Household shocks, infrastructural investments, food and nutrition security linkages in Malawi

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Abstract

Ending extreme hunger requires interaction of both household and community level infrastructural investments. When communities and households are capital infrastructure constrained, effects of extreme events such as droughts can fetter consumption growth and food security. This paper assesses the impact of household shocks on daily per capita food consumption in Malawi. Secondly, the study assesses the impact of community level public infrastructural investment on household food security. The study uses fixed effects regression combined with propensity score matching techniques on a Malawian panel data collected between 2010 and 2016. The study uses three indicators for food security namely food consumption expenditure, the Berry Index of dietary variety and number of days a household went without food. To measure idiosyncratic and covariate shocks, self-reported survey and high-resolution weather station-based data used. To measure infrastructure, survey data, triangulated with remote sensed night time lights, were used to construct an infrastructure index. Results show that while a standard deviation deficit in the one to three-month interval drought reduces consumption by over 80%, access to infrastructure increased consumption by a factor of two during shocks.

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

JEL code: **Q120, D130, D150**

1. Introduction

We cannot end hunger by 2030 if we ignore key complementary investments that enable resilience to economic disruptions. In the absence of proper public and private infrastructure, effects of extreme events can impede food and nutrition security. In African agriculture, investments that are integral for increasing agricultural productivity and resilient livelihoods in the long-run are often not prioritized. Instead, meeting immediate consumption needs of the populace and government recurrent expenditure is what ranks higher (Nation Publication, 2017, Lusaka Times, 2012, Business Daily, 2018). There is also general fear of recovery costs of engaging in public infrastructural investments that would open up rural areas to new markets and increase economic activity (Raballand et al., 2011). However, literature has shown that increased investment in infrastructure is significantly correlated with increased agricultural growth and positive welfare outcomes (Dorosh et al., 2012, Diao and Dorosh, 2007, World Bank, 2018). 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.

Malawi has had 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; CIA, 2019). 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). Flood and drought incidence could lead to unsavoury terms of trade among poor farming households.

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

Although impacts of economic shocks on household welfare have been well documented, there is paucity of literature on the effect of infrastructure on resilience to household and community level shocks. To illustrate, Herrmann and Grote (2015) found that income poverty is low among farm households that had access to out-grower irrigation schemes in Malawi. However, the study did not focus on economic shocks despite tackling effects of out grower schemes, a form of empowerment through community capital assets, on poverty. In addition, Asfaw and Maggio (2018) found that, in Malawi, 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 links 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 – Evaporation Index (SPEI) (Serrano and Vicente, 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.

Further, weather shocks in neighbouring Tanzania lead to reduction in household incomes and later induced a 13 percent 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 et al. (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. In a similar context, Kubik and Maurel (2016) found that Tanzanian rural households migrated when they experienced shocks. Noteworthy, McPeak et al. (2011) found that perceptions of risks varied across different communities.

This paper, therefore, assesses the impact of household shocks on daily per capita food consumption in Malawi using three indicators namely food consumption expenditure, dietary variety and hunger days in a propensity score matching adjusted, fixed effects regression framework. Second, the study assesses the impact of community level infrastructural investment on household food security using the same framework. This adds value to the growing literature, which has mostly relied upon cross-section data (Harttgen et al., 2015), small non-representative samples Harttgen et al. (2012) and computable general equilibrium (CGE) models (Pauw et al., 2013), by bringing evidence from 3 waves of nationally representative surveys with a simple, theoretically consistent and clearly identified methodology which follows foundations of utility of lifetime consumption. Our estimates are identified by first purging data of selection bias using matching and removing nuisance parameters using fixed effects regression techniques. Our potential outcome estimates are eventually compared using t-tests to get proximate impacts of infrastructure on food and nutrition security. To the best of our knowledge, this study is the first to combine high-resolution geospatial data and micro data to assess the mitigating role of infrastructure on food and nutrition security during crises in a Southern African setting. Combining big data and representative, country level surveys enhances 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 reduces food consumption by 83% to 130%. Dietary diversity responds positively to a two-month SPEI indicating that it is a transitory shock coping strategy. In the midst of shocks, households that had one standard deviation more access to infrastructure had twice more consumption. We also found that households that had one standard deviation less access to infrastructure were 22% less dietary diverse.

The paper is structured as follows: Section 2 presents the methodology and data. In section 3 we present results of impacts of shocks on household food security and impacts of community infrastructure on food security amidst shocks. In Section 4 we present a discussion of key results while section 5 provides a summary and conclusion.

2. Methodology

2.1. Theoretical framework

Consumption among Malawian households is wrought with risks and uncertainty. As such, having economic activities that can generate a stream of net benefits can help navigate through risky times. Infrastructure and household assets could help cushion households from impacts of negative outcomes by smoothing consumption. Considering these aspects, it is more appropriate to evaluate the impact of economic shocks using a conceptual framework that accounts for household decision making under risk.

Viewing household decision making from a social planner's perspective, using the Ramsey economic growth framework (Barrow and Sala-i-Martin, 2003), we assume that at time *t*, we have a population $L(t)$ – growing at a rate *n* – having $H(t)$ number of households such that the average household size is $\frac{L(t)}{H(t)}$. These households outlive the planning period, that is, live technically forever in extended families. We assume that each household is small such that it does not affect wages (*w*) and capital (*K*) prices (*r*). We also assume that at community level, initial wealth is defined as total capital infrastructure and assets shared across the households i.e. $\frac{K(0)}{H}$.

Another consideration in this community level economy is that there are many firms that are owned by the households. This is valid since over 76% of households in Malawi are employed in agricultural production (Reserve Bank of Malawi, 2019). We assume that firms in this community use technology ($A(t)$) which also grows exogenously i.e. $\frac{\dot{A(t)}}{A(t)}$. The firms in question also have a production function $Y(t) = F[K(t), A(t)L(t)]$ and experience constant returns to scale such that the marginal productivity of capital equals zero as capital tends to infinity, $\lim_{K\to\infty} \frac{\partial Y(t)}{\partial K(t)} = 0$. Further, the marginal productivity of capital tends to infinity as the amount of capital tends to zero. In the absence of infrastructure there would not be sufficient production as infrastructure facilitates production. Lack of infrastructure would then imply that the marginal productivity of capital is very high, $\lim_{K\to 0} \frac{\partial Y(t)}{\partial K(t)} = \infty$. Malawi faces significant infrastructure constraints

(CIA, 2019) such that we expect the second scenario to occur for most communities.

While public infrastructure – being a public good – is shared across the community, rents from household assets and returns to labour and capital accrue to households. The returns are used for consumption. As an example, households in this community will use their returns for food consumption. A representative household maximizes a quasi-concave twice-differentiable intertemporal utility from consumption (*C(t)*).

$$u\big(C(t)\big) = \frac{\big(A(t)c(t)\big)^{1-\theta}}{1-\theta} \tag{1}$$

where $c(t) = C(t)/A(t)$ and $A(t)$ is given technological change (*see* Barrow and Sala-i-Martin, 2003; Alan et al., 2018). The utility from consumption grows at the rate g. The parameter θ is a measure of relative risk aversion (*see* Nicholson and Snyder, 2008, pg. 210). Of special interest, the quantity ($1/\theta$) summarizes the intertemporal elasticity of substitution between current consumption and wealth accumulation in future. A lower θ means that the household is more willing to tradeoff current consumption for future wealth. Then, $\beta = \rho - g - (1-\theta)g > 0$, where ρ is the discount rate, meaning that lifetime utility is well defined. Alan et al. (2018) reported that equation 1 can be expressed as an exact Euler equation

$$\left(\frac{C_{t+1}}{C_t}\right)^{-\theta}(1+R_{t+1})\beta = \epsilon_{t+1} \tag{2}$$

where ϵ_{t+1} is the innovation in discounted marginal utility – it explains the differences in expected consumption between the two periods. We exploit the innovation in utility by factoring in variables that explain the changes in consumption. Apart from the discount rate, circumstances affecting total household value added can explain ϵ_{t+1}. For example, a drought could mean less value added to farming households which might lead to a change in ϵ_{t+1}. Innovations in utility can also be compared across households. For example, households in a community that has marginal productivity close to infinity – low physical capital, infrastructure or assets – could have different ϵ_{t+1} as compared to a community that has marginal capital productivity close to zero. Kubik and Maurel (2016) exploit this aspect to explain household migration decisions amidst shocks among rural households in Tanzania. Expressing equation 2 in logarithms we get

$$\Delta \ln C_{t+1} = \alpha + \frac{1}{\gamma}\ln(1 + R_{t+1}) + e_{h,t+1} \quad (3)$$

2.2.Estimation strategy

Equation 3 gives a starting point in modelling consumption changes. We can econometrically estimate consumption per capita per day for household *i* in community *j* at time period *t* as

$$\Delta \ln c_{ijt} = \alpha_{0ijt} + \alpha_1 \Delta R_{ijt} + \alpha_2 X_{ijt} + \alpha_3 Z_{jt} + \alpha_4 S_{ijt} + b + e_{ijt} \quad (4)$$

where ln c_{ijt} is the natural log of food consumption in year *t*; R_{ijt} is a first difference of the value of assets - it captures the intertemporal elasticity of food consumption; X_{ijt} is a vector of household level characteristics; Z_{jt} are characteristics in community *j* in year *t*; S_{ijt} is a vector of shocks; α is a vector of unknown parameters to be estimated; b is a vector of time constant fixed effects. This also contains year dummies that capture the trend in food consumption and the discount rate – a measure of patience (Alan et al., 2018). e_{ijt} is an independent and identically distributed error term. We also assume that

$E(e_{ijt}|X_{ijt}) = 0$, $Var\left(e_{ijt}| X_{ijt}\right) = \sigma_e^2$, $\forall t \in T$ and $Cov\left(e_{ijt}, e_{ij}|X, a\right) = 0$ (Wooldridge, 2009). We can estimate $E[\Delta \ln c_{ijt}|X_{ijt}]$ using a dummy variable fixed effects regression with standard errors clustered at the year and household levels.

Noteworthy, since some idiosyncratic and covariate shocks might be temporary, differencing the consumption equation may not fully account for the impact of shocks. In that case, we allow that a consumption function *c(t)* be estimated as a function of asset growth, idiosyncratic and covariate shocks.

At this level, α_4 in equation 4 measures the proximate impact household shocks and a direct measure vulnerability to shock S_{ijt} at time *t*. If $\alpha_4 = 0$, then the households are not vulnerable to shocks. In addition, if $\alpha_1 \neq 0$ then the household's livelihood assets perfectly insure them from risky events.

The second hypothesis assesses the impact of community level infrastructure on household calorie consumption in the event of shocks. One way to test the impact would be to add community infrastructure as explanatory variables to equation 4 and test the hypothesis that community level infrastructure has no effect on food security. This would be possible infrastructure at community level in the sample was exogenously given. Infrastructure such as roads is not randomly assigned. Administrators and social planners make decisions to allocate infrastructure. Since we do not know the selection mechanism, we use propensity score matching (PSM) to predict the probability of access to infrastructure.

Community leaders and respondents at household level reported on the existence and quality of infrastructure at household level. We constructed an indicator *D* based on their responses. For example, if a household reported that the community had electricity and was corroborated by the community leader, then *D=1*. On one extreme both would say that they had no electricity and *D=0.* There were cases where both respondents gave contradicting information. In that case, we used Night Time Light (NTL) data – data gathered by United States' National Oceanic and Atmospheric Administration (NOAA) and National Aeronautics and Space Administration (NASA)'s polar orbiting satellites that cover the entire earth twice per day. Using near infra-red radiance, NTL presents data points illuminated by electricity across the planet. We standardized the radiance such that values 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 $D=1$ before NTL and radiance for the point was greater than or equal to zero, we confirmed that $D=1$. If 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 with confounding factors that could affect infrastructure assignment as covariates (Z_{ijt}). We determined the propensity score as $Pr[z] = Pr(D = 1|Z = z)$. Thus, we predicted propensity scores for infrastructure assignment in 2010. Using full optimal matching technique, a common support was created by using the *MatchIt* R package (Ho et al. 2011). Observations within the region of common support were used for further analysis in the fixed effects regression while observations that were not on common support were discarded. Predicted consumption expenditure, i.e. $Y(1), Y(0) \perp$

$D|X$, given that $Y(1), Y(0) \perp D|Pr[z]$, were subjected to a student's t-test, a comparison of means, to get Average Treatment Effect on the Treated (ATET). These potential outcome model estimates give direct causal effects of infrastructure on household food security amidst shocks [see Caliendo and Kopeinig, 2008, Khandker et al., 2009].

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 Office (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 two-stage stratified sampling design was used for the IHS panel surveys with a sample size of 2,508 households. The NSO reported that the IHS panels surveys are representative at national level, rural/urban, regional and household-level.

2.3.1. Dependent variables

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 the marginal cost of home-produced food consumption was its market price, we converted the quantity of food consumed at home by the median market price to get the food consumption expenditure.

We 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. Using FAO's Food Composition Tables for use in Africa, we disaggregated the quantities of food consumed into macro – and micronutrients. We calculated the share of each food item in the quantity of food consumed. We calculated the Berry-Index of dietary variety as $BI = 1 - \sum s_i^2$ where s_i is the share of the food consumed. A larger index means that the individual consumes a wide variety of foods (see Drescher et al., 2007).

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 within the past seven days.

Table 2 summarizes results of measures of location, dispersion and association between indicators of food security used in the study. Results generally show that indicators of food security are significantly associated in different directions and magnitudes. For example, the Berry index of dietary variety (BI) is 14% positively associated with the value food consumed per capita. That is, higher food expenditures are likely associated with increased economic access to a broad variety of food commodities. Of note, daily calorie intake per person is inversely related with BI – i.e. one percent increase for calories present at household level is associated with 5% reduction in dietary variety (BI). This result follows as a corollary to Bennett's law – 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).

Since the measures of food security are highly correlated, choice of a dependent variable to be used for assessing impact of idiosyncratic and covariate shocks should be measured by its consistency with microeconomic theory. Thus, while the other indicators have been considered as robustness checks, food consumption expenditure per capita is our choice variable for discussion.

Table 1: Associations between food security variables used in the study

	(1)	(2)
VARIABLES	Coef.	Std. Err.
	Means	
Berry index of dietary variety	.181***	.008
Average value of food consumed	.195***	.001
Daily per capita calorie intake	7.133***	.036
No. days without food	.413***	.029
	Variances	
Berry index of dietary variety	.056***	.003
Average value food	.000***	.000
Daily per capita calorie intake	.170***	.055
No. days without food	.761***	.036
	Correlations	
ρ(berry, value)	.141	.016
ρ(berry,calorie)	-.049	.016
ρ(berry,days)	-.041	.016
ρ(value,calorie)	.352	.012
ρ(value,days)	-.088	.016
ρ(calorie,days)	-.109	.016
Observations	4,011	

NOTE: *Significantly different from zero at 90 percent confidence
**Significantly different from zero at 95 percent confidence
***Significantly different from zero at 99 percent confidence
Estimates obtained using maximum likelihood in a structural equation model. Robust standard errors in parentheses

2.3.2. A typology of self-reported household shocks

Table 2 summarizes 21 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. 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: Self-reported shocks used in the study

1	Distress events (Shocks)	Percent
2	Drought/Irregular Rains	55.57[b]

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

NOTE: Letters a,b,c refer to groups selected by Principal Component Analysis using varimax rotation. Later the terms will be shortened to *a*-shock, *b*-shock, *c*-shock and *d*-shock, respectively.

Table 4: 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

The IHS data is geo-referenced. We therefore use the GPS coordinates from the survey and map them onto a global Standardized Precipitation-Evapotranspiration Index, which provides near real-time data on drought conditions with a 0.5° × 0.5°, 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 subtracting potential evapotranspiration from precipitation. 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 November to April period as a measure of the rainy season. Since the 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.

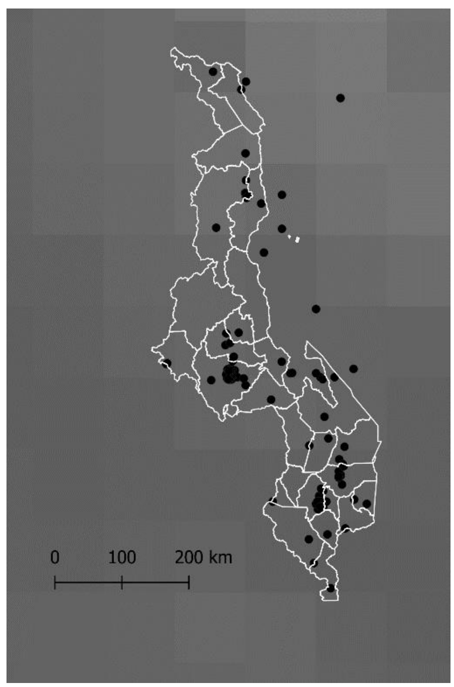

Figure 1: Map of Malawi showing 0.5° resolution SPEI grid and baseline sample distribution.

Results in Table 5 summarize baseline drought conditions across the strata of the sample. Results consistently show positive SPEI for a one-month to six-month duration. The SPEI figures are consistently positive for the time intervals and correspond to self-reported proportions of people who reported that they experienced dry spells. Results show that the Southern region's rural areas had the least values for one-month interval SPEI. Our results are consistent with FEWSNET's observations for the time period (FEWSNET 2010).

Table 5: Average SPEI values for different strata using baseline data

	Stratum	SPEI01	SPEI03	SPEI06	Self-Reported %
1	Center - Rural	0.549	1.435	1.268	26.98
2	Center - Urban	0.261	1.161	0.925	0.54
3	North - Rural	0.749	0.975	0.456	27.06
4	North - Urban	0.800	1.092	0.602	15.73
5	South - Urban	0.132	0.332	0.334	13.19
6	South - Rural	0.193	0.501	0.466	67.35
	National average	0.370	0.905	0.754	34.73

2.3.3. Community and household characteristics

Table 6 summarizes descriptive statistics of key community and household characteristics used in the sample. Results show almost no changes in the number of households with access to irrigation schemes (17%) between 2010 and 2013 but show a 21-percentage point increase in 2016. The proportion of households with access to markets remained between at 39% between 2010 and 2013 but decreased to 30% in 2016. However, the standard errors suggest that results fall within the same 95% confidence interval across all survey periods. Results also show an increase in the number of households that have access to grid electricity from 13% during the baseline to 22% across the two follow up surveys. These results are consistent with Night Time Lights and CIA (2019) estimates which have consistently shown to be within half a standard deviation lower than the national average. This also shows that, in general, the country has poor access to infrastructure. Results further show that between 28% and 35% of households had access to clinics while about 82% had access to roads.

The average age of the household during the baseline was 42 years and 24% of the household heads were female. Over 70% of the household heads were in a formal monogamous marriage union while 7% were polygamous, 4% were separated, 5% were widowed while the rest were never married.

Table 6: Descriptive statistics used in the study

	2010		2013		2016	
VARIABLE	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Community characteristics						
Community has irrigation scheme	.179	.012	.171	.012	.384	.012
Community has weekly market	.387	.015	.393	.012	.305	.012
Community has Electricity	.132	.010	.226	.010	.219	.011
Night time light	-.461	.021	-.466	.003	-.453	.014
Community has a clinic	.279	.014	.348	.012	.312	.012
Community has an all-weather road	.771	.013	.881	.008	.828	.010
Household characteristics						
ln Age of household head	3.686	.013	3.758	.008	3.837	.007
Proportion of females	.244	.006	.147	.004	.160	.004
Married – Monogamous	.684	.016	.777	.011	.811	.010
Married – Polygamous	.073	.009	.064	.006	.086	.007
Married – Separated	.043	.007	.058	.006	.086	.007
Widowed or widower	.048	.007	.055	.006	.066	.006
Δ Value of assets	.044	.159	.001	.119	.003	.086
Access to credit	.414	.006	.723	.062	1.59	.089

3 Household shocks, food security and infrastructure

3.1. Proximate impacts of household shocks on food security

Table 7 summarizes estimates of impacts of shocks on food security outcomes. Explanatory variables were grouped into two categories namely, household shocks, demographic characteristics and fixed effects dummy variables. Table 7 only shows impacts of shocks and omits demographic characteristics and fixed effects dummies (a full table is in the supplementary materials). The table presents three models of shocks. Column 1 presents estimates of the natural logarithm of food expenditure per capita per day. Column 3 presents estimates of the Berry Index of dietary variety while column 5 has estimates of the number of days a household went without food or drastically reduced their daily intake of food.

Table7: Proximate impacts of household shocks on food security

	DEPENDENT VARIABLES					
	Log of food expenditure		Berry-Index		Log No. days without food	
term	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI01	0.832*	0.459	-0.012	0.088	-0.067	0.076
SPEI03	1.273***	0.470	0.218***	0.090	-0.008	0.078
SPEI06	-2.279***	0.661	-0.127	0.127	0.115	0.110
SPEI12	0.638	0.455	-0.063	0.087	-0.044	0.076
a-shock, price related	-0.147	0.125	-0.007	0.024	0.028	0.021
c-shock, pest and diseases	0.157	0.108	-0.090***	0.021	-0.010	0.018
d-shock, misc. idiosyncratic	-0.152	0.111	-0.128***	0.021	0.139***	0.018
Δ Value of assets	0.521***	0.043	0.018**	0.008	-0.035***	0.007
Demographic characteristics	YES		YES		YES	
Regional Rural – Urban FE	YES		YES		YES	
District FE	YES		YES		YES	
Year FE	YES		YES		YES	
No. households	1399		1399		1399	
No. observations	4170		4170		4170	
R-Squared	0.355		0.285		0.209	
Adjusted R-Squared	0.346		0.275		0.198	
F-Statistic, DF(58,4112)	39.004***		28.231***		18.760***	

NOTE: *Significantly different from zero at 90 percent confidence. **Significantly different from zero at 95 percent confidence.***Significantly different from zero at 99 percent confidence. Standard errors clustered at household level.

Results from the food expenditure per day per capita model indicate statistically significant impacts of drought on household food consumption. A unit standard deviation deficit in SPEI during the one-to-three months interval results in 83% to 130% decrease in food consumption. However, considering a six-month interval gets a negative sign for SPEI by a factor of over two. A six-month time interval mixes with the cool dry season – which is mainly a harvest season when food is at its abundance – hence, a negative SPEI value is not counterintuitive. Considering that the average SPEI for the three survey periods is within a unit standard deviation, a standard deviation deficit in SPEI represents drastic changes in weather patterns. SPEI results for the long term 12-month period are not statistically significant but from an economic standpoint, a positive sign is still consistent with the former interpretation that even after accounting for the dry season, a standard deviation deficit in SPEI would negatively affect food consumption when factors of production fully adjust to the impacts of the shocks.

As shown in the Berry-Index model, results also consistently indicate that during the three-month interval, a deficit in SPEI would negatively affect dietary diversity. Drought conditions were not statistically significant in the third model. However, we find that miscellaneous idiosyncratic shocks – labelled *d-shocks* in Table 2 – such as illness, death, reduction in earnings, increased the number of days a household went without food or drastically reduced food consumption by 15%.

As predicted by the theoretical model, household assets play a significant role in smoothing consumption. We see that a 1% growth in assets leads to a 52% increase in food consumption and 2% more diversified diets. It also reduces the number of days without food by 4%.

3.2. Impact of infrastructure on food and nutrition security during shocks

Table 8 summarizes results of the impact of access to infrastructure on household food and nutrition security at household level. Importantly, the predicted expected values were compared using student's t-test to accurately weigh the effects. The resulting estimate is the Average Treatment Effect on the Treated (ATET). All variables are presented in natural logarithms and column 3 presents the mean differences.

Table 8: Impact of infrastructure on household micronutrient consumption per capita per day

Variable	Control Mean	Treated Mean	Difference	t-statistic	DF	[95% Conf. Int.]	
	(1)	(2)	(3)	(4)	(6)	(7)	(8)
Food expenditure	8.874	11.110	-2.236***	-18.008	951.621	[-2.479,	-1.992]
Berry-Index	0.336	0.366	-0.030*	-1.922	896.170	[-.0556,	0.001]
Calories	7.135	7.222	-0.087***	-3.140	827.954	[-0.141,	-0.032]
Protein	6.931	7.028	-0.096***	-2.124	862.804	[-0.096,	-0.007]
Fat	5.730	5.867	-0.138***	-2.859	836.382	[-0.138,	-0.043]
Iron	5.952	6.088	-0.135***	-3.023	870.529	[-0.223,	-0.047]
Phosphorus	8.062	8.325	-0.263**	-2.120	985.322	[-0.507,	-0.020]
Calcium	8.126	8.131	-0.005	-0.096	870.217	[-0.104,	0.094]
Retinol	1.787	2.168	-0.381***	-3.286	810.190	[-0.608,	-0.153]
Riboflavin	3.587	3.277	0.310***	5.161	842.763	[0.192,	0.428]
Thiamine	2.989	2.864	0.125***	2.873	846.603	[0.040,	0.210]
Beta-carotene	6.627	6.649	-0.022	-0.124	811.115	[-0.363,	0.320]

NOTE: *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, results indicate that access to infrastructure has positive impact on food and nutrition security. For example, households that had access to infrastructure had twice more food consumption expenditure than households that did not have. Although dietary diversity is still low, Average Treatment Effects on the Treated from Fixed effects regression (ATT-FE) results show that households with access to infrastructure had 3% more diversified diets. We also measured impacts of infrastructure access on macro-nutrient outcomes and found that households with access to infrastructure had more macro-nutrient availability than households that did not. Presence of macro-nutrients at household level is important because human beings require their consumption in large quantities. Absence of infrastructure can limit access to some of important macro-nutrients such as proteins which are found cheaply in communities that have well-functioning markets. In addition, it is harder to have markets in areas that do not have accessible roads especially during shocks.

We also included micro-nutrient variables in our ATT-FE estimation. Results for micronutrient availability are also consistent with the foregoing discussion with few exceptions in Riboflavin and Thiamine. Results consistently point towards positive infrastructure impacts on micronutrient availability.

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. In this study we have addressed both issues and get two consistent results. First, that shocks have negatively impacted household daily per capita consumption given household and community 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, unusually high commodity prices, and pests and diseases have deleterious effects on household daily consumption per person – comes from a theoretical prediction of our economic model. Any shock that affects total household value added results in reduced intertemporal utility by changing the household discount rate, technological change and the intertemporal elasticity of substitution. Our results show that the a decline in asset growth – usually as a response to a supply side shock that affects earning – results in significant decrease in consumption per capita.

Allowing for many shocks and community level infrastructure variables has several advantages for planning resilience programmes. Results have consistently indicated that communities that have irrigation schemes, all weather roads and weekly markets have higher consumption and varied diets. Highly disaggregated macro- and micro- nutrient data also confirm these observations. This indicates that, all things being equal, community level infrastructure has a positive direct causal effect on household consumption. This observation comes from our theoretical framework that asset accumulation can have positive consumption effect. The Ramsey economic growth model, to which our methodology owes semblance, predicts that capital accumulation, in terms of building assets and savings, leads growth in future consumption [Barrow and Sala-i-Martin, 2003]. 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 accumulated assets accrue to households and can therefore be used to consume and smoothen future consumption possibilities.

5. Conclusion

This study assessed impacts of shocks on household food security in Malawi using three indicators namely: food consumption expenditure, Berry Index of dietary variety and number of days a household went without food. The study used fixed effects regression techniques combined with propensity score matching to assess the impact of household shocks and the role of community infrastructure on food security. Three waves of nationally representative integrated household panel surveys obtained from the National Statistical Office were used. To triangulate the self-reported shocks 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, remoted 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 reduction in daily per capita food consumption by 83% and 127%. Second, investment in complementary infrastructure such as all-weather roads, irrigation schemes 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.

References

Alan, S., Browning, M. and M. Ejrnæs. 'Income and consumption: A micro semistructural analysis with pervasive heterogeneity', *Journal of Political Economy*, Vol. 126(5) (2018) pp. 1827–1864.

Asfaw, S., and Maggio., G. 'Gender, weather shocks and welfare: Evidence from Malawi', *The Journal of Development Studies*, Vol. 54(2) (2018) pp. 271–291.

Atkins, P.; and Bowler, I. *Food in society: economy, culture, geography*. (London, England: Routledge, 2016).

Barrow, R. J., and Sala-i-Martin, X. *Economic Growth*. (Cambridge, Massachusetts, USA: The MIT Press, second edition, 2003).

Beck, U., Pauw, K. and Mussa, R. *Methods matter: The sensitivity of Malawian poverty estimates to definitions, data, and assumptions*. Technical report, WIDER Working Paper (UNU-WIDER: Helsinki, Finland, 2015)

Business Daily. Here's how Kenya can get out of debt crisis. 2018. Available at: https://www.businessdailyafrica.com/ lifestyle/society/how-Kenya-can-get-out-of-debt-crisis/ 3405664-4721238-77tn9vz/index.html (last accessed: 25 October 2018).

Caliendo, M. and Kopeinig, S. 'Some practical guidance for the implementation of propensity score matching', *Journal of Economic Surveys*, Vol. 22(1) (2008) pp. 31–72.

Central Intelligence Agency. Africa: Malawi – The World Factbook. Available at: https://www.cia.gov/library/publications/the-world-factbook/geos/mi.html, 2019 (last accessed: 17 March 2019).

Diao, X. and Dorosh, P. 'Demand constraints on agricultural growth in East and Southern Africa: A general equilibrium analysis.' *Development Policy Review*, Vol. 25(3) (2007) pp. 275–292.

Dorosh, P., Wang, H. G., You, L. and E. Schmidt. 'Road connectivity, population, and crop production in Sub-Saharan Africa', *Agricultural Economics*, Vol. 43(1) (2012) pp. 89–103.

Doss, C.. If women hold up half the sky, how much of the world's food do they produce? In *Gender in Agriculture*, (Springer, pp. 69–88, 2014).

Drescher, L S., Thiele, S., and Mensink, GB. 'A new index to measure healthy food diversity better reflects a healthy diet than traditional measures.' *The Journal of nutrition* Vol.137(3) (2007) pp. 647-651.

Gourinchas, P.O. The R amsey-Cass-Koopmans model. Available at: https: //eml.berkeley.edu/~webfac/gourinchas/e202a_f14/Notes_ Investment_pog.pdf, 2014 (last accessed: 22 October 2018).

Government of Malawi. Malawi growth and development strategy. Available at: http://www.malawi.gov.mw/Publications/MGDS%20November%202006%20-%20MEPD.pdf , (last accessed 14 May 2015).

Harttgen, K., Klasen, S., et al. *Analyzing nutritional impacts of price and income related shocks in Malawi and Uganda.* Working Paper, 14, (Regional Bureau for Africa: United Nations Development Progra/RBA, 2012).

Harttgen, K.S. Klasen, and Rischke, R. *Analyzing nutritional impacts of price and income related shocks in Malawi: Simulating household entitlements to food*. Poverty, Equity and Growth-Discussion Papers, No. 166 (Courant Research Centre, University of Göettingen: Göettingen, 2015).

Herrmann, R. and Grote, U. Large-scale agro-industrial investments and rural poverty: evidence from sugarcane in Malawi. *Journal of African Economies*, Vol. 24(5) (2005) pp.645–676.

Ho, D.E., Imai, K, King, G, Stuart E.A. "MatchIt: nonparametric preprocessing for parametric causal inference." *Journal of Statistical Software,* 42(8) (2011) pp. 1-29.

Khandker, R., Koolwal, G. B. and Samad, H. *Handbook on impact evaluation: quantitative methods and practices* (Washington DC, USA: The World Bank, 2009).

Kudamatsu, M., Persson, T. and Strömberg, D. *Weather and infant mortality in Africa*. CEPR Discussion Paper No. DP9222 (Centre for Economic Policy Research: Stockholm, 2012).

Lusaka Times. Government's budget for maize purchase exhausted, FRA asked to borrow money to pay farmers. Available at: https://www.lusakatimes.com/2012/10/03/ governments-budget-maize-purchese-exhausted-fra-asked-borrow-money-pay-farmer (last accessed 25 October 2018).

Kubik, Z. and Maurel, M. 'Weather shocks, agricultural production and migration: Evidence from Tanzania.' *The Journal of Development Studies,* Vol. 52(5) (2016) pp. 665-680.

McPeak, J. G., Doss, C. and Little, P. D. *Risk and social change in an African rural economy: livelihoods in pastoralist communities*. (London, England: Routledge, 2011).

Miguel., E. Poverty and witch killing. *The Review of Economic Studies*, Vol. 72(4) pp. 1153–1172, 2005.

Nation Publication. Admarc gets K23 billion bailout. Available at: https://mwnation. com/admarc-gets-k23bn-bailout/, (last accessed: 25 October 2018).

Nicholson, W. and C. Snyder. *Microeconomic Theory: Basic Principles and Extensions* (Mason, USA: Thomson South-Western 2008).

Pauw, K., Dorosh, P. and Mazunda, J. *Exchange rate policy and devaluation in Malawi*, Discussion Paper No. 1253. (International Food Policy Research Institute: Washington D.C. 2013).

Raballand, G., Thornton, R., Yang, D., Goldberg, J., Keleher, N., and A. Müller. *Are rural road investments alone sufficient to generate transport flows? Lessons from a randomized experiment in rural Malawi and policy implications*. Policy Research Working Paper No. 5535 (The World Bank: Washington D.C., 2011).

Vicente-Serrano, Sergio M., et al. 'A new global 0.5 gridded dataset (1901–2006) of a multiscalar drought index: comparison with current drought index datasets based on the Palmer Drought Severity Index.' *Journal of Hydrometeorology,* Vol. (11) 4 (2010) pp. 1033-1043.

Von Braun, J., Teklu, T. and Webb, P. *Famine in Africa: Causes, responses, and prevention* (Washington D.C.: International Food Policy Research Institute, 1999).

Woodridge, J. *Introductory econometrics: A modern approach*. (Mason, USA: Cengage Learning, 2009).