WPS8667

Policy Research Working Paper 8667

Extreme Weather and Poverty Risk

Evidence from Multiple Shocks in Mozambique

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WORLD BANK GROUP
Poverty and Equity Global Practice
December 2018

Abstract

This paper investigates the effects of multiple weather shocks on household welfare in Mozambique, as well as some of the coping responses and price mechanisms at play. The analysis employs a triple-difference strategy that exploits variation in the shocks across space, time, and cropping cycles. The findings demonstrate high levels of vulnerability across various weather risks. Experiencing a cyclone, flood, or drought leads to a drop of up to 25–30 percent in per capita food consumption and around 0.4 fewer meals per day per person. Poverty increased by 12 and 17.5 percentage points in two of the three events analyzed. Human capital accumulation, as measured by school participation and morbidity, is disrupted. Households follow risk-coping strategies, such as increasing the labor supply of their children or selling assets, which entail partial protection in the aftermath of the shock at the cost of lower income growth in the future. In disentangling the channels, the paper shows that maize prices exhibit higher volatility in food markets that are spatially close to the most affected areas. The results are robust to several robustness checks, including analysis of bias from selective migration, and indicate that household welfare and economic mobility in low-income environments are constrained by uninsured weather risks.

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Extreme Weather and Poverty Risk: Evidence from Multiple Shocks in Mozambique*

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JEL Classification: I3, J2, O1
Keywords: Natural disasters, long-term human welfare, poverty, human capital.

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1. Introduction

Weather variability characterizes the livelihoods of individuals in agrarian economies. Uninsured weather risk is a significant cause of fluctuations in household consumption in low-income environments with incomplete credit and insurance markets. Due to limitations on consumption smoothing mechanisms, high weather variability induces lower efficiency since risk averse, uninsured households tend to opt for investment portfolios that exchange lower risk exposure for lower average returns. In dealing with extreme weather ex post, households also engage in suboptimal risk coping strategies such as depleting productive and basic non-productive assets or cutting back on investments in human capital. Community or extended family risk sharing mechanisms are ineffective for managing covariate risks such as excess rain, droughts, freezes, and high winds. It is therefore expected to see that household well-being in these contexts is particularly vulnerable to extreme weather events, especially when farming remains a major source of income.

The evidence on the relationship between weather anomalies and a wide range of economic outcomes has been growing fast (Dell et al. 2014). This body of research includes studies that examine how extreme weather influences key dimensions of household welfare such as income, expenditures, health, labor productivity, and agricultural investments, among other outcomes. The standard approach for identifying causative effects in this strand of the literature is to exploit geographic variation for one extreme realization of the climate distribution (for example, a drought in a given year) using panel or cross-sectional methodologies with pre- and post-shock data. In this paper, we extend the scope of this approach by looking at three spatially and temporarily independent weather shocks to more broadly document the vulnerability of households to different types of uninsured weather risks, as well as coping responses and channels. Looking at multiple shocks while keeping the population and economic context "constant" strengthens the external validity of the empirical relationship between weather risk and household well-being.

The analysis of this paper is performed for Mozambican households over the period 2002-2008. Mozambique provides an interesting setting for this study. The country has recorded strong economic growth in the last two decades, which boosted the incomes and living standards of part of the population, chiefly in urban areas. Notwithstanding this progress and a slow economic

transformation towards modern sectors such as manufacturing and services, the country continues to depend largely on the agricultural sector for national production and above all employment. Agriculture accounts for about a quarter of the GDP and provides work for over 70% of the labor force. Around 8 in 10 rural households are smallholders primarily engaged in subsistence agriculture.

Mozambique is also a risk-prone country. It ranks third among African countries exposed to risks from multiple weather-related hazards such as flooding, epidemics, cyclones and droughts (IFRC 2014). Nearly a quarter of the population lives in areas with high probability of experiencing a natural disaster (World Bank 2018a). Intense droughts are experienced in 7 out of 10 years in the Southern Region, and in 4 out of 10 years in the Central Region. The Mozambican coastline borders one of the most active basins of tropical cyclones. Floods generally occur every two or three years, mostly during the rainy season and along the nine major international river systems that cross the country or across the low-lying, densely-populated coastal areas (World Bank, 2012). Climate change is expected to intensify these trends. The average likelihood that a tropical storm will impact an enumeration area included in the Mozambican Integrated Agricultural Survey during the country's nine-month storm season increased by a factor of four between 1968-1990 and 1991–2015 (World Bank 2018a).

We employ a triple-difference strategy that exploits variation in the shocks across space, time and cropping cycles using detailed information from household surveys, remote sensing data on weather outcomes and the geographic distribution of the main cropping cycles across the country. The shocks analyzed include 1) the floods that occurred between late 2006 and early 2007 along the Zambezi River Basin, 2) a category 3 cyclone (Jokwe) that struck northeastern Mozambique between March 8 and 18, 2008, and 3) a drought that affected parts of central and southern Mozambique between May 2005 to January 2006.

The findings demonstrate high levels of vulnerability. Irrespective of the type of weather anomaly, food security is systematically undermined among affected households. Experiencing any of the shocks leads to a drop of up to 25-30% in per capita food consumption and 0.4 fewer meals per day per person. Conservative back-of-the envelope calculations suggest that the shortfall in food consumption may be equivalent to a daily caloric reduction in the order of 150-200 calories

per person. Affected households also cut back on expenditures in basic non-food items. Taken together, the reduction in consumption pushed a large share of households below the poverty line – poverty increased by 12 and 17.5 percentage points after the 2005 drought and the 2008 Cyclone Jokwe, respectively. Human capital accumulation is also largely sensitive. Either as a coping response or because of a lower supply of education services – or a combination of both, affected children are less likely to attend school. Children ages 5 to 17 in flooded areas at the time of the cropping cycle show 8.3 percentage points lower school participation relative to comparison children. Changes in health outcomes also point in the same direction. Morbidity rates for children rose steeply, increasing by more than fourfold in flooded districts.

Households are also found to follow other costly coping strategies that entail partial protection in the aftermath of a disaster at the cost of lower income growth in the future. Like adults, children in households undergoing severe hardship after a disaster often seek to increase their supply of labor as an attempt to supplement their incomes. Asset holdings are depleted by between 20% and 30%. These responses have welfare implications in the long-term. Lower human capital (lower school attendance, weaker health, etc.) and reduced asset ownership carry dynamic costs, possibly trapping households in poverty (Carter and Lybbert 2012).

The evidence also shows that weather shocks are important in explaining food price variability. Prices of maize, the staple most widely produced and traded in Mozambique, are found to fluctuate relatively more in food markets that are geographically close to the areas more directly hit by the disasters. In the case of the drought that took place between 2005 and 2006, for instance, prices rose by up to 78.9% for a reduction of a standard deviation in the precipitation index. The inflationary effects started to dissipate 9 months after the beginning of the shock, but prices remained 29.3% higher one year after the onset of the drought. It is plausible that higher food price effects contributed to drive food insecurity and reduced household consumption among net buyers.

This report is structured as follows. Section 2 presents the empirical strategy and data sources used to empirically estimate the direction and size of the effects of extreme weather. Section 3 presents and discusses the main results of the analysis. Next, Section 4 presents the results of some robustness tests. Finally, section 5 concludes by summarizing the findings and discussing policy recommendations.

2. Research Design

2.1 Identification Strategy

The central goal of this paper is to empirically estimate the impacts of three different types of weather shocks (floods, storms and droughts) on variables related to household well-being such as food, non-food consumption and total consumption, and poverty and on proxy indicators of inputs that contribute to building human capital such as school attendance and child morbidity. Establishing these empirical relationships in a causal sense is far from straightforward as it requires variation in exposure to extreme weather that is independent of unobserved household-level heterogeneity and spatial or temporal confounds. In addition, for the external validity of the findings, it is necessary that the context (demographics, location, economic systems, risk exposure, etc.) of the population analyzed is relatively representative of the livelihoods of a typical household in Mozambique.

To attain identification, we exploit three separate quasi-experimental designs (one for each of the three natural disasters) using triple difference econometric estimation. The source of variation for the first difference originates from temporal changes in the incidence of weather shocks. Although Mozambique is rather vulnerable to natural disasters, they do not occur every year in the same place. The second difference is obtained from spatial variation in the location of the natural disaster. While some districts are hit by natural disasters at some point in time, others are not. Given the importance of agriculture in determining the livelihoods of the population, the third control structure exploits variation in the seasonality of the cropping cycles across affected and non-affected areas. Since most agriculture in Mozambique is rainfed, it matters if excess or lack of rainfall and strong winds arise during the key stages of the growth and harvest cycle or outside of it. Because of the variation in the growing cycles for the same crops, the types of crops planted and the occurrence of shocks throughout the year, the “sensitive” periods of the crop cycles vary across districts and crops.

The triple difference strategy used in this paper compares households in affected localities for whom the timing of the shock overlaps with the growing cycle of their main crops relative to those in the same locality but whose crops are outside the relevant agricultural cycle. The latter group is expected to provide a cleaner comparison group than traditional contrasts in the literature based

on standard double-difference analysis, where households from areas that undergo weather shocks (treatment units) are compared against households from unaffected areas (control units) over time. The underlying assumption for the identification of impacts under the triple-difference analysis is also less restrictive. It simply requires that there be no contemporaneous shocks that affect the relative outcomes of treatment households in the same district-growing cycle-years as the natural disasters.

Following the triple difference approach outlined above, the impacts of the weather shocks on the outcomes of interest are estimated as follows:

$$Y_{ijt} = \beta_1(A * S * G)_{jt} + \beta_2(S * G)_j + \beta_3(A * S)_{jt} + \beta_4(A * G)_{jt} + \partial_1 A_t + \partial_2 D_j + \partial_3 X_{ijt} + \varepsilon_{ijt} \quad (1)$$

Where i indexes households, j indexes districts (J =128) and t indexes years (1 if after the shock, 0 if before). Y is the outcome of interest, for instance household per capita consumption, A is a fixed year effect, S is a standardized weather shock indicator at the district level, G is a fixed effect for districts where the typical agricultural growing cycle matches the time of the shock, D is a district fixed effect, X is a vector of observable household characteristics such as gender and age of the household head and area of location (urban or rural). The term ε_{idt} denotes a zero-mean error term. The parameter of interest, β_1, captures the variation in the outcome variable Y specific to households in districts affected by extreme weather (relative to unaffected households) in areas where the timing of shock overlaps with the cropping cycle (relative to areas where shocks occur outside the growing cycle) after the shock (relative to pre-shock years). All standard errors are clustered at the district level.

Finally, we employed the following model to estimate the magnitude and timing of the effects on food prices:

$$Log(P_{it}) = \sum_{m=1}^{12}(\gamma_m S_{it} * I_m + I_m) + \alpha_i + \beta_t + \alpha_i * \beta_t + \varepsilon_{it} \quad (2)$$

Where S_{it} is the weather shock experienced in market *i* at time *t*. S_{it} takes value one if any of the districts within the radius experienced a shock, namely recording a z-score greater than 1.5 for the floods and the storm, and below -1 for the drought. I_m is a monthly indicator variable, α_i are market

fixed effects, which control for all time-invariant market specific determinants of prices, β_t are year fixed effects, and ε_{it} are other time-varying, location-specific shocks to prices. Coefficients γ_m capture the monthly impact of disaster on prices, interpreted as the 100*γ_m percent change in prices associated with a standard deviation of the weather index.

2.2 Data

Household-level data

Household-level information is used to construct both outcome variables, such as household per capita consumption, children's school attendance, among others, as well as control variables, including demographic structure, family composition, school attainment, gender and age of household heads, and area of location, etc. These data come from the national household survey of living conditions (*Inquérito aos Orçamentos Familiares*, known as IOF for its acronym in Portuguese), collected over a 12-month survey period by the National Statistics Office of Mozambique (Instituto Nacional de Estatistica, INE). We use three waves of the IOF survey: the IOF 2002/03 (collected between July 2002 and June 2003), the IOF 2008/09 (collected between September 2008 and August 2009) and the IOF 2014/15 (collected between August-2014 and July-2015). The 2002/03 and 2008/09 IOFs are cross-sectional surveys whereas the latest one, the IOF-2014/15, was designed and implemented as a panel survey but used as pooled cross section for the purposes of this analysis.[1]

All IOF surveys are representative at the national, rural-urban, and provincial levels. The information collected by these surveys captures the main variables included in the regression analysis, such as household welfare (total, food and non-food consumption, and poverty status), education, labor outcomes, health, morbidity, food security and possession of assets. The IOF 2002/03 interviewed 8,700 households and provides the baseline information for shocks that occurred between 2003 and 2007. The IOF 2008/09 visited 10,832 households and provides the baseline information for the shocks that took place between 2009 and 2013. Finally, the IOF 2014/15 provides the follow-up data for 10,369 households.

[1] The 2014/15 survey was originally designed to interview over 11,000 households four times (once in each quarter) during a 12-month survey period starting in August 2014 and ending in July 2015. Yet, due to logistical and budget constraints, the survey was carried out only during three quarters: Q1 (August-October), Q2 (November-January) and Q4 (May-July).

Market-level data

Maize price effects are estimated using price data from the Agricultural Market Information System (SIMA), which is run by the Ministry of Agriculture of Mozambique. The database tracks weekly retail prices for a range of core agricultural products (particularly maize, cassava, rice and beans) in 25 markets in cities and towns spread across all provinces in Mozambique.

Weather data

Determining historical weather distributions as well as the timing, intensity and spatial location of anomalies requires long time series and spatially disaggregated data on weather observations. We first listed all weather-related natural disasters that took place in Mozambique within the time frame determined by the dates of the household surveys (IOFs) using the disaster profile information publicly available in the International Disaster Database (EM-DAT 2018). In addition to providing information on the timing, geographical coverage, and human impact of the disasters, the EM-DAT database provides estimates of their economic damages.[2]

In a second stage, we initially cross the long list of floods with daily precipitation data recorded by the Tropical Rainfall Measurement Mission (TRMM) in the Multi-Satellite Precipitation Analysis (TMPA) for the period 2000 to 2012. These data have a resolution of 0.25 by 0.25 degrees, which in Mozambique corresponds to grids of approximately 25 by 25 kilometers (Huffman et al. 2007). In contrast to other high-resolution precipitation data sets such as CHIRPS and CRUTS, which combine remote sensing data with readings from weather, TMPA contains rainfall data based only from satellite records, ensuring consistency in the measurement methodology.

To obtain quantitative measures on the intensity and location of cyclones, we use daily wind speed data from the U.S. National Oceanic and Atmospheric Administration (NOAA) and the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS). This database stores wind speed records for the period 1950-2017 for grids with resolution of 0.25 by 0.25 degrees The GFS is a global weather forecast model that contains data on dozens of

[2] For a disaster to be entered into this database, at least one of the following criteria must be fulfilled: 1) 10 or more people reported being killed, 2) 100 or more people being affected directly by the event, 3) declaration of a state of emergency by the corresponding authorities and 4) a formal request for international assistance.

atmospheric and land-soil variables such as temperature, winds, soil moisture and atmospheric ozone concentration.

Finally, the area of influence and intensity of the droughts in Mozambique during the period of analysis is measured using weather data from the African Flood and Drought Monitor (AFDM) system. This is an initiative developed by Princeton University that monitors and forecasts meteorological, agricultural and hydrological droughts for countries in Sub-Saharan Africa. AFDM data span the period 1950-2015 and are also available with a resolution of 0.25 by 0.25 degrees (Sheffield et al., 2014).

Cropping cycle data

Agricultural production cycles are defined based on the temperature and moisture conditions suitable for crop growth across districts in Mozambique. The Harvest Choice Project developed by IFPRI provides information on the start and end dates of the growing cycle across countries in Sub-Saharan Africa with a 10km x 10km resolution. These data are derived from the Enhanced Vegetation Index (EVI) data set produced by the MODIS satellite images for the period 2001-2004. Since treatment is determined at the district level, we generate area-weighted averages of the start and end dates of the growing cycle for each of the districts in the sample.[3] Figure 1 shows the distribution in the number of days for the main cropping cycle across the country.

2.3 Weather Shocks

After validating the occurrence and spatial position of the weather shocks listed in the EM-DAT database using remote sensing data, we chose three extreme events based on their scale and timing with respect to the dates of the household surveys: 1) the floods that occurred between late 2006 and early 2007 along the Zambezi River Basin, 2) a category 3 cyclone (Jokwe) that struck northeastern Mozambique between March 8 and 18, 2008, and 3) a drought that affected parts of central and southern Mozambique between May 2005 to January 2006.

[3] We use only the between-district variation in growing cycles, which is substantially larger than the variation within districts. The standard deviations for the start and end dates of the growing periods are 72.8 and 226.7 days across districts (between-district variation) and 39.6 and 36.7 within districts (within-district variation).

The 2007 flood began in late December 2006 after the dam in the Cahora Bassa lake (situated in the Tete Province) overflowed following heavy rains in Northeastern South Africa. The flooding conditions worsened after heavy rains hit the area in February 2007 and the Zambezi river flooded parts of Zambezia, Tete, Sofala and Manica provinces. The devastating floods resulted in massive destruction of crops and public infrastructure, weakened food security and disrupted the provision of critical services. To measure the location and intensity of the floods, we first calculate daily rainfall averages for each grid within a district using TMPA data. Next, area-weighted averages are aggregated at the district level. Given that the floods unfolded over 2.5 months, daily area-weighted averages are aggregated over this period to obtain cumulative rainfall values for each district. Finally, flood intensity is expressed in standardized z-scores of rainfall totals in the months of the disaster in 2007 using the historical distribution from the reference period 2000-2012 for each district. The first graph in the top (left to right) of Figure 2 shows the distribution of accumulated rainfall for the 2007 flood during the reference period.

The second event examined is Jokwe, a tropical cyclone that struck parts of Central Mozambique in March 2018, particularly Nampula province. Jokwe reached gusty winds of up to 270 km/h (165 mph) that jointly with heavy rains caused serious agricultural damage and destroyed schools, health centers, roads and housing. Storm intensity is defined in a similar fashion as flood intensity. Daily grid-level wind speed data are aggregated over the days of Cyclone Jokwe using area weights and expressed as Z-scores.[4] The second graph in the top (left to right) of Figure 2 shows the distribution of accumulated windspeed across the country during the reference period.

Finally, we investigate the impacts of a severe drought experienced in 2005. Several parts of Central and Southern Mozambique recorded large rainfall deficits. The most severe dry spells happened in January and February, overlapping with critical stages of planting and crop development in affected areas. Large crop losses, particularly of maize, led to weak food security conditions. We measure the intensity and location parameters of this drought using the one-month

[4] Gust wind speed is the more accurate information that can be used to measure the intensity and timing of storms and hurricanes. Gusts winds are measured as the average wind speed over a 2-3 seconds period. Using gust windspeed for this study requires data on the exact time (day/hour/minute/second) of the maximum windspeed to accurately track the path of the storm across districts. Data with this fine temporal resolution are not available for Mozambique. A second option, followed in this study, relies on the daily average wind speed, provided by the African Flood and Drought Monitor. The indicator measures the accumulated daily intensity over the days of the duration of the storm as reported by the EM-DAT database.

Standardized Precipitation Index (SPI) from the AFDM system. The SPI is calculated using data from the bias-corrected TMPA and hybrid observational reanalysis,[5] including data from 1950 to 2015. The SPI-1 is defined across districts and over time following an aggregation and standardization process analogous to the one employed for the rainfall and windspeed Z-scores. For ease of interpretation, the SPI district-level Z-scores are multiplied by negative -1 to invert the scale.[6] The graph at the bottom of Figure 2 shows the distribution of the SPI during the period of reference.

3. Results

3.1 Household consumption and poverty status

Evidence available in the literature illustrates the high levels of income and consumption variability in risky agricultural contexts (Dercon 2002). We first focus on the effects of exposure to each of the three weather shocks on food and total per capita consumption, a traditional measure of household monetary welfare. Since subsistence farming is widespread across Mozambique, the variable used to measure household food consumption includes not only the actual expenditures incurred in purchasing food items, both for food eaten at home and outside, but also self-consumption. Consumption from gifts and wages in-kind is also included in the calculation of the consumption aggregate. Consumption levels are valued using price data obtained from surveys of local markets that were fielded around the same time as the household survey. As noted above, all specifications include districts fixed effects, year fixed effects, agricultural growing cycle fixed effects, gender fixed effects (for individual-level regressions), and control variables such as age and urban status.

The first set of results of the triple difference estimation (equation 1) is presented in Table 1. The coefficients are expressed as the effect on the dependent variable of a change of one standard deviation in the shock intensity measure (Z-score). One interesting pattern in the findings is that the three shocks pushed exposed households to cut back on their food consumption – all the point

[5] Bias-correction and hybrid observational reanalysis methods are widely used to improve the accuracy of satellite data products by matching the moments of satellite observations with station observations where both types of data are available.

[6] Negative SPI indicates lack of precipitation, thus, a negative SPI with a large absolute value is associated with a more severe drought intensity. In order to be consistent with the other disasters interpretation (interpreting our coefficients as the impact of disasters as intensity increases) we multiplied the intensity by -1.

estimates of β_1 in columns 1, 3 and 5 are negative but two out of the three are statistically significant. The size of the impacts also indicates that the negative effects are quantitatively meaningful. Daily food consumption per capita fell by 1.85 meticais (corresponding to 24.8% of the median value at baseline) among households exposed to a one standard deviation of the shock intensity caused by the 2008 Cyclone Jokwe during the cropping cycle. Similarly, on average, food consumption per capita was 2.3 meticais (31.8%) lower for households hit by the 2005 drought.

Roughly speaking, the decline in food consumption attributed to the shocks translates into a decline of 150 to 200 calories per person per day,[7] enough to deteriorate the nutritional status of individuals at the margin of falling into malnutrition. Related to this, we explore whether food security worsened among households affected by the natural disasters. The outcome variable for this part is a proxy indicator that measures the average number of meals eaten per person per day. The results are in line with the observed decline in food consumption (Table 1, columns 2, 4 and 6). On average, the number of meals fell by 0.72 (2007 floods), 0.21 (Cyclone Jokwe) and 0.13 (2005 drought) by an increase of one standard deviation in the intensity of the shock. With an average baseline value of 3.35 meals per person per day, these effects amount to a reduction in the number of meals that ranges between 3.8% and 21.4%.

The negative effects of extreme weather on total (food and non-food) household consumption per capita are also evident in the data. The results are summarized in Table 2, columns 1, 3 and 5. Cyclone Jokwe and the drought reduced the total level of consumption among affected households by over half (54.8%) (-7.31/13.26) and 21% (-2.83/13.26), respectively, relative to the median consumption at baseline. The decline in consumption brought about by the shocks pushed some households below the poverty line, a threshold that defines the minimum consumption deemed enough to meet the basic food needs and other non-food essential expenditures of the average household in Mozambique.[8] The negative effects are not trivial (columns 2, 4 and 6). The floods led to a large increase in poverty in affected areas, 36 percentage points (66.6%) relative to baseline poverty. Similarly, the drought and the cyclone increased the poverty headcount by 12 and 17.5 percentage points (32% and 22%), respectively.

[7] Using calorie-income elasticities in the 0.2-0.5 range as reported by Strauss & Thomas (1995) and Subramanian & Deaton (1996).
[8] The poverty lines used in the analysis are 9.3 meticais in 2002/03 and 18.8 meticais in 2008/09 (World Bank 2018b).

3.2 Human capital

The analysis now turns the attention to the impacts of the three natural disasters on proxy determinants of human capital accumulation such as school participation and morbidity among children 5 to 17 years old. The first outcome variable is a binary indicator that measures regular school attendance for the two-week period preceding the household interview. The results are summarized in Table 3 and are presented for the entire group of children as well as split into two age groups (5 to 11 and 12 to 17) to investigate possible differences in impacts across children in primary and secondary school ages.

Results for the floods and the cyclone show large negative effects. Overall, children from households located in areas flooded overlapping the time of the cropping cycle were on average 8.3 percentage points less likely to attend school regularly relative to the comparison children (Table 3, column 3). With an average enrollment of 87.9% at baseline, this impact translates into a reduction of 9.4%. As shown in column 1 of Table 3, children ages 5 to 11, who are expected to be enrolled in primary education, bore the heaviest burden. Their attendance rates fell by 19.2 percentage points (20%). These impacts are in line with the direction –and even size– of the effects attributed to the cyclone. Children 5-17 years old from areas in the path of the storm during the relevant agricultural cycle are on average 8.6 percentage points (9.7%) less likely to go to school (Table 3, column 6). Yet, in contrast to the distribution of impacts attributed to the floods, the school attendance rates of children from both age groups dropped by 10-12 percentage points (10.4%-14.8%).

The effects of the drought on school attendance are not even across age groups. On one hand, primary school age children located in areas affected by the drought are found to attend school less regularly, on average, by 3.6 percentage points (3.75%) (Table 3, column 7). On the other hand, older children in the same areas increased their school attendance (8.8 percentage points or 11%) when compared against the school attendance trend for control children (Table 3, column 8). Since the impact coefficients are obtained from reduced-form estimation, it is challenging to disentangle the mechanisms driving the changes in opposite direction. However, given the slow onset nature of droughts –in contrast to the fast and often destructive development of cyclones, storms and floods, it is plausible that their effects on school participation are driven by demand-side factors.

One possible hypothesis is that the opportunity costs of attending school fall as the drought unfolds and more people, particularly older children and adults, engage in economic activities, reducing the incentives to withdraw children from secondary school.

The results on health outcomes indicate that natural disasters such as floods can create a breeding ground for increased child morbidity (Table 4). The results discussed above show that households tend to reduce their expenditures in the aftermath of a disaster, including possibly lower consumption of goods and services that improve health (staples, safe water, basic sanitation, preventive and curative health services, etc.). Floods and droughts also weaken health status through more direct channels. Floods, for instance, can potentially increase the communication of water-borne and vector borne diseases. In fact, the findings show that morbidity rates for children 0 to 17 years old increased more than fourfold in flooded areas, as measured by the effect of a standard deviation increase in rainfall (Table 4, column 1). Counterintuitively, we also find that child morbidity fell by nearly half in districts after the 2005 drought (Table 4, column 3). Further analysis is needed to understand what is driving the lower burden of disease in this case.

3.3 Household coping strategies

Households and individuals are known to engage in various formal and informal strategies to avoid consumption shortfalls caused by risk. They can follow (ex-ante) risk management strategies such as income diversification, namely engaging in activities that have low positive covariance, and income skewing, in other words, opting for lower-risk, lower return activities. Households and individuals can also employ formal and informal strategies to cope with the effects of risks after they materialize (ex-post). These risk coping strategies include informal group-based risk sharing (e.g. mutual insurance arrangements between households such as informal loans, gifts, transfers, labor pooling, children fostering, etc.), self-insurance or precautionary savings (saving income and food or building up assets in good years to buffer consumption in bad years) or attempting to earn extra income during periods of crisis. We examine whether affected households undergoing the hardship brought about by any of the disasters engaged in the following coping strategies: adjustments in the labor supply (extensive margin) of adult members and children, changes in productive and non-productive asset holdings, and informal risk sharing in the form of cash and in-kind transfers from households' networks.

Starting with the labor supply response, the results from estimating equation 1 provide an indication that household members, adults and children, are more likely to engage in paid and unpaid work after the disaster (Table 5). The effects are particularly strong in the case of the floods. Individuals 18 to 65 years old are 33 percentage points more likely to be either working or actively looking for work (Table 5, column 1). Younger individuals (ages 5 to 17) also exhibit a remarkably higher participation in the labor market (paid or unpaid work) or in household chores, corresponding to 45.4 percentage points or a fourfold increase relative to baseline values (Table 5, column 2). A similar response is observed among households that were in the path of the cyclone at the time of the relevant cropping cycle. The effects in this case are, however, concentrated among children. Their labor supply increased by 8.7 percentage points (79 percent) (Table 5, column 4).

The findings summarized in Table 6 also reveal the possibility of changes in the ownership of assets among affected households. To explore this, we constructed an asset wealth index based on the asset holdings observed in our sample using principal component analysis. We include the ownership of the following assets: cell phone, stove, TV, fridge, computer, motorcycle, car, telephone, iron, bed, bike and radio. After obtaining the principle component, we further normalize it into an index that ranges from 0 to 100, where 0 stands for having the least amount of assets and 100 means having the most amount of assets. Households affected by the cyclone and the drought show a reduction in the asset wealth index of about one-third in the former (-5.38/15.62) and 18.6% in the latter (-2.91/15.62). These effects are quantitatively large but marginally significant in the statistical sense. It is not possible to disentangle if the reduction in asset ownership that took place in the context of Cyclone Jokwe was driven by the damages caused by the disaster, the need of households to sell off some assets (e.g. productive assets, livestock, etc.) or both. However, in the case of the drought, a phenomenon with far less direct destructive power on assets (except on livestock), it is more plausible to think that households undergoing the hardship triggered by the disaster had to deplete some of their assets to avoid a larger drop of their consumption.

Finally, the results point to an increase in the movement of transfers flowing into households from affected areas, possibly signaling risk sharing between members of informal mutual insurance pools. The outcome indicator for this part of the analysis is a binary variable that

identifies households that report receiving transfers (e.g. gifts or loans) from other households.[9] The magnitude of the increase is particularly strong after Cyclone Jokwe. The point estimates, presented in Table 6, indicate that treated households were almost twice as likely to receive transfers compared to the levels recorded in baseline. This corresponds to an increase of 11.2 percentage points, relative to a baseline value of 12.4%. The receipt of transfers also rose (by approximately 50%) after the drought – the coefficient of interest shows an increase of 6.6 percentage points.

3.4 Food crop prices

We use data on food prices from markets across the country to investigate both the degree to which prices respond to weather shocks and the extent of the impacts. Agriculture in Mozambique is largely traditional, practiced mostly by smallholders that rely on rainfall for water and have low input utilization and technology adoption. Hence, extreme weather is expected to disrupt crop yields, triggering supply- and demand-side effects in food markets. Moreover, the livelihoods of rural households are largely linked to crop performance either for self-consumption or market transactions. Food price volatility also matters for urban dwellers, the majority of which are net buyers. Even in rural areas most farmers tend to be net buyers of food (Baez et al 2018). While the overall perception is that weather shocks are inflationary, the direction of the change is an empirical matter since the supply and demand effects are expected to push food prices in opposite directions.

We focus on maize prices for several reasons. First, maize is the staple most widely produced and marketed. Data from 2015 show that about 72.5% of farmers cultivated maize. Maize production represented 77% of the domestic production of cereals during the period 2010-2015. Second, maize yields are highly determined by weather conditions. The total production in a given year is a function of the timing and quantity of rain. Third, maize constitutes a significant part of the Mozambican diet. While an average household in Mozambique spends nearly 25% of its food budget in maize, this budget share is higher among rural households. Because of the limited availability of storage (within season and inter-annually) and other inventory smoothing

[9] The survey does not ask any information (geographic location, family or ethnic ties, etc.) about the households and the motives for the transfers.

mechanisms, most of the crop that is commercialized (around 20% of the total output) is sold shortly after harvest. Therefore, maize prices show strong seasonal variation due to the timing of the production cycle, usually peaking between December and March. Transaction costs between markets are considerable (World Bank, 2018a).

Results of the month-price effects (γ_m in equation 2) are presented in Figure 3 and Table 7. Overall, the findings indicate that maize prices in markets close to affected areas are very sensitive to the occurrence of weather shocks. Yet, the direction and persistence of the effects depend on the weather shock and the timing of the event with respect to the crop cycle. In the case of the drought in 2005, the findings show that prices begin to rise as the shock unfolds following the harvest season and peak at month 9, increasing by 78.9% per a reduction of a standard deviation in the precipitation index. After this, the inflationary effect begins to dissipate. However, a year after the onset of the drought, maize prices remained 29.3% higher in markets within a 50-kilometer radius from affected villages compared to markets in areas less or not affected. The upward trend for the price effects associated to Cyclone Jokwe (2008) is quite similar although the increase in maize prices starts to level off and reverse earlier.

The pattern of the effects associated with the floods in 2007 is the opposite. The point estimates show a reduction in maize prices of up to 46.9% in affected areas during the first three months following the disaster. This interval of time overlaps with the lean season in affected areas, a period where the demand-side effects brought about by the shock are likely strongest. The results show that the deflationary pressure starts to dissipate as the harvest season progresses and the supply-side effects begin to take effect.

4. Robustness Analysis

This section presents results of tests performed to check the robustness of the main findings. One of the threats to the internal validity of the study lies with the definition of treatment, namely the triple interaction (*Shock* x *After* x *Growing Cycle*), which may be capturing changes in the outcomes of interest caused by factors other than the weather anomalies, or simply a spurious relationship. The lack of comparable household surveys to measure the outcome variables for at least two data points over a pre-shock period forbids testing the identifying assumption of common

trends. While not a substitute for that test, we performed a series of placebo checks to assess the robustness of the findings to the definition of treatment. The placebos consist of re-estimating the empirical model of equation 1 using "fake" treatments that were generated by randomly shuffling the spatial location of the disasters. These "fake" treatments were performed 100 times for each of the three natural disasters. The results of this robustness checks show that, on average, only around 5% of the point estimates of the triple difference parameter are statistically significant and have the same sign as those obtained using the "true" geographical location of the shocks. Figure 4 illustrates the results of these pseudo-treatments on food consumption per capita, total household consumption per capita and poverty status for each of the natural disasters analyzed. Most of the point estimates from the placebos are not statistically distinguishable from zero.

The regression results of this paper are based on the location of a household at the time of the survey. A concern is the possibility of selective migration, namely that households with certain characteristics (for instance, higher incomes or expenditures, more parental education, larger extended networks, etc.) were systematically more or less likely to move out of affected areas after the weather shocks but before the survey was in the field. This would hinder the comparability of the treatment and control groups before and after the shock, creating a potential bias in the estimates. Several steps were followed to assess the extent and consequences of non-random migration. First, the evidence in the sample suggests that the three events are indeed associated with the probability to migrate (Table 8). The direction of the effect, however, varies across them. Whereas households from areas affected by the floods and Cyclone Jokwe reported to be less likely to migrate, those from treatment areas surveyed after the drought were more likely to change their place of residence after the shock.[10] Overall, however, the share of migrant households in the sample is small (2.5%).

In a second step, we compared non-migrants and migrants at baseline on a range of observable characteristics arguably related to household well-being (consumption, education, assets, etc.). On average, migrant households are better off than non-migrants, something that could potentially lead to an upward bias in the estimates of β_1. To address this issue, we reclassified all households that lived elsewhere during and after the shocks as residing in affected areas. Recoding these

[10] The direction of these effects is in line with findings from previous literature (Baez et al. 2017b).

control units of analysis as treated households is a conservative way to bound the direction of the main regression results because some of the households that moved in the post-shock period may have in fact lived in non-affected areas. Table 9 summarizes the effects on food and total household consumption per capita and poverty status estimated on this modified sampled.[11] All the findings hold (qualitatively and quantitatively) after the regressions are re-estimated on a sample where migrant households are reclassified as non-migrant units of analysis.

Finally, we exploited a different natural experiment as an additional robustness check. This natural experiment is generated by the severe floods that affected Zambezia, Nampula and Niassa provinces in central and northern Mozambique in early 2015. Weeks of heavy rainfall in December 2014 and January 2015 caused several rivers to swell, flooding several parts of districts in these provinces. The floods inflicted significant damage to crops as well as to public and private infrastructure, including roads, bridges, schools, health centers, telecommunication networks and housing. On January 12, 2015, the Government of Mozambique declared an institutional red alert for the affected areas of the country.

We run the triple difference model specified in Equation 1 to investigate if the negative effects identified for the floods in 2007, Cyclone Jokwe 2008 and the droughts in 2005 are observed again among the population exposed to a natural disaster that occurred a few years after. The empirical model for this event is implemented using data from the IOF survey 2014/15. Given the timing of the 2015 floods, we use as baseline the first wave of the survey (collected between August and October 2014) whereas the third wave (collected between May and July 2015) provides the post shock data point. Given the spatial part of the source of variation used for identification (*Shock* x *Cycle*), this analysis uses the cross-sectional rather than panel nature of the data.[12] The results, summarized in Table 10, show that the floods in 2015 also led to short-term negative impacts that resemble the direction of the effects identified in the base models. The only exception is a positive point estimate for the effect on consumption per capita although this happened along with an increase in the overall poverty rate. A closer look at the data reveals that the average increase in consumption in the treated districts was largely driven by a large increase in consumption for

[11] Results from the other outcomes are available from the authors upon request.

[12] Household fixed effects estimation requires within-household variation of shock intensity over quarters. There is almost no variation of this short variation in the sample used for this analysis since there are only a few households that migrated between affected and non-affected districts in the period from Q1 to Q4.

households in the top (7th and 8th) deciles of the pre-shock distribution, something that requires further inspection.

5. Conclusions

Risk is an inherent aspect of day-to-day daily lives, particularly so for societies that rely largely on agriculture for their livelihoods. Few other sectors are as exposed or vulnerable to a wide array of shocks ranging from natural disasters, erratic rainfall, extreme temperatures, pests and diseases, and crop failure, among other risks. The projected scenarios of climate change will only exacerbate these risks and the stress that they place on agricultural systems. This paper empirically investigates the short- and medium-term consequences of three types of natural disasters (floods, cyclones and droughts) in Mozambique on proxy variables of household welfare (consumption, food security and poverty status), human capital accumulation (school attendance) and household coping responses (labor supply, management of basic productive and non-productive assets and group-based risk sharing). Looking at three spatially and temporarily independent weather shocks for the same population and economic context allows testing the external validity of the empirical relationship between weather risk and household well-being, which is often based on studies that look at one natural disaster in isolation.

The findings show that household welfare is systematically affected by different types of natural disasters. Affected households are consistently found to cut back on basic consumption of food, non-food expenditures and even durable goods. The effects are not trivial. Reductions in food consumption, for instance, are in the order of 25-30% range, raising the risk of food insecurity. Households also reduce consumption on items beyond food. Total consumption per capita of households in the direct area of influence of the drought in 2005 recorded an average decline of 21%, increasing the poverty headcount by 12 percentage points. In disentangling the mechanisms at play, we show that food prices (proxied by prices of maize, the most important staple) exhibit higher volatility in markets geographically close to the most affected areas.

Children's human capital accumulation is also at risk. The empirical findings show that children 5 to 17 years old from households located in areas flooded in early 2007, overlapping the time of the cropping cycle, were on average 8.3 percentage points less likely to attend school regularly relative to the comparison children. Although the empirical strategy and data used in this

study do not allow teasing out whether demand- and/or supply side factors are behind the reduced school participation, the negative effects on attendance causally related to the drought hint at household risk coping motives as a key driver. An examination of health outcomes for children also indicates that floods increase the burden of disease. Morbidity rates for this group rose steeply, increasing by more than fourfold in districts flooded in 2007 during the cropping cycle.

Households adopt other risk coping strategies that entail partial protection in the aftermath of the shock at the cost of reduced income growth in the future. Tracking changes on a composite measure of wealth based on basic productive and non-productive assets, we find evidence of asset depletion among affected households. The fact that the drop in the wealth index is also seen among households affected by the 2005 drought, a phenomenon characterized by having limited direct damage on physical assets (except livestock), suggests that the need to sell some assets may have been the main mechanism at play.

The evidence of this paper indicates that strong and repeated uninsured climate risks will not only have sizable welfare effects in the short term but also set the most vulnerable households in lower income trajectories. Three overarching objectives could guide policy to increase resilience in this context. First, it is necessary to increase (ex-ante) the protection of households to reduce the probability and size of bad outcomes. That protection can arise from investments in services required to build human capital and public capital such as increased provision of education, water, immunization, transportation, communications and information, including early warning systems. A second objective is to address market failures that undermine the functioning of critical markets for risk management in agricultural settings, including markets for inputs, outputs and viable credit and insurance mechanisms. Finally, considering that the frequency and severity of shocks is projected to increase, ensuring minimally acceptable standards of living during crises hinges on the availability of scalable safety nets.

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Table 1. Effects of weather shocks on food consumption and number of meals

Variable	Floods (2007)		Cyclone Jokwe (2008)		Drought (2005)	
	Food consumption (1)	Number of meals (2)	Food consumption (3)	Number of meals (4)	Food consumption (5)	Number of meals (6)
Shock x After x Growing Cycle	-0.794	-0.722***	-1.858***	-0.215***	-2.330***	-0.138***
	(0.645)	(0.015)	(0.635)	(0.040)	(0.695)	(0.040)
Shock x Growing Cycle	6.373***	0.130	0.980	0.815***	-3.302	0.223
	(0.822)	(0.097)	(1.217)	(0.061)	(2.166)	(0.217)
Shock x After	-0.076	-0.020	-0.628**	-0.015	-0.018	-0.000
	(0.275)	(0.013)	(0.274)	(0.015)	(0.383)	(0.014)
After x Growing Cycle	1.533***	-0.277***	0.504	0.029	-0.555	-0.158***
	(0.425)	(0.013)	(0.448)	(0.029)	(0.459)	(0.030)
Constant	9.015***	3.179***	7.239***	3.522***	8.799***	3.193***
	(0.318)	(0.035)	(0.883)	(0.031)	(0.322)	(0.035)
R-squared	0.029	0.442	0.029	0.442	0.030	0.444
Outcome mean at baseline	13.266	3.355	13.266	3.355	13.266	3.355
Observations	19,453	19,453	19,453	19,453	19,453	19,453

Note: Consumption variable defined in per capita terms. Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data

Table 2. Effects of weather shocks on total household consumption per capita and poverty status

Variable	Floods (2007)		Cyclone Jokwe (2008)		Drought (2005)	
	Total consumption (1)	Poverty status (2)	Total consumption (3)	Poverty status (4)	Total consumption (5)	Poverty status (6)
Shock x After x Growing Cycle	7.483	0.360***	-7.313***	0.175***	-2.834**	0.120***
	(6.528)	(0.019)	(2.727)	(0.051)	(1.354)	(0.041)
Shock x Growing Cycle	-1.497	0.192*	-2.039	0.125	1.396	0.012
	(4.345)	(0.107)	(2.778)	(0.142)	(3.964)	(0.266)
Shock x After	0.303	-0.018	0.443	0.004	0.764	0.025
	(0.743)	(0.017)	(0.735)	(0.015)	(0.878)	(0.021)
After x Growing Cycle	10.257***	-0.028*	2.474	-0.092***	0.042	-0.022
	(3.919)	(0.015)	(1.740)	(0.026)	(0.987)	(0.027)
Constant	11.236***	0.542***	9.097***	0.677***	10.659***	0.565***
	(0.949)	(0.037)	(1.473)	(0.102)	(0.870)	(0.031)
R-squared	0.063	0.142	0.063	0.142	0.063	0.144
Outcome mean at baseline	13.266	0.545	13.266	0.545	13.266	0.545
Observations	19,453	19,453	19,453	19,453	19,453	19,453

Note: Consumption variable defined in per capita terms. Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data

Table 3. Effects of weather shocks on the school participation of children across age groups

Variable	Floods (2007)			Cyclone Jokwe (2008)			Drought (2005)		
	School attendance children ages …			School attendance children ages …			School attendance children ages …		
	5-11	12-17	5-17	5-11	12-17	5-17	5-11	12-17	5-17
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Shock x After x Cycle	-0.192***	0.024	-0.083*	-0.102**	-0.128**	-0.086***	-0.036**	0.088***	-0.004
	(0.018)	(0.063)	(0.050)	(0.043)	(0.017)	(0.026)	(0.017)	(0.030)	(0.018)
Shock x Cycle	-0.007	0.086	0.002	-0.064	-0.048	-0.004	-0.331***	-0.148	-0.259*
	(0.033)	(0.064)	(0.047)	(0.077)	(0.084)	(0.071)	(0.058)	(0.214)	(0.148)
Shock x After	-0.039***	0.001	-0.032**	-0.031***	0.016	-0.018*	0.049***	-0.011	0.038***
	(0.011)	(0.013)	(0.013)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.013)
After x Cycle	-0.100***	-0.035	-0.070**	-0.056**	-0.076***	-0.060***	-0.062***	-0.057***	-0.077***
	(0.009)	(0.037)	(0.029)	(0.022)	(0.011)	(0.015)	(0.014)	(0.019)	(0.015)
Constant	0.140***	1.474***	0.680***	0.105*	1.372***	0.658***	0.151***	1.505***	0.683***
	(0.046)	(0.051)	(0.032)	(0.063)	(0.041)	(0.058)	(0.049)	(0.064)	(0.029)
R-squared	0.294	0.125	0.091	0.293	0.125	0.091	0.294	0.126	0.092
Mean at baseline	0.958	0.800	0.879	0.958	0.800	0.879	0.958	0.800	0.879
Observations	16,824	16,824	16,824	16,824	16,824	16,824	16,824	16,824	16,824

Note: Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).

Source: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data

Table 4. Effects of weather shocks on morbidity rates among children

Variable	Floods (2007)	Cyclone Jokwe (2008)	Drought (2005)
	Children sick	Children sick	Children sick
	(1)	(2)	(3)
Shock x After x Growing Cycle	0.539***	-0.050	-0.058***
	(0.041)	(0.037)	(0.011)
Shock x Growing Cycle	-0.116***	-0.053	-0.068
	(0.037)	(0.063)	(0.092)
Shock x After	-0.001	-0.006	0.005
	(0.006)	(0.005)	(0.005)
After x Growing Cycle	0.389***	0.138***	0.020
	(0.025)	(0.017)	(0.0142)
Constant	0.248***	0.272***	0.238***
	(0.022)	(0.010)	(0.032)
R-squared	0.035	0.037	0.036
Outcome mean at baseline	0.113	0.113	0.113
Observations	46,495	46,495	46,495

Note: Outcome variable defined for children ages 0 to 17. Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data

Table 5. Labor supply responses to exposure to weather shocks

Variable	Floods (2007)		Cyclone Jokwe (2008)		Drought (2005)	
	Labor supply of …		Labor supply of …		Labor supply of …	
	Ages 18-65	Ages 5-17	Ages 18-65	Ages 5-17	Ages 18-65	Ages 5-17
	(1)	(2)	(3)	(4)	(5)	(6)
Shock x After x Growing Cycle	0.337***	0.454***	0.018	0.087**	-0.018	0.038
	(0.096)	(0.175)	(0.032)	(0.035)	(0.023)	(0.028)
Shock x Growing Cycle	-0.114*	0.156	0.043	0.141**	0.213***	0.102
	(0.061)	(0.121)	(0.043)	(0.058)	(0.054)	(0.094)
Shock x After	-0.026*	-0.010	-0.029**	0.008	0.029	-0.009
	(0.015)	(0.013)	(0.013)	(0.0094	(0.016)	(0.015)
After x Growing Cycle	0.132**	0.185*	-0.003	0.005	-0.022	-0.003
	(0.057)	(0.105)	(0.0215)	(0.026)	(0.019)	(0.020)
Constant	0.735***	-0.146***	0.753***	0.007	0.731***	-0.196***
	(0.032)	(0.032)	(0.031)	(0.040)	(0.034)	(0.031)
R-squared	0.133	0.256	0.133	0.255	0.133	0.256
Outcome mean at baseline	0.840	0.110	0.840	0.110	0.840	0.110
Observations	42,237	33,857	42,237	33,857	42,237	33,857

Note: Labor force measured on the extensive margin. Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data

Table 6. Effects of weather shocks on household assets and influx of inter-household transfers

Variable	Floods (2007)		Cyclone Jokwe (2008)		Drought (2005)	
	Wealth index (1)	Received transfers (2)	Wealth index (3)	Received transfers (4)	Wealth index (5)	Received transfers (6)
Shock x After x Growing Cycle	5.928	-0.304	-5.386*	0.112***	-2.918*	0.066***
	(4.013)	(0.655)	(2.813)	(0.028)	(1.642)	(0.023)
Shock x Growing Cycle	-26.208***	-0.142***	-3.456	-0.160***	-8.170**	-0.116
	(5.556)	(0.054)	(3.720)	(0.035)	(3.4253)	(0.2183)
Shock x After	-0.487	0.018*	-1.158**	0.0009	0.945	-0.043**
	(0.686)	(0.010)	(0.448)	(0.012)	(0.8139)	(0.017)
After x Growing Cycle	4.346*	-0.246***	-2.037	-0.121***	-3.432***	-0.019
	(2.366)	(0.037)	(1.480)	(0.018)	(1.175)	(0.021)
Constant	-2.652	0.180***	-2.240	0.035	-2.845	0.166***
	(2.018)	(0.018)	(1.810)	(0.027)	(1.891)	(0.016)
R-squared	0.424	0.075	0.424	0.075	0.425	0.075
Outcome mean at baseline	15.620	0.124	15.620	0.124	15.620	0.124
Observations	15,380	8,348	15,380	8,348	15,380	8,348

Note: Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data

Table 7. Effects of weather shocks on retail prices of maize

Moths after the shock	Floods (2007)		Cyclone Jokwe (2008)		Drought (2005)	
	γ_m	Standard error	γ_m	Standard error	γ_m	Standard error
1	-0.469***	0.067	0.268***	0.031	0.152***	0.043
2	-0.447***	0.064	0.254***	0.029	0.213***	0.034
3	-0.411***	0.061	0.289***	0.032	0.281***	0.034
4	-0.212***	0.064	0.348***	0.040	0.401***	0.035
5	-0.188***	0.064	0.338***	0.043	0.492***	0.033
6	-0.190***	0.065	0.519***	0.045	0.538***	0.044
7	-0.129**	0.058	0.578***	0.047	0.629***	0.050
8	-0.179***	0.056	0.575***	0.049	0.789***	0.046
9	-0.162***	0.056	0.226***	0.044	0.786***	0.043
10	-0.109*	0.061	0.100**	0.042	0.783***	0.037
11	-0.001	0.071	0.171***	0.029	0.720***	0.064
12	0.226***	0.042	0.242***	0.035	0.297***	0.078
Observations	6,730		6,730		6,730	

Note: Robust standard errors clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district.
Source: World Bank staff calculations using SIMA, TMPA and NCEP data.

Table 8. Relationship between the weather shocks and the probability to migrate

Weather shock	Did household head migrate into the current district in the last 5 years?
Floods (2007)	-0.0195***
	(0.0042)
Cyclone Jokwe (2008)	-0.0170***
	(0.0034)
Drought (2005)	0.0167***
	(0.0038)

Note: Partial results of regression analysis on factors correlated with the probability of migration. Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2008/09, TMPA and NCEP.

Table 9. Effects of weather shocks on consumption and poverty based on potential residency at the time of the shocks

Variable	Floods (2007)			Cyclone Jokwe (2008)			Drought (2005)		
	Total consumption	Food consumption	Poverty status	Total consumption	Food consumption	Poverty status	Total consumption	Food consumption	Poverty status
Shock x After x Cycle	5.774	-0.851	0.369***	-7.500***	-1.861***	0.175***	-2.806**	-2.331***	0.119***
	(6.593)	(0.574)	(0.014)	(2.718)	-0.634	(0.054)	(1.359)	(0.697)	(0.041)
Shock x Cycle	-9.098	1.023	-0.337***	4.219	1.778***	-0.204***	-2.138	1.965**	-0.108
	(6.368)	(0.845)	(0.025)	(2.972)	(0.682)	(0.059)	(2.481)	(0.780)	(0.074)
Shock x After	1.677***	0.017	-0.027***	0.652	-0.626**	0.002	0.764	-0.017	0.025
	(0.526)	(0.144)	(0.008)	(0.738)	(0.274)	(0.015)	(0.877)	(0.383)	(0.021)
After x Cycle	10.878***	1.556***	-0.034**	2.864	0.515	-0.087***	0.309	-0.537	-0.023
	(3.944)	(0.436)	(0.014)	(1.817)	(0.452)	(0.030)	(0.994)	(0.464)	(0.028)
Constant	12.233***	9.079***	0.536***	9.109***	8.757***	0.580***	10.377***	8.890***	0.562***
	(1.063)	(0.304)	(0.038)	(1.170)	(0.313)	(0.036)	(0.949)	(0.319)	(0.033)
R-squared	0.064	0.143	0.142	0.064	0.029	0.143	0.064	0.030	0.144
Mean at baseline	13.266	13.266	0.545	13.266	13.266	0.545	13.266	13.266	0.545
Observations	19,453	19,453	19,453	19,453	19,453	19,453	19,453	19,453	19,453

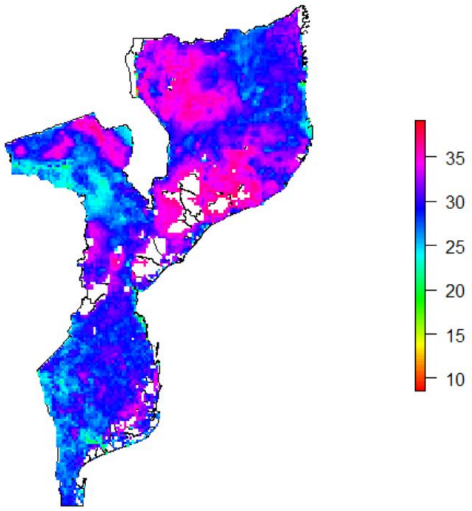
Note: Consumption variables defined in per capita terms. Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data

Table 10. Effects of the 2015 floods on household welfare, human capital and coping responses

Variable	Food consumption	Total consumption	Poverty status	School attendance (5-11)	School attendance (12-17)	Children sick (0-17)	Labor supply (18-65)	Labor supply (5-17)	Wealth index
Shock x After x Cycle	0.082	1.512***	0.013***	0.000	-0.014***	0.006***	0.004**	0.001	-0.257***
	(0.117)	(0.292)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.020)
R-squared	0.040	0.059	0.189	0.063	0.148	0.039	0.112	0.204	0.563
Mean at baseline	10.857	32.979	0.327	0.952	0.820	0.085	0.800	0.173	30.759
Observations	21,495	21,495	21,497	16,669	14,201	51,751	47,760	40,365	21,416

Note: Outcome variables defined as in the rest of the paper. Robust standard errors in parenthesis clustered at the district level. Asterisks denote increasing statistical significance: *p < 0.1, **p < 0.05, ***p<0.01. Weather shocks defined in standardized z-scores of totals in the year of the event using the historical distribution from the reference period 2000-2012 for each district. Parameter of interest given by the triple interaction (Shock x After x Growing Cycle). Other covariates include gender and age of the household head and area of location (urban or rural).
Source: World Bank staff calculations using IOF-2014/15, TMPA and NCEP data.

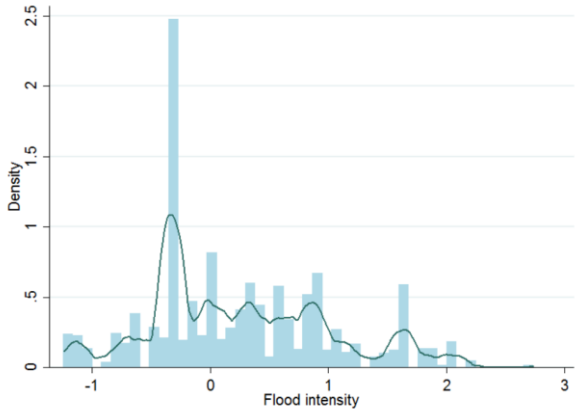
Figure 1. Distribution in the number of days for the main cropping cycle across Mozambique



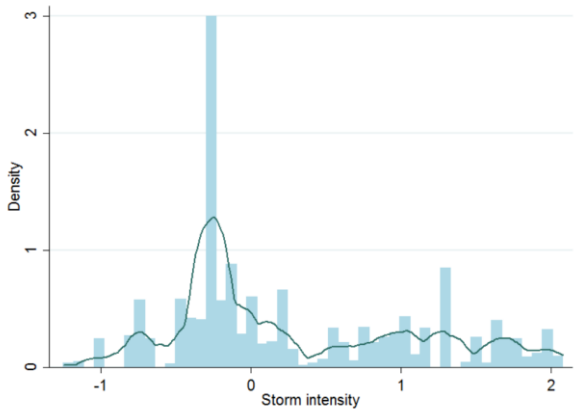
Source: HarvestChoice, 2010. "Measuring Growing Seasons." International Food Policy Research Institute, Washington, DC., and University of Minnesota, St. Paul, MN. Available online at http://harvestchoice.org/node/2253.

Figure 2. Distribution of the shock intensity across the three natural disasters

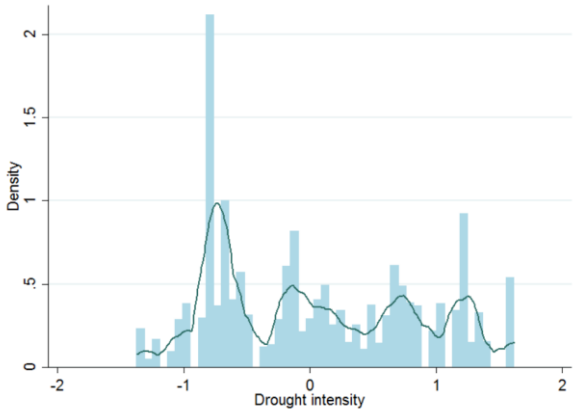
(Floods – 2007)



(Cyclone Jokwe -2008)

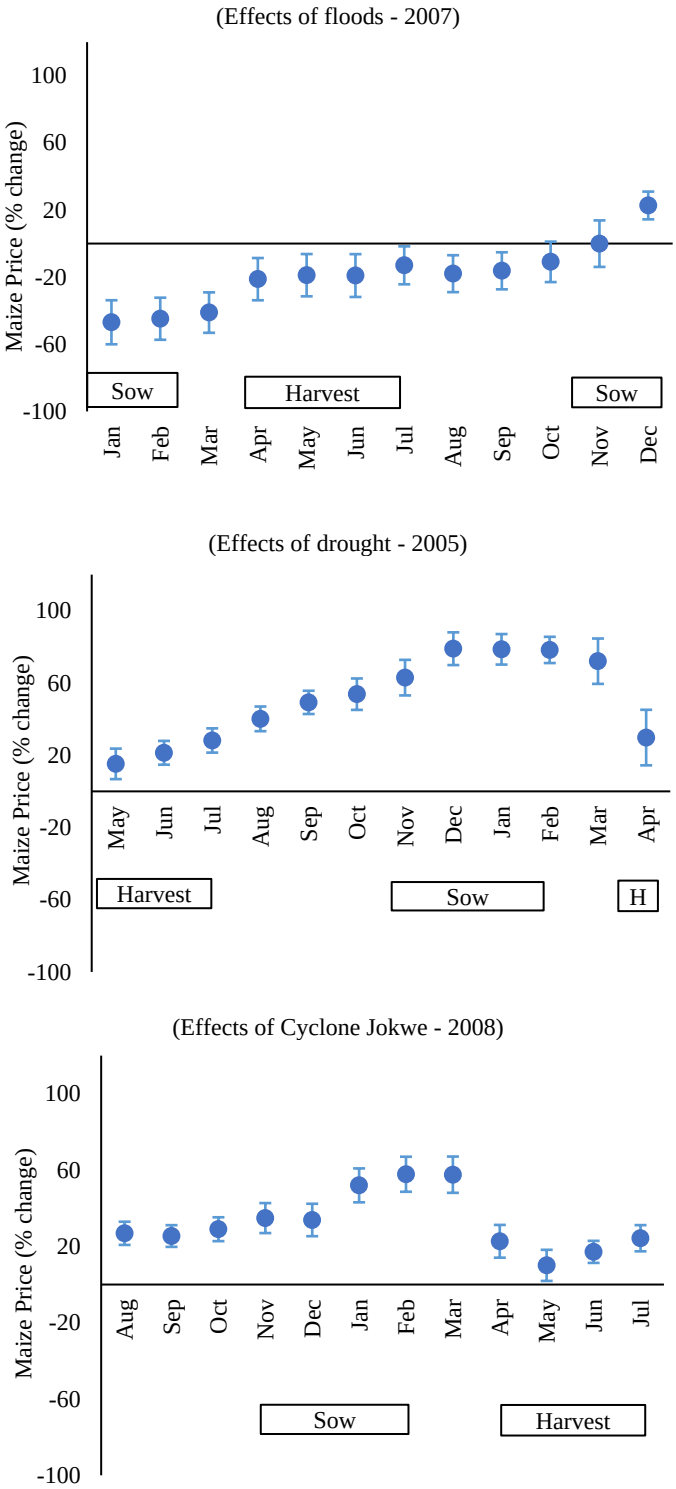


(Drought – 2005)



Source: World Bank based on data from TMPA and NCEP

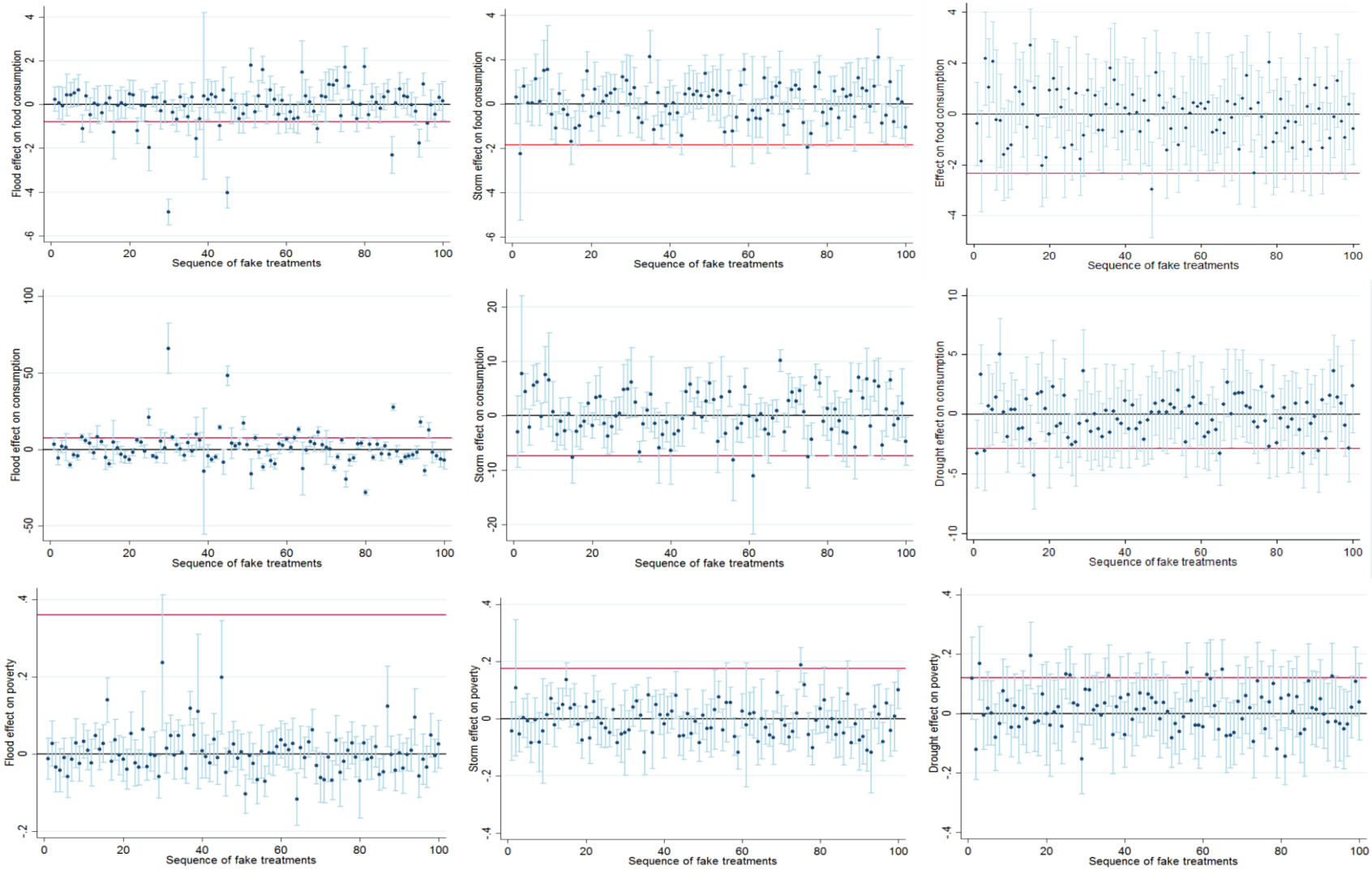
Figure 3. Effects of weather shocks on maize prices



Note: Graphs show point estimates of γ_m in equation 2 for an increase of a standard deviation in the disaster intensity. Bars show 10% confidence intervals. Impact estimates calculated for each month in a 12-month period following the weather shock.
Source: World Bank staff calculations using IOF-2014/15, TMPA, NCEP and SIMA data.

Figure 4. Effects of "fake" treatments" on food and total consumption and poverty

(flood 2007) (Cyclone 2008) (Drought 2005)



Note: Points estimates and 5% confidence intervals for 100 "fake" treatments for each shock based on a random shuffle of the geographic location of the disasters. The horizontal line in red shows the value of the point estimate from the "true" treatment. *Source*: World Bank staff calculations using IOF-2002/03, IOF-2008/09, TMPA and NCEP data.