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Abstract: Between 2014 and 2016 unprecedented and consecutive climatic shocks ravaged Malawi, one of the poorest countries in the world. This paper uses a unique data set combining longitudinal household survey data with both GIS-based climatic measures and longitudinal administrative data on the World Food Programme's aid distribution. The paper aims to understand the drivers of humanitarian aid distribution and evaluate the impact of aid and weather shocks on outcomes related to household production and consumption in Malawi. Results suggest that there were likely geographic, and to a lesser extent household, targeting errors. Results also show that negative impacts of weather shocks in the current period primarily affected non-food consumption, while weather shocks tended to only affect consumption outcomes for those experiencing consecutive shocks. Finally, irrespective of targeting errors, results show positive impacts of aid receipt on a subset of livelihood outcomes, particularly for those who experienced consecutive shocks.

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1. Introduction

The frequency and intensity of extreme weather events and weather-induced food crises have increased across Africa and are expected to increase in the future with continued climate change (Venäläinen et al., 2016; Chinsinga, 2012). As described in our literature review below, empirical evidence across the continent reveals that weather shocks reduce agricultural production and income among smallholder households, and, to the extent that farm households are limited in their ability to shield consumption losses from production losses, can lead to reduced food consumption, less diverse diets, lower expenditures on health and education, and lower school enrollment rates among school aged children.

Between late 2015 and 2016, an unprecedented drought ravaged Southern Africa. Malawi was the worst-hit country in the region and faced the largest humanitarian emergency in its history, and given the 60% poverty rate prevailing at the time, many households were extremely vulnerable to impacts of the drought (National Statistical Office of Malawi and World Bank, 2018). It was forecasted at the time that nearly 7 million people (about 40%) would be unable to meet their food requirements between April 2016 and March 2017 - the 12-month period following the main harvest (MVAC, 2016). The drought came on the heels of devastating floods that had occurred the previous January, which had been catalyzed by the highest rainfall on record (a 1 in 500-year event) and that had been projected to affect the ability of over 2.8 million people to meet their food requirements in the post-harvest period (MVAC, 2015). Many farm households suffered severe crop losses in both seasons, particularly those located in southern Malawi (World Bank Group, United Nations, European Union, 2016).

A large body of literature establishes that when covariate shocks hit, some degree of risk-sharing takes place, but consumption is not entirely smoothed out (Hill, 2019; de la Fuente, Gine and Hill, 2013). Del Ninno et al. (2001) review the large-scale 1998 flooding in Bangladesh and find negative impacts on food security, with food consumption and calorie intake falling. A study of Ethiopian rural households documented a 16% reduction in consumption per adult in households that reported a serious drought shock in the previous two years (Dercon, 2004). Reardon and Taylor (1996) find that poverty increased in Burkina Faso's agro-ecological zones of Sahelian (2% to 19%) and Sudanian (12% to 15%) following the 1984-85 drought. Drought in Malawi is shown to reduce household consumption per capita by a third (McCarthy, Brubaker, and de la Fuente, 2016), and a moderate drought that causes a 30% yield loss is predicted to reduce consumption by 15% and 9% in Uganda and Ethiopia, respectively (World Bank 2015, 2016).

Much less evidence exists around the socioeconomic impacts of experiencing successive weather shocks, which in principle makes it even more difficult to smooth consumption (Deaton, 1992; Dercon, 2002). For instance, there is a general consensus that the 1998 Bangladesh floods had a lower impact on the affected population than the 1988 floods, even though the 1998 floods were of a considerably longer duration in most places. One of the reasons for this was that prior to 1988 there had been two major floods, in 1987 and 1984, which left many poorer households in a precarious situation and unable to recover their pre-disaster situation before the next disaster occurred (Beck, 2005).

Furthermore, there is limited evidence on the quality of targeting of large-scale humanitarian relief efforts, and the effectiveness of these efforts in helping households mitigate the adverse impacts of extreme weather events. Understanding the effectiveness of these mechanisms, and how they might be improved, is precisely the type of information we need to better inform humanitarian relief activities and to develop and implement effective climate change adaptation strategies. Yamano et al. (2005) found that food aid offset the surge in malnutrition among children (0.5 to 2 years old) tied to the harvest failure following the 1995-96 drought in Ethiopia. World Bank (2010) reported that households that were affected by the 2007-08 drought in Ethiopia and that also received transfers from the Productive Safety Net Programme (PSNP) consumed 30% more calories than non-beneficiaries.

However, important challenges remain in the implementation of humanitarian aid operations. There are few studies on the efficiency and targeting of food aid (e.g. Owens et al., 2003). A study looking into relief aid after cyclone Gafilo hit Madagascar in March 2004 found that the likelihood of aid relief was higher in cyclone-affected areas, but there were still communes hit by cyclones that did not receive aid (errors of exclusion) and others not hit but that received aid (errors on inclusion) (Francken et al., 2009). A similar finding is documented by Dercon and Krishnan (2004) regarding food aid in Ethiopia, which was found to be reasonably responsive to local conditions, but with many affected communities not receiving aid in the early 1990s. Other studies have revealed that assistance may be ineffectively allocated due to political reasons or errors in targeting (del Ninno and Lundberg (2002) looking at 1998 floods in Bangladesh; Jayne et al. (2002) for food allocation in Ethiopia; Francken et al. (2009) in Madagascar).

In this paper, we estimate impacts of extreme weather events in Malawi on household livelihood outcomes. We hypothesize that shocks directly reduce agricultural production and productivity and indirectly affect livelihoods through lowered food availability. Households exposed to sequential weather shocks are hypothesized to experience larger negative impacts on consumption outcomes compared to those facing a shock only in the current period. We then investigate whether household access to humanitarian aid may have mitigated these negative impacts.

To explore these hypotheses, we leverage (i) the 2013 (pre-flood and pre-drought) and 2016 (post-flood and post-drought) rounds of the nationally-representative, multi-topic Integrated Household Panel Survey (IHPS), (ii) the 2015 (post-flood) Flood Impact Assessment Survey (FIAS) that followed a subset of households surveyed by the IHPS 2013 and that were located in districts where flooding was most pronounced; (iii) monthly data on humanitarian aid distribution by the World Food Programme and partners over the period of 2012-2017 aggregated at the traditional authority (TA)-level[2] and matched to

[2] In Malawi, TAs are in charge of administration of traditional land within a particular territory, and they perform various other cultural and administrative roles. There are around 250 TAs in Malawi, ranging from 3-15 TAs per district (NSO, 2008).

each sampled household in accordance with the TA in which the household is residing in a given survey round; and (iv) GIS-based measures of weather shocks and climate conditions that are matched to georeferenced household locations in each survey round.

Our results contribute to the literature in three main ways. First, we provide a comprehensive analysis of the impacts of weather shocks on household production and consumption outcomes and on geographic distribution of humanitarian aid. In addition to poverty rates and other variables that guide targeting of aid distribution in "normal" years, the expanded aid distribution in the drought and flood years was aimed at locations that were expected to have had poor agricultural outcomes (Babu et al., 2018; DoDMA, 2016; ALNAP, 2003). Geographic targeting decisions were driven by a set of geospatial weather variables and other criteria. In our analysis, we identify the weather variables that predict TA-level aid distribution but at the same time, do not predict household-level maize yields. In particular, while total season rainfall is a significant predictor of TA-level aid distribution, flowering period rainfall predicts household-level production and consumption outcomes.

This is useful information for improving geographic targeting of aid, but it also gives rise to exogenous variation in aid distribution that bolsters our identification strategy, our second contribution. More specifically, we leverage TA-level aid and a series of dichotomous variables that capture likely targeting errors to instrument for household receipt of aid in the regressions of consumption outcomes. This line of research contributes to a relatively limited body of research that leverages data on availability of external resources to instrument for household access to those resources, and to an even more limited evidence base for impacts of humanitarian aid.

Third, we consider two specifications to control for weather shocks. While the first includes a dichotomous variable that identifies exposure to a weather shock in the current period, the alternate specification includes dichotomous variables that identify (i) exposure to a weather shock *only* in the current period, and (ii) exposure to weather shocks in the current period only vs in consecutive periods.

The latter captures households that experienced both floods in 2015 and droughts in 2016 and enables us to provide evidence on the ability of households to smooth consumption when faced with a single weather shock versus sequential weather shocks.

To preview, we find that both weather shocks and TA-level WFP aid distribution exert a positive effect on the likelihood of household receipt of aid in general, while the dichotomous variables that identify likely targeting errors also significantly influence household aid receipt. Consistent with the local-level targeting criteria, female-headed households, households that are composed of only elderly adults, and households with lower levels of wealth are shown to be more likely to receive aid. However, under a weather shock, wealth is no longer a significant predictor of aid receipt, indicating that discriminating over wealth for aid targeting purposes breaks down when a weather shock occurs. Furthermore, in evaluating the impacts of weather shocks on our consumption outcomes, we show that as a result of being exposed to a weather shock only in the current period, households were able to maintain pre-shock levels of food consumption outcomes but had to reduce non-food consumption. Conversely, we demonstrate that being exposed to weather shocks in sequential years negatively affects food consumption outcomes. Household receipt of aid has fewer significant impacts, and mainly for those who experienced sequential shocks. However, restricting the sample to only poor households or to only those households interviewed during the months where aid distribution was highest – both of which should arguably increase the signal to noise ratio – results in more significant positive effects of aid on food consumption outcomes.

2. Empirical Strategy

Our ultimate goal is to estimate the impact of aid receipt on household consumption outcomes. To do that, we address the potential endogeneity of household aid receipt by relying on instrumental variable regressions and novel instrumental variables that are strong predictors of household aid receipt but that do not directly affect household consumption outcomes, except through their impact on household aid receipt. Our instrumental variables are derived from a monthly data set on humanitarian aid distribution data provided by the World Food Programme and covering the period 2012-2017. Data is provided at the traditional authority (TA)-level and includes food and cash aid recipient households.

Following the instrumental variable strategy pursued in Ravallion and Wodon (2000), we first estimate TA-level aid distribution as a function of explicit geographic targeting characteristics as well as other factors that may affect aid receipt. We do this for three reasons. The first is to generate evidence on factors affecting aid distribution, which provides important policy-relevant evidence in and of its own right. The second is to establish that included variables actually do a good job predicting placement, supporting the validity of our instrumental variable strategy. The third reason is to evaluate the potential for identifying additional instruments.

Specifically, we argue that the rainfall metrics used by the Food Assistance Response Programme (FARP) and the Malawi Vulnerability Assessment Committee (MVAC)[3] introduce exogenous variation in the aid distribution. Previous work on the impact of extreme weather events on crop production outcomes, using the same data set informing our analysis here, evaluated a wide range of GIS-based drought and flood measures, and determined that the best drought and flood measures were constructed using different variables and data sources than those used by the FARP (McCarthy et al., 2021). The empirical analysis allows us to compare the predictive power of FARP's rainfall variables versus weather shock variables used in the production analysis, namely flood and drought indices. As results show, aid distribution was not necessarily greater in areas that suffered the greatest maize yield losses due to

[3] The FARP was called the Food Insecurity Response Programme in 2015 and 2016. The FARP relies, in part, on inputs provided by MVAC. MVAC is a government-led committee set up in early 2002, following the 2001-2002 hunger crisis. It is comprised of government ministries and institutions, UN agencies and NGOs, together with a small secretariat that provides technical and administrative support.

weather shocks, even when controlling for other geographic targeting criteria used by FARP and MVAC, such as predominant livelihood strategies. This allows us to generate additional instrumental variables by using categories of targeting outcomes under weather shocks and under no weather shocks, as explained more fully after the aid distribution regression results are reported.

To estimate aid distribution at the TA-level, we employ a random effects model with robust standard errors, using both sets of weather variables as follows:

$$TA_{jt}^{Aid} = \nu_{jt} + \tau_S S_{ij}^{FARP} + \tau_{TA} TA_{jt}^{C} + e_{ijt}^{TA} \quad [1]$$

$$TA_{jt}^{Aid} = \zeta_{jt} + \xi_S S_{ij}^{Crop} + \xi_{TA} TA_{jt}^{C} + e_{ijt}^{TA} \quad [2]$$

where TA_{jt}^{Aid} is aid distribution in TA j at time t; S_{ij}^{FARP} is a vector of weather variables that influence FARP targeting; S_{ij}^{Crop} is a vector of weather variables that predict crop outcomes; TA_{jt}^{C} are TA-level variables that include other targeting criteria as well as additional control variables; and, e_{ijt}^{TA} are robust standard errors.

The second step is to investigate how aid receipt, weather shocks, and aid receipt under weather shocks affect six different household-level outcomes, namely (i) non-food expenditures per capita, (ii) value of food consumed per capita, (iii) food expenditures per capita, (iv) calorie consumption per capita, (v) food consumption score (a measure of dietary diversity),[4] and (vi) school participation rate.[5] Because the survey covers one year with widespread flood followed by another year with widespread droughts, we can also evaluate whether those suffering from sequential shocks had worse outcomes than those suffering just one shock. In the first case, we instrument for both aid receipt and aid receipt interacted with exposure to a weather shock in the current period (irrespective of potential exposure to past weather

[4] WFP (2008) provides more information on the measurement of the food consumption score.
[5] School participation rate is the number of school-aged children (5-17) that are attending school divided by the total number of school-aged children. The measure is not defined for households with no school-aged children.

shocks); and in the second case, we instrument for aid receipt, aid receipt interacted with exposure to a weather shock *only* in the current period, and aid receipt interacted with exposure to a weather shock in consecutive periods.

In a standard instrumental variable regression, the first stage estimations of the endogenous variables are linear probability models. While linear probability models (LPM) often perform well when the observed event happens relatively often, biased estimates are more likely to arise when applying the LPM model under relatively rare events (Kosmidis et al., 2020; King and Zeng, 2001). Household aid receipt, and more importantly, the interaction terms of aid receipt and shocks are relatively rare. Hence, we are concerned about bias using the first-stage LPM results.

To mitigate potential bias, we follow Wooldridge (2003) by running the estimations in three steps. In the "zero" stage, we run household aid receipt and the relevant shock interaction terms using a probit, bias-reduction generalized linear model (BRGLM), which allows us to retain observations that include variables that would otherwise be "perfect predictors" in a standard panel probit model (Kosmidis et al., 2020). Predicted probabilities from the zero stage are then used as instruments in the first stage of the standard instrumental variable correlated random effects (CRE) model. Specifically, the estimated equations are as follows:

Zero Stage:

$$P_{ijt}^{Aid} = \alpha_{ijt} + \beta_W TA_{jt}^{Aid} + \beta_{WS} TA_{jt}^{Aid} S_{ijt} + \beta_{WC} TA_{jt}^{C} + \beta_{TS} TS_{jt} + \beta_{TNS} TNS_{jt} + \beta_{TG} HH_{ijt}^{TG} + \beta_{HHC} Z_{ijt}^{HH,C} + e_{ijt}^{P} \quad [3]$$

$$P_{ijt}^{Aid} S_{ijt} = \delta_{ijt} + \kappa_W TA_{jt}^{Aid} + \kappa_{WS} TA_{jt}^{Aid} S_{ijt} + \kappa_{WC} TA_{jt}^{C} + \kappa_{TS} TS_{jt} + \kappa_{TG} HH_{ijt}^{TG} + \kappa_{HHC} Z_{ijt}^{HH,C} + e_{ijt}^{PS} \quad [4]$$

P_{ijt}^{Aid} is the probability that household i located in TA j at time t receives aid. Since we only use the shock variables that are significant predictors of crop outcomes, we simplify notation to S_{ijt}, so that $P_{ijt}^{Aid} S_{ijt}$ is the probability of receiving aid when the household has also suffered a shock. For the second specification (not shown), there are two equations to capture aid interacted with shocks in the current period only and sequential shocks, $P_{ijt}^{Aid}S_{ijt}^{Curr}$ and $P_{ijt}^{Aid}S_{ijt}^{Seq}$.

As above TA_{jt}^{Aid} is TA-level aid distribution, TA_{jt}^{C} is a vector of TA-level control variables, and $TA_{jt}^{Aid}S_{ijt}$ is the interaction term between TA-level distribution and a weather shock. TS_{jt} is a vector of targeting categories when a shock occurs; and TNS_{jt} is a vector of targeting categories when no shock occurred. The vectors of targeting categories are defined in the subsequent section, and together with TA_{jt}^{Aid}, constitute our instrumental variables.

HH_{ijt}^{TG} is a vector of household characteristics that are used as targeting criteria for aid receipt; $Z_{ijt}^{HH,C}$ is a vector of additional household and community characteristics that may influence aid receipt, including climate and location*time fixed effects; and $e_{ijt}^{P}, e_{ijt}^{PS}$ are the cluster-robust error terms. From these regressions, we obtain the relevant predicted probabilities, $\hat{P}_{ijt}^{Aid}$ and $\hat{P}_{ijt}^{Aid}S_{ijt}$, which are in turn used in the first stage regressions that are defined as:

First Stage:

$$Aid_{ijt} = \mu_{ijt} + \eta_P \hat{P}_{ijt}^{Aid} + \eta_{PS}\hat{P}_{ijt}^{Aid}S_{ijt} + \eta_W TA_{jt}^{C} + \eta_{TG}HH_{ijt}^{TG} + \eta_{HH}Z_{ijt}^{HH,C} + e_{ijt}^{A} \quad [5]$$

$$Aid_{ijt}S_{ijt} = \mu_{ijt} + \eta_P \hat{P}_{ijt}^{Aid} + \eta_{PS}\hat{P}_{ijt}^{Aid}S_{ijt} + \eta_W TA_{jt}^{C} + \eta_{TG}HH_{ijt}^{TG} + \eta_{HH}Z_{ijt}^{HH,C} + e_{ijt}^{AS} \quad [6]$$

where Aid_{ijt} and $Aid_{ijt}S_{ijt}$ are household aid receipt and the aid receipt-shock interaction term; and all other variables are as defined above. The second specification has three equations, Aid_{ijt}, $Aid_{ijt}S_{ijt}^{Curr}$ and $Aid_{ijt}S_{ijt}^{Seq}$, with the relevant substitutions for the three predicted terms. Note that using the predicted probabilities means that our instrumented equation is exactly identified.

Second Stage:

$$C_{ijt} = \upsilon_{ijt} + \gamma_P Aid_{ijt}^{IV} + \gamma_{PS}\left(Aid_{ijt}S_{ijt}\right)^{IV} + \gamma_S S_{ijt} + \gamma_W W_{jt}^{C} + \gamma_{TG} HH_{ijt}^{TG} + \gamma_{HH} Z_{ijt}^{HH} + \gamma_C Z_{jt}^{C} + e_{ijt}^{C} \qquad [7]$$

C_{ijt} are our household-level outcomes of interest, as specified above, Aid_{ijt}^{IV} and $\left(Aid_{ijt}S_{ijt}\right)^{IV}$ are instrumented aid receipt and aid receipt interacted with the shock variables and all other variables are identified above.

3. Data and Context

Our analysis uses data from the 2013 and 2016 waves of the Integrated Household Panel Survey (IHPS), which is representative for all Malawi, and for urban/rural areas. The IHPS was implemented by the Malawi National Statistical Office (NSO), as part of the World Bank Living Standards Measurement Study -Integrated Surveys on Agriculture (LSMS-ISA) initiative. The data include 1,907 households that were interviewed in 2013, and 2,507 households that were interviewed in 2016 and that could be traced back to the 1,907 households in 2013. For 2015, we have data on 558 households that were interviewed as part of the Flood Impact Assessment Survey (FIAS), that were mainly located in districts in the Southern Region, plus two districts in Central Region that also experienced flooding. Of the 558 households that were interviewed during both the IHPS 2013 and the FIAS 2015, 299 households were also interviewed during the IHPS 2016.

3.1. Household Aid Receipt and Livelihood Outcomes

Both the IHPS and FIAS collected information on whether the household received food or cash aid from a variety of sources. We use a dichotomous variable equal to 1 if the household received aid from any government or NGO source. Both surveys also elicited comprehensive information on household food and non-food consumption, which allow us to construct our dependent variables, namely total non-food expenditures per capita in natural logarithms, the total value of food consumption per capita in natural logarithms; total value of food purchases per capita; total calories consumed per capita in natural logarithms; and food consumption score. We hypothesize that shocks will reduce these outcomes. With respect to food aid, we hypothesize that the total value of food consumption, calories per capita, food consumption score and school participation rates will increase with aid receipt. Food purchases may either increase or decrease, in part because some aid is distributed in cash.

3.2. Crop Production and Extreme Rainfall Events

While our goal in this paper is to evaluate the impacts of extreme rainfall events on welfare outcomes, it is instructive to look at impacts on plot-level maize yields that are computed from the survey data.[6,7] McCarthy et al. (2021) systematically evaluated the explanatory performance of a wide range of drought and flood shock measures from different data sources using IHPS and FIAS sample data. That work finds that the most robust measure for flood shocks is a dichotomous measure based on an index of mean flood intensity from the Global Flood Monitoring System (GFMS) data set (Merz et al., 2007), elevation, and distance to river. The flood shock measure takes a value of one where the flood index is more than 30% above the average flood index value. The drought measure is based on the difference between the National Oceanic and Atmospheric Administration (NOAA) African Rainfall Climatology version 2 (ARC2) flowering period rainfall in the current period versus the historical average. We use a dichotomous variable that takes a value of one when current period rainfall is at least 30% below the

[6] Maize yield estimates provided by the agricultural extension services at the extension planning area level are also used in the MVAC model for targeting purposes, as detailed in the subsequent section.
[7] Maize harvest is computed in dried grain- and kilogram-equivalent terms. In doing that, harvests that are reported in non-standard measurement units are converted into kilogram-equivalent terms using the IHPS conversion factors. Subsequently, maize harvest is divided by GPS-based plot area in hectares to obtain plot-level maize yields.

historical mean and is otherwise equal to zero.[8] Finally, we control for climate conditions by including historical flowering period rainfall mean and coefficient of variation, as well as standard production function variables. As shown in Online Appendix 1, the flood and drought shocks have significant negative impacts on plot-level maize yields.

3.3. Aid Distribution and Explanatory Factors

For aid distribution, we use monthly data on the number of households who received food and cash aid in TA's where aid was distributed.[9] The vast majority of aid was distributed through a consortium of international and local NGOs, coordinated by the Ministry of Disaster Management Affairs and the WFP (Babu et al., 2018). The monthly data are aggregated, starting with the month that distribution began following the end of the current period rainy season through to March of the subsequent rainy season. We subsequently divide the number of households to whom aid was distributed by the projected total number of households in the TA to get a measure of aid availability within the TA. To simplify terms, we hereafter use "aid distribution" to refer to this variable.

MVAC forecasts of the number of people who are expected to suffer from food deficits in the upcoming lean season using data from a wide range of primary and secondary data collected by dedicated team, which feed into a Household Economic Analysis model, and model results form the basis for the first-level of geographic targeting (MVAC, 2013; Svesve, 2015; FEWSNET, 2016; Babu et al., 2018). Though it is unclear exactly which rainfall estimate data was used to quantify hazards in the MVAC model – or that are subsequently taken into consideration by FARP – we tested a number of rainfall variables constructed

[8] McCarthy et al. (2021) use a slightly different measure for drought. That measure is semi-continuous, taking the absolute value of the percent difference between current period rainfall and the historical mean when more than 30 percent below, and otherwise equal to zero. However, as shown in Online Appendix 1, the simple dichotomous measure is also significant, and facilitates interpretation of coefficients.

[9] We have data on amounts of cash distributed and quantities and caloric equivalent of food aid distributed, but we chose to use number of households receiving aid since this variable does not require us to create a variable that has the same unit across different types of aid.

using different sources and covering different periods noted in those documents. We chose to retain those variables that had the best predictive power in explaining aid distribution and that included:

(i) the percent difference in total crop season (last dekad of November through the final dekad of March) rainfall realizations when rainfall was below the long- mean using the decadal rainfall estimates from the University of California at Santa Barbara's Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data set (covering 1981-2015),

(ii) the percent difference in total season rainfall realizations when rainfall was above the same long-term mean derived from the CHIRPS data set,

(iii) the median 3-month Standardized Precipitation Index (SPI) values for the period December-January, as provided by the Instituto Pirenaico de Ecología, and

(iv) the median total crop season Normalized Difference Vegetation Index (NDVI) constructed from Climate Data Record of Advanced Very High-Resolution Radiometer (AVHRR) Surface Reflectance, as provided by the National Oceanic and Atmospheric Administration (NOAA).

MVAC also bases its needs assessment on extension planning area (EPA)-level agricultural production estimates. Given data quality issues that a range of specific crops – and not knowing how these were handled – we instead use third-round EPA-level maize yields estimates for the main growing season October-March.[10] We match these EPA-level estimates to households in our analysis sample and then construct the sample-weighted TA-level median of the EPA long-term average mean maize yields, and percent difference from the long-term mean as explanatory variables.

Furthermore, targeting is based on the 2010 district poverty rates provided by the Malawi National Statistical Office (NSO, 2012). Additional explanatory variables that can explain aid distribution

[10] Maize yield estimates data had many fewer missing data points.

across TAs include the TA population density,[11] the median accessibility index in the TA,[12] median slope, and elevation. While not explicitly used by the MVAC, in view of the political economy considerations that have been shown to impact decisions related to humanitarian aid distribution elsewhere in Africa (Francken et al., 2009), we include information on the political party of the member of the parliament (MP) associated with the communities in our sample. Using the publicly-available data on the election results provided on the Malawi Electoral Commission (MEC) website, we match data on the political party composition of MPs elected to TA's.[13] In some cases, TAs map to more than one constituency, so we construct a simple mean of constituency-level political alignment dummies at the TA level to capture the proportion of political representation in the TA that is part of the president's party, in opposition to the president's party, or independent. The 2009 parliamentary election results are applied to observations in 2013, and 2014 parliamentary election results are applied to observations in 2015 and 2016.

Finally, MVAC has constructed livelihood zone categories that also inform the Household Economic Analysis, to capture the extent to which households in different locations are more vulnerable to shocks and less able to cope with those shocks. Thus, we control for livelihood zone fixed effects in our regressions of TA-level aid distribution.[14]

3.4. Additional Explanatory Variables

<u>Explicit Household Targeting Characteristics</u>

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[11] TA population estimates are derived from NSO (2008). TA area is derived from publicly available geospatial data. TA population density is calculated by the authors as population divided by area.
[12] The accessibility index captures density of road networks and proximity to urban centers.
[13] Maps of the constituencies were accessed at https://mec.org.mw/maps-district/ to allow linking to TAs, since our data lacks GPS-confirmed constituency information. Election results were accessed at: https://mec.org.mw/2014-tripartite-elections for the 2014 elections and https://mec.org.mw/2009-general-elections/ for the 2009 elections.
[14] Livelihood zones are constructed by FEWS NET, and were accessed at https://fews.net/southern-africa/malawi/livelihood-zone-map/july-2015.

At the local level, aid distribution should be targeted to less wealthy, female-headed households, households with babies and infants (we use a dummy for households with children under three years old), households where all adults are elderly (defined as all adults older than 59), and households with any disabled adult member (Babu et al., 2018; MVAC, 2016; ALNAP, 2003).

To proxy wealth, we use an index of household durables, which is created from a principal component factor analysis of consumer durables and household dwelling characteristics[15]; the number of mobile phones owned by family members; an index of agricultural implements, created from a principal component factor analysis[16]; and the natural logarithm of total landholdings.[17] Additional household demographics include size; the maximum number of years of education completed by any household member; the proportion of adult household members who are literate in English; and a dichotomous variable for whether the household had moved during survey periods.

In addition, we include a series of dichotomous variables to control for whether the household faced other idiosyncratic shocks such as having any member that lost employment or facing high food prices in the last 12 months. The dichotomous variables are equal to one if the household ranked either of these shocks as being in the top three most important shocks. Further, we include a dichotomous variable that identifies whether any household member was ill during the two weeks preceding the survey interview.

Potential risk coping mechanisms include the number of adult children living in separate households, a dummy for whether any member holds a financial account, and three market network

[15] 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; 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.

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

[17] Agricultural land is "held" if it was acquired by grant from local leaders, inheritance, bride price, purchase, lease, or gift. The land of the household's dwelling is "held" if the dwelling is owned or was authorized for free.

variables. The network variables are constructed using data from the Household Network Roster module, which collected information on the set of people or businesses with whom household members conducted transactions within the course of purchasing agricultural inputs and/or selling agricultural outputs. The three variables are (i) the number of contacts located within the village, (ii) the number of contacts in nearby villages and (iii) the number of contacts located in the district center or further away.

Complementing household-level explanatory variables, we control for a number of community characteristics that are expected to impact household welfare and ability to cope with shocks. We include a dummy for whether or not households in the community have access to a MASAF program or to school feeding programs. We include two community leadership characteristics -- the proportion of community-level key informants who are women and who have no education. Additional variables include a measure of landholding inequality in the community, the number of groups operating in the community, an index of infrastructure and services in the community, the number of radio stations operating in the district, and the number of government marketing warehouses in the district.

Finally, the regressions control for (i) interactions of survey year and livelihood zone fixed effects to control for time-varying livelihood zone-specific unobserved heterogeneity, and (ii) dichotomous variables identifying the survey interview months to control for potential seasonality effects on household aid receipt and welfare outcomes.

3.5. Descriptive Statistics

Table 1 presents the descriptive statistics for the key covariates, and the full results are found in Online Appendix 2. Note that the monetary consumption variables are expressed in nominal terms. Thus, the increases across time can be attributed primarily to inflation, which is taken into account by our multivariate analyses through the inclusion of time fixed effects. The shock measures are based on geospatial data, as explained above. The flood shock affected 29% of the sample in 2015. In 2016, 40% of the sample was affected by the drought. Nine percent of the sample was affected by sequential shocks, i.e. both of drought in 2016 and flooding in 2015.

The drought and flood shocks led to a substantial drop in maize yields, which could jeopardize consumption outcomes particularly for poor and vulnerable households. The value-based consumption figures are in nominal terms, potentially masking the true impact of the shocks on consumption since inflation was high over this time period as well.[18] Households did experience reductions on their average caloric intake, and experienced lower food consumption scores over time as the shocks unfold. School participation rates were in fact higher in the flood year, and unchanged from 2013 in the drought year.

The humanitarian response to the 2015 floods and particularly to the drought in 2016 was of unprecedented scale with almost 40% of the population expected to receive either in-kind food or cash transfers or some combination of the two, distributed in-kind or in cash. The vast majority of such transfers were made by the World Food Programme (Babu et al., 2018). Aid distribution eventually covered all 24 affected districts out of a total of 28 districts in Malawi (Babu et al., 2018). As shown in Table 1, aid distribution rates were much higher in 2015 and 2016 versus 2013, with a TA-level average of more than one distribution per household. The summary statistics in 2016 provide a rough proxy for aid distribution across Malawi, while the 2015 estimates only provide information about aid distribution in the FIAS districts, which are primarily in the Southern Region.

Despite the increase in aid distributed, household receipt of aid is more stable across time than might be presumed given the aid distribution data. The imperfect overlap between the receipt of aid and climate shocks is shown by the lower aid distribution rates and the lower incidence of household aid receipt when interacting with shock dummies. Since our TA-level measure of aid distribution is continuous

[18] We use the nominal values in the analysis below, and control for inflation with time and location fixed effects. Given Malawi's currency devaluation in 2012, it is difficult to adequately convert nominal to real Malawi kwacha with publicly available data. We did calculate an inflation correction factor to generate real values, but given data issues, we felt it was better to use nominal values with fixed effects.

and the household variable is dichotomous, it is helpful to consider the magnitude of the difference in terms of standard deviations. The mean household interaction is 5.7 SD lower than mean household aid in 2015, and 12.9 SD lower in 2016, while the aid interaction is 13.7 SD lower in 2015 and 19.5 SD lower in 2016.

Explicit household targeting demographics are somewhat more stable across time. The trend is upward on the number of mobile phones, which is consistent with increasing mobile penetration.

Table 1. Descriptive Statistics

	2013 N = 1907 Mean	2013 N = 1907 SE	2015 N = 299 Mean	2015 N = 299 SE	2016 N = 2507 Mean	2016 N = 2507 SE
Consumption Variables						
Non-Food Expenditure	49820	1272	46238	1762	80297	1561
Value of Food Consumed	81538	1320	85993	3163	116858	1641
Food Purchases	60291	1635	61539	2851	100956	2026
Calorie Consumption	17959	196	16963	558	15677	149
Food Consumption Score	58.652	0.471	44.331	1.093	52.172	0.448
School Participation Rate	0.799	0.009	0.864	0.018	0.790	0.008
Weather Shocks†						
Weather Shock	0	0	0.288	0.026	0.400	0.010
Current Shock	0	0	0.288	0.026	0.310	0.009
Sequential Shock	0	0	0	0	0.090	0.006
WFP Distribution						
WFP HH Distribution Rate	0.394	0.017	1.028	0.050	1.651	0.046
WFP * Weather Shock	0	0	0.344	0.042	0.755	0.032
WFP * Current Shock	0	0	0.344	0.042	0.501	0.026
WFP * Sequential Shock	0	0	0	0	0.253	0.021
HH Receipt of Aid						
Aid	0.126	0.008	0.207	0.023	0.156	0.007
Aid * Weather Shock	0	0	0.077	0.015	0.066	0.005
Aid * Current Shock	0	0	0.077	0.015	0.039	0.004
Aid * Sequential Shock	0	0	0	0	0.027	0.003
Explicit HH Targeting Characteristics						
Dummy, Female Head	0.232	0.010	0.318	0.027	0.251	0.009
Dummy, Children<3	0.424	0.011	0.368	0.028	0.352	0.010
Dummy, All Members>59	0.016	0.003	0.037	0.011	0.022	0.003
Dummy, HH Member Disabled	0.261	0.010	0.211	0.024	0.257	0.009
Wealth						
Wealth Index	0.254	0.005	0.212	0.009	0.276	0.004
# Mobile Phones	0.902	0.027	0.746	0.050	1.081	0.025

Notes: The table is constructed across all household observations used in the analysis. † **Weather Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in the current period (irrespective of potential exposure to past weather shocks), and 0 otherwise. **Current Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock *only* in the current period, and 0 otherwise. **Sequential Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in consecutive periods, and 0 otherwise.

4. Estimation Results and Discussion

4.1. TA-Level Aid Distribution

Table 2 presents results for a random effects models using weather variables mentioned in aid distribution documents in the first column and the flood and weather shock dummies from the crop production analysis in the second column.[19] In the first specification, both low and high rainfall deviations increased aid distribution, while higher estimated maize yield differences and higher December-January SPI values decrease aid distribution. The explanatory power is reasonably high at .46 R^2-overall and .58 R^2-between. However, looking at column 2, we see that neither drought nor flood shocks have a significant impact on aid distribution. On the other hand, as shown in Online Appendix 1, both drought and flood shocks have significant negative impacts on maize yields. Additionally, the high rainfall difference has a significant positive impact on maize yields *and* aid distribution, while December-January SPI has a negative impact on both maize yields *and* aid distribution. The results thus suggest that the reliance by MVAC on certain rainfall variables provides a source of exogenous variation in aid distribution through geographic targeting discrepancies that are captured in the descriptive statistics.

[19] Full results are found in Online Appendix 3.

Table 2: TA-Level Aid Distribution – Cumulative Households Reached per Capita
Random Effects Model

	Aid Distribution			
	Aid Docs.		*Production Shocks*	
Low Rain |% Diff from Mean|, Rainy Season	0.033	***		
	(.009)			
High Rain |% Diff from Mean|, Rainy Season	0.069	*		
	(.041)			
Drought Shock			-0.078	
			(.299)	
Flood Shock			0.141	
			(.286)	
SPI, Dec-Jan	-0.369	***	-0.491	***
	(.141)		(.143)	
NDVI, Nov-Mar	1.530			
	(1.051)			
EPA % Diff Maize Yields	-1.398	***	-1.796	***
	(.435)		(.441)	
EPA Mean Maize Yields	-0.026		0.023	
	(.217)		(.215)	
District Poverty Rate (2010)	0.004		0.003	
	(.005)		(.005)	
Proportion Independent MPs	0.236		0.224	
	(.217)		(.221)	
Proportion Opposition MPs	-0.025		-0.030	
	(.187)		(.180)	
Constant	1.531	*	2.169	
	(.897)		(2.640)	
Livelihood Zone Dummies	Yes		Yes	
Number of Observations	600		600	
R-squared (within)	0.342		0.334	
R-squared (between)	0.581		0.567	
R-squared (overall)	0.456		0.448	

Notes: ***/**/* denote statistical significance at 1/5/10 percent respectively. Standard Errors in parentheses.

To capture potential targeting errors, we generate different categories of targeting outcomes. To do so, we must address the fact that aid is distributed throughout the country even in relatively normal rainfall years due to high rates of poverty and food insecurity even in good years. Although 2010 district poverty rates do not directly impact aid distribution conditional on all other characteristics including the livelihood zone dummies, their inclusion in the MVAC model and their positive unconditional correlation with aid distribution rates suggest an important role. Thus, in addition to the weather shocks, we base our categorization on whether 2010 district poverty rates were lower than 50% vs. greater than or equal to 50%. Specifically, we create four mutually exclusive categories when shocks occur and four mutually exclusive categories when shocks do not occur:

<u>Concerning areas that received a weather shock</u>:

1. Correct inclusion, poor district is defined as a dichotomous variable equal to 1 when aid distribution rates are greater than median distribution rates (.93), and the 2010 district poverty rate is greater than 50%.
2. Incorrect exclusion, non-poor district is defined as a dichotomous variable equal to 1 when aid distribution rates are less than median distribution rates, and the 2010 district poverty rate is less than or equal to 50%.
3. Correct inclusion, non-poor district is defined as a dichotomous equal to 1 when aid distribution rates are greater than median distribution rates, and the district poverty rate is less than or equal to 50%.
4. Incorrect exclusion, poor district is defined as a dichotomous variable equal to 1 when aid distribution rates are less than overall median distribution rates, and the 2010 district poverty rate is greater than 50%.

We expect that poor households located in areas that experienced a shock, where aid distribution rates are relatively high, and in districts with high poverty rates would be most likely to access food aid. We expect households in the other three categories would be less likely to receive aid, especially in non-poor districts.

<u>Concerning areas that did not receive a shock</u>:

1. Correct exclusion, non-poor district is defined as a dummy equal to 1 when aid distribution rates are zero, and the 2010 district poverty rate is less than or equal to 50%.
2. Correct exclusion, poor district is defined as a dummy equal to 1 when aid distribution rates are zero, and the district poverty rate is less than or equal to 50%.
3. Incorrect inclusion, poor district is defined as a dummy equal to 1 when aid distribution rates are greater than zero, and the 2010 district poverty rate is greater than 50%.
4. Incorrect inclusion, non-poor district is defined as a dummy equal to 1 when aid distribution rates are greater than zero, and the 2010 district poverty rate is less than or equal to 50%.

We expect that households in non-poor districts that neither received weather shocks nor any aid distribution would be least likely to receive aid. Thus, the expectation is that households in the other three categories would be more likely to receive aid, particularly in poor districts.

Table 3 gives the percentage of households falling into each of these categories for the IHPS and FIAS samples in 2016, for the subset of households falling into each category. Looking at the IHPS sample for when a shock occurred, the highest percentage of households were located in "correctly" targeted poor districts that received a shock (35%), but 19% of households facing a shock in poor districts only received limited aid, capturing potential geographic errors of exclusion. Looking at areas where shocks did not occur, we note that most households were located in districts with positive distribution rates despite no shock occurring, and in fact 16% were located in non-poor districts with positive distribution rates, capturing geographic errors of inclusion. Looking at the FIAS sample, results suggest somewhat lower errors of exclusion (11%) but higher errors of inclusion (19%).

We include these targeting category dummy variables as instrumental variables for household receipt of aid, omitting the correct inclusion, poor district dummy under shocks and the correct exclusion, non-poor district under no shocks.

Table 3: Targeting Categories and Errors in 2016

	IHPS		FIAS	
	# Obs	Percent	# Obs	Percent
Shock Occurred	1003		569	
Moderate+ distribution, poor district	351	35%	293	51%
Limited distribution, non-poor district	232	23%	71	12%
Moderate+ distribution, non-poor district	229	23%	149	26%
Limited distribution, poor district	191	19%	56	10%
Shock Did Not Occur	1504		383	
No distribution, non-poor district	552	37%	16	4%
No distribution, poor district	262	17%	52	14%
Positive distribution, poor district	456	30%	244	64%
Positive distribution, non-poor district	234	16%	71	19%

4.2. Instrumental Variables, Zero Stage Results

Table 4 presents select coefficient results from the zero stage BRGLMs for the IHPS sample and using the current period shock specification.[20] The second column gives results for the probability that a household receives aid (Aid), while the third column gives results for the probability of receiving aid when a shock occurred (Aid*Shock). We first note that experiencing a weather shock increases the probability of receiving aid and receiving aid under a weather shock. Aid distributions also have a significant impact on the probability that a household received aid but have no impact on aid receipt under a weather shock (column 2). The interaction term of aid distribution and current shock increases also has no significant impact on the probability that a household receives aid under shocks (column 3). Thus, while a shock occurring at the household level does increase household aid receipt, aid distribution at the TA level does not lead to a higher probability of aid receipt in geographic locations that experienced a shock versus those that did not. The latter in part captures potential targeting errors and is consistent with the results for the targeting dummies as defined in the previous section. For the targeting dummies when a shock

[20] Results are similar across the different samples and shock specifications; full results are given in Online Appendix 4.

occurred, we expect all of the included dummies to have a negative impact on household aid receipt vis-à-vis the omitted category of aid distributions in poor districts. The estimated coefficients are indeed all negative and significant in both equations. For the targeting dummies when a shock did not occur, we expect the included dummies to have a positive impact vis-à-vis the omitted category of no aid distributions in non-poor districts. All of the dummies are positive and significant.

Looking at the household targeting characteristics, we note that female-headed households and households that are composed only of elderly individuals were more likely to receive aid in general, and under weather shocks. However, the coefficients on the dichotomous variables identifying households with babies or infants and those with disabled members are not significant. The wealth index, which is based on consumer durables and housing characteristics, is negative and significant in the Aid equation as we expect but is not significant in the Aid*Shock equation. The latter suggests that targeting aid within the TA was less successful in reaching the poorer members when many households received a weather shock.

Overall, the results suggest that though there were geographic targeting errors and likely some household targeting errors, aid distribution nonetheless increased the likelihood of receiving aid, as did being in a female-headed household and being in a household that is composed only of elderly individuals.

Table 4: Results from Zero Stage BRGLM, Household Receipt of Aid

	Aid		Aid * Shock	
Weather Shock†	1.263	***	2.549	***
	(.238)		(.225)	
WFP Distribution				
WFP HH Distribution	0.077	***	-0.018	
	(.024)		(.020)	
WFP * Weather Shock	-0.044		0.064	
	(.045)		(.044)	
Shock Occurred				
Limited distribution, poor district	-0.524	**	-0.667	***
	(.230)		(.244)	
Limited distribution, non-poor district	-1.582	***	-1.367	***
	(.292)		(.358)	
Moderate+ distribution, non-poor district	-0.903	***	-1.042	***
	(.199)		(.222)	
Shock Did Not Occur				
Positive distribution, non-poor district	0.305	**		
	(.150)			
Positive distribution, poor district	0.902	***		
	(.194)			
No distribution, poor district	1.14	***		
	(.194)			
Explicit HH Targeting Characteristics				
Dummy, Female Head	0.178	***	0.283	***
	(.059)		(.083)	
Dummy, Children<3	-0.012		0.082	
	(.059)		(.085)	
Dummy, All Members>59	0.603	***	0.589	***
	(.176)		(.215)	
Dummy, HH Member Disabled	0.066		0.04	
	(.060)		(.086)	
Wealth				
Wealth Index	-0.532	**	-0.415	
	(.245)		(.393)	
Landholdings per cap.	0.365	**	0.439	**
	(.150)		(.179)	
Constant	-0.505		1.472	
	(1.036)		(1.511)	
# of Obs.	4412		4412	
Goodness of Fit	0.503		0.605	

Notes: Standard Errors in parentheses. ***/**/* denote statistical significance at 1/5/10 percent respectively. Goodness of Fit statistic is calculated as the squared correlation between dependent variable and predicted dependent variable. † **Weather Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in the current period (irrespective of potential exposure to past weather shocks), and 0 otherwise.

4.3. Instrumental Variables Results, First Stage Results

As shown in Table 5, the predicted household receipt of aid and predicted household receipt of aid * shock variables obtained from the zero-stage estimation are strong instruments in the first stage. Since the equation is exactly identified, no test of overidentifying restrictions is presented.

Table 5: First Stage IV Results, Predicted Household Receipt of Aid

	Aid		**Aid * Shock**	
Predicted Aid	1.124	***	0.029	
	(.079)		(.033)	
Predicted Aid * Shock	0.311	***	1.145	***
	(.087)		(.073)	
# of Obs.	4412		1999	
Centered R2	0.2451		0.372	
Uncentered R2	0.340		0.392	
Partial R2 of excluded instruments	0.075		0.202	
F-test of excluded instruments	141.13		124.89	
Weak identification F statistic		120.19		

Notes: ***/**/* denote statistical significance at 1/5/10 percent respectively. Standard Errors in parentheses.

4.4. Instrumental Variables Results, Second Stage Results

Table 6 below provides selected results for key co-variates across our six dependent variables.[21] The columns that are labeled as "1" include the results from the regressions with the dichotomous variable that identifies exposure to a shock in the current period (irrespective of potential exposure to past weather shocks). The columns that are labeled as "2" show the results from the regressions with the dichotomous variables that identify exposure to a shock (i) *only* in the current period and (ii) in consecutive periods. We report the results for each variable using these two specifications, first for the IHPS sample and then for the FIAS sample.

[21] Full results are found in Online Appendix 5.

The direct impact of a current period weather shock is negative and significant on non-food expenditures for both samples and for school participation rates in the IHPS sample. The coefficients on the weather shock for the food-based variables are never significant. The results using the two shock dummies shows that while the current-period only shock is never significant in the food-based variable regressions, there is a significant negative impact of a sequential shocks on value of food consumed and food purchases in both samples, and a significant negative impact on the food consumption score in the IHPS sample.

Looking next at the Aid and Aid*Shocks results, we note that there is no direct impact of aid receipt on non-food expenditures, though there is a positive and significant impact of aid when interacted with the current shock in the first specification, and interacted with the sequential shock in the second specification for the FIAS sample. The overall impact of receiving aid when experiencing these shocks is positive and significant. Looking next at food purchases, we note that the impact of aid is negative for those households who did not experience a weather shock, but the overall impact is positive and significant when interacted with the sequential shock for the IHPS sample. The overall impact of aid on the food consumption score is positive for households experiencing sequential shocks in the IHPS sample. And aid leads to higher schooling under both the current weather shock and the sequential shock in the IHPS sample and leads to higher schooling rates irrespective of weather shocks in the FIAS sample.

Overall, the results suggest that aid was particularly important for households who had received sequential shocks, with significant positive impacts for non-food expenditures for the FIAS sample, and for food purchases, food diversity and school participation rates for the IHPS sample. On the other hand, the coefficient on aid interacted with current period only weather shock is not significant in any of the equations. Nonetheless, aid receipt had limited impacts on the value of food consumed and calories per capita across all specifications.

The point estimates of the magnitude of the impact of shocks on consumption outcomes was substantial given the high levels of poverty prevailing in Malawi. The weather shock reduced non-food consumption by about 5% and 20% for the IHPS and FIAS samples, respectively. The sequential weather shock reduced the value of food consumption by 14% and 20% in IHPS and FIAS respectively, while food purchases were reduced by about 26% for both samples. Aid had meaningful impacts on consumption outcomes when significant. For instance, aid receipt under sequential shocks increased non-food consumption by 20% in the FIAS sample. And the net impact of a sequential shock on food purchases for IHPS households was about zero, meaning that those households were able to maintain food purchases despite experiencing sequential shocks. For IHPS households, a sequential shock reduced the food consumption score by 6 points, which is a 12% decline from the average. And school participation rates fell by 5% for IHPS households under a sequential shock but increased by 24% when households also received aid.

Table 6: Second-Stage Instrumental Variable Regression Results

	Log Total Non-Food Expenditure Per Capita				Log Total Value of Food Consumed Per Capita				Log Total Value of Food Purchases Per Capita			
	IHPS		FIAS		IHPS		FIAS		IHPS		FIAS	
	1	2	1	2	1	2	1	2	1	2	1	2
Weather Shocks†												
Weather Shock	-0.055 *		-0.233 ***		-0.05		-0.088		-0.043		-0.17	
	(0.032)		(0.067)		(0.032)		(0.07)		(0.05)		(0.111)	
Current Shock		-0.038		-0.22 ***		-0.047		-0.082		-0.033		-0.162
		(0.033)		(0.071)		(0.032)		(0.073)		(0.051)		(0.115)
Sequential Shock		-0.04		-0.108		-0.152 *		-0.228 *		-0.308 **		-0.325 *
		(0.075)		(0.104)		(0.078)		(0.117)		(0.145)		(0.189)
Aid * Shock												
Aid	0.047	0.075	-0.235	-0.204	-0.129	-0.155	-0.193	-0.235	-0.323 *	-0.345 *	-0.304	-0.335
	(0.104)	(0.107)	(0.144)	(0.146)	(0.098)	(0.101)	(0.148)	(0.154)	(0.189)	(0.19)	(0.259)	(0.266)
Aid * Weather Shock	0.011		0.467 ***		-0.023		0.064		-0.241		-0.01	
	(0.124)		(0.173)		(0.134)		(0.186)		(0.233)		(0.341)	
Aid * Current Shock		-0.219		0.337		-0.019		0.01		-0.379		-0.085
		(0.146)		(0.215)		(0.139)		(0.22)		(0.275)		(0.421)
Aid * Sequential Shock		0.113		0.389 *		0.196		0.395		0.644 *		0.385
		0.174		0.201		0.223		0.248		0.364		0.344
HH Targeting Criteria												
Dummy, Female Head	-0.131 ***	-0.134 ***	-0.144 ***	-0.147 ***	-0.063 *	-0.064 *	-0.11 **	-0.112 **	-0.142 **	-0.151 ***	-0.051	-0.054
	(0.034)	(0.035)	(0.055)	(0.055)	(0.034)	(0.034)	(0.053)	(0.053)	(0.057)	(0.057)	(0.081)	(0.08)
Dummy, Children<3	-0.001	0	0.013	0.013	-0.019	-0.018	-0.009	-0.006	-0.025	-0.023	-0.011	-0.007
	(0.021)	(0.021)	(0.034)	(0.034)	(0.021)	(0.021)	(0.035)	(0.035)	(0.034)	(0.033)	(0.061)	(0.06)
Dummy, All Adults>59	-0.295 ***	-0.299 ***	-0.257 ***	-0.252 ***	-0.117 *	-0.118 *	-0.11	-0.117	-0.292 *	-0.308 *	-0.332	-0.349
	(0.074)	(0.075)	(0.097)	(0.096)	(0.069)	(0.069)	(0.108)	(0.11)	(0.162)	(0.162)	(0.235)	(0.238)
Dummy, Disabled	-0.012	-0.011	0.052	0.055	-0.024	-0.024	0	-0.003	-0.068 *	-0.071 *	0.026	0.025
	(0.024)	(0.025)	(0.041)	(0.041)	(0.024)	(0.024)	(0.042)	(0.042)	(0.039)	(0.038)	(0.064)	(0.063)
Wealth												
Wealth Index	1.028 ***	1.027 ***	0.792 ***	0.794 ***	0.643 ***	0.645 ***	0.519 ***	0.53 ***	1.119 ***	1.13 ***	1.303 ***	1.317 ***
	(0.091)	(0.092)	(0.161)	(0.163)	(0.094)	(0.095)	(0.183)	(0.188)	(0.138)	(0.139)	(0.283)	(0.286)
# Mobile Phones	0.098 ***	0.097 ***	0.098 ***	0.094 ***	0.054 ***	0.055 ***	0.015	0.018	0.047 ***	0.048 ***	0.025	0.027
	(0.013)	(0.013)	(0.026)	(0.026)	(0.012)	(0.012)	(0.022)	(0.023)	(0.017)	(0.017)	(0.035)	(0.035)
Constant	10.975 ***	11.017 ***	10.611 ***	10.677 ***	11.514 ***	11.467 ***	10.889 ***	10.852 ***	10.595 ***	10.522 ***	9.685 ***	9.631 ***
	(0.308)	(0.311)	(0.549)	(0.545)	(0.297)	(0.298)	(0.535)	(0.542)	(0.516)	(0.515)	(0.899)	(0.907)
# of Obs.	4412	4412	1999	1999	4412	4412	1999	1999	4412	4412	1999	1999
R2 (within)	0.491	0.488	0.342	0.348	0.323	0.321	0.24	0.229	0.307	0.312	0.231	0.234
R2 (between)	0.764	0.764	0.575	0.578	0.624	0.624	0.468	0.467	0.603	0.605	0.404	0.406
R2 (overall)	0.682	0.682	0.473	0.478	0.518	0.517	0.373	0.368	0.506	0.509	0.325	0.328

Notes: ***/**/* denote statistical significance at 1/5/10 percent respectively. Standard Errors in parentheses. **† Weather Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in the current period (irrespective of potential exposure to past weather shocks), and 0 otherwise. **Current Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock *only* in the current period, and 0 otherwise. **Sequential Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in consecutive periods, and 0 otherwise.

Table 6: Second-Stage Instrumental Variable Regression Results, Continued

	Log Total Calorie Consumption Per Capita				Food Consumption Score				School Participation Rates			
	IHPS		FIAS		IHPS		FIAS		IHPS		FIAS	
	1	2	1	2	1	2	1	2	1	2	1	2
Weather Shocks†												
Weather Shock	-0.022		0.017		-1.625		1.149		-0.042 *		-0.002	
	(0.028)		(0.063)		(1.17)		(1.919)		(0.024)		(0.047)	
Current Shock		-0.038		-0.018		-1.368		1.084		-0.042 *		0.021
		(0.027)		(0.064)		(1.201)		(2.004)		(0.024)		(0.049)
Sequential Shock		-0.075		-0.114		-6.616 ***		-2.619		-0.011		0.101
		(0.077)		(0.11)		(2.089)		(2.962)		(0.05)		(0.074)
Aid * Shock												
Aid	-0.028	-0.084	-0.023	-0.082	-3.352	-4.327	4.645	3.649	-0.035	-0.021	0.135	0.177 *
	(0.087)	(0.091)	(0.13)	(0.135)	(3.362)	(3.443)	(4.37)	(4.501)	(0.076)	(0.077)	(0.102)	(0.107)
Aid * Weather Shock	-0.15		-0.241		-1.861		-2.697		0.195 ***		0.035	
	(0.138)		(0.182)		(3.674)		(4.875)		(0.075)		(0.114)	
Aid * Current Shock		0.041		-0.053		-3.085		-2.711		0.09		-0.131
		(0.136)		(0.203)		(4.124)		(5.849)		(0.086)		(0.134)
Aid * Sequential Shock		-0.106		-0.051		10.583 **		5.22		0.293 ***		0.107
		(0.23)		(0.25)		(4.779)		(5.537)		(0.112)		(0.135)
HH Targeting Criteria												
Dummy, Female Head	-0.04	-0.038	-0.118 **	-0.115 **	-0.972	-1.074	-1.911	-1.959	0.053 **	0.05 **	0.054	0.046
	(0.031)	(0.031)	(0.051)	(0.051)	(1.043)	(1.046)	(1.547)	(1.55)	(0.025)	(0.025)	(0.035)	(0.035)
Dummy, Children<3	-0.039 **	-0.04 **	0.015	0.016	-0.085	-0.051	0.085	0.134	-0.009	-0.009	0.015	0.018
	(0.019)	(0.019)	(0.032)	(0.033)	(0.68)	(0.681)	(1.02)	(1.018)	(0.016)	(0.016)	(0.024)	(0.025)
Dummy, All Adults>59	-0.157 **	-0.154 **	-0.196	-0.207	-3.172	-3.275 *	-5.347 **	-5.745 **				
	(0.063)	(0.061)	(0.129)	(0.129)	(1.973)	(1.983)	(2.466)	(2.465)				
Dummy, Disabled	0.012	0.013	0.033	0.028	-1.937 ***	-1.957 ***	-1.362	-1.347	0.012	0.012	0.053 *	0.058 **
	(0.022)	(0.022)	(0.041)	(0.041)	(0.75)	(0.748)	(1.092)	(1.096)	(0.018)	(0.018)	(0.029)	(0.029)
Wealth												
Wealth Index	0.256 ***	0.254 ***	0.259	0.257	32.252 ***	32.356 ***	33.435 ***	33.571 ***	0.102	0.108	0.058	0.075
	(0.082)	(0.082)	(0.168)	(0.171)	(3.42)	(3.437)	(5.632)	(5.699)	(0.071)	(0.071)	(0.123)	(0.125)
# Mobile Phones	0.021 **	0.022 **	0.019	0.024	1.284 ***	1.296 ***	0.035	0.113	-0.001	-0.002	0.01	0.006
	(0.01)	(0.01)	(0.019)	(0.019)	(0.442)	(0.447)	(0.678)	(0.693)	(0.008)	(0.008)	(0.013)	(0.013)
Constant	10.199 ***	10.152 ***	10.22 ***	10.164 ***	54.481 ***	52.41 ***	60.828 ***	58.898 ***	0.293	0.357	-0.096	0.007
	(0.256)	(0.26)	(0.47)	(0.474)	(10.06)	(10.1)	(15.52)	(15.44)	(0.239)	(0.24)	(0.401)	(0.409)
# of Obs.	4412	4412	1999	1999	4412	4412	1999	1999	3257	3257	1539	1539
R2 (within)	0.177	0.175	0.181	0.182	0.2	0.198	0.247	0.243	0.086	0.085	0.109	0.099
R2 (between)	0.415	0.415	0.379	0.382	0.578	0.578	0.47	0.469	0.195	0.197	0.239	0.241
R2 (overall)	0.311	0.31	0.283	0.285	0.452	0.45	0.373	0.371	0.152	0.153	0.172	0.168

Notes: */**/*** denote statistical significance at 1/5/10 percent respectively. Standard Errors in parentheses. † **Weather Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in the current period (irrespective of potential exposure to past weather shocks), and 0 otherwise. **Current Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock only in the current period, and 0 otherwise. **Sequential Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in consecutive periods, and 0 otherwise.

With respect to the key household explanatory variables, results show that female-headed and elderly households generally experienced worse consumption outcomes, indicating that these types of households are indeed vulnerable to consumption shocks. However, households with babies and infants and those with disabled members in general did not fare worse on consumption measures. It is interesting to note that these types of households also were not more likely to receive food aid, despite these characteristics being explicitly mentioned as being among the targeting criteria. The wealth index and number of mobile phones both have positive and significant impact on all nearly all measures of consumption as we expect, with the exception of school participation rates. Overall, these results indicate that targeting criteria are generally consistent with reaching households that need aid most.

Finally, we summarize some additional results of interest, reported in Online Appendix 5. As can be seen there, both employment loss and high price shocks generally led to lower consumption outcomes, while potential risk coping mechanisms (adult children outside the home, network densities) had limited impacts, though positive when significant. Overall, the results suggest that poor households in Malawi are vulnerable to a wide range of shocks, including covariate weather and price shocks as well as idiosyncratic shocks such as job loss.

4.5. Alternative Specifications

We report results here in the text for two alternative specifications.[22] In particular, we run regressions on two sub-samples, one that only includes relatively poor households and one that includes households interviewed from September to March, when weather shock-driven aid distribution was highest.

[22] In addition to these two, we also evaluated whether using real values for variables expressed in nominal values had any impact, and found that results were generally robust, and we also ran traditional 2SLS IV regressions, directly using the instruments in the first stage LPM for aid receipt. Results can be found in Appendices 6 and 7 respectively.

4.5.1: Restricting the Sample to Relatively Poor Households. The limited impacts of aid on food consumption outcomes may be due to a number of reasons. The first is that aid really does have limited impacts on food consumption outcomes. The second is that the sample does not provide sufficient power to estimate modest impacts of aid on food consumption outcomes. For value of food consumed and calories per capita in particular, we would expect that the impacts of aid would be relatively higher for those with low levels of food consumption outcomes, since aid would then form a larger percentage of the food sourced. Targeting errors can then exacerbate the difficulty in estimating the impacts of aid on food consumption, since we would expect more muted impacts if aid is received by relatively wealthy households. But we cannot introduce yet additional instrumented variables. Instead, we limit the sample to those households with wealth index levels below the median (.195). The results for the four food consumption outcomes are reported in the top panel of Table 7 for the two-shock specification.[23]

As can be seen, we are more likely to observe impacts of aid on food consumption outcomes versus results from the full sample, particularly for those households that have experienced a sequential shock. For the both the IHPS and FIAS samples, there are significant negative impacts of a sequential shock on the value of food consumed per capita, but also significant positive impacts of receiving aid under a sequential shock. For FIAS, calories per capita are also negatively affected by a sequential shock but aid under a sequential shock has a positive impact. For IHPS, households who experienced a current-period only shock but also received aid reduced food purchases. We do lose significance on the food consumption score for the IHPS sample, however.

4.5.2: Restricting the Sample to Households Interviewed during September-March. Another reason we might not be able to detect changes in food consumption outcomes from receipt of food aid under shocks may be due to the time between receipt of aid and the household interview date. While WFP distributed

[23] Full results for the poorer household sub-sample are in Online Appendix 8.

at least some aid in all months across all three years in our sample, the weather shock-related aid distribution occurred in September through the following March. We thus restrict our sample to households who were interviewed in September through March. The results for the four food consumption outcomes for the two-shock specification are provided in the bottom panel of Table 7.[24] Again, we see more positive interactions between aid interacted with the sequential shock, with higher calories per capita and a higher food consumption score for the IHPS sample, and higher value of food production and calories per capita for the FIAS sample.

[24] Full results for the September-March sub-sample are in Online Appendix 9.

Table 7: Consumption Outcomes; Poor Households Only Sample and Households Interviewed September-March

	Value of Food Consumed		Calorie Consumption		Food Consumption Score	
	IHPS	FIAS	IHPS	FIAS	IHPS	FIAS
Poorer HH Sample						
Current Shock	-0.018	-0.045	0.04	-0.039	-0.363	2.134
	(0.054)	(0.106)	(0.05)	(0.104)	(1.655)	(2.586)
Sequential Shock	-0.217 *	-0.348 **	-0.118	-0.372 **	-5.54 **	-1.916
	(0.112)	(0.158)	(0.119)	(0.159)	(2.716)	(4.112)
Aid	-0.205	-0.216	-0.104	-0.176	3.305	7.235
	(0.174)	(0.221)	(0.172)	(0.217)	(5.309)	(6.288)
Aid * Current Shock	-0.029	-0.159	-0.128	-0.107	-4.201	-10.257
	(0.217)	(0.263)	(0.223)	(0.258)	(5.3)	(6.326)
Aid * Sequential Shock	0.564 *	0.892 ***	0.139	0.598 **	8.878	3.716
	(0.288)	(0.307)	(0.304)	(0.304)	(6.506)	(7.304)
# of Obs.	2135	1158	2135	1158	2135	1158
R2 (within)	0.269	0.257	0.181	0.197	0.269	0.255
R2 (between)	0.434	0.404	0.348	0.334	0.31	0.368
R2 (overall)	0.389	0.37	0.299	0.288	0.307	0.335
Sept-March Sample						
Current Shock	0	-0.09	-0.046	-0.068	-1.895	3.705
	(0.045)	(0.098)	(0.039)	(0.092)	(1.691)	(2.959)
Seq. Shock	-0.171	-0.307 **	-0.179 *	-0.17	-6.087 *	0.069
	(0.113)	(0.144)	(0.099)	(0.137)	(3.357)	(4.418)
Aid	0.105	-0.311	-0.175	-0.274	2.039	9.354
	(0.2)	(0.267)	(0.177)	(0.225)	(7.115)	(8.113)
Aid * Current Shock	-0.485 **	0.147	-0.056	0.271	-6.329	-9.759
	(0.243)	(0.291)	(0.228)	(0.266)	(8.02)	(9.095)
Aid * Sequential Shock	0.413	0.874 ***	0.479 **	0.475 *	14.873 **	5.288
	(0.288)	(0.309)	(0.223)	(0.259)	(7.265)	(9.179)
# of Obs.	1968	1068	1968	1068	1968	1068
R2 (within)	0.323	0.215	0.225	0.224	0.233	0.198
R2 (between)	0.598	0.524	0.42	0.41	0.592	0.546
R2 (overall)	0.549	0.411	0.359	0.327	0.505	0.401

Notes: ***/**/* denote statistical significance at 1/5/10 percent respectively. Standard Errors in parentheses. **Current Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock *only* in the current period, and 0 otherwise. **Sequential Shock** is a dichotomous variable that is equal to 1 if the household has been exposed to a weather shock in consecutive periods, and 0 otherwise.

5. Conclusion

In this paper, our ultimate objective was to uncover the impact of weather shocks and aid receipt on household consumption outcomes. To do so, we first looked at where weather shocks had the largest impacts on maize yields, as we expect that negative impacts will occur primarily through lower agricultural outcomes. Point estimates give substantial negative impacts of droughts ranging from 33% to 40% across the two samples, and even greater negative impacts of floods ranging from 47% to 54% across the samples. We next considered the relationship between predictors of maize yields and WFP distribution rates, since we expect that well-targeted distribution would occur where maize yields suffered most. There are a number of different GIS-based data sources and specific variables on which to construct measures of droughts and floods, and our analysis suggests that using different variables from different sources matters when defining droughts and floods. This is important because geographic targeting of aid distribution is also based in part on specific GIS-based weather shock variables. Our results show that weather shock variables that explain maize yields do not explain aid distribution. Even more disconcerting is the fact that two rainfall variables that explain aid distribution also have significant impacts on maize yields, but exactly in the opposite direction vis-à-vis the expected impacts. These results suggest that there were significant geographic targeting errors.

Subsequently, we estimated the households' probability of aid receipt, and aid receipt interacted with a weather shock. Those living in areas subject to a weather shock and with higher WFP distributions were more likely to receive food aid, as we expect. However, the interaction between aid distribution and the weather shock was not significant. The targeting errors also explained household aid receipt, indicating errors of exclusion (negative impact on aid receipt for households subject to weather shocks in poor districts with limited aid distribution) and errors of inclusion (positive impact on aid receipt for households not subject to weather shocks in non-poor districts with positive aid distribution). At the household level, we documented that households headed by women and those with all elderly members were more likely to receive aid, as were less wealthy households. However, looking at the probability of receiving aid under a weather shock, we showed that wealth no longer had a significant negative impact. The latter results suggest that applying wealth criteria at the community level was not effective under weather shocks, which likely reduced access to aid by poorer households.

We then evaluated the impact of weather shocks and aid receipt on six consumption outcomes, non-food consumption per capita, value of food consumed per capita, food purchases per capita, calories per capita, the food consumption score, and school participation rates for households with school-aged children. We documented consistent negative impacts of weather shocks on a range of consumption outcomes, particularly for those households subject to sequential weather shocks. Interestingly, the ALNAP (2003) document discusses sequential and concurrent shocks in the context of targeting vulnerable households, but it does not yet seem to be operationalized as a targeting criterion.

We also showed some impacts of aid receipt, again particularly for those households subject to sequential shocks. For the FIAS sample, aid led to 20% greater non-food expenditures and enabled households to maintain food purchases under sequential shocks. For the IHPS sample, aid increased the food consumption score and school participation rates under sequential shocks. However, we found limited impacts on the value of food consumed or calories per capita. When we restricted the samples to only include relatively poor households or to only those interviewed from September to March (months when most weather-shock based WFP distributions were made), we documented positive impacts of aid under sequential shocks on value of food consumed and calories per capita.

On the whole, our results suggest that those involved in determining which geographic locations require aid distribution should revisit the weather variables, data sources and model parameters used as part of the larger decision-making process. As more household data continues to become available, further research can improve the ability of governments and their aid relief partners in improving geographic targeting under extreme weather events, which will become ever more crucial as impacts of climate change intensify.

With respect to local-level targeting, in areas that do experience a weather shock, more emphasis needs to be placed on ensuring that wealth levels continue to be used to select recipient households. It may be that under extreme weather conditions, all households, irrespective of where they are on the income gradient, face large losses that local leaders can feel sympathy for, but of course poorer households will be far less able to smooth consumption with existing assets. Our results also suggest that having babies and infants or a disabled household member does not predict aid receipt even though these are targeting criteria. At the same time, these two characteristics also do not lead to worse consumption outcomes. It may be that these characteristics have no additional explanatory power, once other criteria – such as being in a relatively poor household with elderly adults or headed by a woman – are controlled for. It may be worth further evaluating the value of these criteria in targeting aid beneficiaries and also determining if other variables may better predict low consumption outcomes, such as recently experiencing additional idiosyncratic shocks, including loss of employment.

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