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Shelter from the Storm? Household-Level Impacts of, and Responses to, the 2015 Floods in Malawi

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Abstract As extreme weather events intensify due to climate change, it becomes ever more critical to understand how vulnerable households are to these events and the mechanisms households can rely on to minimize losses effectively. This paper analyzes the impacts of the floods that occurred during the 2014/15 growing season in Malawi, using a two-period panel data set. The results show that maize yields and value of production per capita were lower for all households, particularly for those located in moderate and severe flood areas. However, drops in food consumption expenditures were less dramatic, and calories per capita were higher. Only the food consumption score, which is a measure of dietary diversity, was significantly lower, particularly for households located in areas of severe flooding. Although access to social safety nets increased food consumption outcomes, particularly for those located in areas of moderate flooding, the proportion of households with access to certain safety net programs was lower in 2015 compared with 2013. The latter finding suggests that linking these programs more closely to disaster relief efforts could substantially improve welfare outcomes during and after a natural disaster. Finally, potential risk-coping strategies, proxied by access to off-farm income sources, having financial accounts, and social networks, were generally ineffective in mitigating the negative impacts of the floods.

Keywords Extreme weather · Floods · Household welfare · Malawi · Sub-Saharan Africa

JEL Codes D60 · I38 · Q12 · Q54

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Introduction

Rural households in developing countries rely on rain-fed farming as a significant source of income. In the sub-Saharan African context, the average share of rural household income originating from agriculture can be up to 69% (Davis et al. 2017). As of 2013, only 3.4% of cultivated land was irrigated, representing an increase of just a 0.1 percentage point since 1993 (FAO 2016). Smallholders are clearly vulnerable to crop losses due to extreme weather events, whose frequency, intensity and duration has been increasing over the past decades (Ummenhofer and Meehl 2017). Further, climate scientists are providing new links between the increase in extreme events and climate change (Alexander 2016; Ummenhofer et al. 2015; Cai et al. 2014; IPCC 2012;). This suggests that farmers are likely to suffer more frequent and severe crop losses in the future.

There is a dearth of evidence of the impact of extreme events on household-level outcomes, precisely because extreme events are relatively rare and the scheduling of household survey data collection activities are generally anchored in other needs. As such, the availability of micro data after an extreme event typically happens by chance. There is some evidence of the impacts of extreme events on crop yields, but very limited evidence on impacts on household welfare, such as food consumption and dietary quality. Additionally, there is limited evidence on the mechanisms that farm household members rely on to buffer large losses in crop harvest when they – and many of their neighbors – are hit by an extreme weather shock. This is precisely the type of information needed to better inform disaster risk management strategies, to develop and implement effective climate change adaptation strategies, and to optimally integrate disaster risk management with adaptation efforts.

During the 2014/15 growing season in Malawi, severe flooding affected large numbers of farmers across the country. An assessment undertaken by the United Nations Disaster Assessment and Coordination unit (UNDAC) estimated that over a million people were directly affected by the floods, with over 200,000 displaced and over 100 killed (UNDAC 2015). Consistent with the global and regional evidence on the increased frequency and severity of extreme weather events, evidence from Malawi also suggests that the frequency of both flood and drought events is increasing, and likely to increase further still with climate change (Venalainen et al. 2016; Chinsinga 2012). Farmers are particularly vulnerable to weather shocks in Malawi, where landholdings are very small and irrigation is near non-existent (Asfaw et al. 2016; Frenken 2005). Crop revenues per family member are correspondingly small, and rural poverty rates remain stubbornly high at 57% (World Bank 2016; Ricker-Gilbert et al. 2014).

In this paper, we estimate the impacts of these flood events on household welfare outcomes in the period following the floods, including the impacts on food consumption expenditures, caloric intake, and the food consumption score. The latter is a measure of dietary quality developed by the World Food Programme that is based on dietary diversity (World Food Programme 2008). Further, we are interested in determining which factors helped households minimize the negative impact of floods on welfare; we focus particularly on potential household risk-coping strategies as well as access to social safety nets. Our analysis relies on a multi-topic, panel household survey that was implemented by the Malawi National Statistical Office in November–December 2015, and that tracked and re-interviewed 590 households in Southern Malawi that had previously been interviewed by the national Integrated Household Panel Survey (IHPS) in 2010 and 2013 under the World Bank Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) initiative. Our ability to link all available rounds of household survey data to publicly available geospatial biophysical and agro-climatic data created a unique opportunity to study the impact of a natural disaster.

The paper contributes to the literature in three main ways. First, it provides direct evidence of the impact of a severe weather event on household food consumption measures using a panel data set, and is one of a very limited number of studies to do so. Second, we evaluate the impacts of flood events on a range of consumption measures; doing so enables us to highlight that the primary impact of the floods was to reduce the quality of the food consumption basket rather than quantity consumed per se. This result has important policy implications; increasing the accessibility to a wider range of food groups in response to natural disasters can significantly increase dietary quality. Third, we are able to document the importance of three social safety net programs – direct food aid, school feeding programs[1], and Malawi Social Action Fund (MASAF) assistance for work – with implications for how such programs may be made more effective in responding to natural disasters in the future.

The results show that while crop production was much lower overall, and particularly for those located in moderate and severe floods areas, drops in food consumption expenditures were less dramatic, and calories even increased. However, food consumption scores were significantly lower for households located in both moderate and severe floods areas. At the same time, while the floods did lead to lower food consumption outcomes for some households, many were able to shield consumption outcomes from production losses. Access to social safety nets increased food consumption outcomes, particularly for those in moderate flood areas. However, we note that the proportion of households with access to certain safety net programs declined in 2015 versus 2013, suggesting that linking these programs more closely to disaster relief efforts could substantially improve welfare outcomes during and after a natural disaster. Finally, risk-coping variables, including financial accounts, access to off-farm income sources, and adult children living away from home, were generally not effective in mitigating negative impacts of the floods.

Literature Review

The primary impact of weather shocks on rural households' welfare is through impacts on crop production. Due to data limitations, only a limited number of studies have attempted to uncover the impacts of extreme weather events on crop production at the household level. Michler et al. (2016), using panel data from Zimbabwe, find that extreme weather events have significant negative impacts on crop yields; descriptive statistics show that average yields in extremely low rainfall years were about 34% lower than in normal years. Similarly, Wineman et al. (2017), using panel data from Kenya, find that extremely low rainfall conditions result in a 29% decrease in the value of crop production per adult equivalent.[2] Estimates of flood impacts on crop production, and in particular those that are based on panel data sets, are more scarce. Del Ninno et al. (2001), using cross-sectional data collected after the large-scale 1998 floods in Bangladesh, document crop losses of 42 to 62% for the flood-affected households, with many households losing their entire harvest.

Several studies attempt to estimate the impacts of extreme weather on a range of household welfare outcomes, most often those that are linked to consumption. Wineman et al. (2017) find

[1] The specific programs captured under "school feeding programs" were the School Feeding Programme, free distribution of Likuni Phala to children and mothers, and supplemental feeding for malnourished children at a nutritional rehabilitation unit. The most frequent of these three is by far the School Feeding Programme.

[2] Fafchamps et al. (1998) use panel data collected in six villages in Burkina Faso, where the sampled villages experienced at least two years of extremely low rainfall compared with the long-term average. The authors find the expected negative impacts of low rainfall on the value of crop production, though the authors do not report the size of these impacts.

that very low rainfall lowered income per adult equivalent per day by 18.3%. And while calories per adult equivalent per day were not affected on the whole, the share originating from own crop and livestock production was lower, and the share of purchased calories was higher as a result of the low rainfall shock. Del Ninno et al. (2001) show that though overall food expenditures were not affected by flood intensity, expenditures on calorie-dense foods fell, as did calorie consumption per capita for most flood-affected household categories, except for the most severely hit. The authors hypothesize that food aid may have helped households in the most severely-hit areas to maintain caloric intake.

Other studies estimate a 5 to 19% drop in consumption expenditures subsequent to a weather shock (Arouri et al. 2015 in Vietnam; Baez et al. 2016 in Guatemala; Christiaensen and Dercon 2007; Dercon et al. 2005 in Ethiopia). Premand and Vakis (2010) document that households in Nicaragua that experienced a drought over three years were 10% more likely to remain impoverished four years later, while Reardon and Taylor (1996) show that the poverty rates in the Sudanian zone of Burkina Faso, and in the drier Sahelian zone were 12 to 15, and 2 to 19 percentage points higher, respectively, after the 1984–85 droughts.

There are numerous mechanisms that households can rely on to reduce the impact of shocks when they do occur. A key finding in the literature is that protection through these mechanisms against disasters is never more than partial, as consumption shortfalls remain high when faced with extreme shocks (Baez and Mason 2008; Dercon 2005; Alderman and Paxson 1994).[3]

The main coping mechanisms identified in the literature include household risk-coping measures such as selling livestock and other productive assets, and reducing food consumption and/or dietary diversity (del Ninno et al. 2001; Kazianga and Udry 2006). The latter mechanisms are potentially "harmful" in the sense that relying on them may lead to lower income in the medium-long term (Heltberg et al. 2015; Hoddinott and Kinsey 2001). Households may also draw on coping mechanisms that are less likely to compromise future income, such as re-allocating labor off-farm, relying on transfers from friends and family, and/or accessing credit (Heltberg et al. 2015; Kochar 1995; Dercon 2002).

The empirical evidence provides a mixed picture on which of these household risk-coping strategies are more effective, suggesting that efficacy of various strategies is context-specific. For instance, Wineman et al. (2017) show that off-farm income fell in response to low rainfall shocks, and, therefore, was not effective in mitigating lower crop incomes. Del Ninno et al. (2001) find that participation in the labor market for day laborers fell initially after the floods, and was still below self-reported pre-flood levels 6 months later, in addition to lower wages as described above. On the other hand, Gröger and Zylberberg (2016) document that internal migration for wage work was effective in securing remittances to help cope with the effects of a typhoon in Vietnam, while Arouri et al. (2015) demonstrate that internal migration enabled households to better cope with natural disasters in Vietnam. There is mixed evidence on the role of livestock to smooth consumption[4], and more consistent positive evidence for credit[5],

[3] Natural disasters of all kinds can push the near poor into poverty (De la Fuente and Dercon 2008). A comparative study on mobility into and out of poverty in 15 countries of Africa, South Asia, East Asia and Latin America with about 9000 household interviews found that natural disasters (along with health adversities and death) were the second most important reason why people became poor (Narayan et al. 2009).

[4] For instance, Kazianga and Udry (2006) and Wineman et al. (2017) find limited or no role for livestock as a risk-coping mechanism, but Miura et al. (2016) and Lybbert et al. (2004) find that livestock sales can offset crop losses, at least for households with larger herds to start with.

[5] See, for instance, Wineman et al. (2017) and Arouri et al. (2015).

but livestock ownership is quite limited in Malawi, outside of chickens, and credit is extremely thin, so we do not include these variables in our analysis.

Additionally, food assistance and cash transfers following a disaster can help households cope by protecting consumption, boosting caloric intake, and potentially avoiding sales of productive assets. Yamano et al. (2005) demonstrate that food aid offset the increase in child (0.5 to 2 years old) malnutrition following drought-induced harvest failure in Ethiopia between 1995 and 1996. By contrast, in the absence of food aid, a 10% increase in crop damage reduced children's growth by 0.12 cm (1.8%). Also in Ethiopia, households that were affected by the drought in 2007 and that received transfers from the Productive Safety Net Programme (PSNP)[6] consumed 30% more calories than the non-beneficiaries (World Bank 2010). De la Fuente et al. (2017) observe that participant households in the conditional cash transfer program *Progresa* in Mexico displayed higher food consumption between 1998 and 2003, even in the presence of drought and flood shocks. Yet other work has found that assistance is often too small and infrequent to play a major role (Gilligan et al. 2008 in Ethiopia; Ahmed et al. 2009 in Bangladesh), or may be ineffectively allocated due to political reasons or errors in targeting (del Ninno and Lundberg 2002 in Bangladesh; Jayne et al. 2002 in Ethiopia; Reardon et al. 1988 in Burkina Faso; Francken et al. 2009 in Madagascar).

In summary, the empirical evidence suggests that households subject to extreme weather events often suffer large losses in agricultural income. The impact on consumption and calories tends to be lower than the impact on crop income but still significant, indicating that households are not able to perfectly smooth consumption. Nonetheless, households can mitigate negative impacts via household risk-coping strategies, such as re-allocating labor and accessing transfers from friends and relatives. Additionally, greater access to a number of institutions enables households to cope with the impacts of extreme weather, including access to social safety net programs.

Data

Our analysis uses data from the Malawi Flood Impact Assessment Survey (FIAS), which was conducted by the National Statistical Office (NSO) in November–December 2015.[7] FIAS attempted to track 590 rural households who had previously been surveyed by the Malawi Integrated Household Panel Survey (IHPS) in 2013.[8,9] Since FIAS builds on a high-quality

[6] For details on the PSNP see Country Spotlight 4. Ethiopia: Deaths from Droughts or Derg?

[7] FIAS 2015 was implemented with technical support from the World Bank Living Standards Measurement Study (LSMS), the World Bank Poverty and Equity Global Practice, and LEAD Analytics, and with the World Bank funding from the Global Facility for Disaster Reduction and Recovery (GFDRR), the Disaster Risk Financing and Insurance team, the Finance and Markets Global Practice, and the Global Solutions Group on Managing Risks within the Poverty and Equity Global Practice.

[8] IHPS was implemented by the NSO, with financial and technical support from the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) program. In 2013, the IHPS was implemented from April to December 2013, with the objective of tracking and resurveying 3246 households across 204 enumeration areas (EAs). The anonymized, unit-record data and documentation from the IHPS 2013 can be accessed through www.worldbank.org/lsms.

[9] FIAS was implemented on a computer-assisted personal interviewing (CAPI) platform that was designed using the World Bank *Survey Solutions* CAPI software (www.worldbank.org/capi). The FIAS CAPI experience was a key input into the design and implementation of the Fourth Integrated Household Survey (IHS4) and Panel Subcomponent later in 2016/17, also using a *Survey Solutions*-powered CAPI platform.

panel household survey infrastructure that was in place prior to the 2014/15 floods, we have two pre-flood data points, coupled with one data point in the post-flood period.

The identification of the target sample of 590 rural FIAS households was driven by several factors. The financial arrangements for the FIAS fieldwork implementation did not permit the preparations to take place prior to August 2015. Once there was clarity around the survey implementation, the budget constraints, together with the research team's desire to maximize inter-annual comparability (i.e. IHPS 2013 versus FIAS 2015) of the timing of the household interviews, led the research team to focus on the IHPS sub-sample that had been interviewed in the time frame of August–December 2013, and that were residing either in a Southern region district or Ntcheu, a Central region district that borders the Southern region and that was the most adversely-affected Central region district during the 2014/15 floods. The target households that moved in their entirety to other districts between the IHPS 2013 and the FIAS 2015 interview were also tracked – a crucial design decision to fully understand flood impacts. The final FIAS sample size was 558 households, representing an impressive attrition rate of 5.3% with respect to the target sample.

FIAS survey instruments were modeled after the multi-topic Household Questionnaire and the Agriculture Questionnaire that had been used for the IHPS 2013. Similar to the IHPS and the IHS3 practice, all FIAS household locations were geo-referenced in order to link the household survey data with publicly available geospatial biophysical and agro-climatic data. The resulting data set has extensive information on agricultural production and productivity; household consumption and expenditures; household caloric intake; as well as risk-coping mechanisms. Bringing in household location-specific geospatial variables, we are also able to compute objective measures of household exposure to flooding, as detailed below.

Descriptive Statistics

Flood Events, Production and Consumption Outcomes

First, we use the National Oceanic and Atmospheric Administration (NOAA) ARC2 rainfall estimate data covering the period 1983–2015, and generate the percent difference in flowering season rainfall in the relevant cropping period and long-term mean flowering season rainfall.[10] Figure 1 depicts the kernel densities of the percent deviation of the 2012/13 flowering season rainfall, and the 2014/15 flowering season rainfall from historical average flowering season rainfall. All household locations in the sample experienced rainfall over the historical average in 2015, and the mean rainfall difference was over 55%, well above the 14.4% mean difference observed in 2013.

The percent difference measure can capture both above and below rainfall yields, so we use the absolute percent difference to capture negative impacts of both high and low rainfall (low rainfall was only experienced in 2012/2013). The measure captures the difference from expected rainfall, and is, thus, expected to have a negative impact on crop production, and possibly on other income-generating activities such as informal employment in the agricultural sector, in both years. The rainfall difference measure alone is not likely to adequately capture the severity of flooding, since severity is also related to geological and topographical features in addition to rainfall, such as distance to rivers, elevation, etc. (Merz et al. 2007). To better

[10] We calculate the flowering season rainfall as the cumulative rainfall over the last dekad in December through the third dekad in January.

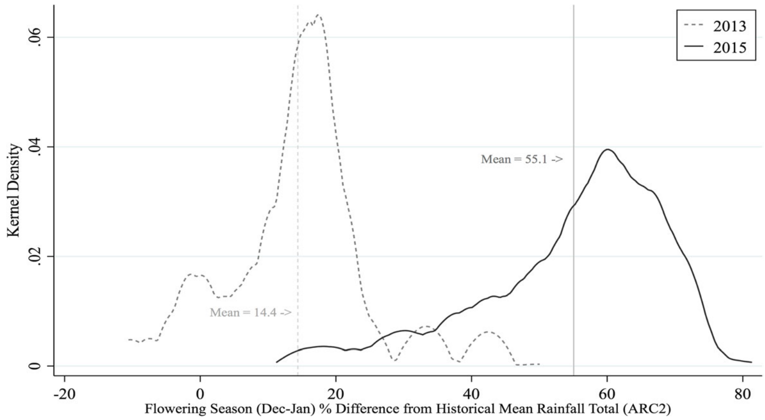

Fig. 1 Kernel density of rainfall deviation, 2013 and 2015

capture the degree of flooding, we match the household location data to the mean flood intensity measure generated from University of Maryland's flood simulation model; flood intensity is the estimated water depth above a flood threshold (Wu et al. 2014)[11]. The flood intensity measure is at a rather coarse resolution, of .125 arc degrees, or approximately 14 km^2 in Malawi. To obtain a more precise estimate of the severity of flooding to which households were exposed, we consider two household-specific variables that are expected to be highly correlated with the severity of flooding at a given location, namely elevation at the household GPS location at 90 m resolution[12], and distance from household GPS location to the nearest river (Merz et al. 2007; National Research Council 2015). We subsequently perform a principal component analysis (PCA) of the mean flood intensity, elevation and distance to nearest river, and compute an index of the extent of flooding. As shown in Table 1, the PCA scores are higher for those areas with a lower mean flood intensity, further from a river, and higher in elevation. We multiply the resulting index by −1 for more intuitive interpretation as a measure of flood severity. Thus, a higher score is associated with higher mean flood intensity, closer to a river, and lower in elevation.

We use the flood index to generate three flood categories, namely low, moderate and severe. These categories correspond to the terciles of the flood index. While analyzing the impacts of floods on crop production is not the focus of this paper, we expect that the primary impact of floods on household welfare measures of interest is through the impact on crop production. As shown in Table 2, maize yields and value of production per capita were lower across all categories in 2015 versus 2013. The percent declines in maize yields were significantly higher for those located in the moderate and severe flood areas vis-à-vis those located in the low flood areas. Value of production per capita was significantly lower for those located in severe and moderate areas versus those located in low flood areas. As shown in the descriptive statistics in Table 5, this is in part because households located in severe flood areas had greater landholdings per capita, indicating the importance of including that variable as a control variable in our consumption analysis.

[11] Wu et al. (2014) provide details of the simulation model, which combines a land surface model with river tracing/water flow model, using satellite-based precipitation data.
[12] The description can be found at: https://lta.cr.usgs.gov/srtmgl3.html.

Table 1 Principal component factor analysis scores for flood affectedness index computation

Mean flood intensity	−0.775
Distance to any river (km)	0.544
Elevation (m)	0.679

To further test whether the flood intensity and flood category variables are significant predictors of value of crop production per hectare, Table 3 below gives correlated random effects panel regression results with cluster standard errors for flood impacts from two specifications – one using the flood index and the other using the flood categories[13]. As can be seen, all coefficients are negative and significant in both specifications. To get an idea of the magnitudes, we note that, all else equal, households in the moderate flood category received 23% lower value of crop production per capita vis-à-vis those in the low flood category, while those in the severe flood category faced 42% lower value of crop production per capita. These estimated reductions are consistent with estimates found in the literature reviewed above.

Consumption Outcomes

Using the three flood categories, we can look at the descriptive statistics on food expenditures per capita, caloric intake per capita, and the Food Consumption Score (FCS). The Food Consumption Score (FCS) is a standardized composite score that brings together information on dietary diversity, food frequency, and the relative nutritional importance of different food groups (WFP 2008). The indicator was developed by the World Food Programme (WFP) and is calculated using a module specifically designed to capture the required information built into the FIAS and the IHPS questionnaires.

Food expenditures per capita include direct cash outlays for food, as well as the value of food consumed from own production and from in-kind food gifts or transfers, such as the value of meals provided to school children.[14] In order to compare expenditures over time, we convert all unit values to 2015 real values, adjusting for the difference in inflation between the household's interview month in 2013 and 2015 using publicly available NSO consumer price index data for rural households, and differentiating between food and non-food inflation. Figure 2 shows that mean food expenditures per capita were significantly lower in 2015 versus 2013 for households located in all three flood categories. Additionally, applying the Kolmogorov-Smirnov equality of distributions test shows that all three flood category distributions have shifted significantly to the left from 2013 to 2015.[15]

Turning next to calories per capita, Fig. 3 illustrates that mean calories per capita in fact increased over time for households in all three categories, though the increase is only significant for those located in severe flood areas. There are a few potential explanations as to why total real expenditures fell but calories increased in 2015 versus 2013. The primary reason is that the real unit values for many food items fell over the period. The Malawi economy suffered from high inflation in 2013, resulting from the currency devaluation in

[13] Full regression reports for value of production per capita are reported in the online appendix, table A1.

[14] Value of food consumption per capita is perhaps a more accurate way to describe the variable; however, we retain food expenditures per capita since it is more widely used in the literature.

[15] The *p*-values for the Kolmogorov-Smirnov tests are (.114) for the low flood, (.003) for the moderate flood, and (.029) for the severe flood categories.

Table 2 Maize yield and value of crop production per capita, 2013 vs. 2015

Flood category		2013	2015	Test of mean differences (p-value)	Percent declines
Low	Maize yield	1451	976	0.000	33%
	Value of crop production per capita	28,176	15,593	0.000	45%
Moderate	Maize yield	1180	689	0.000	42%
	Value of crop production per capita	24,672	11,755	0.000	52%
Severe	Maize yield	941	465	0.000	51%
	Value of crop production per capita	19,668	10,114	0.000	49%

May 2012[16]. As shown in Table 4, the real unit values fell for all food categories, including for the two most important calorie sources, refined and unrefined maize flour. And, households shifted consumption towards the cheaper unrefined maize flour. Thus, even though calories per capita were higher in 2015, lower real unit values and the shift to cheaper maize flour led to lower overall food expenditures per capita in 2015. In particular, total calories from the two types of maize flour and other grains rose from just over 1600 cal per person per day to close to 1900, a statistically significant increase.

The shift towards maize and other grains is consistent with the large decreases in the food consumption score for households located in all three categories in 2015 versus 2013, as shown in Fig. 4. Although the reductions are significant across the board, the drop is particularly marked for households located in the moderate and severe flood areas. Thus, while households could maintain calories, dietary diversity suffered as food expenditures per capita fell.

Rainfall, Flood Index, and Coefficient of Variation of Rainfall

In our regressions, we use the percent difference of absolute flowering season rainfall from the long-term mean, which captures the potential impact of deviations from expected rainfall in both years, 2013 and 2015. We complement this variable with the dichotomous variables for moderate and severe flood categories, low flood being the omitted category.[17] The regressions also control for a long-term measure of rainfall variability, the coefficient of variation of flowering season rainfall, calculated over the period of 1983–2015. It has long been recognized that farmers subject to riskier climates are more likely to grow lower-yielding but more stable crops, use fewer purchased inputs, and invest less in land (Hardaker et al. 2004; Hazell 1992; Hurley 2010 and references cited therein). Additionally, McCarthy and Kilic (2015) provide empirical evidence that this long-term

[16] Another potential explanation is that food aid deliveries kept the market prices of maize flour in check. The WFP Malawi country office provided us with district-level data on food aid deliveries over the period January – July 2015. The simple correlation coefficient between calories of food aid delivered and unrefined maize flower prices in 2015 is significant but fairly low, at −.22. In many districts, households fell into all three flood categories, meaning that the food aid delivery data may be too coarse to adequately capture local market price effects. We believe being able to document the impact of food aid deliveries on local prices may show important indirect impacts on consumption, and would hope that such data will be made available on a more disaggregated scale in the future.

[17] We considered using in our regressions the flood affectedness PCA index itself, in addition to the dichotomous variables for the flood categories. The index did not perform as well as the dichotomous variables, particularly when we included the interaction terms with our social safety net variables. As our results highlight, the interaction terms indicate that impacts on consumption outcomes are inconsistent with a linear specification of flood intensity.

Table 3 Value of production per capita, natural logs

	Coefficient	Coefficient
Flood Index	−0.343 ***	
Moderate Flood, dummy		−0.438 **
Severe Flood, dummy		−0.857 ***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

measure of risk has a significant negative impact on maize yields in Malawi. Thus, we hypothesize that the coefficient of variation of growing season rainfall will have a negative impact on crop productivity, with subsequent negative impacts on household consumption outcomes.

Household Demographics and Wealth

Household demographic controls include the number of adult equivalents; the dependency ratio calculated as the number of household members below 15 years old and over 60 years old divided by the number of members between 15 and 60 years old; the natural logarithm of the age of the household head; and a dichotomous variable capturing whether the household head is female. We expect that larger households will have higher values of crop production, while the dependency ratio may reduce time allocated to productive versus domestic activities. Older household heads may have higher crop production due to greater experience, and potentially to more dense information networks., and female-headed households may experience lower on and off-farm income, due mainly to social norms that can limit their ability to access resources in general and in times of crises (Kilic et al. 2015; Aguilar et al. 2015). We use the maximum number of years of education completed by any member in the household to capture productivity and income-generating capacity, anchored in the evidence on positive intra-household spillovers stemming from individual educational attainment (Mussa 2014; Basu et al. 2001). Lastly, we include three measures of household wealth, namely (1) a PCA index of household consumer durables and dwelling attributes[18]; (2) the total number of agricultural implements[19], and (3) the total land-holdings per capita. Greater household wealth is expected to exert a positive effect on welfare outcomes, both directly and indirectly through crop production.

Risk Management Strategies

The regressions include several independent variables to capture households' ability to manage farming risks *ex ante*. Risk management strategies include "sustainable land management" (SLM) techniques that are hypothesized to lead to more stable yields and thus to more stable crop incomes, specifically the dichotomous variables for whether the household has terraces and drainage ditches; bunds to control erosion; bunds for water

[18] The index is based on (i) the dichotomous variables for whether the household has any bed, table, chair, or other living room furniture; any of fan, air conditioner, clock or solar panel; any of radio or tape/CD/DVD player; any of sewing machine, washing machine, iron; any of TV, VCR, computer, satellite dish, or generator; any mobile phone., and (ii) the dichotomous variables for whether the household's dwelling has improved walls; improved roof; improved floor; improved lighting fuel; electrification; access to an improved drinking water source; access to an improved latrine; insecticide treated .bed nets. The number of dwelling rooms per capita is also included in the index.

[19] The implements include hand hoes, slashers, axes, knapsack sprayers, panga knives, and sickles.

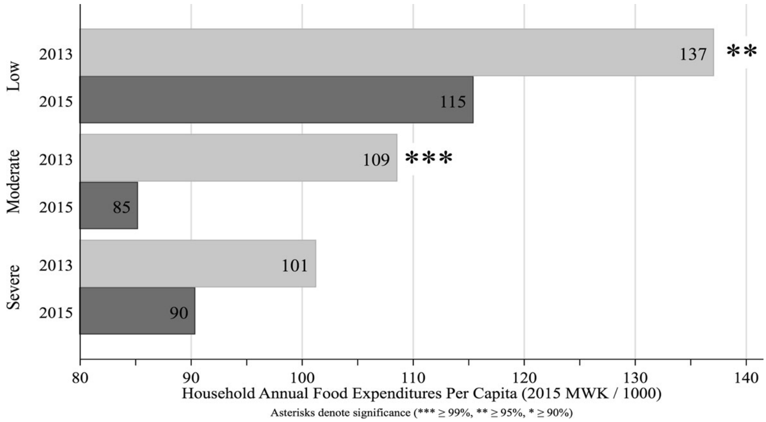

Fig. 2 Food expenditures over time by flood-affectedness

harvesting; and any plots intercropped with legumes. Both types of bunds are included in the analysis, as water harvesting structures may be expected to perform differently, and potentially worse, than those constructed to prevent erosion in the face of flood events, as described in McCarthy et al. (2017).

Risk Coping Strategies and Interaction Terms

Risk coping strategies are captured by the following controls: a dichotomous variable capturing whether any household member has any type of account at a financial institution[20]; the number of adult children living away from home; and three measures of labor diversification, namely a dichotomous variable for whether any household member was receiving formal wages, a dichotomous variable whether any household member was self-employed, and the number of household member days engaged in *ganyu* (informal/casual) labor. Households with savings accounts would have greater coping capacity, as would those with more adult children living away from home since adult children's income is not expected to be perfectly correlated with the household's own. The ability to diversify labor off one's own farm in response to a weather shock should also increase coping capacity.

Without doubt, the ability to access multiple sources of income from work or from one's social network can increase households' income generating capacity in good years as well as bad years. In order to test whether these sources actually provided ex-post risk coping, the regressions include the interaction of each variable with each of the dichotomous flood-affectedness variables.

Finally, we have information on whether the household benefited from three different types of social safety nets, namely direct food assistance; school feeding programs targeted at children; and participation in the Malawi Social Action Fund (MASAF) public works program. These mechanisms should enable households to cope with floods; and we include interaction terms to determine if they are indeed relatively more important to households who were more affected by the floods.

[20] Financial institutions include any of banks, credit unions, micro finance institutions, post offices, village savings organizations, or another financial institution.

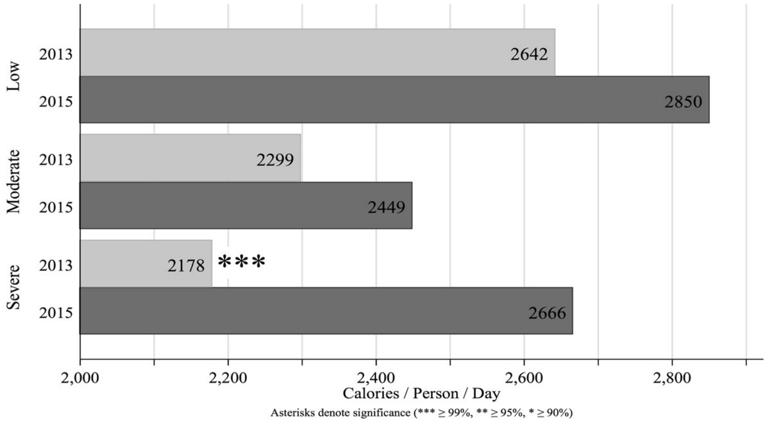

Fig. 3 Calories per capita over time by flood affectedness

While we concede that these variables may be subject to endogeneity bias, we do not have good instruments for the full set of potential risk coping mechanisms. We discuss the evidence for endogeneity and the robustness of results in "Empirical Strategy" section, which details our estimation strategy.

Location Characteristics/Location Characteristics

In addition to household-level variables, the regressions control for community/location characteristics expected to impact household welfare, including district fixed effects; household EA-location specific unrefined maize flour price; and an access index, which is a proxy for the relative ease of transportation and access to infrastructure, services and markets. All else equal, we expect that greater access will increase engagement with markets and lower barriers to information, leading to greater ability to (i) generate larger and more diversified incomes, and (ii) cope with shocks. Another independent variable is the district population density, which is expected to perform similarly to the access index – higher population density should lead to greater opportunity to cope with shocks. We consider two additional district-level controls that proxy for the level of government engagement in agriculture. The first is the number of 50 kg bags of fertilizer sold in the district per capita under the Farm Input Subsidy Program (FISP). More subsidized fertilizer should increase crop productivity in a district. The second is the proportion of households in the district that received any extension advice, constructed from our household survey data.[21] We expect greater access to extension advice to lead to more productive and climate-resilient farming.

Descriptive Statistics

Table 5 provides the descriptive statistics for the explanatory variables used in the analysis, for 2013, and then by flood category for 2015. Of key interest are the potential risk-coping

[21] In cases where we had very few FIAS households in a district due to households moving between survey rounds, households were matched to their district from the previous round. There were 25 households that moved to districts that had 5 or fewer surveyed households located in the new district. We ran the regressions dropping these households; results are nearly identical in terms of signs and significance of coefficients, and thus we include the full sample in our analysis. These results are available upon request.

Table 4 Real caloric unit values, daily calories per capita, real annual expenditures per capita, by food group

Food group	2013			2015		
	Real caloric unit value (2015 MWK)	Daily calories per capita	Real annual expenditures per capita (2015 MWK)	Real caloric unit value (2015 MWK)	Daily calories per capita	Real annual expenditures per capita (2015 MWK)
Unrefined maize flour	57	942	18,859	51	1277	20,087
Refined maize flour	69	478	11,615	49	328	5684
Other grains	177	206	11,050	144	251	10,340
Roots & Tubers	217	100	6110	185	68	3755
Nuts & Pulses	167	235	12,110	160	212	10,344
Fruit & Veg	762	58	13,961	413	133	15,988
Meat, Fish & Dairy	963	83	27,708	475	113	18,792
Fat & Oil	200	74	4953	146	107	4297
Sugar	303	118	7252	189	89	5419
Miscellaneous	500	84	11,448	424	85	9892
Total	143	2379	125,134	109	2662	104,635

strategies and the social safety nets. First, we note that *ganyu* labor market participation and earnings increased substantially from 2013 to 2015, but that there is no significant difference by flood category in 2015. Participation in self-employment also increased significantly between years, but again we see no significant difference between flood category in 2015. We do see that those in severe flood areas were relatively less likely to have a member with formal wage employment. This relationship was the same in 2013, and overall, there is no significant change between years in incidence of wage employment. There are no other significant differences between flood category in 2015 in terms of risk coping strategies.

With respect to the social safety nets, we note that there was an increase in the number of households with children having access to school feeding over time for all three categories, but a decrease in the number of households accessing food aid or engaging in the MASAF

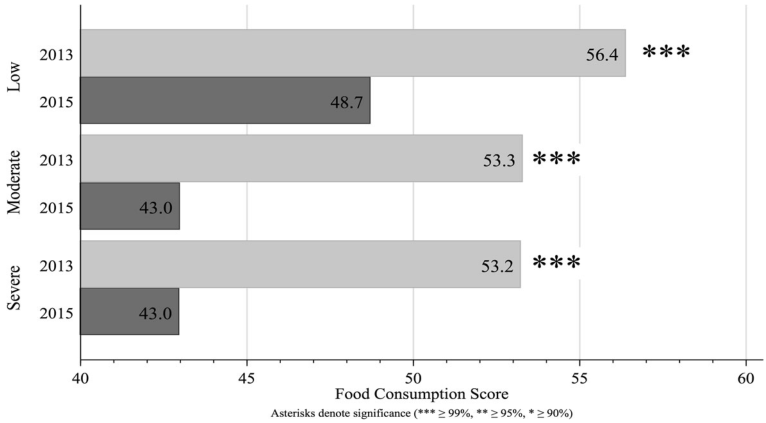

Fig. 4 Food consumption score over time by flood affectedness

Table 5 Descriptive statistics

	2013		2015					
			Low		Moderate		Severe	
	(*n* = 558)		(*n* = 186)		(n = 186)		(n = 186)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables								
Value food consump. p.c. (MWK/1000)	115.6	94.7	115.4	92.3	85.2	68.6	90.4	68.8
Daily calorie consumption p.c.	2373	1444	2850	1552	2449	1705	2666	1537
Food Consumption Score, Weighted	54.3	17.8	48.7	19.7	43.0	18.6	43.0	18.3
Value of crop production p.c. (MWK/1000)	24.2	29.6	15.6	16.2	11.8	16.2	10.1	13.8
Rainfall and flood categories								
|% Diff from Mean Rainfall|	0.15	0.09	0.53	0.16	0.54	0.12	0.58	0.11
2015 Moderate Flood	0	0	0	0	1	0	0	0
2015 Severe Flood	0	0	0	0	0	0	1	0
Household demographics								
Adult equivalents	4.24	1.83	4.20	1.86	4.36	1.91	4.42	1.98
Dependency ratio	1.34	1.00	1.39	1.10	1.37	1.10	1.46	1.10
HH highest years of education	8.72	3.85	9.22	4.14	8.90	3.72	8.72	3.71
Age of HH Head (years)	43.73	16.85	44.38	16.37	45.91	17.32	46.81	16.86
HH Head is female	0.32	0.47	0.32	0.47	0.38	0.49	0.31	0.46
Wealth								
HH wealth index	0.21	0.18	0.26	0.20	0.21	0.17	0.18	0.14
Ag asset index	0.21	0.17	0.17	0.14	0.17	0.17	0.18	0.17
Land Holdings per Person (ha/pers.)	0.13	0.15	0.13	0.14	0.14	0.15	0.18	0.23
Risk management techniques								
Terraces/drainage ditches	0.07	0.25	0.19	0.39	0.19	0.40	0.12	0.32
Bunds, erosion control	0.37	0.48	0.36	0.48	0.22	0.42	0.24	0.43
Bunds, water harvesting	0.05	0.22	0.07	0.26	0.05	0.23	0.05	0.22
Intercropped with legumes	0.60	0.49	0.54	0.50	0.45	0.50	0.43	0.50
Potential risk coping strategies								
Financial account	0.27	0.44	0.37	0.48	0.29	0.46	0.29	0.46
Self-employed	0.30	0.46	0.39	0.49	0.45	0.50	0.39	0.49
Wages	0.22	0.41	0.30	0.46	0.23	0.42	0.14	0.35
N of days, informal labor	37.85	62.32	43.93	76.77	52.58	89.77	54.38	82.03
N adult children, left home	1.11	1.90	0.97	1.84	1.02	1.64	1.11	1.90
Social safety net								
Food Aid	0.18	0.38	0.05	0.22	0.12	0.32	0.29	0.46
School Feeding	0.23	0.42	0.30	0.46	0.33	0.47	0.31	0.46
MASAF	0.15	0.36	0.12	0.32	0.08	0.26	0.13	0.34
Community/Location Characteristics								
EA Access Index	0.83	0.52	1.06	0.83	0.89	0.93	0.62	0.50
Population Density (100 persons/km2)	2.01	0.83	2.85	3.56	2.55	3.18	1.65	0.55
Total deliveries of fertilizer / 1000	7.01	2.31	7.90	1.95	6.90	2.07	5.25	2.36
Prop. of HH in District, ext. advice	0.56	0.13	0.67	0.09	0.65	0.10	0.68	0.14
EA Mean Price, Unrefined Maize/ 100	1.95	0.36	1.73	0.29	1.74	0.35	1.73	0.23

program. While the overall number of households with access to food aid decreased, households located in severe flood areas were significantly more likely to receive food aid than those in moderate and low flood areas, and those in moderate flood areas were significantly more likely to receive food aid than those in low flood areas. Also, if we combine food aid to the household and to the children via school feeding programs, we see that the incidence of receiving any food aid increased significantly from 27.5 to 39.4% of households, a 43% increase.

Empirical Strategy

We have a balanced, two-period panel data set, and three outcomes of interest, namely the logarithmic transformations of real household annual food consumption expenditures per capita and household caloric intake per capita, and the household food consumption score. These outcomes are denoted as Y for household i at time t *(2013, 2015)* in the following linear regression:

$$Y_{it} = \alpha_{it} + \beta F_{i15} + \gamma RF_{it} + \partial RC_{it} + \delta(F_{i15}{*}RC_{it}) + \theta SN_{it} + \mu(F_{i15}{*}SN_{it}) + \omega RM_{it} + \pi H_{it} + \sigma C_{it} + \tau T_{it} + \varphi \overline{M}_i + \varepsilon_{it} \quad (1)$$

where $\boldsymbol{F}$ is a vector of dichotomous variables capturing households' moderate and severe flood status in 2015, as defined above, with households in low flood areas excluded as the reference category; $\boldsymbol{RF}$ is the percent difference of absolute flowering season rainfall from the long-term mean; $\boldsymbol{RC}$ and $\boldsymbol{SN}$ are vectors of household-level risk coping strategies and social safety nets, respectively, which are interacted with the vector $\boldsymbol{F}$; $\boldsymbol{RM}$ is a vector of household-level risk management strategies; $\boldsymbol{H}$ is a vector of controls on household demographics and wealth; $\boldsymbol{C}$ is a vector of household EA- or district-location specific control variables; $\boldsymbol{T}$ is the time fixed effect – i.e. a dichotomous variable that is equal to 1 for the survey year 2015; $\overline{\boldsymbol{M}}$ is a vector of household-level inter-annual averages for the set of explanatory variables in $\boldsymbol{H}$, $\boldsymbol{RC}$, $\boldsymbol{SN}$, and $\boldsymbol{RF}$ with inter-annual variation greater than 4%; and ε and $\boldsymbol{\alpha}$ are the error term and the constant, respectively. The variables included in the vectors ***H, RM, RC*** and ***SN,*** and ***C*** have been noted above in "Risk Management Strategies", "Risk Coping Strategies and Interaction Terms", "Community/Location Characteristics", and "Descriptive Statistics" sections, respectively. This panel regression is estimated with random effects, and the inclusion of the vector $\overline{\boldsymbol{M}}$ transforms it into a correlated random effects model, and enables us to still control for time-invariant household-level unobserved heterogeneity that may otherwise jointly predict the outcomes and explanatory variables of interest.[22] The standard errors are clustered at the EA-level.

Finally, we can test the extent to which losses in value of crop production per capita drove consumption outcomes. On the one hand, most of our households grew at least one crop, and

[22] With standard errors clustered at the EA-level, following each estimation of Eq. 1 with an alternative dependent variable, we test whether the household-level inter-annual averages included in the vector X are jointly statistically significant. This is known as the Mundlak (1978) test, and in each instance, as reported in the online appendix table A3, we find that the coefficients are not jointly statistically significant in the food expenditures per capita and food consumption score equations, providing support for the use of the correlated random effects model instead of the fixed effects estimation. The joint test for calories per capita gives a p-value very close to .1 (.097). The results from the fixed effects estimations, i.e. the estimations of Eq. 1 with household-level fixed effects but net of the vector M, are provided in the online appendix table A4, which highlights the similarities with respect to the findings from the correlated random effects models, even for the calorie per capita equation. Finally, we performed a number of robustness checks, including, among others, omission of insignificant variables and exclusion of variables with relatively high correlations with household wealth. The results were very robust to these sensitivity analyses, which are available upon request.

we have shown that the floods had significant negative impacts on the value of crop production per capita. Thus, we expect that lower crop production would lead to lower consumption outcomes, all else equal. At the same time, households do have risk-coping strategies as well as access to safety nets that can limit the impact of floods on consumption outcomes. To determine the extent of transmission from production to consumption, we thus estimate the direct effect of changes in real household value of crop production per capita on the same set of dependent variables. To do so, we address the endogeneity of real household value of crop production per capita through the use of a linear instrumental variable (IV) regression, which involves the joint estimation of two equations:

$$CP_{it} = \alpha_{1it} + \beta_1 Z_{it} + \partial_1 RC_{it} + \theta_1 SN_{it} + \pi_1 H_{it} + \sigma_1 C_{it} + \tau_1 T_{it} + \varphi_1 \overline{M_i} + \varepsilon_{1it} \quad (2)$$

$$Y_{it} = \alpha_{2it} + \beta_2 \widehat{CP}_{it} + \partial_2 RC_{it} + \theta_2 SN_{it} + \pi_2 H_{it} + \sigma_2 C_{it} + \tau_2 T_{it} + \varphi_2 \overline{M_i} + \varepsilon_{2it} \quad (3)$$

where Eqs. 2 and 3 are the first and the second stage regressions, respectively; and ***CP*** is the logarithmic transformation of real household value of crop production per capita. The subscripts 1 and 2 are used to denote the comparable vector of coefficients across the first and the second stage regressions. The variables included in the vectors ***RC, SN***, ***H***, ***C*** and ***T*** are identical to those included in Eq. 1. The vector $\overline{\boldsymbol{M}}$ in Eqs. 2 and 3 includes inter-annual household-level averages of the variables included in the vectors ***RC***, ***SN***, and **H**. Equation 2 includes the vector ***Z*** of identifying instrumental variables (IVs) that are assumed to affect the food consumption outcomes of interest only through their effects on the real household value of crop production per capita, known as the exclusion restriction. Drawing from the results of a value of crop production per capita regression, we selected a number of candidate IVs. The IVs chosen include the moderate and severe flood dummies, the coefficient of variation of flowering season rainfall over the period 1983–2015, and the total number of weedings performed by the household during the agricultural season. The predicted values of **CP**, denoted as $\hat{\boldsymbol{CP}}$, that are obtained from Eq. 2 are in turn fed into Eq. 3 to recover the coefficient of interest β_2.

As will be shown in the subsequent section, the predictive power of the IVs is sufficiently large to avoid weak instrumental variable bias, and the results from the Hansen's J tests provide additional support for the exclusion restriction. While the latter is only suggestive of the orthogonality of the IVs to the error term (i.e. instrumental validity), it is not contested that the impacts of extreme weather effects on rural households' welfare in primarily rain-fed smallholder production systems are expected to be manifesting through their impacts on the farm, and controlling for time-invariant household-level unobserved heterogeneity as well as an extensive set of time-varying controls clamp down on the possibility that our IVs would affect the welfare outcomes of interest over and above their direct impacts on crop production.

Results

Table 6 presents the selected results from the estimations of Eq. 1[23]. Looking first at the rainfall and flood category dummies, we note that the deviation from expected rainfall has significant negative impacts on all consumption outcomes, whereas the additional impact from the moderate

[23] The full regression results are reported in the online appendix table A2. All dependent variables are in natural logarithms.

Table 6 Selected correlated random effects regression results

	Food Cons. per capita, 2015 MWK, logs	Calories per capita, logs	Consumption Score
Time	0.122	0.524 ***	0.710
Rainfall and Flood Variables			
|% Diff from Mean Rainfall|	−0.647 ***	−1.166 ***	−17.119 ***
2015 Moderate Flood	−0.220 **	−0.170	−5.090 *
2015 Severe Flood	0.004	0.076	−5.728 **
Potential Risk Coping Strategies			
Financial Account	0.077	0.040	2.459
Self-employed	0.162 ***	0.058	2.975
Wages	0.072	0.044	2.297
N of days, informal labor	0.041	0.027	−0.352
N adult children, left home	0.002	0.008	0.301
Flood * Risk Coping			
Social Safety Net			
Food Aid	0.079	0.010	−0.932
School Feeding	−0.139 **	−0.092	−2.650
MASAF	0.148 **	0.111	3.672 *
Flood * Social Safety Net			
*Moderate*Food Aid*	0.015	0.052	2.086
*Severe * Food Aid*	0.038	0.099	5.606 *
*Moderate*School Feeding*	0.225 ***	0.219 **	8.551 ***
*Severe *School Feeding*	0.055	0.006	2.961
*Moderate*MASAF*	0.342 **	0.394 ***	3.530
*Severe *MASAF*	0.001	0.012	−2.880
Household Demographics & Wealth	Yes	Yes	Yes
Risk Management Practices	Yes	Yes	Yes
Community/Location Characteristics	Yes	Yes	Yes
Mean Across Time Correlated Random Effects Model	Yes	Yes	Yes ***
Constant	12.059 ***	13.845 ***	76.554 ***
Number of Observations	1116	1116	1116
R-squared (within)	0.311	0.216	0.285
R-squared (between)	0.611	0.405	0.495
R-squared (overall)	0.527	0.334	0.420

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and severe flood dummies is a further reduction in food consumption scores. The negative i8mpact of deviation from expected rainfall across all consumption outcomes indicates that households are not able to self-insure and maintain consumption when rainfall differs from expectations, even for rainfall events that are not extreme. Deviations from expectations can have direct negative impacts on consumption outcomes if resources are committed to various income-generating activities before rainfall is realized, and/or when re-allocating resources is costly.

The results of the impact of rainfall and flood category dummies are distinct from impacts on the value of crop production per capita, where the flood dummies have large negative impacts but the deviation from expected rainfall is not significant. As discussed above, one way to cope with a production shock is to alter the consumption basket, even though this can be a costly coping strategy. Our results indicate that severity of flooding led to an additional shift towards less diverse food consumption for households located in areas that experienced moderate and severe floods, but not necessarily to additional impacts on calories or food expenditures per capita.

Looking at other potential household-level risk-coping strategies, we note that only self-employed income has a positive impact on food expenditures but has no impact on calories consumed or the food consumption score. Regarding risk coping strategies interacted with the flood categories, we note that only one of the coefficients on the 12 interaction terms was statistically significant in the three consumption outcome equations, so we do not include these variables in Table 6. This result is interesting in and of itself; potential risk coping strategies simply were generally ineffective in mitigating negative impact of suffering from moderate and severe floods. At the same time, the result is also consistent with responses to questions asked in the "households shocks" sub-module of the questionnaire. One-third of the households that reported a significant shock from experiencing floods or erratic rains noted that they "did not do anything" in response. Another 23% mentioned changing their consumption habits; 21% reported that they received support from family members and friends; and only 7% in total noted selling assets or livestock, accessing credit, or migrating for work.

Turning to the direct impact of social safety nets, we note that receiving food assistance had no impact on any of our food consumption measures. Households with access to the school feeding program had lower food expenditures, indicating that households disproportionately reduced the value of food provided at home. However, this substitution towards cheaper foods at home did not lead to significant reductions in calories per capita or the food consumption score. Finally, the direct impact of access to MASAF work led to increased food expenditures and higher food consumption scores.

Finally, our interaction terms show that having access to food assistance increased food consumption scores for households located in severe flood areas vis-à-vis those located in low flood areas. On the other hand, access to school feeding led to improvements in all three of our consumption measures, but only for those found in moderate flood areas. Similarly, access to MASAF led to higher food expenditures and calories consumed, but only for those in moderate flood areas.

Overall, the evidence suggests that only food aid was an important safety net for households in severe flood areas, whereas access to school feeding and MASAF generally led to improved consumption outcomes for those located in moderate flood areas. At the same time, it is worth noting that the proportion of households with access to food aid and MASAF decreased between 2013 and 2015. Access to school feeding increased between 2013 and 2015, but access to school feeding only improved outcomes for those in moderate flood areas. While safety nets do improve consumption outcomes, there appears to be ample room to improve the reach of these programs into areas that suffer severe weather events, particularly food assistance.

In Table 7, we present the results from the IV estimations, in which we instrument for the logarithmic transformation of real household value of crop production per capita. We present only the results for the instruments in the first stage, and the value of crop production per capita in the second stage.[24] We note that the number of observations does not match in Tables 6 and 7 due to the necessary exclusion of households that did not produce any crops in 2015 from the analysis. Our instruments are strong, with Angrist-Pischke F-statistics over 27. In addition, the *p*-values associated with the Hansen's J statistics stand at 0.11 in the food expenditures equation, and at 0.49 in the food consumption score equation, in support of the exclusion restriction.[25] From the second stage results, we note that the coefficient on the value of crop

[24] The full set of results from the IV regressions are found in the online appendix table A5.

[25] The IV estimations are net of the analysis of log calories per capita, since at 10% statistical significance, we reject the null hypothesis that the IVs are orthogonal to the error term.

Table 7 Selected instrumental variable regression results

	First Stage Value of crop production per capita, logs	Second Stage Value of food consumption per capita, logs	First Stage Value of crop production per capita, logs	Second Stage Food Consumption Score
Instruments				
2015 Moderate Flood	−0.247 **		−0.239 *	
2015 Severe Flood	−0.589 ***		−0.579 ***	
Coef. Variation Rainfall	−0.379		−0.329	
N Weedings Performed	0.192 ***		0.194 ***	
Value of Production per capita		0.101 *		4.469 ***
Number of Observations	1016	1016	1016	1016
R-squared (overall)	0.369	0.458	0.298	0.298
Angrist-Pischke F statistic	27.48		27.57	
Hansen's J p-value		0.113		0.490

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

production per capita is statistically significant and positive in the food expenditures equation. However, the estimated elasticity is just 10%, implying relatively limited transmission from production to consumption. In line with this finding, Darko et al. (2018) report that, all else being equal, a 1% increase in maize yields in Malawi leads only to an estimated 0.13% increase in consumption per capita. In our analysis, higher values of crop production per capita are also estimated to lead to higher food consumption scores. At variable means, the marginal effect of value of crop production per capita is equivalent to a 20% increase in the food consumption score.

Concluding Comments

The floods that occurred during the 2014/15 growing season in Malawi had significant and large impacts on maize yields and value of crop production per capita. Households located in severe flood areas faced maize yield and value of crop production per capita reductions of approximately 50%, and even households located in the low and moderate areas faced lower crop production. Nonetheless, additional impacts of flood dummies on food expenditures per capita were less pronounced, and even more so for calories consumed per capita. The flood dummies did have an additional negative impact on food consumption scores, leading to 20% lower scores for those in medium-affected areas, and 25% lower scores in high-affected areas. Overall, then, the primary impact was to reduce the quality of the food consumption basket rather than quantity per se. These results are also in line with the empirical evidence discussed in the literature review. For instance, Michler et al. (2016) and Wineman et al. (2017) find reductions in crop production of 34% and 29%, respectively, for areas suffering from droughts, while Del Ninno et al. (2001) find crop losses between 42 and 62% for households suffering from floods. At the same time, both Wineman et al. (2017) and Del Ninno et al. (2001) find significant, though more muted, impacts on consumption outcomes, similar to the results reported here.

Additionally, we find that all three of our consumption outcomes are negatively affected by deviations from expected rainfall. This result suggests that households are ill-equipped to cope with even modest deviations from expectations. One reason may well be that it impossible or too costly to re-allocate resources when after such deviations are realized. Combined with the results on crop production per capita, the result also suggests that deviations from expectations is likely to have negative impacts on re-allocating resources to a wide range of potential income-generating, consistent with the lack of significant results on most of our risk coping variables.

On the other hand, a number of social safety net programs did help households maintain food quantity and quality, particularly for those located in moderate flood areas. In severe flood areas, only access to food aid was effective, but access to MASAF and school feeding programs were not. On the whole, the evidence suggests a great deal of scope for aligning different social safety net programs with disaster risk management and emergency food aid programs to achieve better consumption outcomes after extreme rainfall events that cause large crop production losses, particularly for those located in the worst hit areas.

Finally, our results contribute to a very limited body of research of the impacts of extreme weather events on household consumption outcomes, and the factors that enable households to mitigate negative impacts of rainfall shocks on consumption outcomes. More research is needed on access to safety nets in particular, and how these programs operate both in “normal” years as well as years characterized by extreme weather. Additional work is needed on identifying whether and which mechanisms can help smallholders re-allocate resources when rainfall deviates from expectations.

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References

Aguilar A, Carranza E, Goldstein M, Kilic T, Oseni G (2015) Decomposition of gender differentials in agricultural productivity in Ethiopia. Agric Econ 46:311–334

Ahmed AU, Quisumbing AR, Nasreen M, Hoddinott J, Bryan E (2009) Comparing food and cash transfer to the ultra-poor in Bangladesh. International Food Policy Research Institute (IFPRI) Research Monograph No. 163. http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/17394. Accessed 9 April 2018

Alderman H, Paxson CH (1994) Do the poor insure? A synthesis of the literature on risk and consumption in developing countries. In: Bacha EL (ed) Economics in a changing world. Macmillan, London, pp 48–78

Alexander LV (2016) Global observed long-term changes in temperature and precipitation extremes: a review of the progress and limitations in IPCC assessments and beyond. Weather Clim Extremes 11:4–16

Arouri M, Nguyen C, Youssef AB (2015) Natural disasters, household welfare, and resilience: evidence from rural Vietnam. World Dev 70:59–77

Asfaw S, McCarthy N, Lipper L, Arslan A, Cattaneo A (2016) What determines farmers’ adaptive capacity? Empirical evidence from Malawi. Food Sec 8:1–22

Baez JE, Mason A (2008) “Dealing with climate change: household risk management and adaptation in Latin America.” Background paper for the 2008 flagship report on climate change in Latin America and the Caribbean. The World Bank, Washington, DC

Baez JE, Lucchetti L, Genoni ME, Salazar M (2016) Gone with the storm: rainfall shocks and household wellbeing in Guatemala. J Dev Stud 53:1253–1271

Basu K, Narayan A, Ravallion M (2001) Is literacy shared with households? Theory and evidence for Bangladesh. Labour Econ 8:649–665
Cai W, Borlace S, Lengaigne M, Van Rensch P, Collins M, Vecchi G, Timmermann A, Santoso A, McPhaden MJ, Wu L, England MH (2014) Increasing frequency of extreme El Nino events due to greenhouse warming. Nat Clim Chang 4:111–116
Chinsinga B (2012). The political economy of agricultural policy processes in Malawi: a case study of the fertilizer subsidy programme. *Future Agricultures Working Paper No. 39. Brighton, UK: Institute of Development Studies*
Christiaensen L, Dercon S (2007) Consumption risk, technology adoption and poverty traps: evidence from Ethiopia. J Dev Econ 96:159–173
Darko FA, Palacios-Lopez A, Kilic T, Ricker-Gilbert J (2018) Micro-level welfare impacts of agricultural productivity: evidence from rural Malawi. J Dev Stud 54:915–932
Davis B, Di Giuseppe S, Zezza A (2017) Are African households (not) leaving agriculture? Patterns of households' income sources in rural Sub-Saharan Africa. Food Policy 67:153–174
De la Fuente A, Dercon S (2008) "Disasters, growth and poverty in Africa: revisiting the microeconomic evidence." Background paper for the 2009 global assessment report in disaster risk reduction. The World Bank, Washington, DC
De la Fuente A, Borja-Vega, C, Yaschine I (2017) El rol del Programa Oportunidades ante desastres generados por fenómenos naturales. *Mimeo*
Del Ninno C, Lundberg M (2002) Treading water: the long-term impact of the 1998 flood on nutrition in Bangladesh. Econ Hum Biol 3:67–96
Del Ninno C, Dorosh PA, Smith LC, Roy DK (2001) The 1998 floods in Bangladesh: disaster impacts, household coping strategies, and response. IFPRI Research Report No 122
Dercon S (2002) Income risk, coping strategies, and safety nets. World Bank Res Obs 17:141–166
Dercon S (2005) Risk, poverty and vulnerability in Africa. J Afr Econ 14:483–488
Dercon S, Hoddinott J, Woldehanna T (2005) Shocks and consumption in 15 Ethiopian villages, 1999-2004. J Afr Econ 14:559–585
Fafchamps M, Udry C, Czukas K (1998) Drought and saving in West Africa: are livestock a buffer stock? J Dev Econ 55:273–305
FAO (2016) AQUASTAT. Accessed on 9 April 2018 from https://goo.gl/3rXDxM
Francken N, Minten, B., Swinnen, J. F. M. (2009). The political economy of relief aid allocation: evidence from Madagascar. LICOS Centre for Institutions and Economic Performance Discussion Paper No. 237
Frenken K (ed) (2005) "Irrigation in Africa in figures, AQUASTAT survey – 2005." FAO Water Reports No. 29. Rome, The Food and Agriculture Organization of the United Nations
Gilligan DO, Hoddinott J, Taffesse AS (2008) The impact of Ethiopia's productive safety net Programme and its linkages. J Dev Stud 45:1684–1706
Gröger A, Zylberberg Y (2016) Internal labor migration as a shock coping strategy: evidence from a typhoon. Am Econ J: Appl Econ 8:123–153
Hardaker JB, Huirne RBM, Anderson JR, Lien G (eds) (2004) *Coping with risk in agriculture*. CABI Publishing, Wallingford and Cambridge
Hazell PB (1992) The appropriate role of agricultural insurance in developing countries. J Int Dev 4:567–581
Heltberg R, Oviedo AM, Talukdar F (2015) What do household surveys really tell us about risk, shocks, and risk management in the developing world? J Dev Stud 51:209–225
Hoddinott J, Kinsey B (2001) Child growth in the time of drought. Oxf Bull Econ Stat 63:409–436
Hurley T (2010). A review of agricultural production risk in the developing world. IFPRI Harvest Choice Working Paper No. 11
IPCC (2012) Managing the risks of extreme events and disasters to advance climate change adaptation. Cambridge University Press, Cambridge
Jayne TS, Strauss J, Yamano T, Molla D (2002) Targeting of food aid in rural Ethiopia: chronic need or inertia. J Dev Econ 68:247–288
Kazianga H, Udry C (2006) Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. J Dev Econ 79:413–446
Kilic T, Palacios-Lopez A, Goldstein M (2015) Caught in a productivity trap: a distributional perspective on gender differences in Malawian agriculture. World Dev 70:416–463
Kochar A (1995) Explaining household vulnerability to idiosyncratic income shocks. Am Econ Rev 85:159–164
Lybbert TJ, Barrett CB, Desta S, Coppock DL (2004) Stochastic wealth dynamics and risk management among a poor population. Econ J 114:750–777
McCarthy N, Kilic T (2015) The nexus between gender, collective action for public goods and agriculture: evidence from Malawi. Agric Econ 46:375–402

McCarthy N, Brubaker J, Kilic T (2017). Analysis of the impacts of the 2015 floods on smallholder crop production in Malawi. Final report delivered to the Bill and Melinda Gates Foundation

Merz B, Thieken AH, Gocht M (2007) Flood risk mapping at the local scale: concepts and challenges. In: Begum S et al (eds) Flood risk management in Europe. Springer, Dordrecht, pp 231–251

Michler J, Baylis K, Arends-Keunning M, Mazvimavi K (2016) Conservation agriculture and climate resilience. Accessed on 9 April 2018 from https://goo.gl/35dv55

Miura K, Kanno H, Sakurai T (2016) Shock and livestock transactions in rural Zambia: a re-examination of the buffer stock hypothesis. Jpn J Rural Econ 14:20–34

Mundlak Y (1978) On the pooling of time series and cross section data. Econometrica 46:69–85

Mussa, R. (2014). Externalities of education on efficiency and production uncertainty of maize in rural Malawi. MPRA Paper No. 54628

Narayan D, Pritchett L, Kapoor S (2009) Moving out of poverty: volume 2 success from the bottom up. The World Bank, Washington, DC

National Research Council (2015) Tying flood insurance to flood risk for low-lying structures in the floodplain. In: Methods for assessing risk. The National Academies Press, Washington, DC, pp 23–34

Premand P, Vakis R (2010) Do shocks affect poverty persistence? Evidence using welfare trajectories from Nicaragua. Well Being Soc Pol 6:95–129

Reardon T, Taylor JE (1996) Agro-climatic shock, income inequality, and poverty: evidence from Burkina Faso. World Dev 24:901–914

Reardon T, Matlon P, Delgado C (1988) Coping with household-level food insecurity in the drought-affected areas of Burkina Faso. World Dev 16:1065–1074

Ricker-Gilbert J, Jumbe C, Chamberlin J (2014) How does population density influence agricultural intensification and productivity? Evidence from Malawi. Food Policy 48:114–128

Ummenhofer CC, Meehl GA (2017) Extreme weather and climate events with ecological relevance: a review. Philos Trans R Soc B 372:20160135. https://doi.org/10.1098/rstb.2016.0135

Ummenhofer CC, Xu H, Twine TE, Girvetz EH, McCarthy HR, Chhetri N, Nicholas KA (2015) How climate change affects extremes in maize and wheat yield in two cropping regions. J Clim 28:4653–4687

United Nations Disaster Assessment and Coordination (UNDAC) (2015). UNDAC assessment report, floods: Malawi. Accessed on 9 April 2018 from https://goo.gl/owqqfN

Venalainen A, Pilli-Sihvola K, Tuomenvirta H, Ruuhela R, Kululanga E, Mtilatila L, Kanyanga J, Nkomoki J (2016) Analysis of the meteorological capacity for early warnings in Malawi and Zambia. Clim Dev 8: 190–196

Wineman A, Mason N, Ochieng J, Kirimi L (2017) Weather extremes and household welfare in rural Kenya. Food Sec 9:281–300

World Bank (2010) Natural hazards, unnatural disasters: the economics of effective prevention. The World Bank, Washington, DC

World Bank (2016) Republic of Malawi poverty assessment. Accessed on 9 April 2018 from https://openknowledge.worldbank.org/handle/10986/26488

World Food Programme (2008). Technical guidance sheet - food consumption analysis: calculation and use of the food consumption score in food security analysis. Accessed on 9 April 2018 from https://goo.gl/8D4pLQ

Wu H, Adler RF, Tian Y, Huffman GJ, Li H, Wang J (2014) Real time global flood estimation using satellite-based precipitation and a coupled land surface and routing model. Water Resour Res 50:2693–2717

Yamano T, Alderman H, Christiaensen L (2005) Child growth, shocks, and food aid in rural Ethiopia. Am J Agric Econ 87:273–288