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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 while yields were dramatically lower for households severely affected by the floods, drops in food consumption expenditures and calories per capita were less dramatic. However, dietary quality, as captured by the food consumption score, was significantly lower for flood-affected households. Although access to social safety nets increased food consumption outcomes, particularly for those in moderately-affected areas, 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, risk-coping strategies, including financial account ownership, access to off-farm income sources, and adult children living away from home, were generally ineffective in mitigating the negative impacts of the floods.

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Produced by the Research Support Team

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1. Introduction

Rural households in developing countries rely on rain-fed farming as a significant source of income. In the African context, the average share of rural household income originating from agriculture could be up to 69 percent (Davis et al., 2017), and as of 2013, only 3.4 percent of cultivated land in Sub-Saharan Africa was irrigated, with a 0.1 percentage point increase since 1993 (FAO, 2016). Smallholders are, therefore, 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 (IPCC, 2012; Alexander, 2016). For instance, Cai et al. (2014) provide evidence that the frequency of El Nino events could double, which would in turn lead to increased extreme weather events around the world. Other research suggests that La Nina events can similarly lead to greater frequency of extreme weather events (Ummenhofer et al., 2015). 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 rare and because household data collection activities are generally scheduled following other concerns, so that collecting household data after an extreme event has generally happened 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). A Government of Malawi Post-Disaster Needs Assessment estimated the total costs of the flood damages at USD 335 million (Government of Malawi, 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, generally less than one hectare (Asfaw et al., 2016). Mirroring the continent-wide outlook, 2.3 percent of cropland in Malawi is irrigated, but, according to FAO's AQUASTAT, nearly all irrigated land is on large estates, meaning that irrigation on smallholder plots is virtually non-existent (Frenken, 2005). Crop revenues per family member are correspondingly small (Asfaw et al., 2016; Ricker-Gilbert, Jumbe and Chamberlain, 2014), and rural poverty rates remain stubbornly high at 57 percent in 2010 based on the latest available official statistics on poverty for the country (World Bank, 2016).

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 approximately 600 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. Southern Malawi showed great variability in the extent and intensity of floods, and the existence of the pre-flood IHPS infrastructure in the country, as well as the 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[2], 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 in areas severely affected by the floods, drops in food consumption expenditures and calories per capita were less dramatic. However, food consumption scores were significantly lower for households located in both medium- and high-affected flood 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 moderately affected 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.

[2] 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.

The paper is organized as follows. Section 2 reviews the literature on the micro-level impacts of extreme weather impacts. Section 3 describes the data and provides descriptive statistics. Section 4 explains our empirical approach to studying the household-level impacts of the 2015 floods in Malawi. Section 5 discusses the results and Section 6 concludes.

2. 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 percent 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 percent decrease in the value of crop production per adult equivalent.[3] 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 percent 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 that very low rainfall lowered income per adult equivalent per day by 18.3 percent. 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 percent drop in consumption expenditures subsequent to a weather shock (Arouri et al., 2015 in Vietnam; Baez et al., 2016 in Guatemala; Christiansen and Dercon, 2007 and Dercon et al., 2005 in Ethiopia). Premand and Vakis (2010) document that households in Nicaragua that experienced a drought over three years were 10 percent 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 Sahalian zone were 12 to 15, and 2 to 19 percentage points higher, respectively, after the 1984-85 droughts.

[3] 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.

Weather shocks can also have *indirect* effects on welfare through their effects on prices and wages. Banerjee (2007) finds that agricultural wages decrease during months with floods in Bangladesh, and decline more when floods are "extreme." Likewise, focusing on the extreme 1998 flooding in Bangladesh, Mueller and Quisumbing (2010) estimate wages to have declined 4 percent for every foot the flood deviated from normal flood depth in agricultural markets (an effect which "stabilizes" over time), and about 7 percent in nonagricultural markets (an effect which grows over time). Del Ninno et al. (2001) also find that wages for day laborers fell after the floods. With respect to staple food prices, Hill and Fuje (2017) examine the impact of drought on local food prices in Ethiopia over 17 years. On average, local grain prices in the months following harvest were estimated to increase by 2.5 percent subsequent to a 10 percent loss in yields, but this effect dissipated until no significant effect on grain prices was observed 6 months after the shock had realized. A higher local price after a drought would likely have a negative impact on consumption expenditures for net-grain purchasing households.

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). This inability to smooth consumption has implications for poverty in a direct way.[4]

The main coping mechanisms identified in the literature include household risk-coping measures such as selling livestock (particularly smallstock) 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, Groger 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.

[4] 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 9,000 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).

Kazianga and Udry (2006) showcase a limited role of livestock sales in aiding households to smooth consumption in response to a severe drought shock in Burkina Faso, consistent with households' attempting to maintain current assets to ensure future income. Wineman et al. (2017), too, estimate no impacts of very low rainfall on livestock incomes in Kenya. Other evidence suggests that selling livestock is an important risk-coping mechanism for households, particularly those with larger herds who are able to retain the most productive animals (Lybbert et al., 2004; Miura et al., 2016).

The evidence on the importance of access to credit to smooth consumption in the face of shocks is more consistent. For instance, Wineman et al. (2017) find that credit availability within a village reduced a household's chances of falling into poverty due to the low rainfall shock, but that participation in a savings group had no impact. Arouri et al. (2015) show that greater credit availability enabled households to better cope with the effects of natural disasters in Vietnam.

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 percent increase in crop damage reduced children's growth by 0.12 centimeters (1.8 percent). Also in Ethiopia, the households that were affected by the drought in 2007 and that received transfers from the Productive Safety Net Programme (PSNP)[5] consumed 30 percent 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. Undoubtedly, important challenges remain for food aid programs in the aftermath of disasters, so one should not draw broad conclusions from a limited set of case studies in any direction. Previous work has argued 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).

Finally, market integration can further buttress the impact of safety nets by reducing the inflationary effects in local markets (Christiaensen and Subbarao, 2005). In Bangladesh, the openness to private rice markets (by decreasing import tariffs and caps on rice imports and expediting the customs process) helped stabilize prices and maintain households' purchasing power and thus ease the impacts of the 1998 floods. The analysis indicates that the impacts of the food transfers combined with trade liberalization contributed between 64 and 133 kilocalories to each person's daily consumption. Without these changes in trade policy, it is estimated that targeted transfers would have had to be 3 to 5 times higher to make

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

the same calorific contribution (del Ninno, Dorosh and Smith, 2003).[6] Hill and Fuje (2017) note that the impact of droughts on local grain prices has diminished over time, particularly in areas where market access has improved.

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, selling assets and accessing transfers from friends and relatives. Additionally, greater access to a number of institutions also enables households to cope with the impacts of extreme weather, including access to credit, to well-functioning markets and to social safety net programs.

3. 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, and before that by the Malawi Third Integrated Household Survey (IHS3) in 2010.[8,9] Since FIAS

[6] Despite huge floods in September 1998 and the loss of 10 percent of annual food consumption, these safety nets combined with the longer-term changes in economic structure meant that recovery from the floods was relatively rapid. By April 1999, income for flood-affected households had increased 45 percent on that of the previous December following the floods, and a further 50 percent by the following November.

[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 and IHS3 were both 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 3,246 households across 204 enumeration areas (EAs) that had been previously surveyed as part of the IHS3 2010/11. The IHPS sample had been designed in 2010 to be representative at the national-, urban/rural, regional levels, and for the six strata defined by the combinations of region and urban/rural domains. In 2013, IHPS targeted all individuals that were part of the IHS3, including those that moved away from the IHS3 dwelling locations between 2010 and 2013. Once a split-off individual was located, the new household that he/she formed or joined since the IHS3 interview was brought into the IHPS sample. As a result, the overall IHPS database includes 4,000 households, which could be traced back to 3,104 IHS3 households. Attrition was limited to only 3.8 and 7.4 percent of households and individuals, respectively. The anonymized, unit-record data and documentation from the IHPS 2013 and the IHS3 2010/11 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.

builds on a high-quality 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 percent 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. The Household Questionnaire collected individual-disaggregated information on demographics, education, health, wage employment, nonfarm enterprises, as well as data on housing, food consumption, food and non-food expenditures, food security, and durable and agricultural asset ownership, among other topics. The sample households that were involved in agricultural activities (through ownership and/or cultivation of land, and/or ownership of livestock) were administered the Agriculture Questionnaire, which solicited information on land areas, labor and non-labor input use, crop cultivation and production at the plot[10] level for the 2014/15 growing season. 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. 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.[11] 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 households in the sample experienced rainfall over the historical average in 2015, and the mean rainfall difference was over 55 percent, well above the 14.4 percent mean difference observed in 2013.

[10] A plot was defined as a continuous piece of land on which a unique crop or a mixture of crops is grown, under a uniform, consistent crop management system, not split by a path of more than one meter in width. Plot boundaries were defined in accordance with the crops grown and the operator.

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

3.1. Descriptive Statistics

3.1.1. Flood Events, Welfare Outcomes

The percent difference measure can capture both above and below rainfall yields, though we note here that in 2015, all areas received greater than average rainfall. The measure captures deviations from expected rainfall and is expected to have a negative impact on yields. Alone, the deviation measure is not likely to adequately capture the extent of flooding, since flood damage is also related to geological and topographical features in addition to rainfall (Merz et al., 2007). To better capture the extent of flooding, we match the data to the mean flood intensity generated from University of Maryland's flood simulation model, which is at a rather coarse resolution, of .125 arc degrees, or approximately 14 km^2 in Malawi. In order to obtain a more precise flooding estimate, we consider two household-specific variables that are expected to be highly correlated with flood events, namely elevation at household GPS location at 90m 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 flood affectedness. As shown in Table 1, the PCA scores are lower for those areas with higher 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 affectedness; thus, a higher score is associated with higher mean flood intensity, closer to a river, and lower in elevation.

To present descriptive statistics in a meaningful way, we define three categories of flood-affectedness using index thresholds. Since maize is the dominant crop in Malawi, with 87 percent of the households in our sample cultivating maize, we define the thresholds by maximizing the difference between mean yields across three groups, while keeping a minimum of 20 percent of the sample in each group. This leads to 154 households categorized as being low-affected, 256 households as medium-affected, and 148 households as high-affected.

As shown in Table 2, maize yields were indeed much lower in 2015 versus 2013, for all three categories of flood affectedness, and for both local and hybrid maize. The differences in mean and distribution of overall, local and hybrid yields are significantly different for households located in the medium- and high-affected areas. In low-affected areas, the mean local maize yield is not statistically different across years, though the distribution is; on the other hand, while the mean hybrid yield is significantly lower in 2015, the distribution of hybrid yields is not statistically different in 2015 versus 2013.

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. McCarthy et al. (2017) use the flood-affectedness index to analyze the impact of floods on

[12] The description can be found at: https://lta.cr.usgs.gov/srtmgl3.html.

maize yields and value of crop production per hectare, and find that it is a strong negative predictor. Below, we will instrument for the value of crop production per capita as a regressor in our consumption equations to examine the link between production and consumption.

Using the three flood-affected categories, we can look at the impacts 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 considers 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. The FCS has been shown to relate strongly with detailed measures of household calorie consumption in a study across Burundi, Haiti, and Sri Lanka (Weismann et al., 2009).

For food expenditures, 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 food expenditures per capita were significantly lower in 2015 versus 2013 for both low- and medium-affected households. The drop in food expenditures for high-affected households, however, is not significant. On the other hand, when we look at the distributions of food expenditure per capita over time, 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.[13]

Turning next to calories per capita, Figure 3 illustrates that calories per capita in fact increased over time for both the medium and high affected households, but there was no significant change for low-affected households. There are many reasons 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. As noted above, the Malawi economy was suffering high inflation resulting from the currency devaluation in May 2012. As shown in Table 3, the real unit values fell for all categories shown, including for the two most important calorie sources, refined and unrefined maize flour. And, households shifted consumption of maize 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 1,600 calories per person per day to close to 1,900, a statistically significant increase. Calories from other sources increased for certain food items and decreased for others. The increase in meat, fish & dairy is primarily driven by increases in consumption of fish, which is relatively low in cost compared to other components of the food type.

[13] The p-values for the Kolmogorov-Smirnov tests are (.114) for the low-affected, (.003) for the medium-affected, and (.029) for the high-affected.

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.[14]

Finally, despite the increase in calories per capita, the food consumption score decreases significantly across time as seen in Figure 4. Although the reductions are significant across the board, the drop is particularly marked for the high-affected households. The shifts in FCS suggest that although diet quantity is remaining steady or increasing, the shifts in household consumption are coming at a price in terms of diet quality, and thus weakening food security.

3.1.2. Weather and Climate Variables

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 medium and high flood-affectedness, with low affectedness being the omitted category.[15] 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 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 welfare outcomes of interest.

3.1.3. 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

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[14] We believe being able to document the impact of food aid deliveries on local prices may show important indirect impacts on consumption, and hope that such data will be made available on a more disaggregated scale in the future.

[15] We considered using in our regressions the flood affectedness PCA index itself, in addition to the dichotomous variables for flood affectedness categories. The index did not perform as well as the dichotomous variables, particularly when we include 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.

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[16]; (2) the total number of agricultural implements[17], and (3) the total landholdings per capita. Greater household wealth is expected to exert a positive effect on welfare outcomes, both directly and indirectly through crop production.

3.1.4. 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 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).

3.1.5. 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[18]; 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

[16] 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.

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

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

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; we expect that access to formal sector wages would provide greater relative coping capacity than self-employed or *ganyu* work.

Sale of assets can further help households to cope in the short-term, though at the expense of the longer-term productivity. However, the data set does not have information on asset sales, so we cannot directly control for this as a coping strategy. We do have information on livestock sales. Livestock, however, except for chickens, are not widely held in Malawi. For instance, only 3.2 percent of the FIAS households have had cattle during any survey round.

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.

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 section 4, which details our estimation strategy.

3.1.6. Community/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 kilograms 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.[19] We expect greater access to extension advice to lead to more productive and climate-resilient farming.

Table 4 provides the descriptive statistics for the explanatory variables used in the analysis, for 2013, and then by flood affectedness category for 2015. Of key interest are the potential risk-coping 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-affectedness in 2015. Participation in self-employment also increased significantly between years, but again we see no significant difference between flood-affectedness groups in 2015. We do see that the high-affected 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-affectedness groups in 2015 in terms of risk coping strategies.

With respect to the social safety nets, we note that there was an increase in children having access to school feeding over time, but a decrease in households accessing food aid or engaging in the MASAF program. The overall decrease in household access to food aid is somewhat surprising given that food aid was provided extensively in response to floods; nonetheless, households in high affected areas were significantly more likely to receive food aid than those in medium and low affected areas, and those in medium affected areas were significantly more likely to receive food aid than those in low affected 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 percent of households: a 43 percent increase.

4. 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:

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

where ***F*** is a vector of dichotomous variables capturing households' medium and high flood affectedness status in 2015, as defined above, with low flood affectedness excluded as the reference category; ***RF*** is the percent difference of absolute flowering season rainfall from the long-term mean; ***RC*** and ***SN*** are

[19] 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.

vectors of household-level risk coping strategies and social safety nets, respectively, which are interacted with the vector ***F***; ***RM*** is a vector of household-level risk management strategies; ***H*** is a vector of controls on household demographics and wealth; ***C*** is a vector of household EA- or district-location specific control variables; T s; ***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 ***H***, ***RC***, ***SN***, and ***RF*** with inter-annual variation greater than 4%; and $\boldsymbol{\varepsilon}$ 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 sections 3.1.3, 3.1.4, 3.1.5, and 3.1.6, 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.[20] The standard errors are clustered at the EA-level.

Further, given our hypothesis regarding the household flood exposure affecting the food consumption outcomes of interest through its adverse effects on household crop production, we attempt to recover 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:

$$CP_{it} = \alpha_{1it} + \beta_1 Z_{it} + \partial_1 RC_{it} + \theta_1 SN_{it} + \pi_1 H_{it} + \sigma_1 C_{it} + \tau_1 T_{it} + \varphi_1 \overline{M_\iota} + \varepsilon_{1it} \ \ [\mathbf{2}]$$

$$Y_{it} = \alpha_{2it} + \beta_2 \widehat{CP}_{it} + \partial_2 RC_{it} + \theta_2 SN_{it} + \pi_2 H_{it} + \sigma_2 C_{it} + \tau_2 T_{it} + \varphi_2 \overline{M_\iota} + \varepsilon_{2it} \ \ [\mathbf{3}]$$

where Equation 2 and Equation 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 Equation 1. The vector $\overline{\boldsymbol{M}}$ in Equation 2 and Equation 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. The IVs include the flood-affectedness index, the coefficient of variation of flowering season

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[20] With standard errors clustered at the EA-level, following each estimation of Equation 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 Appendix Table A2, we find that the coefficients are not jointly statistically significant, providing support for the use of the correlated random effects model instead of the fixed effects estimation. The results from the fixed effects estimations, i.e. the estimations of Equation 1 with household-level fixed effects but net of the vector *M*, are nevertheless provided in the Appendix Table A3, which highlights the similarities with respect to the findings from the correlated random effects models.

rainfall over the period 1983-2015, and a binary variable identifying whether the household had any maize plots that were intercropped with legumes during the 2014/15 season. The predicted values of **CP**, denoted as $\widehat{\boldsymbol{CP}}$, that are obtained from Equation 2 are in turn fed into Equation 3 to recover the coefficient of interest β_2. The predictive power of the IVs is sufficiently large to avoid weak instrumental variable bias, and they take on statistically significant coefficients in Equation 2 with the expected signs, as discussed in the subsequent section. The empirical tests additionally provide support for the exclusion restriction.

5. Results

Table 5 presents the selected results from the estimations of Equation 1. Regarding the household-level risk coping strategies, only one of the coefficients on the interaction terms was statistically significant, so we did not include these in Table 5.[21] This result is interesting in and of itself; none of the identified potential strategies provided additional protection against floods. This is also consistent with the fact that one-third of the households that reported experiencing floods or erratic rains in 2015 as one of the three most significant shocks noted that they "did not do anything" in response. Among those that have reported suffered from floods or erratic rains in 2015, 23 percent mentioned changing their consumption habits; 21 percent reported that they received support, including from family members and non-relative friends; just over 7 percent noted selling assets or livestock, accessing credit, or migrating for work. While it may be difficult to reconcile the self-reported data with the actual actions, in this case, the self-reported information is consistent with the lack of statistical significance on the household-level risk-coping strategies we have considered.

As shown in Table 5, the percent difference in flowering season rainfall from the long-term mean led to lower food expenditures and calories consumed per capita. This variable is observed in both years, and indicates that rural households are not able to perfectly protect against even more modest deviations from expected rainfall such as those occurring in 2013.

Turning to the dichotomous variables capturing flood-affectedness, we see that medium-affected households had significantly lower per capita food expenditures compared to their low-affected counterparts, but there were no additional negative impacts on food expenditures for those residing in high affected areas. Furthermore, there were no statistically significant impacts on calories per capita for households in medium- and high-affected areas. These results suggest that, for the most part, the impacts on food and calorie consumption per capita are adequately captured by the percent difference in flowering season rainfall from the long-term mean. However, those in medium- and high-affected areas did have significantly lower food consumption scores than households located in low-affected areas. Thus, the main non-linear impacts of the floods are found on food quality rather than quantity per se.

Looking at household-level risk-coping strategies, only self-employed income has a positive impact on food expenditures but has no impact on calories consumed. For the social safety nets, receiving food

[21] The full regression results are reported in Appendix Table A1. All dependent variables are in natural logarithms.

assistance had no direct impact on any of our food consumption measures. Households with access to the school feeding program had lower food expenditures, but with no subsequent impact on calories or food consumption scores, indicating that households substituted school feeding for home provision of calories and food consumption scores. On the other hand, having access to wages from MASAF led to increased food expenditures similar to those with access to school feeding, it appears that households were able to use the wages to maintain calories and food quality.

Finally, our interaction terms show that having access to food assistance increased food consumption scores for households in both medium- and high-affected areas, vis-à-vis those located in low-affected 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 medium affected areas. Similarly, access to MASAF led to higher food expenditures and calories consumed, but only for those in medium affected areas.

The evidence suggests that only food aid was an important safety net for households in high-affected areas, whereas all three safety nets led to improved consumption outcomes for those located in medium-affected areas. At the same time, it is worth noting that the proportion of households with access to food aid and MASAF actually 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 medium-affected areas. Overall, the evidence suggests that safety nets do improve consumption outcomes, but there is room to improve the reach of these programs into areas that suffer severe weather events.

In Table 6, 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.[22] We note that the number of observations does not match in Table 5 and Table 6. This is due to the necessary exclusion of the few households that did not produce any crops from the analysis in 2015. Our instruments are fairly strong, with F-statistics just below 10 in all three equations, and the p-values associated with the Hansen's J statistic are over .1 in all three equations, in support of the exclusion restriction. We document that while food expenditures are positively correlated with the value of crop production per capita, the estimated elasticity is just 6.7 percent, implying very limited transmission from production to consumption.[23] Higher values of crop production per capita are also estimated to lead to higher food consumption scores, though not necessarily to higher calories per capita.

[22] The full set of results from the IV estimations are available upon request.
[23] In line with this finding, World Bank (2016) also finds that all else being equal, a 1 percent increase in maize yields in Malawi leads only to an estimated 0.13 percent increase in consumption per capita and an estimated 0.06 percent increase in caloric intake per capita.

6. 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 the most highly affected areas faced average yield losses of 35 percent for local maize and over 50 percent for hybrid maize. Impacts on food expenditures per capita were more muted, and even more so for calories consumed per capita. Looking at the direct impact of the value of crop production on food expenditures, we find that the elasticity is 6.7 percent, meaning that a 50 percent drop in value of crop production would translate into just a 3.35 percent drop in food expenditures per capita. One explanation lies in the fact that food prices were lower in 2015 versus 2013, and food expenditures are higher when maize flour prices are higher. Looking at the spatial price variation in 2015, we note a negative correlation between maize flour prices and food aid delivery data at the district level, but the data proved too coarse to test this hypothesis. However, the flooding had a particularly pronounced impact on food consumption scores, leading to 10 percent lower scores for those in medium-affected areas, and 12 percent 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.

Further, we found that the risk coping variables were of limited use in helping households buffer the effects of floods. A number of social safety net programs did help households maintain food quantity and quality, particularly for those located in medium-affected areas. In high-affected areas, only access to food aid was effective, but access to MASAF and school feeding programs were not. Thus, the evidence suggests that ensuring access to these two programs in areas highly affected by extreme weather events like flooding can help ensure households maintain both food quantity and quality. While careful planning ahead of a disaster is needed to make sure such programs are accessible during and immediately after a severe weather event, our data were collected within 9 to 11 months after the floods, and all communities were accessible by that time.

On the other hand, as the descriptive statistics show, the proportion of households with access to direct food aid was actually lower in 2015 versus 2013, though the difference is not statistically different. As we noted earlier, we did not have households located in the most severely-affected areas, where presumably much of the food aid was delivered. Nonetheless, this is a surprising finding, and highlights the need for expanded access to food aid to communities in areas that suffered significant crop damage, even if not located in the most severely-affected areas. Additionally, access to MASAF work was lower in 2015 versus 2013, even while such access has positive impacts on food expenditures and calories per capita. 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.

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TABLES

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

Table 2. Maize Yields (Kgs/Ha), by Maize Type, Year and Flood Affectedness Category

Flood Affectedness Category (2015)	Maize Type	2013	2015	Test of Mean Differences (P-Value)	Test of Distributional Differences (P-Value)
Low	Local	1231	974	(.061)	(.002)
	Hybrid	1677	1069	(.001)	(.063)
	Overall	1532	1070	(.000)	(.002)
Medium	Local	1108	766	(.000)	(.000)
	Hybrid	1379	652	(.000)	(.000)
	Overall	1245	734	(.000)	(.000)
High	Local	876	574	(.008)	(.001)
	Hybrid	1063	503	(.000)	(.001)
	Overall	971	531	(.000)	(.000)

Table 3: Real Caloric Unit Values, Daily Calories Per Capita, Real Annual Expenditures Per Capita, by Food Group

	2013			2015		
Food Group	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	1,277	20,087
Refined maize flour	69	478	11,615	49	328	5,684
Other grains	177	206	11,050	144	251	10,340
Roots & Tubers	217	100	6,110	185	68	3,755
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	4,953	146	107	4,297
Sugar	303	118	7,252	189	89	5,419
Miscellaneous	500	84	11,448	424	85	9,892
Total	**143**	**2,379**	**125,134**	**109**	**2,662**	**104,635**

Table 4: Descriptive Statistics

	2013		2015					
			Low		Medium		High	
	n=558		(n=154)		(n=256)		(n=148)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variables								
Household annual food consumption value per capita (2015 MWK/1000)	116	94.7	116	91.1	89	70.7	91	73.9
Household annual calorie consumption per capita	866	527.2	1026	558	938	607	964	577
Food Consumption Score	54.3	17.8	48.4	20.2	44.5	18.1	41.8	19.0
Value of household crop production per capita (2015 MWK/1000)	202	217	134	97.4	92	78.1	62	62
Biophysical, Climate and Weather Patterns								
2015 medium flood affected †	0	0	0	0	1	0	0	0
2015 high flood affected †	0	0	0	0	0	0	1	0
| December-January % Difference from Historical Mean Rainfall |	0.15	0.09	0.54	0.15	0.53	0.13	0.60	0.11
Household Demographics								
Adult equivalents	4.24	1.83	4.17	1.86	4.32	1.91	4.50	1.99
Dependency ratio	1.34	1.00	1.35	1.07	1.41	1.13	1.47	1.09
Household highest years of education	8.72	3.85	9.19	4.15	8.83	3.84	8.91	3.58
ln(Age of household head (years))	3.70	0.39	3.73	0.35	3.76	0.38	3.77	0.37
Household head is female †	0.32	0.47	0.32	0.47	0.38	0.49	0.28	0.45
Wealth								
Household wealth index (PCA)	0.21	0.18	0.25	0.19	0.21	0.18	0.19	0.15
Household number of ag implements	5.03	3.09	4.66	3.21	4.23	3.14	4.72	3.40
ln (HH land holdings per capita)	-1.28	2.00	-1.15	1.67	-1.14	1.72	-0.77	1.78
Risk Management Techniques								
Any household plot w/ terraces or drainage ditches †	0.07	0.25	0.18	0.38	0.18	0.39	0.13	0.34
Any household plot w/ bunds to control erosion †	0.37	0.48	0.38	0.49	0.22	0.42	0.24	0.43
Any household plot w/ bunds to harvest rainwater †	0.05	0.22	0.08	0.27	0.05	0.21	0.05	0.23
Any household plot intercropped with legumes †	0.60	0.49	0.55	0.50	0.47	0.50	0.41	0.49
Risk Coping Strategies								
Any household member has a financial account †	0.27	0.44	0.37	0.48	0.30	0.46	0.28	0.45
Any household member, self-employed †	0.30	0.46	0.42	0.49	0.39	0.49	0.43	0.50
Any household member, received wages †	0.22	0.41	0.29	0.46	0.22	0.41	0.15	0.36
# of household member days in ganyu labor	0.38	0.62	0.45	0.78	0.54	0.89	0.49	0.77
# of adult children living away from home	1.11	1.90	1.01	1.78	1.04	1.76	1.05	1.87
Social Safety Net								
Household received food assistance †	0.28	0.64	0.05	0.21	0.21	0.54	0.36	0.64
Children received school feeding †	0.23	0.43	0.29	0.45	0.32	0.47	0.34	0.49
Household received MASAF assistance †	0.15	0.36	0.11	0.31	0.10	0.30	0.12	0.33
Community/Location Characteristics								
Enumeration area access index	0.83	0.52	1.06	0.82	0.91	0.87	0.55	0.48
Population density (100 persons / km2)	2.01	0.83	2.98	3.88	2.38	2.75	1.65	0.61
Total deliveries of fertilizer	7.01	2.31	7.90	1.87	6.88	2.06	5.06	2.53
% of households in district receiving extension	0.56	0.13	0.66	0.09	0.66	0.10	0.68	0.15
EA Mean Price of Maize Ufa Mgaiwa / 100	1.95	0.36	1.73	0.25	1.74	0.34	1.73	0.24

Table 5: Selected Correlated Random Effects Regression Results

	Dependent Variable					
	Ln Household Food Consumption Expenditures Per Capita (2015 MWK)		Ln Household Caloric Intake Per Capita		Food Consumption Score	
Time	0.148	*	0.537	***	1.006	
Biophysical, Climate and Weather Patterns						
2015 medium flood affected †	-0.232	***	-0.152		-5.067	*
2015 high flood affected †	0.018		0.118		-7.004	**
| Dec.-Jan. % Difference from Historical Mean Rainfall |	-0.654	***	-1.177	***	-16.264	***
Risk Coping Strategies						
Any household member has a financial account †	0.078		0.04		2.642	
Any household member, self-employed †	0.137	***	0.036		1.87	
Any household member, received wages †	0.083		0.059		3.053	
# of household member days in ganyu labor	0.05		0.031		-0.16	
# of adult children living away from home	-0.005		0.001		-0.076	
Flood Affectedness * Risk Coping Strategies	Yes		Yes		Yes	
Social Safety Nets						
*Household received **food assistance** †*	0.056		-0.006		-1.898	
*Children received **school feeding** †*	-0.148	**	-0.104		-3.212	
*Household received **MASAF assistance** †*	0.135	**	0.104		3.386	
Flood Affectedness * Social Safety Nets						
*Medium * food assistance †*	0.075		0.147		7.228	*
*High * food assistance †*	0.117		0.13		5.693	**
*Medium * school feeding †*	0.251	***	0.26	***	8.992	***
*High * school feeding †*	0.019		-0.032		3.314	
*Medium * MASAF assistance †*	0.237	***	0.288	***	1.372	
*High * MASAF assistance †*	-0.031		-0.01		-4.403	
EA Mean Price of Maize Ufa Mgaiwa	0.11	**	-0.003		1.649	
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	12.138	***	13.879	***	77.325	***
Number of Observations	1116		1116		1116	
R-squared (overall)	0.533		0.339		0.43	

Notes: † denotes dichotomous variables. ***/**/* denote statistical significance at the 1, 5, and 10 percent level, respectively.

Table 6: Selected Instrumental Variable Regression Results

	First Stage		Second Stage				
	Log Value of Household Crop Production Per Capita (2015 MWK)		Log Household Food Consumption Expenditures Per Capita (2015 MWK)		Log Household Caloric Intake Per Capita	Food Consumption Score	
Instrumental Variables							
Flood-affectedness index (PCA)	-0.207						
December-January long-term rainfall CoV‡	-6.736	*					
Any household plot intercropped with legumes †	1.401	***					
Instrumented Variable							
Log value of household crop production per capita			0.07	**	0.014	1.655	*
Observations	1072		1072		1072	1072	
R-Squared (Overall)			0.45		0.298	0.347	
Kleibergen-Paap Wald rk F-Statistic			9.88		9.38	9.93	
Hansen's J P-Value			0.240		0.408	0.897	

Notes: ***/**/* denote statistical significance at the 1, 5, and 10 percent level, respectively. † denotes dichotomous variables. ‡ CoV stands for coefficient of variation.

FIGURES

Figure 1. Kernel Density of Rainfall Deviation, 2013 and 2015.

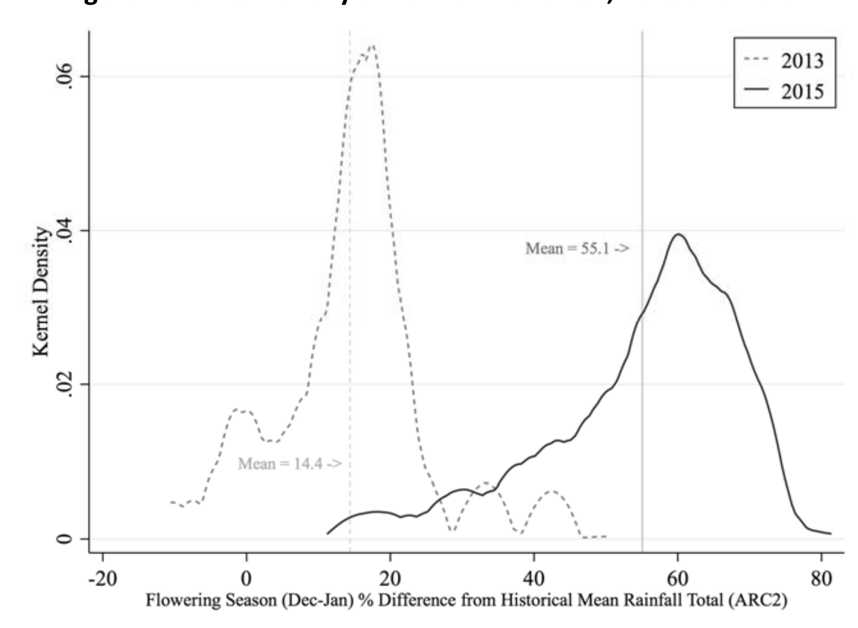


Figure 2: Food Expenditures over Time by Flood-Affectedness

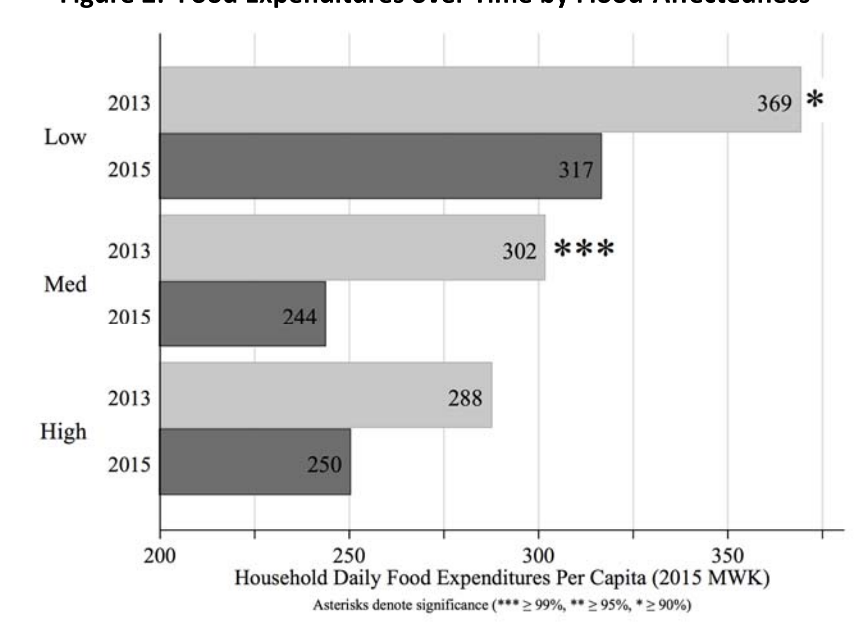


Figure 3. Calories Per Capita over Time by Flood Affectedness

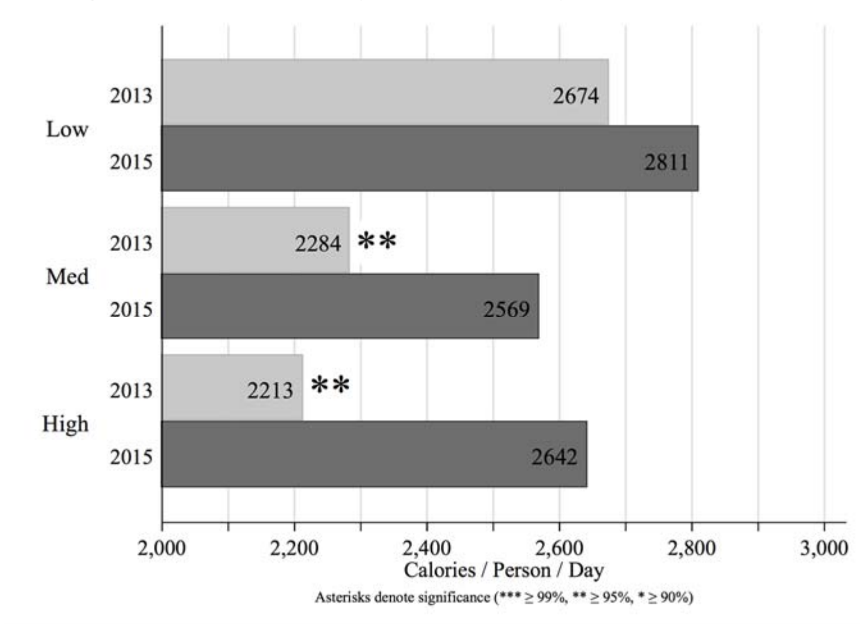
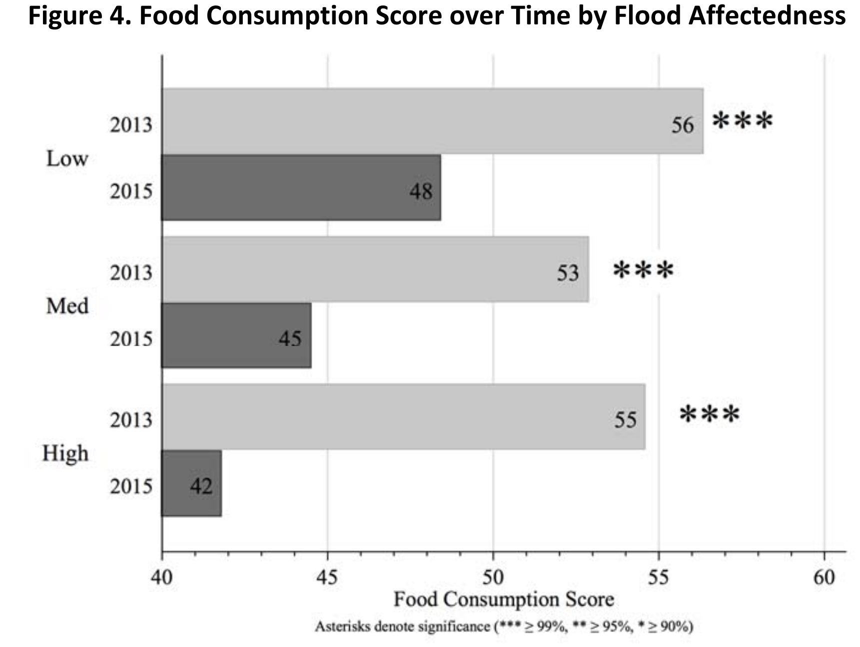


Figure 4. Food Consumption Score over Time by Flood Affectedness



APPENDIX

Table A1: Full Correlated Random Effects Regression Results

	Dependent Variable					
	Log Household Food Consumption Expenditures Per Capita (2015 MWK)		Log Household Caloric Intake Per Capita		Food Consumption Score	
Time	0.148	*	0.537	***	1.006	
Biophysical, Climate and Weather Patterns						
2015 medium flood affected †	-0.232	***	-0.152		-5.067	*
2015 high flood affected †	0.018		0.118		-7.004	**
| December-January % Difference from Historical Mean Rainfall |	-0.654	***	-1.177	***	-16.264	***
Household Demographics						
Adult equivalents	-0.171	***	-0.142	***	-0.519	
Dependency ratio	-0.057	*	-0.023		-0.847	
Household highest years of education	0.005		0.005		0.432	***
ln(age of household head (years))	0.015		0.082		-4.373	**
Household head is female †	-0.009		-0.003		0.735	
Wealth						
HH wealth index (HH + Dwelling)	0.707	**	0.174		21.535	**
HH Number of Ag Hand Tools	0.03	***	0.019	*	1.158	***
ln(Land Holdings per Person)	0.01		-0.002		-0.669	*
Risk Management Practices						
Any household plot w/ terraces or drainage ditches †	0.012		-0.053		2.107	
Any household plot w/ bunds to control erosion †	-0.089	*	-0.095	*	-1.826	
Any household plot w/ bunds to harvest rainwater †	0.017		0.077		-3.165	
Any household plot intercropped with legumes †	0.158	***	0.097	*	2.731	**
Risk Coping Strategies						
Any household member has a financial account †	0.078		0.04		2.642	
Any household member, self-employed †	0.137	***	0.036		1.87	
Any household member, received wages †	0.083		0.059		3.053	
# of household member days in ganyu labor	0.05		0.031		-0.16	
# of adult children living away from home	-0.005		0.001		-0.076	
Flood Affectedness * Risk Coping Strategies						
*Medium * Financial Account*	0.123		0.041		0.537	
*High * Financial Account*	-0.054		-0.047		2.052	
*Medium * Self-Employed*	-0.043		0.013		-1.774	
*High * Self-Employed*	-0.081		0.012		0.295	
*Medium * Receiving Wages*	-0.059		-0.032		-4.088	
*High * Receiving Wages*	0.262	**	0.162		3.738	
*Medium * Days Ganyu Labor*	-0.012		-0.027		-0.227	
High Days Ganyu Labor*	-0.048		0.002		0.42	
*Medium * Children Living Away from Home*	0.002		0		-0.109	
*High * Children Living Away from Home*	-0.027		-0.029		0.051	

Table A1 (Cont'd)

	Dependent Variable					
	Log Household Food Consumption Expenditures Per Capita		Log Household Caloric Intake Per Capita		Food Consumption Score	
Social Safety Nets						
HH Received Food Assistance †	0.056		-0.006		-1.898	
HH Received Child Feeding Program †	-0.148	**	-0.104		-3.212	
HH Received MASAF Assistance †	0.135	**	0.104		3.386	
Flood Affectedness * Social Safety Nets						
*Medium * Food Assistance †*	0.075		0.147		7.228	*
*High * Food Assistance †*	0.117		0.13		5.693	**
*Medium * Child Feeding Program †*	0.251	***	0.26	***	8.992	***
*High * Child Feeding Program †*	0.019		-0.032		3.314	
*Medium * MASAF Assistance †*	0.237	***	0.288	***	1.372	
*High * MASAF Assistance †*	-0.031		-0.01		-4.403	
Community/Location Characteristics						
EA Access Index	0.007		-0.061	*	1.362	
Population Density (100 persons / km2)	-0.039	***	-0.013		-1.002	***
Total deliveries of fertilizer / 1000	-0.07	***	-0.03		-1.793	**
Proportion of HH in District that Received Extension	-0.163		-0.014		-9.805	*
EA Mean Price of Maize Ufa Mgaiwa / 100	0.11	**	-0.003		1.649	
District Fixed Effects	Yes		Yes		Yes	
Mean Across Time Correlated Random Effects Model	Yes		Yes		Yes	
Constant	12.138	***	13.879	***	77.325	***
Observations	1116		1116		1116	
R-squared (Overall)	0.533		0.339		0.43	
Goodness of Fit (corr(Y,Yhat))	0.554		0.380		0.424	

Notes: ***/**/* denote statistical significance at the 1, 5, and 10 percent level, respectively. † denotes dichotomous variables.

Table A2: Results from Tests of Joint Significance of Inter-Annual Household Averages for Control Variables (Mundlak Test)

Welfare Outcome	Chi2	P-Value
Log Household Food Consumption Expenditures Per Capita	0.33	(.568)
Log Household Caloric Intake Per Capita	0.65	(.420)
Food Consumption Score	0.74	(.389)

Table A3: Full Fixed Effects Regression Results

	Dependent Variable					
	Log Household Food Consumption Expenditures Per Capita		Log Household Caloric Intake Per Capita		Food Consumption Score	
Time	0.216	**	0.629	***	2.34	
Biophysical, Climate and Weather Patterns						
2015 Medium Flood Affected	-0.188	*	-0.147		-5.989	*
2015 High Flood Affected	0.163		0.193		-4.728	
Dec-Jan |% Diff. from Hist. Mean Rain|	-0.827	***	-1.38	***	-18.799	***
Household Demographics						
Adult equivalents	-0.214	***	-0.207	***	0.036	
Dependency ratio	-0.047		-0.014		-1.055	
Household highest years of education	0.008		0.005		0.193	
ln(age of household head (years))	-0.066		0.066		-4.757	
Household head is female †	-0.052		-0.055		0.383	
Wealth						
HH wealth index (HH + Dwelling)	0.621	*	0.157		19.141	**
HH Number of Ag Hand Tools	0.032	***	0.021	**	1.079	***
ln(Land Holdings per Person)	0.008		-0.008		-0.659	
Risk Management Practices						
HH Plot had terraces or drainage ditches	0.009		-0.067		1.885	
HH Plot had bunds to control erosion	-0.085		-0.085		-1.46	
HH Plot had bunds to harvest rainwater	0.008		0.063		-2.857	
HH Crop was intercropped with legumes	0.143	***	0.074		2.313	*
Risk Coping Strategies						
Any HH Member, Financial Account	0.086		0.054		2.827	
Any HH Member, Self-Employed	0.146	**	0.041		1.868	
Any HH Member, Receiving Wages	0.021		-0.035		5.099	*
N of HH member days in ganyu labor / 100	0.073	*	0.038		0.379	
N of adult children living away from home	-0.008		-0.004		-0.263	
Flood Affectedness * Risk Coping Strategies						
*Medium * Financial Account*	0.143		0.065		-0.355	
*High * Financial Account*	0.032		0.018		6.657	
*Medium * Self-Employed*	-0.058		-0.042		0.34	
*High * Self-Employed*	-0.194		-0.018		-1.147	
*Medium * Receiving Wages*	-0.04		0.062		-3.93	
*High * Receiving Wages*	0.079		0.108		-5.786	
*Medium * Days Ganyu Labor*	-0.066		-0.052		-0.934	
High Days Ganyu Labor*	-0.087		0.021		0.057	
*Medium * Children Living Away from Home*	0.013		0.004		1.055	**
*High * Children Living Away from Home*	-0.066	***	-0.066	**	-0.432	

Table A3 (Cont'd)

	Log Household Food Consumption Expenditures Per Capita		Log Household Caloric Intake Per Capita		Food Consumption Score	
Social Safety Net s						
HH Received Food Assistance	0.069		-0.002		-1.424	
HH Received Child Feeding Program	-0.119		-0.091		-2.073	
HH Received MASAF Assistance	0.145	*	0.116		3.873	
Flood Affectedness * Social Safety Nets						
*Medium * Food Assistance*	0.11		0.15		6.726	
*High * Food Assistance*	0.059		0.14		3.156	
*Medium * Child Feeding Program*	0.194	*	0.283	**	8.562	***
*High * Child Feeding Program*	0.036		-0.067		-1.903	
*Medium * MASAF Assistance*	0.118		0.183		-1.554	
*High * MASAF Assistance*	-0.089		-0.07		-3.35	
Community/Location Characteristics						
EA Access Index	-0.02		-0.125	***	0.926	
Population Density (100 persons / km2)	-0.028	**	-0.013		-0.55	
Total deliveries of fertilizer / 1000	-0.027		-0.011		-1.538	
Proportion of HH in District that Received Extension	-0.205		-0.079		-9.464	
EA Mean Price of Maize Ufa Mgaiwa / 100	0.109	*	0.032		2.078	
Location Dummies	Yes		Yes		Yes	
Constant	12.341	***	14.154	***	77.712	***
Number of Observations	1116		1116		1116	
R-squared (overall)	0.31		0.148		0.194	
Goodness of Fit (corr(Y,Yhat))	0.557		0.385		0.440	

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