In Table 5, we estimate fixed effects with within effects only assuming that infrastructure access is exogenously given. Then we modeled an instrumental variable within effects model in Table 6 assuming that infrastructure is endogenous.

As part of robustness checks, the natural the Berry index of dietary diversity, and Shannon Entropy Index were used. Table 5 to 6 only show impacts of shocks and omits control variables and fixed effects dummies (a full table is in the supplementary materials). Across the tables, we present three models of the impact of seasonal shocks – drought or floods on food and nutrition security. Other shocks were highly collinear with the SPEI indicator such that we deem the measures of associations presented earlier to suffice.

3.2. Food consumption expenditure

Tables 5 to 6 in columns 1 and 4 present estimates of the effects on food expenditure shares. In general, infrastructure mitigates impacts of extreme weather events on food security. Results from the food expenditure shares' models indicate that extreme weather conditions during an agricultural growing season in Malawi i.e. December to March, result in increased food expenditure shares. To illustrate, a unit standard deviation increase in SPEI during the critical one-to-three months interval results in 4% increase in food budget shares. That is, given the sample SPEI mean of 1.18 ± 0.85, a standard deviation increase from the mean will result in a 4% decline in the economic access to food ($p < 0.01$) assuming zero infrastructural provision. Noteworthy, a standard deviation increase in SPEI from the mean means that it is a flooding condition.

When we instrument the endogenous placement of infrastructural projects with whether the Member of Parliament comes from the same community, we find that the instrument induces the impact of extreme weather events to be $26 \pm 11\%$ lower economic access to food, after setting infrastructure to zero ($p < 0.10$) (Table 6). The effect is in the same direction as the within effects only model. The interaction between infrastructure and the drought index is negative meaning that infrastructure plays a mitigating role against extreme weather events. Specifically, conditional on infrastructure, the impact of extreme weather events is $54 \pm 32\%$ improvement in economic access to food at household level represented by the food budget shares ($p < 0.10$).

Figure 2 presents a graphical version of the model to demonstrate the effects substantively. In panel A, the graph shows that as we increase infrastructure by 1%, the share of expenditure allocated to food decreases by $11 \pm 1\%$ ($p < 0.05$) assuming normal historical weather conditions i.e. SPEI equal to zero.[1] Panel B presents effects of extreme weather events on food security. That is, in the remotest area without infrastructure, a standard deviation increase in the SPEI is associated with a $5 \pm 1\%$ ($p < 0.01$) increase in the food budget share. Panel C presents the effect of extreme weather conditional on infrastructure – i.e. the interaction effect. Results, indicate that if we increase infrastructure by 1% the coefficient for the impact of extreme weather events on the food budget share decreases by $8 \pm 2\%$ ($p < 0.01$). Of note, the 95% confidence bands widen as we get close to the infrastructure index equal to 1 showing that our level of uncertainty in this region increases. This is also evidenced by the data histogram superimposed at the bottom – i.e. we have more data points with values of the infrastructure index between 0.25 and 0.75. The note at the bottom right of the panel shows the 95% confidence intervals of the difference between conditioned effects of extreme weather on food budget shares at the minimum and maximum values of the composite infrastructure index. Panel D illustrates the prediction of the food budget share against the extreme weather events for the minimum and maximum values of infrastructure. Clearly, households with minimum infrastructure (solid line) have consistently increasing food budget shares as compared to households with access to infrastructure (dotted line). Other indicators of food security in Table 5 and 6 may aid interpretation of the results of the food budget share.

3.3. Household dietary diversity and nutrition

Do seasonal droughts or floods influence household dietary diversity patterns? To answer that question, we present results of the Berry and the Shannon Entropy indexes of dietary diversity models in tables 5 and 6 columns 2,3,5 and 6, respectively. The Berry index ranges from 0 to 1 where zero means that the household is not dietary diversified – meaning that they only consume one food group – and 1 means that the household is fully dietary diversified. Lower values of the Shannon Entropy index mean that the household has less varied diets – signifying lower economic access or lower production and exchange entitlement to nutritious food – while higher values imply more varied diets. Dietary variety is linked to higher nutrient intake (Drescher, Thiele, and Mensink 2007; Kennedy et al. 2007). For ease of interpretation, we transform the coefficients to elasticities (Thiele and Weiss 2003).[2]

Results generally show that in the absence of infrastructure, extreme weather events are associated with lower household dietary diversity. Under a within effects only model while

[1] The sample average SPEI represents the mean SPEI for the 3 panel surveys while a historical SPEI refers to the long term average which is 0 – see Figures 8,9 and 10.

[2] We transform the coefficients to elasticities as follows $\epsilon_i = \beta_i \cdot \left(\frac{\overline{x}}{\overline{y}}\right) \approx \frac{\partial y}{\partial x} \cdot \frac{x}{y}$ for a random individual drawn from the population.

setting infrastructure to zero, results show that a standard deviation deficit in a 3 month SPEI results in 0.04 unit reduction in household dietary diversity, using the Shannon Entropy Index. Albeit the results not being robust, a percentage increase in SPEI would lead to a 2% decrease in dietary diversity – i.e. an elasticity equal to 0.02 after the transformation. The within effects with instrumental variable model for the Shannon Entropy index of dietary diversity indicates that a standard deviation deficit in SPEI results in 1.97 ± 0.613 units reduction in dietary diversity ($p < 0.10$). That is, a percentage increase in the seasonal drought index is associated with a $68 \pm 35\%$ decrease in dietary diversity.

Table 5 Impacts of drought on food and nutrition security: Within effects only

	Food budget share (1)	Berry Index (2)	Shannon Entropy index (3)
Seasonal drought index	0.040^{**}	−0.003	−0.039
	(0.018)	(0.038)	(0.090)
Composite infrastructure index	-0.149^{***}	0.125	0.458^{*}
	(0.054)	(0.116)	(0.273)
Interaction of infrastructure and drought	-0.063^{*}	−0.002	−0.017
	(0.037)	(0.080)	(0.189)
Controls	YES	YES	YES
Observations	4,060	4,205	4,205
R^2	0.191	0.149	0.199
F Statistic	27.989^{***}	21.968^{***}	31.028^{***}
	(df = 21; 2485)	(df = 21; 2628)	(df = 21; 2628)

NOTE: Standard errors in parentheses
*Significantly different from zero at 90 percent confidence
**Significantly different from zero at 95 percent confidence
***Significantly different from zero at 99 percent confidence

Noteworthy, infrastructure mitigates impacts of extreme weather events on dietary diversity. The conditional elasticity – i.e. the elasticity of the interaction between infrastructure and seasonal drought index — is 1.42 ± 0.78 ($p < 0.10$) implying that household dietary diversity is highly responsive to infrastructural availability. A percentage increase in infrastructure mitigates the effects of shocks on dietary diversity by 142%. The result for the Berry Index is also positive but not robust.

Results also show that the joint effect of infrastructure and extreme weather events on nutrition is noteworthy (table 7). Holding infrastructure at the sample average, a standard deviation increase in SPEI would reduce protein consumption by 17% and fat by 16%. Further, results also show that under the same conditions, there would be a 20% reduction in both iron and Calcium, respectively. Although not statistically robust, results also show a reduction in Phosphorus consumption. Thus, consistent with earlier observations, an extreme weather event reduces dietary diversity which in turn reduces nutrient intake. When we consider vitamin availability, given the same condition, results also point in the same direction.

Importantly, at micro-nutrient level, the infrastructure coefficient did not have enough explanatory power as it was only significant as an interaction except in the Calcium and Vitamin B2 equations. However, the interaction is statistically negative showing that the infrastructural effect is outweighed by the SPEI effect or some measurement error.

Table 6 Impacts of impacts of drought on food and nutrition security: IV and within effect

	Food Budget share (1)	Berry Index (2)	Shannon Entropy Index (3)
Seasonal drought index	0.256^{*}	-0.191	-1.197^{*}
	(0.110)	(0.308)	(0.613)
Composite infrastructure index	-0.103	-1.406	-3.461^{*}
	(0.384)	(0.926)	(-1.610)
Interaction of infrastructure and drought	-0.537^{*}	0.376	2.521^{*}
	(0.243)	(0.684)	(1.372)
Controls	YES	YES	YES
Observations	4,060	4,205	4,205
R^2	0.073	0.077	0.112
F Statistic	203.750^{***}	357.143^{***}	484.814^{***}
Weak instruments (Infrastructure)	22.475^{***}	21.391^{***}	17.130^{***}
	$(DF_1 = 4)$	$(DF_1 = 4)$	$(DF_1 = 4)$
	$(DF_2 = 4042)$	$(DF_2 = 4186)$	$(DF_1 = 4181)$
Weak instrument (SPEI × Infrastructure)	11.814^{***}	11.604^{***}	23.198^{***}
	$(DF_1 = 4)$	$(DF_1 = 4)$	$(DF_1 = 4)$
	$(DF_2 = 4042)$	$(DF_2 = 4186)$	$(DF_2 = 4181)$

NOTE: Standard errors in parentheses
*Significantly different from zero at 90 percent confidence
**Significantly different from zero at 95 percent confidence
***Significantly different from zero at 99 percent confidence

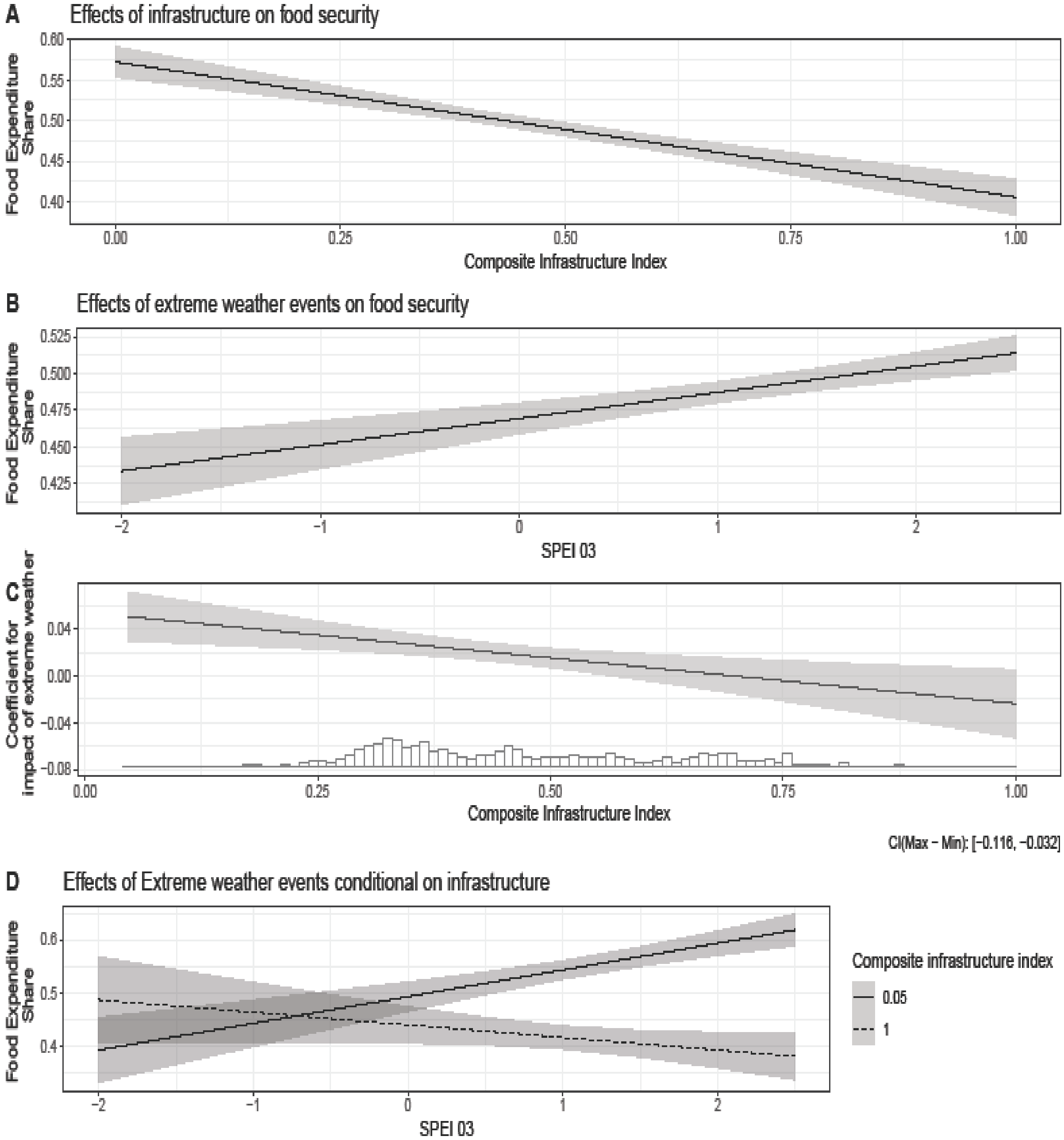

Figure 4 Impact of extreme weather events conditional on infrastructure availability.

Y-axis is household food budget share adjusted for equivalence scales. Panel A presents effects of infrastructure on food security holding all variables at their mean values. Panel B presents effects of extreme weather events on food security holding all other variables at their mean values. Panel C shows how increasing infrastructure affects the magnitude of the impact of extreme weather events on food security. Clearly, as infrastructure increases by one percent, the effect of extreme weather events on the food budget decreases by 8\%. Panel D disaggregates the conditional relationship by two extreme levels of infrastructure availability i.e. the dotted line presents full infrastructure availability by Malawian standards with an index value of 1 and the solid line is for households without access with an index value equal to 0.05. Pooled model using sjPlot (Solt and Hu, 2015) and interplot R Package (Lüdecke, 2015).

Table 7 Conditional effects of infrastructure and extreme weather events on nutrition

	Food budget	Proten	Fat	Fe	P	Ca	Vit. A1	Vit. B2	Vit. B1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Seasonal drought index	-0.880^{***}	0.094	0.004	0.019	−0.373	0.158	1.470^{***}	-0.169^{**}	−0.122
	(0.118)	(0.097)	(0.098)	(0.098)	(0.275)	(0.107)	(0.192)	(0.083)	(0.115)
Composite infrastructure index	-1.875^{***}	0.014	−0.045	0.181	−0.896	0.683^{**}	−0.543	-0.464^{*}	−0.325
	(0.361)	(0.297)	(0.299)	(0.299)	(0.839)	(0.327)	(0.586)	(0.253)	(0.351)
Asset index	0.089^{***}	0.030	0.029	0.027	0.053	0.033	−0.037	0.027	0.023
	(0.031)	(0.025)	(0.025)	(0.025)	(0.071)	(0.028)	(0.050)	(0.022)	(0.030)
Education Diploma	0.676^{***}	0.195	0.135	0.285	0.610	0.259	0.401	0.321^{*}	0.316
	(0.256)	(0.212)	(0.213)	(0.213)	(0.599)	(0.234)	(0.419)	(0.181)	(0.251)
Education JCE	0.729^{***}	0.461^{***}	0.451^{***}	0.450^{***}	1.061^{**}	0.472^{**}	1.096^{***}	0.442^{***}	0.525^{***}
	(0.204)	(0.167)	(0.168)	(0.168)	(0.473)	(0.184)	(0.330)	(0.143)	(0.198)
Education MSCE	0.502^{***}	0.190^{*}	0.099	0.137	0.290	0.213^{*}	0.257	0.147^{*}	0.145
	(0.126)	(0.102)	(0.102)	(0.102)	(0.287)	(0.112)	(0.201)	(0.087)	(0.120)
Education None	0.594^{***}	0.285^{***}	0.187^{*}	0.293^{***}	0.611^{**}	0.326^{***}	0.142	0.255^{***}	0.279^{**}
	(0.128)	(0.104)	(0.104)	(0.104)	(0.293)	(0.114)	(0.205)	(0.089)	(0.123)
Education College	−0.017	−0.059	−0.065	−0.050	−0.166	−0.056	-0.387^{***}	−0.023	−0.061
	(0.092)	(0.074)	(0.074)	(0.074)	(0.209)	(0.082)	(0.146)	(0.063)	(0.088)
Married – monogamous	0.504	0.530	0.353	0.604	1.149	0.645	2.166^{***}	0.574^{*}	0.547
	(0.483)	(0.396)	(0.398)	(0.398)	(1.118)	(0.436)	(0.781)	(0.338)	(0.468)
Married – polygamous	0.150	0.060	0.119	0.066	0.153	0.094	−0.111	0.103	0.112
	(0.117)	(0.096)	(0.096)	(0.096)	(0.271)	(0.106)	(0.189)	(0.082)	(0.113)
Separated	0.441^{***}	0.213^{**}	0.193^{**}	0.260^{***}	0.616^{**}	0.252^{**}	−0.216	0.232^{***}	0.267^{**}
	(0.113)	(0.093)	(0.093)	(0.093)	(0.262)	(0.102)	(0.183)	(0.079)	(0.110)
Divorced	0.489^{***}	0.302^{***}	0.299^{***}	0.312^{***}	0.363	0.319^{***}	−0.229	0.217^{**}	0.249^{**}
	(0.123)	(0.101)	(0.102)	(0.102)	(0.286)	(0.112)	(0.200)	(0.086)	(0.120)
Widow/widower	0.440^{***}	0.135	0.136	0.150^{*}	0.329	0.235^{**}	-0.307^{*}	0.132^{*}	0.125
	(0.108)	(0.089)	(0.089)	(0.089)	(0.251)	(0.098)	(0.175)	(0.076)	(0.105)
log. land holding size (ha)		-0.621^{***}	-0.657^{***}	-0.684^{***}	-0.758^{***}	-0.578^{***}	-0.138^{*}	-0.578^{***}	-0.723^{***}
		(0.042)	(0.042)	(0.042)	(0.117)	(0.046)	(0.082)	(0.036)	(0.049)
Interaction of infrastructure and drought	0.733^{***}	-0.588^{***}	-0.359^{*}	-0.489^{**}	0.019	-0.800^{***}	-1.984^{***}	−0.027	−0.177
	(0.248)	(0.205)	(0.206)	(0.206)	(0.578)	(0.226)	(0.404)	(0.175)	(0.242)

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	Food budget (1)	Proten (2)	Fat (3)	Fe (4)	P (5)	Ca (6)	Vit. A1 (7)	Vit. B2 (8)	Vit. B1 (9)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,061	4,205	4,205	4,205	4,205	4,205	4,205	4,205	4,205
R^2	0.114	0.131	0.128	0.144	0.040	0.103	0.090	0.149	0.119
F Statistic	22.824^{***}	26.393^{***}	25.768^{***}	29.480^{***}	7.259^{***}	20.168^{***}	17.461^{***}	30.864^{***}	23.619^{***}
	$(df = 15)$	$(df = 15)$	$(df = 15)$	$(df = 15)$	$(df = 15)$	$(df = 15)$	$(df = 15)$	$(df = 15)$	$(df = 15)$
	$(df_2 = 2634)$	$(df_2 = 2634)$	$(df_2 = 2634)$	$(df_2 = 2634)$	$(df_2 = 2634)$	$(df_2 = 2634)$	$(df_2 = 2634)$	$(df_2 = 2634)$	$(df_2 = 2634)$

3.4. Potential mechanisms

Given the theoretical framework, several mechanisms can drive our results. Thus, the innovation in household utility from food consumption may not only be driven by seasonal extreme weather or infrastructure placement but also other miscellaneous shocks, household and community characteristics. In figures 4, 5 and 6 we present other factors that may drive our results. We divide our results by the household's level of commercialization namely subsistence farming (Figure 5) and commercially oriented farming (Figure 6)[3]. We consistently find that effects of extreme weather events are much higher on subsistence farming households than commercially oriented households.

Consistent with what we observed in literature and also from our guiding theoretical model, we find that asset holding is positively associated with food consumption ($p < 0.01$). Our results are consistent with Janzen and Carter (2018; Giesbert and Schindler 2012) who reported that poor people who sell their assets after extreme weather conditions such as drought consistently ended up with poor food security outcomes. Controlling for education of the head of the household, we find that education had positive food security outcomes. Noteworthy, a comparison between household heads that only had primary school education and those that had none showed that there were no statistical differences.

Household dynamics, in terms of gender composition, were positively associated with household consumption expenditure. Although both presence of both male and female adults was positively correlated with food consumption expenditure, our results show that an additional male adult was associated with 13 percentage point higher food consumption expenditure ($p < 0.01$). An additional male child was also associated with more food consumption expenditure. In addition, Kassie, Ndiritu, and Stage (2014), Little, Ilbery, and Watts (2009) found that gender plays a significant role in home food preparation and consumption decisions. Thus, in addition to the gender disparity in consumption expenditure, household composition may also influence dietary diversity outcomes. We find that households with more males have lower dietary diversity compared to households with more females. Further, we also find that households that were in any form of a civil union had more consumption expenditures compared to household heads who had never married before. This also has to do with household size and food consumption needs. Lastly, households that had 1% higher land holding sizes had 41% lower food consumption expenditures ($p < 0.01$). This accounts for the autarkic and trading households. Thus, households with more land holding sizes spend less on food and are also 5% less dietary diverse. The less dietary diversity is not

[3] Following Von Braun, Kennedy, and others (1994; Carletto, Corral, and Guelfi 2017), we compute a measure of commercialization as a ratio of the value of agricultural sales in markets to the value of agricultural production. Lower ratios imply subsistence while higher ratios commercial agricultural production. Households below the median are subsistence.

surprising because Kankwamba, Kadzamira, and Pauw (2018) reported that in Malawi cropping is less diversified with maize dominating.

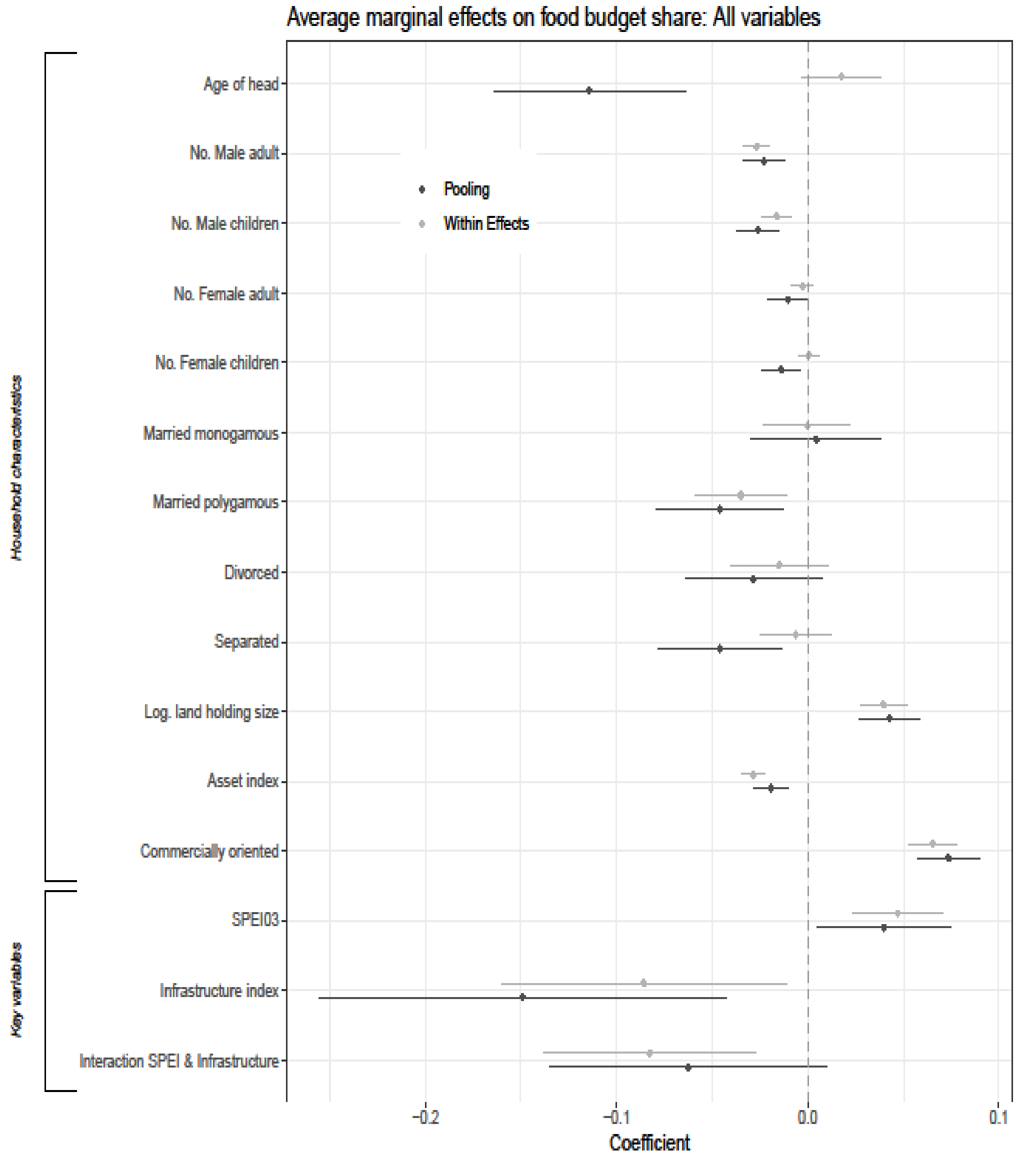

Figure 5 Summarizes mechanisms controlled for during the analysis.

The dependent variable is the share of expenditure allocated to food per day. A pooled and within effects model is considered. A dot represents the marginal effect while the lines to the left and right of the dot represent the lower and upper 95% confidence intervals.

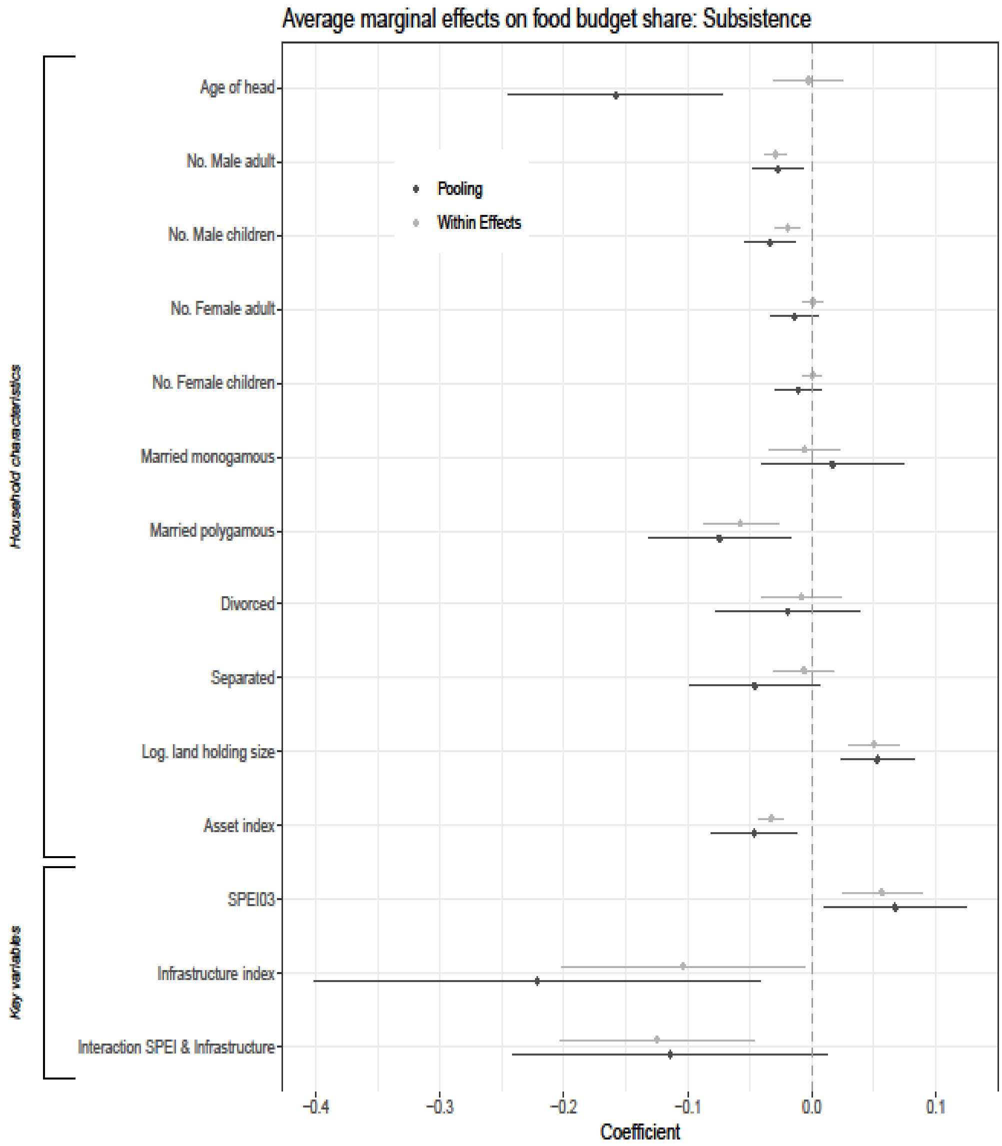

Figure 6 Summarizes mechanisms controlled for during the analysis.

The dependent variable is the share of expenditure allocated to food per day adjusted for net food buying households. A pooled and within effects model is considered. A dot represents the marginal effect while the lines to the left and right of the dot represent the lower and upper 95% confidence intervals.

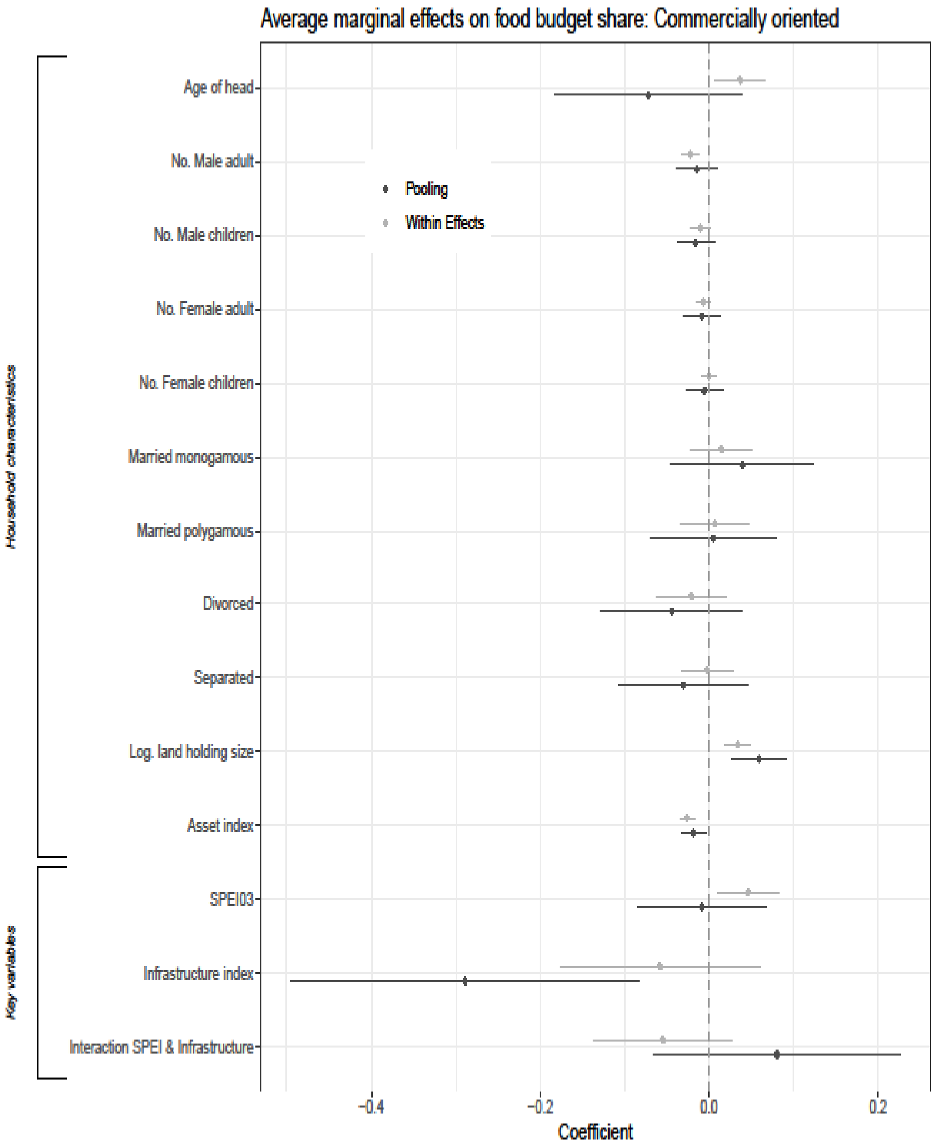

Figure 7 Summarizes mechanisms controlled for during the analysis.

The dependent variable is the share of expenditure allocated to food per day. A pooled and within effects model is considered. A dot represents the marginal effect while the lines to the right and left represent the lower and upper 95% confidence intervals.

4. Discussion

Economic disruptions have important implications for welfare and development policy. A clear identification of the shocks and households that are affected is critical in order to trace direct causal effects at household and community level. Throughout the analysis in this study we have addressed both issues and get three consistent results. First, that seasonal shocks have negatively impacted household daily per capita consumption given household characteristics. Second, in the presence of shocks, public infrastructure plays a pivotal role in smoothing consumption.

The first result – that effects of extreme weather events have deleterious effects on household consumption expenditure – comes from the theoretical predictions of our economic model. Any shock that affects the total household value added results in reduced indirect utility. Our results show that a supply side shock that affects earning – results in significant decrease in consumption per capita. Further, a supply side shock such as floods (SPEI values in excess of 2) bid up food prices thereby making households pay more for the same bundle of food items. Due to seasonal shocks, food production may fail thereby reducing household earning capabilities which in turn may affect food consumption possibilities. Devereux (2007) refers to this as an entitlement failure.

Accounting for community level infrastructure has clear advantages for welfare. Our results throughout all the models suggest that infrastructure is associated positively associated with food security. This observation comes from our theoretical framework that infrastructure can have positive consumption effect by reducing transaction costs.

Our results are consistent with findings by Donaldson (2018) who, while assessing effects of road infrastructure in India, found that infrastructure placement decreased transaction costs, also further deflated prices, increased trade and raised income levels. Thus, from a policy planning perspective and owing to the representativeness of our data, it is important that at household and community level, capital infrastructure be given priority. At community level, it can fairly be assumed that returns to infrastructure, being mostly non-excludable, accrue to households and can therefore be used for current consumption and smoothen future consumption possibilities. Our observation is consistent with Banerjee, Duflo, and Qian (2012) who, while assessing impacts of infrastructure on economic growth in China, found a moderate positive effect on economic growth and income growth.

Although several studies have addressed effects of some of these shocks in isolation (Ellis and Maliro, 2013, Ellis and Manda, 2012, Harttgen et al., 2012, 2015, Pauw et al., 2013), our study is the first to exploit the combined impact of several shocks and in a panel data framework combined with triangulated station based and remote sensed data. Thus, not only are our results internally consistent but can also be generalized at national level considering the representative nature of our data-set. This is a great advantage considering that other studies which had small sample sizes, were single cross-sectional surveys or forward-looking simulations.

5. Conclusion

This study assessed impacts of shocks on household food security in Malawi using three indicators namely: food consumption expenditure shares, Berry Index of dietary diversity, and the Shannon Entropy Index of dietary diversity. The study used fixed effects regression techniques to assess the impact of seasonal weather shocks on food security. Second, the study assessed the impact of community infrastructure on household food security using fixed effects regression techniques. Three waves of nationally representative integrated household panel surveys obtained from the Malawi National Statistical Office were used. To triangulate the self-reported shocks conditions in the survey, long term station weather data was used to come up with the Standardized Precipitation – Evapotranspiration Index from the Climatic Research Unit of the University of East Anglia. To triangulate infrastructure conditions, remote sensed Night Time Light data from US National Oceanic and Atmospheric Administration (NOOA) and National Aeronautics and Space Administration (NASA) was used. The study finds that extreme weather events result in increase in food consumption expenditure by 26%. Second, investment in complementary infrastructure enable households smoothen their consumption and have varied diets. Therefore, in attempting to address impacts of shocks on household welfare, it is important to also account for community level assets and infrastructure.

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