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Vulnerability to natural shocks

Assessing the short-term impact on consumption and poverty of the 2015 flood in Mozambique

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Abstract: Mozambique is among the most disaster-prone countries in the world. A bigger than usual, and mostly unexpected, flood occurred in the central-northern region of the country in the first few months of 2015, causing huge damage to infrastructures. In this paper, we use a nationally representative household budget survey that was being carried out in the field during those months to assess the short-term impact of the 2015 flood on household consumption and poverty levels. Applying a difference-in-difference approach, we find that, for those exposed to the flood, consumption reduced significantly in the short term, in the range of 11–17 per cent, depending on the specification. Poor households and households living in rural areas were affected significantly more. Poverty levels also increased due to the flood, by about 6 percentage points. These results are relevant for policy planning, natural disaster management, and for ex ante vulnerability assessment in Mozambique and other risk-prone developing countries with similar characteristics.

Keywords: welfare impacts of natural shocks, flood, difference-in-difference, Mozambique
JEL classification: I30, Q51, Q54, Q56

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1 Introduction

Mozambique is among the most disaster-prone countries in the world. Throughout its history, Mozambique has been exposed to many natural disasters such as floods, droughts, and cyclones (Gall 2004; Lumbroso et al. 2008; Albertsen 2009; INFORM 2018, 2019; Brakenridge 2019). The most extreme events have often been linked to the El Niño-Southern Oscillation (ENSO) phenomenon, but substantial natural events have also occurred in non-ENSO years (Borges Coelho and Littlejohn 2000; Vitart et al. 2003; Matyas 2015). One such event was the flood that occurred in the central-northern region of the country in the first few months of 2015. After weeks of heavy rains in December 2014 and January 2015, some of the main rivers of the Southern Africa region, including the Licungo and other rivers in coastal Mozambique, started to swell between the end of January and the beginning of February 2015 (GoM-World Bank-UN-EU 2015; NOAA 2015; NASA Earth Observatory 2019).

In this paper, we use a nationally representative household budget survey that was being carried out in the field during those months to assess the short-term impact of the 2015 flood on household consumption and poverty levels. The literature on the effect of natural disasters is rich and increasing over time, but it is not at all common or easy to observe and survey the same households before and immediately after a major natural event. Most studies either analyse the effect of natural disasters at a more aggregate or macro level, or make use of panel data, but using survey data collected a few years apart (Karim and Noy 2016). Hence, our broader objective is to expand the literature on the short-term economic effects of natural disasters in developing countries, which we believe is an area that will become increasingly relevant in the economic literature given the growing population dynamics and changing climatic conditions. The paper is structured as follows: Section 2 presents the literature and context; Section 3 contains the information on data and methodology; Section 4 presents and discusses the main results; and Section 5 concludes.

2 Literature and context

Caruso (2017), citing Helmer and Hilhorst (2006) and Van Aalst (2006), suggests that an increasing number of natural disasters have been recorded over the last 50 years, particularly in relation to global warming. Citing Prestemon and Holmes (2000), Caruso (2017) highlights that, on infrastructure alone, natural disasters cost an average annual estimate of US$901 million. Wossen et al. (2014), citing Conway and Schipper (2011) and Seipt et al. (2013), highlight that Sub-Saharan Africa (SSA) is particularly susceptible, suggesting it can be considered the region that is most vulnerable to climate change. Arouri et al. (2015), citing De Haen and Hemrich (2007), Kaplan (2010) and Ludwig et al. (2007), highlight that natural disasters cause more human losses in developing countries than in developed ones and are likely to afflict the poor the most. This is reaffirmed by Hallegatte et al. (2015), who stress that poor people and poorer countries are more exposed and vulnerable to all types of climate-related shocks, including floods.

Focusing on Vietnam, Narloch (2016) sought to contribute to a better understanding of how household income is affected by different types of weather variation—annual, seasonal, abnormal and extreme weather conditions and events related to temperature but also, and more relevant to our case, rainfall. Narloch (2016) suggests that these effects are also dependent on the socioeconomic group and income activities of those experiencing the weather variation and finds that poorer households in wetter regions, particularly poor rural ones, are more vulnerable to severe rainfalls and flooding. Also focusing on Vietnam, Arouri et al. (2015), find that per capita income reduces by 5.9 per cent and per capita expenditure reduces by 4.4 per cent due to floods.[1] They find that smaller households with higher levels of education, a higher proportion of members of working age, access to micro-credit, remittances and social protection, and living in richer and more equal communities are more resilient than others to the effects of natural disasters.

Like Vietnam, Mozambique is a country of concern regarding natural disasters and, notably, flooding. Groover et al. (2015), citing FAO (2007), show that, out of the 128 districts in Mozambique, 37 are prone to flooding. They highlight that the country's northern region has high exposure to the annual flooding of the Zambezi River, and the coast is afflicted by the cyclone season during five months of the year. Yet, citing Shendy et al. (2009), they stress a lack of data analysing the impact of these and other climatic shocks on the poverty of Mozambican households.

Few (2003), reviewing theoretical and applied research on the vulnerability and adaptive capacity of households and communities in flood-prone areas, documents that a previous flood in 2000 caused people to be displaced and to be accommodated in local schools (Christie and Hanlon 2001) and disrupted water and sanitation systems in Maputo, the country's capital, with consequent dysentery and cholera outbreaks (Sanderson 2000).

Using an endogenous treatment effects model, Groover et al. (2015) estimate that, among other climate shocks and agricultural pests, floods and cyclones have the strongest impact on households' food expenditure, with a reduction of 32.2 per cent. Rural households, particularly those dependent on agriculture appear to be more vulnerable than others. Finally, they note that households in the northern provinces are more vulnerable and prone to experience transient poverty due to floods.[2] The strong link they find between rainfall and transient poverty leads them to recommend that rainfall should be used to support social assistance-targeting procedures in the country. Arndt and Thurlow (2015) find similar results. In their analysis, they find that flooding is the principal driver of the detrimental impacts of climate change in a country, and that they therefore merit the attention of policy makers and further research.

Quisumbing (2007) finds that various factors are associated with a higher probability of being chronically poor. These include years of schooling of the household head, the value of non-land assets, and the proportion of children under the age of 15 and adults aged 55 and older. Illness shocks, particularly those afflicting income earners or livelihood providers within the household, are also highlighted as important contributors to a fall into poverty. Such factors, as noted by Groover et al. (2015), (citing Devereux et al. (2006); Dorward and Kydd (2004); Devereux (2002)), are likely to affect the impact of a climate shock such as a flood. Households with access to remittances or social protection may be able to cope better with the shock. Others, may have to resort to asset depletion or reduce investment in physical and human capital, including choosing to take their children out of school. For households like this, the short-run impact of a flood is more likely to be compounded by following shocks, especially in countries like Mozambique that are prone to repeated flood events.

Quisumbing (2007) cites Hoddinott and Quisumbing (2003) and their comprehensive list of shocks, aggregated into agroclimatic, economic, political/social/legal, crime, health, and life-cycle shocks. While, in their list, floods fit into the agroclimatic type of shock; they arguably originate in

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[1] These estimates compare with reductions in per capita income and per capita expenditure reductions of 1.9 per cent and 1.5 per cent due to storms and 5.2 per cent and 3.5 per cent due to droughts.

[2] Conversely, households in southern and central provinces are more prone to experience transient poverty due to droughts.

others such as erosion (also an agroclimatic shock), asset and property losses (economic shocks), death and illness such as correlated cholera outbreaks (health shocks), or even, in the case of the death of the father in patriarchal societies, property division (a life-cycle shock). In our study, we focus on the effects of flood-related shocks on consumption, compounding them into one single short-run effect. One might expect that direct shocks, and some indirect shocks, such as loss of crops and land to erosion, asset and property losses, or incapacitation of income earners due to injury, may lead to measurable impacts on household consumption in the short run. It can be argued, however, that some effects will only be measurable after a longer period has passed. In our study, we seek to capture the short-run effects while fully acknowledging that they are partial.

The effects of natural disasters like flooding extend beyond consumption. Caruso (2017) finds that natural disasters affect the education, health, labour outcomes, and wealth of the individuals exposed. He cites other authors who, focusing on the effects of shocks experienced in early childhood, have reported effects on child development (Currie 2009) and on education, height, self-reported health, or socioeconomic outcomes (Almond et al. 2005; Alderman et al. 2006; Maluccio et al. 2009). Focusing on floods and, as is the case in Mozambique, usually related tropical cyclones, Caruso (2017) notes that they are particularly harmful to education, fertility, and employment, including the probability of people incurring employment disability.

3 Data and methodology

As mentioned in the Introduction, a repeated interview (mini-panel) survey—the 2014/15 Mozambican Household Budget Survey, henceforth called IOF1415—was in the field during the period from August 2014 to August 2015 (INE 2015). We base our analysis on this database, which contains data from a representative sample of around 11,000 households (11,505 in the first quarter of the survey, 10,368 in the second, and 11,315 in the fourth quarter).[3] The sample is representative of the Mozambican population, of rural and urban populations, and of those in each of the country's eleven provinces including Maputo City. The main household questionnaire is accompanied by a community questionnaire for rural areas only.

The IOF1415 provides information on a wide set of individual, household, and community characteristics, including demographics; education; health; employment; daily, monthly and annual expenditures; durable goods, land and livestock; and receipts and transfers. Additional information about the IOF1415 is available in the survey report by INE (2015) and in the Fourth Poverty Assessment Report by the Government of Mozambique's Ministry of Economics and Finance, (DEEF 2016). In addition to the IOF1415 data, we used the maps and shapefiles made available by the United Nations Institute for Training and Research (UNITAR) relating to the 2015 flood in Mozambique (UNITAR 2019). These allowed us to identify the areas affected by the flood and measure the distance of the households from these areas.[4]

The IOF1415 survey was designed for each household to be interviewed four times over the four quarters of the year. The 12-month period between mid-August 2014 and mid-August 2015 was subdivided as follows: Quarter 1, mid-August to mid-November; Quarter 2, mid-November to

[3] The occurrence of a major flood during the first months of 2015 affected the possibility of reaching and interviewing several households in the second quarter, especially in the centre-north of the country. This explains the lower number of households in quarter two.

[4] The analysis was conducted with QGIS v2.2.0.

mid-February; Quarter 3, mid-February to mid-May; and Quarter 4, mid-May to mid-August.[5] Therefore, the 2015 flood fell entirely within Quarter 2 and we were able to observe the same households both before and after the event. Since household consumption was measured in all quarters, it was possible to apply a difference-in-difference (DID) approach to measure the impact of the 2015 flood on household consumption and poverty levels, using the consumption information collected in the first and last survey quarters.[6] As widely known, the DID approach seeks to measure the difference in average outcome in the treatment group before and after the treatment minus the difference in average outcome in the control group before and after treatment (see, for example, Angrist and Pischke 2009; Lechner 2011).

The model used is presented in Equation 1:

$$Y_i = \alpha + \beta T_i + \gamma P_i + \delta(T_i \cdot P_i) + \varepsilon_i, \tag{1}$$

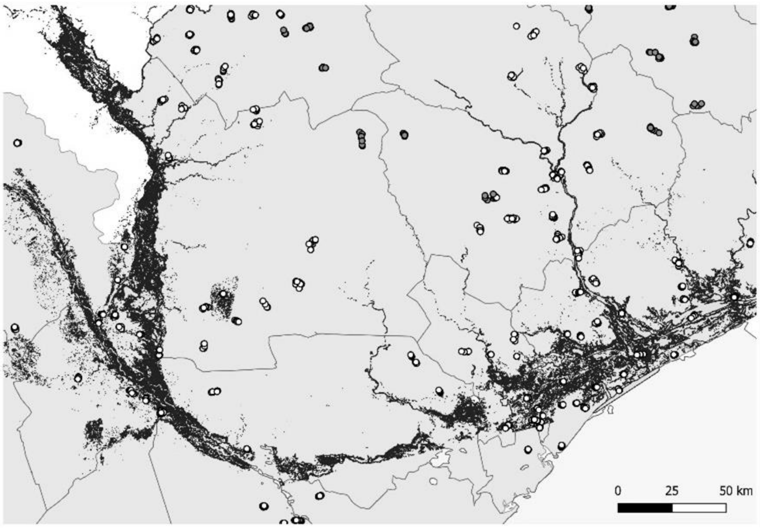
where Y_i is the outcome variable, T_i is the treatment variable, P_i indicates the time period, and the last two variables are interacted in the term $(T_i \cdot P_i)$, which represents the main variable of interest. In this model, the coefficient α corresponds to the baseline for the control group, the coefficient β estimates the treatment group specific effect (i.e. the difference between the two groups before the intervention), the coefficient γ measures the effect of the time trend, and the coefficient δ estimates the difference in changes occurred over time. Hence, we are mainly interested in the coefficient δ as this represents the effect of treatment (DID estimator). In our estimations, we also include a set of covariates not included in the simplified model of Equation 1 for ease of notation. Our dependent variable (Y_i) is the logarithm of daily real consumption per capita, whereas the additional covariates used in the analysis are the household head's gender, age, education level and occupation, the household dependency ratio and household size, whether a disabled/permanently sick household member was present in the household, whether the household was residing in a rural or urban area, in which province and at which altitude.

In our study, the treatment group (*T*) is represented by households residing up to 20 kilometres from the flooded area, indicated by white dots in Figure 1. With respect to the time dimension, we only consider two time periods, Quarter 1 and Quarter 4: Quarter 1 represents the pre-flood situation and Quarter 4 is the post-flood situation. Quarter 2 is ignored because due to the flood it was not possible to interview many of the households residing close to the flooded area, either because it was not possible to find them or because it was impossible for the enumerators to reach the affected areas. Hence, in our analysis, the variable *P* is a dummy variable that assumes value 0 in Quarter 1 and value 1 in Quarter 4. The summary statistics for the variables used are presented in Table 1 for the entire sample and for affected provinces only. In this study, we consider affected provinces to be only the areas up to 500 kilometres from the flooded areas and within the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala, as those are the provinces in which most damage was recorded (GoM-World Bank-UN-EU 2015). In Table 2, we also present the summary statistics separately for the treatment and control groups.

[5] For various reasons, the Quarter 3 survey did not take place.

[6] We also apply a panel regression approach but focus more on the DID results in what follows. Nonetheless, similar results are obtained and are shown in the robustness checks section.

Figure 1: Map showing a portion of the flooded area and the treatment and control groups



Note: White dots = households in treatment group; grey dots: households in control group. Treatment group = households residing up to 20 kilometres from the flooded areas (in black); control group = households residing more than 20 kilometres from the flooded areas, only in the affected provinces (areas at up to 500 kilometres from the flooded areas and within the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala.).

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415) and UNITAR (2019).

Table 1: Summary statistics for the entire sample and for affected provinces only

	Entire sample					Only affected provinces				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Treated	22,813	0.152	0.359	0	1	10,676	0.253	0.435	0	1
Period	22,813	0.510	0.500	0	1	10,676	0.527	0.499	0	1
Treated x Period	22,813	0.081	0.273	0	1	10,676	0.134	0.341	0	1
Daily per capita real consumption	22,813	48.168	92.530	0.502	8432.777	10,676	40.334	70.516	0.502	8432.777
Head woman	22,142	0.240	0.427	0	1	10,676	0.186	0.389	0	1
Dependency ratio	22,126	0.519	0.202	0	1	10,676	0.538	0.196	0	1
Head no education	22,813	0.318	0.466	0	1	10,676	0.335	0.472	0	1
Head 5 years education	22,813	0.375	0.484	0	1	10,676	0.382	0.486	0	1
Head 7 years education	22,813	0.149	0.356	0	1	10,676	0.141	0.348	0	1
Head 10 years education	22,813	0.092	0.289	0	1	10,676	0.084	0.278	0	1
Head 12 years education	22,813	0.044	0.205	0	1	10,676	0.043	0.202	0	1
Head +12 years education	22,813	0.022	0.146	0	1	10,676	0.016	0.125	0	1
Head age	22,126	43.895	14.124	14	99	10,676	42.702	13.938	14	97
Head in agriculture	22,015	0.610	0.488	0	1	10,618	0.683	0.465	0	1
Household size	22,813	6.283	2.955	1	31	10,676	6.165	2.665	1	25
Disability	22,813	0.018	0.132	0	1	10,676	0.015	0.123	0	1
Altitude	22,787	247.403	248.948	0	994	10,670	273.035	247.027	0	994
Rural	22,813	0.683	0.465	0	1	10,676	0.744	0.436	0	1

Notes: Province dummies not shown. In this study, we consider as affected provinces only the areas up to 500 kilometres from the flooded areas and in the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala. The treatment group is represented by households residing up to 20 kilometres from the flooded area. The variable 'period' is a dummy variable that assumes value 0 in Quarter 1 and value 1 in Quarter 4; our dependent variable is the logarithm of daily per capita real consumption; the additional covariates used in the analysis are household head's gender, the household dependency ratio, household head's education level (no education, complete primary-first cycle (five years), complete primary-second cycle (seven years), secondary-first cycle (ten years), complete secondary (12 years), tertiary), household head's age, household head's occupation (in agriculture or not), household size, whether a disabled/permanently sick household member is present in the household, the altitude of the place where the household resides, whether the household resides in a rural or urban area and in which province (not shown).

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

Table 2: Summary statistics for control and treatment groups

	Treated	Mean	Std. Error	
Daily per capita real consumption	No	40.530	0.862	
	Yes	40.017	0.970	
Head woman	No	0.188	0.004	
	Yes	0.183	0.007	
Dependency ratio	No	0.541	0.002	*
	Yes	0.533	0.004	
Head no education	No	0.346	0.005	***
	Yes	0.299	0.009	
Head 5 years education	No	0.377	0.005	**
	Yes	0.400	0.009	
Head 7 years education	No	0.140	0.004	
	Yes	0.143	0.007	
Head 10 years education	No	0.081	0.003	*
	Yes	0.093	0.005	
Head 12 years education	No	0.042	0.002	
	Yes	0.042	0.004	
Head +12 years education	No	0.014	0.001	***
	Yes	0.023	0.003	
Head age	No	42.673	0.157	
	Yes	42.853	0.268	
Head in agriculture	No	0.695	0.005	***
	Yes	0.645	0.009	
Household size	No	6.068	0.029	***
	Yes	6.464	0.058	
Disability	No	0.015	0.001	
	Yes	0.018	0.003	
Altitude	No	320.619	2.849	***
	Yes	133.105	3.176	
Rural	No	0.754	0.005	***
	Yes	0.721	0.008	

Notes: Province dummies not shown. *** p<0.01, ** p<0.05, * p<0.1. Only the affected provinces are considered (areas up to 500 kilometres from the flooded areas and within the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala). The last column shows whether the means for the two groups are statistically different.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

The DID approach was also chosen because the parallel trend assumption, which is essential for the DID approach to work, seemed to be satisfied. This is depicted graphically in Figure 2 and analysed in Table 3. It can be seen that for both the control and treatment groups there was a comparable decline in consumption following Quarter 1. This is quite normal in Mozambique, as the months included in Quarter 2 are the months that usually represent the core of the rainy season, and they are normally associated with scarce food reserves, high food prices, hunger, and higher poverty rates. Nonetheless, when we analyse Quarter 4, we notice that while the control group completely recovers from the rainy (hungry) season, the treatment group only partially recovers from it, and we attribute this loss in consumption to the effect of the flood (Figure 2).

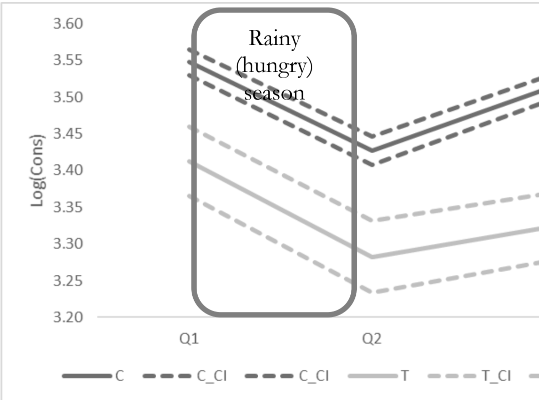
It can also be seen that, when compared to the rest of the country, the treatment group is worse off in terms of consumption levels than the control group (Figure 2, Panel a.) but its consumption levels are comparable to those of the control group when we consider only the affected provinces (Table 2 and Figure 2, Panel b).[7] However, the households in the control group have, on average, a higher prevalence of household heads without education and a lower prevalence of household

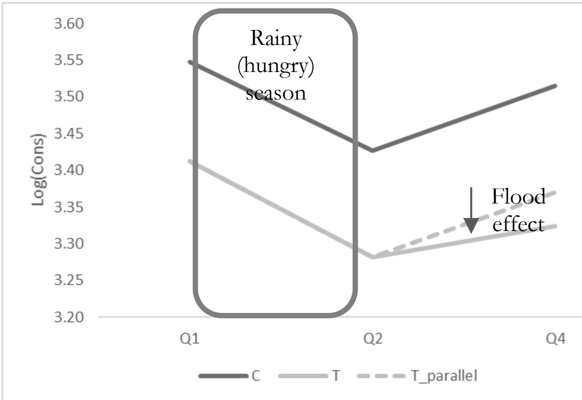
[7] This is because in the entire sample we also have households from the southern provinces and the capital Maputo that present much higher consumption levels compared to the provinces affected by the 2015 flood (DEEF 2016). In this study, we consider affected provinces to be only the areas up to 500 kilometres from the flooded areas and within the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala.

heads with tertiary levels of education . The percentage of rural households in the control group is also higher than in the treatment group, and the percentage of households in the control group whose head works in agriculture is also higher than that for the treatment group. One explanation for the difference in the consumption levels when we consider the entire sample is that the treatment group is disproportionally located in Zambezia (about 72 per cent of total households in the treatment group) and in a few other central-northern provinces which over time have been consistently among the poorest provinces in the country from a consumption poverty point of view (DEEF 2016). Moreover, in 2014/15, Zambezia was classified as the most deprived province in terms of multidimensional poverty (DEEF 2016). Indeed, when we compare (not shown) the treatment and control groups with respect to poverty rates, we also find that the treatment group presents a significantly higher prevalence of consumption poverty (51 versus 47 per cent, difference significant at the 1 per cent level).

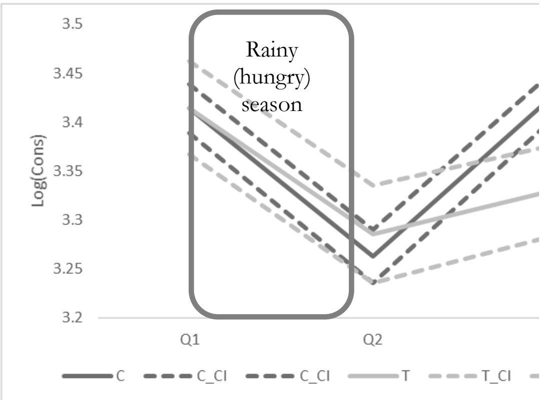
Figure 2: Parallel trend assumption and flood effect

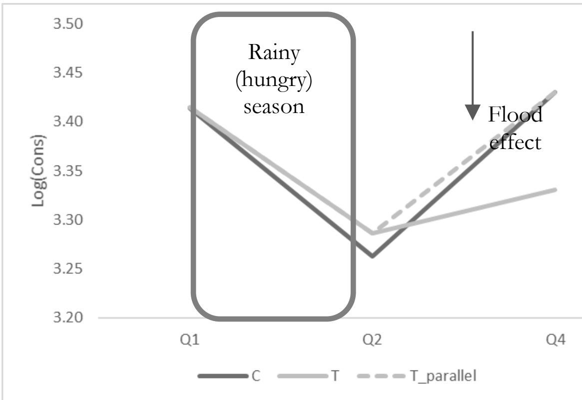
Panel a: Entire sample





Panel b: Only affected provinces





Notes: Log(Cons) = logarithm of consumption (actual values); C = control group; T = treatment group; CI = confidence intervals. In this study we consider as affected provinces only the areas up to 500 kilometres from the flooded areas and within the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

Table 3: Parallel trends assumption

Entire sample							
Variable	Quarter	Treated	Mean	Std. Err.	[95% Conf. Interval]		
Log(cons)	1	No	3.55	0.01	3.53	3.56	
Log(cons)	1	Yes	3.41	0.02	3.37	3.46	***
Log(cons)	2	No	3.43	0.01	3.41	3.45	
Log(cons)	2	Yes	3.28	0.03	3.23	3.33	***
Log(cons)	4	No	3.51	0.01	3.50	3.53	
Log(cons)	4	Yes	3.32	0.02	3.28	3.37	***
Only affected provinces							
Variable	Quarter	Treated	Mean	Std. Err.	[95% Conf. Interval]		
Log(cons)	1	No	3.41	0.01	3.39	3.44	
Log(cons)	1	Yes	3.41	0.02	3.37	3.46	
Log(cons)	2	No	3.26	0.01	3.24	3.29	
Log(cons)	2	Yes	3.29	0.03	3.24	3.34	
Log(cons)	4	No	3.43	0.01	3.41	3.45	***
Log(cons)	4	Yes	3.33	0.02	3.28	3.38	

Notes: *** p<0.01, ** p<0.05, * p<0.1. In this study we consider as affected provinces only the areas up to 500 kilometres from the flooded areas and within the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala. The last column shows whether the means for the two groups are statistically different, in each quarter.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

Another important element to validate our empirical strategy is to demonstrate that the 2015 flood was indeed bigger than usual and mostly unexpected. If this were not so, then it could be argued that households living close to rivers are accustomed to these phenomena and can fully anticipate their effects and smooth consumption over the year, taking recurring floods into account. In this regard, the 'Mozambique 2015: Damage Assessment and Early Recovery/Sustainable Reconstruction Priorities Joint Rapid Assessment following the January–February 2015 Hydro-Meteorological Events in the Central and Northern Regions' (GoM-World Bank-UN-EU 2015) is very informative. It reports that the cost of the damage could be estimated at around US$371 million, about 2.4 per cent of GDP, and that about three-quarters of these costs could be attributed to damage to roads and bridges. Moreover, it is reported that 326,000 people were affected, 140 were killed, 104,430 hectares of crops were lost, and that about 30,000 houses, 2,362 classrooms, and 17 health units were either partially or totally destroyed.

Due to the damage, most of the northern region (provinces of Niassa, Cabo Delgado, and Nampula) was left without electricity for about three months. Such damage does not occur every year, even in a disaster-prone country like Mozambique. Moreover, the 'Africa Hazards Outlook' by the US-based National Oceanic and Atmospheric Administration's Climate Prediction Center reports that precipitation rose to approximately 150 per cent of its normal level for the season (NOAA 2015). Therefore, even though the literature shows that residents of some central-northern regions of Mozambique are accustomed to floods and have developed strategies to cope with such events (see, for example, Lumbroso et al. 2008; Albertsen 2009), the information available supports the view that, even by local standards, the 2015 flood was unusually massive and violent (GoM-World Bank-UN-EU 2015; NOAA 2015; NASA Earth Observatory 2019).

4 Results

In this section, we present our results on the effects of the flood on household consumption and poverty, obtained from a series of estimation procedures and using different specifications. In most of our estimations and robustness checks, we find that the flood had a non-negligible effect on consumption. Table 4 first presents a basic estimation in which the treatment group is composed of households residing up to 20 kilometres from the flooded area, and the control group is formed by all the remaining households in the country (Table 4, Column 1), including households from the southern region and the capital Maputo, which were not affected at all by the flood and instead experienced severe drought in the last months of 2015 and first months of 2016. Even though a non-negligible negative effect of the flood is found in this case as well—8.2 per cent—in the rest of the estimations presented, we limit the subset of potential controls to households living in the most affected provinces in order to obtain more precise comparisons. As mentioned earlier, in this study we consider affected provinces to be only those areas up to 500 kilometres from the flooded areas and within the provinces of Niassa, Nampula, Zambezia, Tete, and Sofala. Those are the provinces in which most of the damage was recorded (GoM-World Bank-UN-EU 2015). Indeed, in Column 2 of Table 4 we estimate a bigger (-10.6 per cent) effect on consumption. Moreover, if the controls are only selected from within a shorter distance from the affected areas (in this case, 200 kilometres), we obtain even bigger estimates (-14.1 per cent—Column 3).

The magnitude of the coefficient of interest is confirmed even when a household or a village fixed-effect regression is used (Column 4 and Column 5 of Table 4, respectively), or when province-specific trends are included in the analysis (Column 6). All the estimations presented use robust and clustered standard errors.

A bigger effect of the flood on household consumption is estimated when the treatment and the control groups are only selected in rural areas. Rural households were more affected by the 2015 flood than urban ones, and about 72 per cent of the households in the treatment group are from rural areas. In this case, we find a reduction in consumption of about 16.5 per cent (Column 7 of Table 4). In Column 8 of Table 4, we also present the results for the case in which a continuous, instead of a binary, treatment is used. In this case we use the distance in kilometres from the affected areas as treatment, and we find a coefficient of 0.0010, meaning that each additional kilometre is associated with an increase in consumption of about 0.10 per cent.[8]

[8] In the estimation, we also include the quadratic term for distance in order to take nonlinear effects into account. As expected, we get a negative and significant coefficient for this term, meaning that the effect of distance increases at decreasing rates.

Table 4: Estimation of the effect of the flood on household consumption using different specifications

	1	2	3	4
Method	DID, all provinces	DID, only affected provinces	DID, only households within 200 kms	Household FE reg
Dep variable	Log(cons)	Log(cons)	Log(cons)	Log(cons)
DID	-0.082***	-0.106***	-0.141***	-0.112***
Std. Err.	(0.023)	(0.025)	(0.027)	(0.034)
	5	6	7	8
Method	Village FE reg	DID, province-specific time trends	DID, only rural	Continuous treatment (distance in kms)
Dep variable	Log(cons)	Log(cons)	Log(cons)	Log(cons)
DID	-0.109***	-0.134***	-0.165***	0.0010***
Std. Err.	(0.025)	(0.055)	(0.032)	(0.0003)

Notes *** p<0.01, ** p<0.05, * p<0.1. Treatment group = households residing up to 20 kilometres from the flooded areas. Column 1: the control group is formed by all the households in the country residing more than 20 kilometres from the flooded areas, including households in non-affected provinces. Columns 2–8: the control group is formed by the households residing more than 20 kms from the flooded areas, but only in the affected provinces. Column 3: the control group is formed by the households residing between 20 and 200 kilometres from the flooded areas. Columns 4–5: the household and the village fixed-effect regressions were run using the Stata command *areg*. Column 6: province-specific time trends were added in the regression. Column 7: both the treatment and the control groups are only selected in rural areas. Column 8: here we use a continuous treatment variable represented by the distance in kilometres from the flooded areas; we also include the squared distance in kilometres in order to take nonlinear effects into account, and we get a negative and significant coefficient for this term. All the estimations presented use robust and clustered standard errors.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

In our analysis, we also estimate the effect, using the DID approach, of the flood on other outcome variables of interest such as poverty rate and food and non-food consumption. This provides additional insight into the mechanisms at work and the extent of the welfare losses experienced by the affected households. We find an increase of close to 6.2 per cent in the poverty rate for the affected households. We also obtain the result that non-food consumption reduced slightly more than food consumption (11.2 versus 10.8 per cent) (Table 5, Columns 2 and 3). Similar to what we observed in the case of consumption, the estimated effects obtained for rural areas only are much more pronounced, an increase of 10.1 per cent for the poverty rate, -14.9 per cent for food consumption, and -18.6 per cent for non-food consumption (all statistically significant at the 1 per cent level, not shown in the table). In this case, non-food consumption was reduced much more than food consumption, which is coherent with the rational behaviour of reducing non-necessary expenditures more than essential ones, especially for rural areas.

Table 5: Estimation of the effect of the flood on poverty rate, and on household food and non-food consumption

	1	2	3
Method	DID	DID	DID
Dep variable	Poverty rate	Log(food_cons)	Log(nonfood_cons)
DID	0.062***	-0.108***	-0.112***
Std. Err.	(0.021)	(0.028)	(0.035)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Treatment group = households residing up to 20 kilometres from the flooded areas; control group = households residing more than 20 kilometres from the flooded areas, but only in the affected provinces. Column 1: the estimation of the DID is obtained using a linear regression (linear probability model). Only about 2.4 per cent of the predicted values for the poverty rate obtained from this regression turned out to be below zero and only 0.75 per cent of the predicted values turned out to be above one. Columns 2 and 3: the outcome variables are the logarithm of food and non-food consumption, respectively. All the estimations presented use robust and clustered standard errors.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

Regarding the possible differentiated effect on different groups of households, in Table 6 we present the estimated effect on poor and non-poor from the consumption poverty point of view, and the estimated effect on poor and non-poor from the multidimensional poverty point of view.

Interestingly, we find a bigger effect on poor than on non-poor from the consumption poverty point of view (Table 6, Columns 1–2),[9] but a noticeably different effect on poor and non-poor from the multidimensional poverty point of view (Table 6, Columns 3-4). In particular, the multidimensionally poor households were affected much more than the non-poor households (-12.8 per cent versus an estimated coefficient of -6.4 per cent, only significant at the 10 per cent level). A possible explanation for this is that the multidimensionally non-poor had either more assets, durables goods, livestock, land, or access to basic services, which helped to smooth the effect on consumption, whereas the poor, from the multidimensional point of view, did not have, on average, this possibility.[10] Overall, these findings suggest that the flood had a greater impact on the poor than on the non-poor.

Table 6: Estimation of the effect of the flood on poor and non-poor households from the consumption poverty and from the multidimensional poverty points of view

	1	2	3	4
Method	DID, non-poor (consumption)	DID, poor (consumption)	DID, non-poor (multidimensional)	DID, poor (multidimensional)
Dep variable	Log(cons)	Log(cons)	Log(cons)	Log(cons)
DID	-0.043*	-0.069**	-0.064*	-0.128***
Std. Err.	(0.024)	(0.032)	(0.036)	(0.033)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Treatment group = households residing up to 20 kilometres from the flooded areas. Control group = households residing more than 20 kilometres from the flooded areas, only in the affected provinces. Column 1: the analysis is only performed on the non-poor from the consumption poverty point of view; Column 2: the analysis is only performed on the poor from the consumption poverty point of view; Column 3: the analysis is only performed on the non-poor from the multidimensional poverty point of view; Column 4: the analysis is only performed on the non-poor from the multidimensional poverty point of view. All the estimations presented use robust and clustered standard errors.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

4.1 Robustness checks

A series of robustness checks were performed to test and validate our results. Firstly, we ran placebo tests, in which we first changed the treatment group to the group of households residing between 50 and 100 kilometres from the affected areas, which were supposed to be only marginally affected or not affected at all. Secondly, we changed the post-treatment period to Quarter 2 instead of Quarter 4. As expected, we observed that both these tests estimate a non-statistically significant effect (Table 7, Columns 1 and 2).[11]

As a robustness check, we also explored the case in which the households living in the immediate surroundings of the flooded areas (0 to 5 kilometres) are excluded from the analysis. This is motivated by the fact that these households are likely to be more accustomed than others to frequent flooding episodes and are thus expected to be better prepared to cope with such events. Hence, in this case, the treatment group is limited to households residing between 5 and 20 kilometres from the flooded areas. Interestingly, and possibly confirming our hypothesis, we obtain a bigger effect in this case than the effect obtained in the main results table, -16.9 per cent

[9] The effect on non-poor being statistically significant only at the 10 per cent level.

[10] Unfortunately, the National Statistics Institute only provided information about most multidimensional deprivation indicators for the first quarter. This makes it impossible to perform an analysis of the impact of the flood on, for example, housing characteristics, durable goods, and access to basic services, among others.

[11] In the latter case, the coefficient is statistically significant only at the 10 per cent significance level, probably because some of the households surveyed in the second quarter were interviewed after the flood had occurred (Quarter 2 in the IOF1415 went from mid-November to mid-February). However, we cannot test this hypothesis as we were only given the information on the date of interview for the first quarter.

(Table 7, Column 3).[12] In Table 7, Column 4, we estimate the flood effect including additional covariates in the analysis[13] and obtain similar results to those found in Table 4. We also find no effect on the average number of rural assets owned, which is expected given the short-term nature of our analysis (see also Carter et al. 2007 on Ethiopia) (Table 7, Column 5).

Finally, a quantile regression was also run to better study the effect of the flood at different quantiles of consumption (Table 8). It can be noticed that the estimated effect is only significant at lower quantiles (quantiles 0.10, 0.25 and 0.50), confirming that the poor are likely to have been more affected than non-poor households, and the effect appears to be slightly bigger at the median of the consumption distribution (-17.0 per cent). Finally, in Table 9, we changed the definition of the treatment group to include households residing at different distances from the areas affected by the flood. The results are shown in Table 9 and are coherent with a situation in which the effect decreases with the distance from the flooded area, which reinforces our main findings.

Table 7: Estimation of the effect of the flood on household consumption and on rural assets owned, robustness checks

	1	2	3	4	5
Method	DID, placebo (treatment group = 50–100 kms)	DID, placebo (Q2 instead of Q4)	DID, treatment group = 5–20 kms	DID, additional covariates	DID, rural assets
Dep variable	Log(cons)	Log(cons)	Log(cons)	Log(cons)	Average number of rural assets
DID	0.064	0.042*	-0.169***	-0.110***	-0.151
Std. Err.	(0.045)	(0.025)	(0.045)	(0.025)	(0.599)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Column 1: the treatment group is formed by households residing between 50 and 100 kilometres from the flooded areas; the control group is formed by all the households in the country residing more than 100 kilometres from the flooded areas, only in the affected provinces. Column 2: the treatment group is formed by households residing up to 20 kilometres from the flooded areas; the control group is formed by all the households in the country residing more than 20 kilometres from the flooded areas, only in the affected provinces, but in this case the post-treatment period is set to Quarter 2 and not to Quarter 4. Column 3: the treatment group is formed by households residing between 5 and 20 kilometres from the flooded areas; the control group is formed by all the households in the country residing more than 20 kilometres from the flooded areas, only in the affected provinces; households residing less than 5 kilometres from the flooded areas are excluded from the analysis. Column 4: additional covariates are added to the standard analysis presented in Column 2 of Table 4 (see footnote 6). Column 5: the treatment group is formed by households residing up to 20 kilometres from the flooded areas; the control group is formed by all the households in the country residing more than 20 kilometres from the flooded areas, only in the affected provinces, but the outcome variable in this case is the average number of rural assets owned by the household. All the estimations presented use robust and clustered standard errors.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

[12] If we only consider rural households residing between 5 and 20 kilometres from the flooded areas as the treatment group, the effect is -21.0 per cent, significant at the 1 per cent level.

[13] We include a binary variable indicating whether a member of the household left the household for a period of time because of migration, work, etc.; a variable on whether there is at least one malnourished child in the household; and a series of variables on possession of basic durable goods, access to safe water, quality sanitation, a good quality roof, access to electricity, and average distance to public services such as primary school, health unit, water, market, main roads, police.

Table 8: Estimation of the effect of the flood on household consumption at different quantiles of the consumption distribution

Quantile regression	q10	q25	q50	q75	q90
Dep variable	Log(cons)	Log(cons)	Log(cons)	Log(cons)	Log(cons)
DID	-0.133**	-0.149***	-0.170***	-0.061	-0.070
Std. Err.	(0.061)	(0.048)	(0.040)	(0.050)	(0.046)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The treatment group is formed by households residing up to 20 kilometres from the flooded areas; the control group is formed by all the households in the country residing more than 20 kilometres from the flooded areas, only in the affected provinces. Results are presented for different quantiles of the (log)consumption distribution. All the estimations presented use robust and clustered standard errors.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

Table 9: Estimation of the effect of the flood on household consumption using different distances to define the treatment group

	1		2
Dep variable	Log(cons)	Dep variable	Log(cons)
Km	DID	Km	DID
10	-0.116***	60	-0.043*
20	-0.106***	70	-0.040*
30	-0.094***	80	-0.034
40	-0.083***	90	-0.028
50	-0.053**	100	-0.027

Notes: *** p<0.01, ** p<0.05, * p<0.1. Treatment group = households residing up to 10, 20 …100 kilometres from the flooded areas. Control group = households residing more than 10, 20 …100 kilometres from the flooded areas, but only in the affected provinces. All the estimations presented use robust and clustered standard errors.

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

4.2 Discussion of the results

Given the enormous damage caused by the flood, the estimated effect on household consumption and poverty seems perhaps smaller than one would expect. However, it should be noted that this effect is measured over a very short period of time (a few months) and thus is not immediately comparable to the medium- to long-term effects found in most of the literature on the impact of natural disasters on household consumption and welfare (for example, Thomas et al. (2010) on Vietnam and Little et al. (2006) on Ethiopia). It likely represents only a percentage of the total effect.[14] Households might have smoothed consumption in the very short term through intra-household transfers and/or food assistance and distribution activities put in place by the government and international organizations.[15] Also, when we focus on rural areas only, or on households who were less prepared for an unusually big flood (those between 5 and 20 kilometres

[14] Even though studies like the one by Khandker (2007) on Bangladesh find that the 1998 flood had no long-term impact on consumption and assets and that about half of rural households managed to mitigate the impact of that flood.

[15] The literature presents evidence that transitory events can be successfully smoothed away if inter-household transfers are in place or in cases where food assistance and distribution activities are efficiently put in place by the government and/or international organizations (Townsend (1994) and Morduch (2003) on India; García-Verdú (2002) on Mexico; Barrera and Pérez (2005) on Colombia and Nicaragua; Little et al. (2006), on Ethiopia; Santos (2006) on Nicaragua; Thomas et al. (2010) on Vietnam). For the 2015 flood, we have very detailed evidence that a strong effort was put in place by the government and international organizations to alleviate the effects of the flood (see, for example, GoM-World Bank-UN-EU (2015); UNRCO (2015a, 2015b); World Bank (2015)).

from the affected areas), we find very significant effects on consumption and poverty, comparable to other findings in the literature (Thomas et al. 2010; Karim and Noy 2016).[16]

Moreover, a special discussion is needed with respect to prices. That is because if prices—especially food prices—in the affected regions increased more than in other areas of the country, then the effect on real possibilities of consumption may have been worse than measured by our variable of consumption.[17] On one hand, we can observe that compared to the rest of the country the treatment group shows both a higher proportion of food consumption over total consumption, which would make them more vulnerable to price variations, and a higher proportion of food consumption obtained from own production on total food consumption, which, conversely, would make them less vulnerable to food price variations (Table 10, Panel 1). On the other hand, it is possible to notice that, on average, the treated households did not increase their proportion of food consumption on total consumption in Quarter 4 compared to Quarter 1, but significantly increased their proportion of food consumption obtained from own production on total food consumption in Quarter 4 with respect to Quarter 1 (Table 9, Panel 2).[18]

Computing an approximation of the elasticity of living costs in relation to changing prices proposed by Deaton (1989),[19] we obtain very low elasticities for both the control and the treatment groups, but especially low for the treatment group (-0.01). This finding makes us less concerned about the broad welfare negative effects due to the (sometimes very significant) price variations

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[16] It is also possible to compute the aggregate loss in consumption experienced by the treated group and compare it to total household consumption as measured in the IOF1415. This provides a measure of the significance of the event at a national scale. In Section 3, we provided an overview of the damage caused by the heavy rains and flood of January–February 2015 and its impact on GDP, but from our results we can also obtain a (rough) measure of the loss in consumption due to this catastrophic event. Using the estimate of Table 4, Column 2, we computed a consumption loss of about 8.2 million Meticais (about US$210,000), equivalent to about 0.7 per cent of total household consumption as measured in the IOF1415. This is certainly a much lower aggregate effect when compared to the damage to infrastructure, but it is significant given the relatively low number of households exposed and their relatively low consumption levels compared to those registered in other areas of the country, especially the southern region and the capital Maputo.

[17] The consumption variable used in this study is the variable that is officially used by the Mozambican Ministry of Economics and Finance to measure poverty in the country. It is a real daily per capita consumption measure in the sense that the nominal (daily per capita) consumption is deflated using both a temporal and a spatial price index in order to take price variations into account, both among different provinces/rural–urban areas and between different survey quarters. However, the macro-regions used to create these two price indexes might be too big to capture the price variations observed in the local markets of the most affected areas.

[18] If we only consider the affected provinces, then the control households have a higher proportion of food consumption over total consumption and a comparable proportion of food consumption on total consumption (Table 10, Panel 3). We can also notice that it is possible to see that both control and treated households did not significantly increase their proportion of food consumption on total consumption in Quarter 4 compared to Quarter 1, but both groups significantly increased their proportion of food consumption obtained from own production in Quarter 4 with respect to Quarter 1 (Table 10, Panel 4).

[19] This approach analyses households' elasticity of living costs in relation to changing prices and can be summarized by the following equation: $\delta w_{ir} = \delta p\_al_r[(PR_{ir} - CR_{ir}) + \eta L_{ir}]$, where δw is the welfare variation, expressed in terms of household *i*'s consumption or income; δp_al_r is the variation in food prices; *PR* is a food production ratio that can be approximated to the ratio of self-consumption to total consumption; *CR* is a food consumption ratio, that is, the ratio between food consumption and total consumption; η is the wage elasticity in relation to changes in food prices; *L* is the proportion of consumption in total consumption that results from wages. Taking into consideration that good quality wage data are not available, partly because of the high prevalence of the informal sector in Mozambique, the last part of the equation on the proportion of consumption that results from wages was not considered in this analysis. Thus, we used a simplified equation: $\delta w_{ir} = \delta p\_al_r[(PR_{ir} - CR_{ir})]$. The interpretation of this equation can be summarized as follows: (i) more self-sufficient households are less affected by rising food prices; and (ii) households with higher ratios of food consumption to total consumption are more affected by rising food prices.

observed in the affected provinces during the first months of 2015, even though it may be that during the few weeks of the flood the rise in the price of some basic food and non-food items sharply impacted the consumption patterns and possibilities of households in flooded areas. In this respect, GoM-World Bank-UN-EU (2015) report that both the Markets Information System (SIMA) price monitoring service of the Ministry of Agriculture and the consumer price surveillance service of the Ministry of Industry and Commerce indicate that the price of some items increased sharply, but the price of other items remained constant or even decreased. In general, locally produced food items seem not to have experienced particularly unusual price surges compared to 'normal' years, whereas the price of those goods produced in other regions, or even in the same provinces but in areas not affected by the flood, greatly increased (GoM-World Bank-UN-EU 2015).[20]

[20] '[…] according to the Markets Information System (SIMA) price monitoring service of the Ministry of Agriculture, wholesale price of selected basic food items (common to all) registered from early January 7 to March 5, has increased sharply for some items, while there has been no price variation or a slight decrease on price for others. This fluctuation of prices before and after the heavy rains is due to a combination of variations on supply and demand in local markets, and intrinsically related to the damage on the road network that disrupted normal transit of cargo. […] On the other hand, the consumer price surveillance service of the Ministry of Industry and Commerce indicates a sharp price variation of selected basic food items from early December 2014 to March 2015. […] Nevertheless, it is important to note that for some items, the price variation in local markets reached typical crisis peak […]. This behavior is explained by the limited stock availability and disruption of transit from countryside producing areas and distribution centers, which ultimately has increased the transportation cost from Maputo and Beira to almost 100 percent.' (GoM-World Bank-UN-EU 2015: 54–56)

Table 10: Proportion of food consumption on total consumption and proportion of food consumption obtained from own production on total food consumption for treated and control households

Panel 1: Entire sample						Panel 2: Entire sample					
Variable	Treated	Mean	Std. Err.	[95% Conf. Interval]		Treated	Quarter	Mean	Std. Err.	[95% Conf. Interval]	
Food consumption/ total consumption	No	0.555	0.002	0.552	0.558	No	1	0.553	0.002	0.549	0.557
	Yes	0.612	0.004	0.605	0.619	No	4	0.557	0.002	0.553	0.562
						Yes	1	0.603	0.005	0.593	0.613
						Yes	4	0.619	0.005	0.610	0.629
Food consumption from own production/food consumption	No	0.571	0.003	0.565	0.576	No	1	0.552	0.004	0.544	0.560
	Yes	0.605	0.007	0.591	0.619	No	4	0.588	0.004	0.580	0.596
						Yes	1	0.573	0.010	0.554	0.592
						Yes	4	0.633	0.010	0.614	0.652

Panel 3: Only affected provinces						Panel 4: Only affected provinces					
Variable	Treated	Mean	Std. Err.	[95% Conf. Interval]		Treated	Quarter	Mean	Std. Err.	[95% Conf. Interval]	
Food consumption/ total consumption	No	0.629	0.002	0.625	0.634	No	1	0.620	0.003	0.614	0.626
	Yes	0.612	0.004	0.605	0.620	No	4	0.638	0.003	0.632	0.644
						Yes	1	0.604	0.005	0.593	0.614
						Yes	4	0.620	0.005	0.610	0.630
Food consumption from own production/food consumption	No	0.654	0.004	0.646	0.662	No	1	0.635	0.006	0.624	0.647
	Yes	0.601	0.007	0.588	0.615	No	4	0.671	0.006	0.659	0.682
						Yes	1	0.568	0.010	0.548	0.587
						Yes	4	0.631	0.010	0.612	0.650

Notes: *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations using the 2014/15 Mozambican Household Budget Survey (IOF1415).

5 Conclusions

The 2015 flood in Mozambique was a bigger than usual and mostly unexpected natural event that caused huge damage to infrastructure, especially roads and bridges, estimated at about 2.4 per cent of GDP (GoM-World Bank-UN-EU 2015). At the same time, using a difference-in-difference approach, we found that it also affected household consumption and poverty levels in a significant way. For those exposed to the flood, consumption seems to have been impacted significantly in the period from May to August 2015 compared to August to November 2014—in the range of 11–17 per cent depending on the specification. In particular, the results suggest that poor households and households living in rural areas were affected significantly more than non-poor and urban households, and that poverty levels also increased by about 6 percentage points due to the flood. We obtained comparable results even using a continuous treatment and a household or a village fixed-effect regression.

These results, we believe, are extremely relevant in a country like Mozambique, which has already been hit in the first months of 2019 by two very strong cyclones (Idai and Kenneth), and flooding followed, causing huge damage and many deaths in the central and northern regions (ReliefWeb 2019a, 2019b). However, they also appear to be relevant for neighbouring countries in the Southern Africa region, as they were also hit by the 2015 flood and by cyclones Idai and Kenneth, and for other risk-prone developing countries. Governments and development partners, not just in the Mozambican context, could include these findings in the evidence-based analyses and tools they use for policy planning, natural disaster management and for more precise ex ante vulnerability assessment. At the same time, these results also seek to expand the literature on the short-term economic effects of natural disasters in developing countries, a research area that has become increasingly important in the economic literature, especially for its practical applications in a world with a growing population and rapidly changing climatic conditions.

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