The Inflationary Costs of Extreme Weather in Developing Countries

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April 18, 2016

Abstract

We examine the inflationary costs of extreme weather in developing countries by constructing a monthly data set of hurricane and flood destruction indices and linking these with price data for 15 Caribbean islands. Our econometric model shows that the inflationary impact of extreme weather events can be large. To illustrate potential welfare losses due to these price effects we combine our estimates with price elasticities obtained from a demand system and with event probabilities for Jamaica. Our results show that while expected monthly losses are small, rare events can cause large falls in monthly welfare due to inflationary pressure.

JEL Classification: E31, I31, Q54.

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1 Introduction

Extreme weather is estimated to have caused nearly US$3 trillion worth of damages globally over the last 35 years, and the rate of growth of such losses is predicted to increase in the future due to climate change (see World Bank 2013). Not surprisingly, there is hence a rising interest in understanding the economic implications of these potentially large negative shocks. The majority of the relevant academic literature tends to focus on the consequences of extreme events for economic growth, see Cavallo & Noy (2011) and Klomp & Valckx (2014) for recent reviews. However, a driving factor behind the extent and duration of any longer term outcome, such as growth, is the nature of the adjustment process in the immediate aftermath of the event. More specifically, the physical losses and subsequent economic disruptions are likely to create at least temporary shortages of many goods and services. Amongst other things, these shortages can in turn translate into higher prices. Importantly, if the price hikes are sufficiently large and last long enough, they could further increase the hardship of those already directly affected, as well as result in larger costs for other consumers. Such inflationary costs could then further exacerbate any long-term consequences, particularly affecting the poor. As a matter of fact, Easterly & Fischer (2001) find that for a sample of 38 developing countries inflation is one of their primary concerns.

From a policy maker's perspective, being able to predict price changes and their impact due to extreme weather events can arguably aid in optimizing relief efforts, as well as in choosing the appropriate policies to limit any longer term effects. This may particularly be relevant for developing countries where inflation is already much higher than for the developed world. However, as to date there is essentially no quantitative assessment of the inflationary costs of natural disasters.[1] The only

[1] As a matter of fact, as noted by Cavallo & Noy (2011) in their literature review on the economics of natural disasters, the monetary aspects of disaster dynamics has been generally neglected. Other notable exceptions include Keen & Pakko (2011) who evaluate the optimal response of monetary policy in a dynamic stochastic equilibrium model and Ramcharan (2007)

exception is the study by Cavallo & Cavallo (2014), which examines the impacts of the 2010 Chile and the 2011 Japan earthquakes on product availability and prices. More specifically, using daily nationwide price and product listings collected from the websites of a large international supermarket retailer in each country and comparing these before and after the events, the authors find that there were sharp falls in the availability of goods immediately ex-post, amounting to 32 per cent in Chile and 17 per cent in Japan. However, surprisingly they find that these shortages did not translate into higher prices.

The finding of price stickiness after a natural disaster seems to run counter-intuitive to the common perception that extreme events go hand in hand with price increases, at least in many developing countries.[2] In this paper we thus take a different approach to Cavallo & Cavallo (2014) to investigate potential inflationary costs of natural disasters. More precisely, we construct time series of potential destructiveness for two types of extreme weather phenomena - hurricanes and floods - for a large number of Caribbean islands over time. Compared to focusing on a single event, like an earthquake, this gives a larger amount of variation and ensures that we are not just capturing the effect of other confounding events. In line with Felbermayr & Gröschl (2014), when building our destruction indices we consider not only the physical features of the events, but also take account of their localized nature and the local heterogeneity in exposure to them, which is shown by Strobl (2012) to be important. We then combine these indices with country specific monthly time series on prices to construct a large panel of cross-country, cross-time variation in prices and extreme weather events. This allows us to econometrically examine whether

who empirically examines the role of exchange rate policy in the degree of damages due to natural disasters.

[2]Internet searches on terms like 'inflation' and 'storms' and/or 'floods' quickly reveal the extent of this view across countries typically subject to extreme weather events; see, for instance, concerns by the Central Bank of the Philippines over Typhoon Lando (http://www.philstar.com:8080/business/2015/10/22/1513320/bsp-weighs-typhoon-impact-inflation) and concerns in the Cayman Islands before the 2014 hurricane season (http://www.ieyenews.com/wordpress/caribbean-risk-outlook-hurricane-season-has-arrived/)

such shocks can drive inflation. Using Jamaica as a case study, we then calculate the potential loss in consumer welfare resulting from the inflationary costs of extreme weather. To do so we estimate price elasticities from an Almost Ideal Demand System (AIDS) using household budget survey data and model the probabilities of extreme weather events using univariate and bivariate Peak Over Threshold (POT) models. Employing the results in combination with our estimated inflation response coefficients enables us to measure potential welfare losses due to extreme weather in terms of compensating variation.

Arguably, the Caribbean offers an ideal context within which to study the impact of natural disasters in general, and their potential inflationary costs in particular. Firstly, the region is known to be subject to a large number and wide variety of potentially disastrous natural events, including tropical storms, earthquakes, volcano outbreaks, landslides, floods, and droughts. [3] Secondly, as a set of mostly small island developing states these countries/territories are particularly vulnerable to such large natural shocks due to their small physical size, geographic isolation, limited natural resources, high population densities, low economic diversification, and poorly developed infrastructure (see Meheux, Dominey & Lloyd 2007). Moreover, since they rely on imports for a large part of their consumption goods, or at least cannot easily and quickly substitute internationally produced goods for domestic ones, they are potentially very sensitive to shortages after a natural disaster. With regard to the two types of natural disasters examined here, one should note that hurricanes and floods are the most common natural shocks in the Caribbean and have been driving most of the observed damages, affecting some part of the region consistently almost every year. Moreover, these events have often had disastrous impacts on affected islands. For example, in 2004 Hurricane Ivan is estimated to have resulted in losses of over 300 per cent of Grenada's annual GDP, while the re-

[3]The Caribbean is subject to a large number and types of disasters, including hurricanes, earthquakes, volcano outbreaks, floods and droughts. For example, the Eastern Caribbean is considered the most disaster prone region globally, see International Monetary Fund (2013)

cent heavy rains due to a tropical trough system in St. Vincent and the Grenadines during Christmas 2013 are believed to have caused damages constituting nearly 15 per cent of its economic output. Worryingly, some studies estimate that rising risks from hurricanes and other extreme weather events will cost Caribbean nations up to 9% of annual GDP in damages and losses by 2030 (see Caribbean Catastrophe Risk Insurance Facility [CCRIF] 2010).

In contrast to Cavallo & Cavallo (2014), the results from our analysis show that there can indeed be large price increases due to natural disasters. This effect is reflected in both aggregate inflation, as well as for subcategories of goods. More precisely, while we find that expected monthly welfare effects due to extreme weather are minimal, low probability but very damaging extreme weather can result in inflationary costs that are multiples of estimated monthly household welfare. However, depending on what one considers a damaging hurricane, poorer households can be either relatively better or worse off than richer households due to their different patterns of consumption.

The remainder of the paper is organized as follows. In the next section we describe our data and provide some summary statistics. We discuss our econometric model and results in Section 3. Subsequently, in Section 4, we use our econometric estimates to derive inflationary cost estimates for Jamaica. Concluding remarks are provided in the final section.

2 Data and Summary Statistics

2.1 Hurricane Destruction Index

Tropical cyclones are storms that form in the North Atlantic and the North East Pacific region and are referred to as hurricanes if they are of sufficient strength, generally above 119 km/hr. Hurricane destruction can take the form of damages due to strong winds, heavy rainfall, and storm surge. The latter two aspects tend to be heavily correlated with the wind of the hurricane, and thus wind is often used as a proxy for all types of damaages (see Emanuel 2005). To capture the potential destruction due to hurricanes we use an index in the spirit of Strobl (2012), which measures wind speed experienced at a very localized level and then uses exposure weights to arrive at an island specific proxy.[4] More precisely, for a set of hurricanes $k = 1, \ldots, K$, and a set of locations $i = 1, \ldots, I$, in island $j = 1, \ldots, J$, we define hurricane destruction during month t as:

$$H_{j,t} = \sum_{i=1}^{I} w_{i,t-1} \sum_{k=1}^{K} \left(W_{j,i,k,t}^{max}\right)^3 \mathbb{1}_{\left\{W_{j,i,k,t}^{max} \geq W^*\right\}}, \tag{1}$$

where $\mathbb{1}_{(.)}$ is an indicator function, for location i in island j, at time t, $W_{j,i,k,t}^{max}$ is the maximum measured wind speed during a storm k, W^* is a threshold above which wind is damaging, and the $w_{i,t-1}$ are exposure weights in the previous month $t-1$ at location i, which aggregate to 1 at the level of island j. As can be seen from Equation (1), our hurricane destruction index $H_{j,t}$ requires local wind speed and exposure weights as inputs. Also we allow local destruction to vary with wind speed in a cubic manner, since, as noted by Emanuel (2011), kinetic energy from a storm dissipates roughly to the cubic power with respect to wind speed and this energy release scales with the wind pressure acting on a structure.[5] As a starting point, we set W^*, the threshold above which winds are considered to be of hurricane strength, equal to 119 km/hr.

2.1.1 Local Wind Speed

What level of wind a location will experience during a passing hurricane depends crucially on that location's position relative to the storm and the storm's movement

[4] Strobl (2012) shows that not weighting for local exposure can substantially underestimate the impact of hurricanes on economic growth.

[5] See Kantha (2008) and American Society of Civil Engineers (2006).

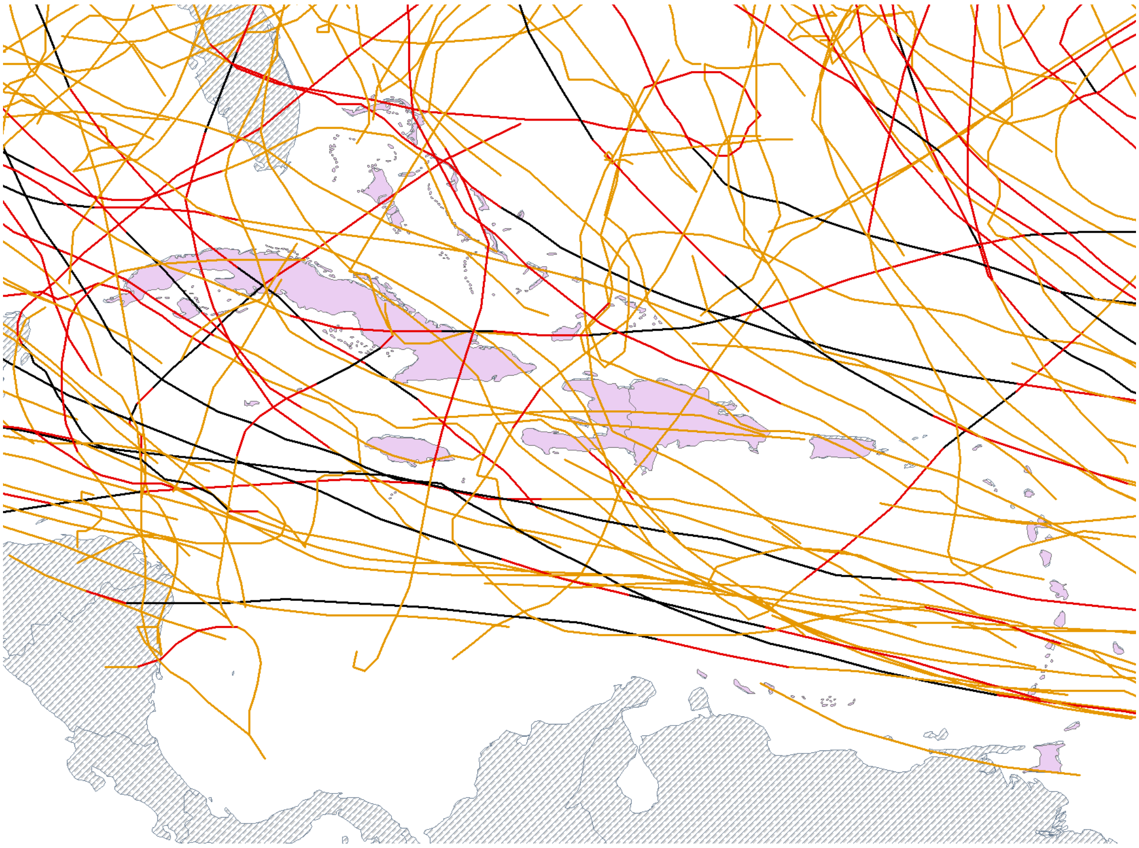
and features, and thus requires explicit wind field modeling. In order to calculate the wind speed experienced due to a hurricane, we use Boose, Serrano & Foster's (2004) version of the well-known Holland (1980) wind field model, described in detail in Appendix A. This model requires as inputs hurricane track data and allows one to estimate the wind speed experienced at any locality at any point in time during the life span of a tropical storm. Our source for hurricane data is the HURDAT Best Track Data, which provides six hourly data on all tropical cyclones in the North Atlantic Basin, including the position of the eye and the maximum wind speed of the storm. We linearly interpolate these to 3 hourly positions in order to be in congruence with our rainfall data, described below. We also restrict the set of storms to those that came within 500 km of our Caribbean islands and that achieved hurricane strength (at least 119 km/hr) at some stage.[6] Figure 1 depicts the tracks of all remaining tropical storms for the period 2000 to 2012, where the red portion of the tracks refers to the segment of the storm that reached hurricane strength. A total of 86 hurricane strength storms traversed the 500km radius of the Caribbean during our sample period of 2000 to 2012.

2.1.2 Exposure Weights

To account for local exposure ideally we would like to have time-varying information on the degree of dispersion of economic activity within islands at the most spatially disaggregated level possible, given that wind speeds due to tropical storms can differ substantially across space. To this end we employ nightlight imagery provided by the Defense Meteorological Satellite Program (DMSP) satellites. Nightlights have now found widespread use in proxying local economic activity where no other measures are available, see for instance Harari & La Ferrara (2013), Hodler & Raschky (2014) and Michalopoulos & Papaioannou (2014). In terms of coverage each DMSP satellite provides global coverage twice per day, at the same local time each day, with a spatial

[6]Tropical cyclones generally do not exceed a diameter of 1000km.

Figure 1: Tropical Cyclones in the Caribbean Region 2000-2012



Notes: Orange, red and black, portions of the tracks indicates tropical storm, hurricane Saffir-Simpson Scale 1 (119-153 km/hr), and at least hurricane Saffir-Simpson Scale 3 (178 km/hr+) strength storms, respectively.

resolution of about 1km near the Equator. The publicly availabe data consist of yearly averages (generated from daily data), where light intensity is normalized to a scale ranging from 0 (no light) to 63 (maximum light).[7] We use the stable, cloud-free series, see Elvidge, Baugh, Kroehl, Davis & Davis (1997)). In order to obtain monthly time-varying values for our weights $w_{i,t-1}$, we linearly interpolate between yearly values.

2.1.3 Flood Events

A flood is a temporary water overflow of a normally dry area due to a rise of a body of water, unusual buildup or runoff of surface waters, or abnormal erosion or undermining of shoreline (see e.g. Samaroo 2010). There are several different types, including flash floods, coastal floods, urban floods, fluvial floods, and pluvial floods, where the main driving factor behind all of these is generally excessive rainfall. Unfortunately there is no complete flood event database providing location and flooding intensity for the Caribbean. An alternative way to identify flood occurrences is to use data on precipitation and simulate water runoff using a hydrological model, but the data required to run such a model is not readily available on a Caribbean wide basis. However, as shown by Montesarchio, Lombardo & Napolitano (2009), in regions where river basin size is less than 400 km^2, which is essentially the case for all of the Caribbean, it is possible to perform flood detection based solely on precipitation data. In following this approach we identify flood events as those above a given threshold level of rainfall. We can then proxy country level flood-induced potential destruction as:

[7] For the years when satellites were replaced, observations were available from both the new and old satellite. In this paper we use the imagery from the most recent satellite, but as part of our sensitivity analysis we also re-estimated our results using an average of the two satellites and the older satellite only. The results of these latter two options were qualitatively identical, and quantitatively extremely close.

$$F_{j,t} = \sum_{i=1}^{I} w_{i,j,t-1} \sum_{d=1}^{t} r_{i,j,d} \mathbb{1}_{\left\{\sum_{d-3}^{d} r_{i,j,d} \geq r^*\right\}}, \tag{2}$$

where $F_{j,t}$ is the exposure-weighted average excess rainfall of country j in month t, $r_{i,j,d}$ is daily rainfall at location i and on day d, and $w_{i,j,t-1}$ are exposure weights for location i as defined in Equation (1). We assume r^* to be 112 mm over a three day window, as suggested by an intensity-duration flood model and actual flood event data for Trinidad, details of which are given in Appendix B. One may want to also note that, unlike for wind speed of tropical storms, we are assuming that potential damages are linearly related to the extent of precipitation during a flood. This is generally in congruence with estimated flood fragility curves, for instance those used by Federal Emergency Management Authority (FEMA) for damage estimation within their HAZUS flood software for the US (see e.g. Federal Emergency Management Agency 2006, Scawthorn, Flores, Blais, Seligson, Tate, Chang, Mifflin, Thomas, Murphy, Jones & Lawrence 2006).

Apart from exposure weights, our only required input in (4) is precipitation r. Since consistent series of rainfall estimates from weather stations are available neither on a temporal nor on a spatial scale for the Caribbean, we instead use the satellite derived TRMM-adjusted merged-infrared precipitation (3B42 V7) product, which have a 3 hourly temporal resolution and a 0.25-degree by 0.25-degree spatial resolution and is available from 1998. Since the TRMM grid cells are of greater size than the location points that we use for our hurricane index and exposure weights, points located within the same TRMM pixels will necessarily have the same local precipitation values.

Finally, it should be noted that a problem in trying to consider hurricane and flood events simultaneously is that many of the excess rainfall events occur during tropical storms. As a matter of fact, as noted for example by Jiang, Halverson & Zipser (2008), the amount of rain and the maximum wind speed during a storm tend to be positively correlated. Moreover, in practice many tropical storms are not powerful enough, or do not come close enough to a locality to cause wind damage, but may still produce enough excess rainfall to cause flooding.[8] We thus in calculating our flood damage index F exclude flood events for a cell within an island during a storm if the corresponding estimated wind speed was above the chosen wind threshold value W^*. In this context, our hurricane destruction index H will capture both wind and accompanying rainfall damage for a locality, as long as winds experienced are of at least hurricane strength. In contrast the flood damage index F is constructed to identify both non-tropical storm-related events, as well as flood damage due to tropical storms that did not translate into local hurricane strength winds.[9]

2.2 Inflation Data

Our source of inflation data are monthly series of the consumer price index (CPI) for a group of 15 island economies in the Caribbean, where our choice of island economies was determined by data availability: Antigua and Barbuda, Bahamas, Barbados, Dominica, Dominican Republic, Guadeloupe, Grenada, Haiti, Jamaica, St. Kitts & Nevis, St. Lucia, Montserrat, Martinique, Trinidad & Tobago, and St. Vincent & the Grenadines. The data are extracted from the island's central bank data sources and covers the period January 2001 to December 2012, but because of missing monthly data for the Bahamas for the years 2001-02, is a marginally unbalanced panel. We use data on total CPI, where inflation is simply the difference in logged monthly prices over time. The richness of our data sources also allows us to homogeneously group goods into three broad sub-categories:[10] (i) Food, which

[8] For example, although Tropical Storm Nicole never reached Hurricane strength, it caused a considerable amount of damage due to heavy rainfall, believed to be around US $239.6 million, in Jamaica; see Planning Institute of Jamaica (2010).

[9] This reduced the correlation between the two potential damage indices from 0.2095 to 0.0128

[10] This choice of categories was restricted by cross-country differences in disaggregation of the CPI.

includes food goods and non-alcoholic beverages, (ii) Housing and Utilities, which includes all goods related to housing construction and repair, furnishings, household equipment, routine household maintenance, and expenditure on water, gas, electricity and other types of fuels, and an (iii) Other category, which consists of all other goods not included in Food and Housing and Utilities, such as alcoholic beverages and tobacco, clothing and footwear, expenditure on health, transport, communication, recreation and culture, education, restaurants and accommodation and miscellaneous goods and services.

2.3 Summary Statistics

Table 1 displays summary statistics for all variables used in the analysis. Accordingly, average monthly aggregate inflation is about 0.4 per cent, translating into about 4.8 per cent annually, although with considerable monthly variation. Also, the rate of food inflation is higher than that of housing and utilities, but less variable. If one examines our benchmark extreme weather proxies ($W^* = 119$km/hr and $r^* = 112$mm) one discovers that the variation is large relative to the mean over our sample period. In part this is due to the large number of non-damaging months for each. More precisely, for our total observations of 2,340 island-months, there are only 142 non-zero occurrences of damaging hurricanes, with a corresponding figure of 673 for flooding.

3 Econometric Results

3.1 Econometric Specification

Our first task is to estimate the impact of extreme weather events on inflation:

$$INFL_{j,t} = \sum_{s=0}^{S} \theta_s^H H_{j,t-s} + \sum_{s=0}^{S} \theta_s^F F_{j,t-s} + \mu_j + \lambda_t + \nu_{j,t}, \tag{3}$$

Table 1: Summary Statistics of Panel Data Set

Variable	Mean	Max	Min	St. Dev.
Hurricane and flooding				
Hurricane ($W^* = 119$)	2602102	1.19e+09	0	3.47e+07
Flooding ($r^* = 112$)	18.05	416.72	0	49.30
Hurricane ($W^* = 178$)	1609246	1.15e+09	0	3.05e+07
Flooding ($r^* = 200$)	15.19	389.67	0	43.48
Inflation				
All	0.37	12.23	-10.64	0.91
Food	0.50	16.79	-13.02	1.36
Housing & Utilities	0.35	46.47	-47.35	2.20
Other	0.41	-11.38	11.63	0.98

This table shows descriptive statistics for the data used to estimate Equation (3). The first panel shows the destruction indices of hurricane, with a threshold of $W^* = 119$ and $W^* = 178$, and flooding, with a threshold of $r^* = 112$ and $r^* = 200$. The second panel shows overall inflation, as well as inflation for food, housing and utilities, and the remaining consumption goods.

where, for country j at time t, $INFL_{j,t}$ is the inflation rate, defined as the difference in logged CPI, $H_{j,t}$ is our hurricane destruction index, $F_{j,t}$ is our flood index, μ_j is a country specific indicator variable, λ_t consists of a set of year and month indicator variables, and $\nu_{j,t}$ is an error term. In order to take account of the country-specific time invariant factors, μ_j, we employ a fixed effects estimator. We allow for cross-sectional and serial correlation of up to four lags by using Driscoll & Kraay (1998) adjusted standard errors.

3.2 Estimation Results

We initially regress the overall inflation rate on the contemporaneous values of our hurricane and flood indices, as shown in Column (1) of Table 2. As can be seen, both have a positive and significant effect on monthly inflation. To see whether there is persistence in these effects we include lags of up to two months after the event in Columns (2) and (3), respectively, but find no evidence of such.[11]

We next investigate whether extreme weather increases prices for our three CPI sub-categories. In this regard, Columns (4) through (6) show that there is also only a contemporaneous increase in food prices due to hurricane shocks, although the quantitative impact is substantially larger, about double that of overall prices. For floods we similarly find an effect about twice that for aggregate inflation, but also now find a smaller, about half of the contemporaneous, lagged effect on food inflation. In contrast, neither weather phenomena appears to play any role in increasing prices of housing and utilities, as shown in Columns (7) through (9). The estimated coefficients on all other goods, shown in the last three columns of the table, suggest that for these there is a contemporaneous effect lying somewhere between the impact on overall prices and that for food.

Thus far we have assumed that hurricane wind damage occurs if localized winds are above 119 km/hr, i.e., of at least Saffir-Simpson (SS) Intensity 1 (119-153 km/hr). In this regard the National Oceanic and Atmospheric Administration (NOAA) notes that when winds are of SS Category 1, typically "..well-constructed frame homes could have damage to roof, shingles, vinyl siding and gutterslarge branches of trees will snap and shallowly rooted trees may be toppled, extensive damage to power lines and poles likely will result in power outages that could last a few to several days.". If, in contrast, one considers Category 3 (178-208km/hr) winds then "...well-built framed homes may incur major damage or removal of roof decking and gable ends, many trees will be snapped or uprooted, electricity and water will be unavailable for several days to weeks after the storm passes".[12] To investigate whether setting the threshold at Category 3 winds changes our findings, we redefine the hurricane destruction index H in Equation (1) using $W^* = 178$ and adjust the flood damage index F accordingly, the results of which are given in Table 3. Compared with

[11]Further lags were also insignificant.

[12]http://www.nhc.noaa.gov/aboutsshws.php.

Table 2: Impact of hurricane and flooding (excluding flood events during hurricane events) on inflation, $W^* = 119$, $r^* = 112$.

Inflation	All			Food			H&U			Other		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
H_t	1.178**	1.210**	1.191**	2.339**	2.414**	2.405**	0.924	0.936	0.911	1.614**	1.165**	1.636**
	(0.328)	(0.344)	(0.356)	(0.448)	(0.470)	(0.487)	(0.524)	(0.532)	(0.544)	(0.397)	(0.399)	(0.412)
H_{t-1}		0.649	0.629		1.045	1.033		0.672	0.64		0.661	0.643
		(0.396)	(0.410)		(0.634)	(0.656)		(0.568)	(0.593)		(0.511)	(0.525)
H_{t-2}			-0.227			0.22			0.389			-0.046
			(0.357)			(0.650)			(0.378)			(0.429)
F_t	0.155**	0.159**	0.157**	0.278**	0.288**	0.286**	0.097	0.0984	0.0923	0.188**	0.193**	0.191**
	(0.051)	(0.052)	(0.052)	(0.077)	(0.080)	(0.081)	(0.090)	(0.089)	(0.089)	(0.061)	(0.063)	(0.063)
F_{t-1}		0.0392	0.0368		0.137*	0.136		-0.0264	-0.0299		0.055	0.053
		(0.053)	(0.053)		(0.068)	(0.070)		(0.088)	(0.087)		(0.053)	(0.054)
F_{t-2}			-0.0405			-0.0534			-0.13			-0.049
			(0.049)			(0.081)			(0.094)			(0.054)
F-test(θ=0)	8.101	7.708	7.482	10.19	11.21	12.15	4.013	4.591	4.724	8.92	9.39	8.77
R^2	0.027	0.028	0.029	0.045	0.048	0.048	0.016	0.016	0.017	0.034	0.035	0.036

This table shows estimation results for different lag specifications of the regression of inflation on hurricane and flooding:

$$INFL_{j,t} = \sum_{s=0}^{S} \theta_s^H H_{j,t-s} + \sum_{s=0}^{S} \theta_s^F F_{j,t-s} + \mu_j + \lambda_t + \nu_{j,t}, \tag{4}$$

For country j at time t, $INFL_{j,t}$ is the inflation rate, computed as the difference in the log the consumer price index, $H_{j,t}$ is the hurricane destruction index, computed with a maximum wind speed of $W^* = 119$ km/hr, $F_{j,t}$ is the flood destruction index, computed with a rainfall threshold $r^* = 112$ excluding flood events during hurricane events, μ_j is a country fixed effect, λ_t is a yearly and monthly time dummy, and $\nu_{j,t}$ is an error term. $H_{j,t}$ and $F_{j,t}$ are divided by 10^{11} and 10^4, respectively, to make coefficients more readable. F-test(θ=0) is the F-test of the regression, which includes the effect of hurricane and flooding destruction for all lags. Driscoll & Kraay (1998) standard errors are shown in parentheses. ** and * indicate 1 and 5 per cent significance levels, respectively. All regressions are run with 2,145 observations.

Table 2, there is now a lagged effect of hurricane damage for overall and for food prices. Perhaps more importantly, we now find both significant contemporaneous and lagged effects of hurricane strikes on the price of housing and utilities.

We also experimented with the use of an alternative threshold for identifying flood events in (4). More specifically, parameter estimates of an intensity-duration model of excess rainfall induced landslides worldwide by Hong, Adler, Negri & Huffman (2007) suggested to set r^* at 200mm. Using this threshold we replicated Table 2 and Table 3, with the corresponding series of flood damage F. Our results, not reported here, showed, however, that while our findings on H still held, floods no longer had any discernable impact on inflation. This suggests that setting the threshold too high may result in excluding too many flood events, and thus introduce too much measurement error into our flood damage proxy.

One can use the estimated coefficients in Table 2 to assess the economic significance of extreme weather on inflation over our sample period and, as an example, we do so for aggregate prices. In this regard it is helpful to recall that monthly mean aggregate inflation rate in our sample was 0.37. Our estimated coefficient suggests that overall average monthly rate rose by 0.003 percentage points due to damaging hurricanes if we use the 119 threshold. In those months with non-zero damage the average impact is about 0.05, while the implied maximum observed price hike is 1.4 percentage points. In contrast to hurricanes, average monthly expected flood-induced inflation is considerably larger, standing at about 0.024 percentage points. Similarly when flooding occurs in a month, the average effect (0.083) is also higher than for hurricanes. However, when one considers the most extreme event month observed over our time period, the implied price hike due to floods is less than half (0.604 percentage points).

Using the estimates under the higher H threshold from Table 3 suggests similarly sized inflationary costs for floods in absolute value compared to the lower cut-off

Table 3: Impact of hurricane and flooding (excluding flood events during hurricane events) on inflation, $W^* = 178$, $r^* = 112$.

Inflation	All			Food			H&U			Other		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
H_t	1.311**	1.336**	1.325**	2.764**	2.799**	2.801**	1.376**	1.406**	1.394**	1.900**	1.628**	1.921**
	(0.233)	(0.244)	(0.248)	(0.347)	(0.359)	(0.363)	(0.476)	(0.470)	(0.472)	(0.249)	(0.269)	(0.267)
H_{t-1}		1.058**	1.060**		1.613**	1.626**		1.096**	1.117**		1.156**	1.163**
		(0.264)	(0.267)		(0.437)	(0.445)		(0.392)	(0.400)		(0.329)	(0.333)
H_{t-2}			0.0618			0.475			0.702			0.242
			(0.253)			(0.586)			(0.401)			(0.382)
F_t	0.119*	0.123*	0.122*	0.240**	0.249**	0.249**	0.0421	0.043	0.0401	0.146*	0.151*	0.149*
	(0.057)	(0.059)	(0.060)	(0.075)	(0.079)	(0.081)	(0.085)	(0.084)	(0.085)	(0.063)	(0.065)	(0.066)
F_{t-1}		0.0316	0.0295		0.102	0.101		-0.0371	-0.0402		0.035	0.034
		(0.067)	(0.069)		(0.092)	(0.094)		(0.079)	(0.078)		(0.069)	(0.071)
F_{t-2}			-0.0454			-0.0366			-0.103			-0.047
			(0.062)			(0.077)			(0.118)			(0.066)
F-test(θ=0)	11.73	10.61	10.43	23.72	26.13	25.43	3.711	6.242	5.909	12.11	10.9	11.37
R^2	0.026	0.028	0.029	0.046	0.049	0.05	0.016	0.016	0.017	0.033	0.035	0.036

This table shows estimation results for different lag specifications of the regression of inflation on hurricane and flooding:

$$INFL_{j,t} = \sum_{s=0}^{S} \theta_s^H H_{j,t-s} + \sum_{s=0}^{S} \theta_s^F F_{j,t-s} + \mu_j + \lambda_t + \nu_{j,t}, \tag{5}$$

For country j at time t, $INFL_{j,t}$ is the inflation rate, computed as the difference in the log the consumer price index, $H_{j,t}$ is the hurricane destruction index, computed with a maximum wind speed of $W^* = 178$ km/hr, $F_{j,t}$ if the flood destruction index, computed with a rainfall threshold $r^* = 112$ excluding flood events during hurricane events, μ_j is a country fixed effect, λ_t is a yearly and monthly time dummy, and $\nu_{j,t}$ is an error term. $H_{j,t}$ and $F_{j,t}$ are divided by 10^{11} and 10^4, respectively, to make coefficients more readable. F-test(θ=0) is the F-test of the regression, which includes the effect of hurricane and flooding destruction for all lags. Driscoll & Kraay (1998) standard errors are shown in parentheses. ** and * indicate 1 and 5 per cent significance levels, respectively. All regressions are run with 2,145 observations.

value.[13] Differences arise, however, with regard to the implied effects due to hurricane damages. More specifically, using the contemporaneous and lagged coefficients on H suggests an average monthly inflation effect of about 0.004 percentage points. When a hurricane induces damage the immediate impact is about 0.080 percentage point a rise in inflation with a further 0.063 point rise a month later. The largest observed value of H over our sample period impact is about 1.5 immediately and 1.2 points a month later.

4 Potential welfare losses: the case of Jamaica

Given the short-term nature of extreme weather induced inflation suggested by our econometric results, the obvious question is whether these inflationary effects will really matter from a welfare point of view. Moreover, as noted in the introduction, one concern about the impact of natural disasters on prices is that it may be the poorest of the population who are most affected. We use data on Jamaican household survey data to further investigate these issues. While our choice is driven by data availability, Jamaica is arguably particularly suited for this task. Geographically it is the third largest island in the Caribbean and lies well within the hurricane belt and thus is subject to frequent hurricane strikes. For example, over our sample period, Hurricanes Iris (2001), Lili (2002), Ivan (2004), Emily (2005), Charley (2005), Dean (2007), Gustav (2008), and Sandy (2012) have all caused at least some damage on the island. At the same time Jamaica is also vulnerable to frequent flooding induced by tropical storms, fronts, and troughs. As a matter of fact, major damaging floods are known to have occurred in the years 2004, 2007, 2008, 2009, 2010 and 2012 (see Mandal, Wilson, Taylor, Nandi, Stephenson, Burgess, Campbell & Otuokon 2014). Jamaica is also one of the poorest countries in the Caribbean, with close to 20 per cent of the population living below the official poverty line.

[13] These were for the average mean, non-zero mean, and maximum observed effects 0.023, 0.075 and 0.514 percentage points, respectively.

4.1 Framework for welfare analysis

In order to assess the potential welfare effect of extreme weather-induced price increases, we explore the change in households' consumer surplus due to the subsequent reallocation of expenditures. One should note in this regard that we are abstracting from any impacts of extreme weather on the absolute level of income due to, for example, loss of employment. Moreover, we do not take account of any potential changes in the demand curve of goods due to extreme weather-induced factors other than relative price changes; as, for instance, the need to spend more on housing because of damages incurred. We are thus focusing simply on the price effect of these events. Accordingly, we consider the minimum expenditure function $C(u, p)$ needed to obtain utility u for a given household, at price vector $p = (p_1, \ldots, p_n)$ with p_i the price of good i. The compensating variation due to an extreme weather event is defined as the change in expenditure ΔC, needed to maintain a constant utility u after a change in the price vector from p to $\tilde{p}$:

$$\Delta C = C(u, \tilde{p}) - C(u, p). \tag{6}$$

Using a second order Taylor expansion and reformulating Equation (6) in terms of proportional changes and household budget shares for a set of goods $i = 1, \ldots, n$, Friedman & Levinsohn (2002) show that one can write:

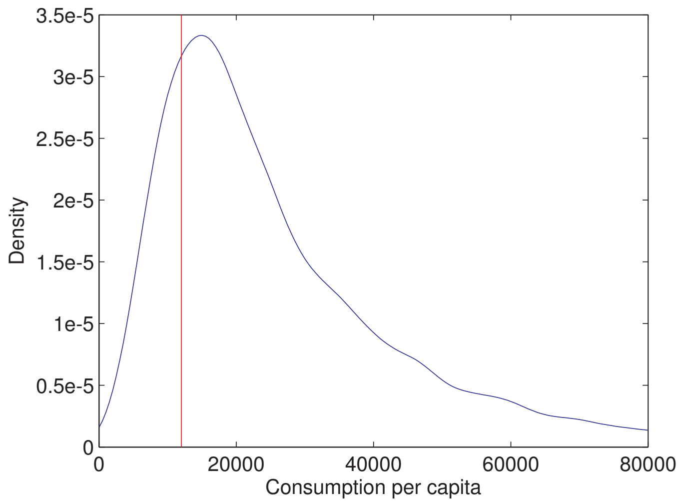
$$\Delta \ln(C) \approx \sum_{i=1}^{n} s_i \Delta \ln(p_i) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} s_i \varepsilon_{ij} \Delta \ln(p_i) \Delta \ln(p_j), \tag{7}$$

where $\Delta \ln(C)$ is compensating variation in relative terms, s_i is the budget share of good i, and ε_{ij} is the compensated (Hicksian) elasticity of the demand for good i with respect to a change in the price of good j, which we estimate from the household budget survey using the almost ideal demand system (AIDS) of Deaton & Muellbauer (1980), as laid out in Section 4.2. Equation (7) thus quantifies the impact on consumer welfare of changes in prices, while accounting for households' ability to substitute away from those goods whose prices have risen in relative terms.

To evaluate the distribution of potential welfare losses implied by extreme weather events we use Equation (7) to calculate the loss in welfare for any household due to a change in the price of goods following a set of possible flood and hurricane events of different strengths, each associated with a quantile that indicates their likelihood of occurrence. More specifically, for any quantile α, we calculate the compensated variation $\Delta \ln(C)^{(\alpha)}$ of a household with budget shares s_i due to a hurricane $H^{(\alpha)} = F_H^{-1}(\alpha)$, or flood event $F^{(\alpha)} = F_F^{-1}(\alpha)$, where $F_H(.)$ and $F_F(.)$, are, respectively, the cumulative distribution function of hurricane and flooding, obtained from a peaks over threshold (POT) model explained in Section 4.3.

We first single out the inflationary effect of hurricanes, $\Delta ln(p_i)^{(\alpha)} = \Theta_i^H H^{(\alpha)}$, or flooding $\Delta ln(p_i)^{(\alpha)} = \Theta_i^{F(\alpha)}$, where Θ_i^H and Θ_i^F are the sum of the significant contemporaneous and lagged effects estimated in Equation (3) for good i. This allows us to associate a welfare loss to any quantile of the distribution of each of these types of events. In contrast, when we consider the joint effect of hurricanes and flooding, we look at the distribution of one type of event conditional on the incidence of the other type. Given the infinite combination of pairs of events, we for demonstrative purposes do so conditioning on a five year return level events (corresponding to a probability of 0.9833). For instance, in the case of hurricanes conditional on flooding, we use $\Delta ln(p_i)^{(\alpha)} = \Theta_i^H H_c^{(\alpha)} + \Theta_i^F F^{(\alpha)}$, where $H_c^{(\alpha)} = F_{H|F}^{-1}(\alpha | F_F^{-1}(0.9833))$. As households' budget shares further depend on their level of consumption, we repeat the analysis for each household and use a Nadaraya-Watson kernel regression of compensating variation on per capita consumption to show how the welfare effect of extreme weather depends on household income.

Figure 2: Distribution of consumption per capita in Jamaica (2012)



Notes: (1) Graph of the kernel density estimate using a Gaussian kernel and a plug-in bandwidth; (2) Red line indicates poverty threshold at J$12,000.

4.2 Budget shares and price elasticities

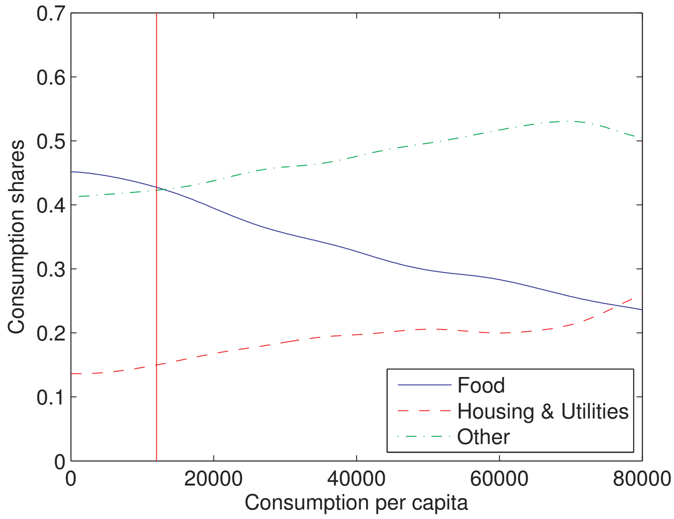
We obtain budget shares s_i for different groups of goods from the 2012 Jamaican Survey of Living Conditions (JSLC), which is a household budget survey covering 6,450 representative households. The official poverty line in Jamaica is about J$143,000 per capita, or about J$12,000 per capita per month, and thus 1,382 out of the total 6,450 households in our data, or 21.4 per cent, would accordingly be defined as poor.[14] We depict the kernel density distribution of per capita consumption per household[15] calculated from the data along with the poverty line threshold in Figure 2. To calculate budget shares of the different goods, we categorize expenditures into food, housing and utilities, and the remaining consumer items to match our cross-country price data. Figure 3 shows the relationship between the budget shares of these three consumption goods and consumption per capita, using a Nadaraya-Watson non-parametric regression. As can be seen, the share spent on

[14]In Jamaica the poverty line is based on consumption data since income data tends to be unreliable. The last official estimate is J$124,408 in 2010 and we convert this into 2012 prices.

[15]As is standard, we weight children half of adults in the consumption per capita calculation.

food decreases with income, standing roughly at around 42 per cent at the poverty threshold. In contrast, expenditure on housing and utilities and on other goods rises with wealth and is about 12 and 41 per cent, respectively, near the poverty line.

Figure 3: Budget Share of different goods, as a function of consumption per capita



Notes: (1) Graph of the kernel regression estimate using a Gaussian kernel and a plug-in bandwidth; (2) Red line indicates poverty threshold at J$12,000.

We take good specific prices, p_{it}, from publications by the Central Bank of Jamaica and aggregated these using their given weights to match our three categories of consumption goods, in line with our analysis above. Since Jamaica calculates its CPI series separately for three regional groupings (the greater Kingston metropolitan, other urban, and rural areas), we match prices to each household using the urban-rural classification associated with each enumeration district that it resides in and to the month that it was surveyed. Hence prices potentially vary over time as well as space across households.

To obtain the elasticities, ε_{ij}, in Equation (7) we estimate an Almost Ideal Demand System (AIDS) as developed by Deaton & Muellbauer (1980). More specifically, we use a linear approximation seemingly unrelated regression (SUR) method and assume that our prices are Laspeyres price indexes. The implied compensated (Hicksian) elasticities from our AIDS estimation are provided in Table 4. As can be seen, all own-price elasticities are statistically significant and of the expected negative sign, where Jamaican households are most responsive to changes in housing and utilities. In terms of the cross-price elasticities the estimated coefficients suggest that all three groups of goods are substitutes, although some are more responsive to price changes in other good groups than others.

Table 4: Price Elasticities

	Food	Housing & Utilies	Other
Food	-0.915**	0.503**	0.412
	(0.182)	(0.097)	(0.206)
Housing & Utilities	0.971**	-2.004**	1.033**
	(0.188)	(0.198)	(0.243)
Other	0.313	0.0406**	-0.719**
	(0.157)	(0.096)	(0.212)

This table shows compensated (Hicksian) elasticities, obtained from the estimates of an Almost Ideal Demand System:

$$s_i = (\alpha_i - \beta_i \alpha_0) + \sum_j \gamma_{ij} \ln(p_j) + \beta_i \left(\ln(x) - \sum_k \alpha_k \ln(p_k) - \frac{1}{2} \sum_k \sum_j \gamma_{kj} \ln(p_i) \ln(p_j) \right), \tag{7}$$

where s_i and p_i are, respectively, the budget share and the price of good i, and x is total expenditure. The Marshallian elasticities obtain as follows:

$$\varepsilon_{ij}^{(M)} = \frac{\gamma_{ij} - \beta_i \left(s_j - \beta_j \left(\ln(x) - \sum_k \alpha_k \ln(p_k) - \frac{1}{2} \sum_k \sum_j \gamma_{kj} \ln(p_i) \ln(p_j) \right) \right)}{s_i} - \delta_{ij},$$

where $\delta_{ij} = 1$ when $i = j$, and 0 otherwise. Income elasticities are given by $\varepsilon_i = \frac{\beta_i}{s_i} + 1$, and compensated (Hicksian) elasticities are given by:

$$\varepsilon_{ij} = \varepsilon_{ij}^{(M)} + s_i \varepsilon_i.$$

Standard errors are in parentheses. **, and * indicate 1 and 5 per cent significance levels.

4.3 Distribution of Hurricanes and Flooding

It is common practice to model the probabilities of rare occurrences, such as weather shocks, using extreme value theory, see for instance Jagger & Elsner (2006) for hurricane wind modeling. A standard approach in this regard is to use Peaks Over

Threshold (POT) models (see e.g. Smith 1987, Davison & Smith 1990). POT models consist of fitting exceedances over a large threshold by a Generalized Pareto Distribution (GPD), whose shape parameter captures the fatness of the tails of the distribution, which indicates how likely it is to observe extreme weather events. We refer to Appendix C for more details on the POT models and their estimation.

As a starting point we model hurricane and flood events independently as univariate POT models; see the estimates given in Table C.1 of Appendix C. Accordingly, for both thresholds, we find a positive, although not significant, shape parameters for hurricanes which suggests that they both have slowly decaying power tails, implying a non-negligible probability of extreme events. In contrast, shape parameters for flooding are very significantly negative, which implies that the distribution has a finite domain, with an upper bound, beyond which the probability drops to zero, and thus there is less reason for concern about very extreme events. We follow the literature and use return periods to state how extreme an event is and return plots to visualize the distribution of extreme events. So, for instance, a 10 year return period event happens on average every 10 years, and with monthly data, this corresponds to the $1 - \frac{1}{10\times 12} = 0.997$ quantile (α) of the distribution. In line with our estimations, the return plots for the hurricane series are convex, while for flooding they are concave and seem to be bounded; see Figure C.2 in Appendix C.

Of course damaging flood and hurricane events are not completely independent occurrences, given that similar climate factors are likely to be driving both. Firstly, even if they do not produce hurricane level winds, tropical storms are still driven by the same underlying temporal variation in climatic factors as hurricane strength ones in any month. Similarly, climate that induces non-tropical storm excessive rainfall may also play a role in tropical storm formation. The possible importance of joint occurrence is already suggested by our data, where 13 per cent of extreme weather damaging months are characterized by both hurricane and flood events. To investigate how joint dependence might influence potential consumer welfare losses, we extend our probability modeling using bivariate POT models. While the GPD embodies all possible limit cases for univariate extremes, there is not a unique class of distributions for joint extremes.

We consider six popular bivariate POT models, which combine univariate GPDs into proper bivariate distributions of extremes, characterized by one or several dependence parameters; namely, the logistic (Gumbel), the negative logistic (Galambos), and the mixed model, as well as their asymmetric counterparts. All bivariate POT models, regardless of the functional form, show very significant dependence parameters between hurricane and flooding, see Table C.1. This is also reflected in the Chi statistic, a measure of tail dependence, the dependence that exists between the extremes of hurricane and flooding.[16] More specifically, for the 119 km/hr (178 km/hr) series the tail dependence is around 0.5 (0.4) for all series, indicating that there is about a 50 percent (40 percent) chance of an extreme flood event conditionally on an extreme hurricane event, or vice-versa using the 119 (178) km/hr series. An information criterion such as the Akaike (AIC) shows that all symmetric models are preferred over their asymmetric counterparts, while a comparison of likelihoods between the three symmetric models suggest that there is no significant difference between them, which is confirmed by a series of pairwise Vuong tests.[17] As a consequence, we decide to proceed with the Gumbel model, which is the most commonly used.[18]

[16]Mathematically, for extreme weather events F and H, $\chi = P(F_F(F) > \alpha | F_H(H) > \alpha) = P(F_H(H) > \alpha | F_F(F) > \alpha)$, where $F_H(.)$ and $F_F(.)$, are, respectively, the cumulative distribution function of hurricane and flooding.

[17]We use a Vuong test, since the models are not nested and a simple comparison of likelihoods is not appropriate. The values of the standard normal test statistics are all less than 0.7, which is well below the 95% value of 1.96.

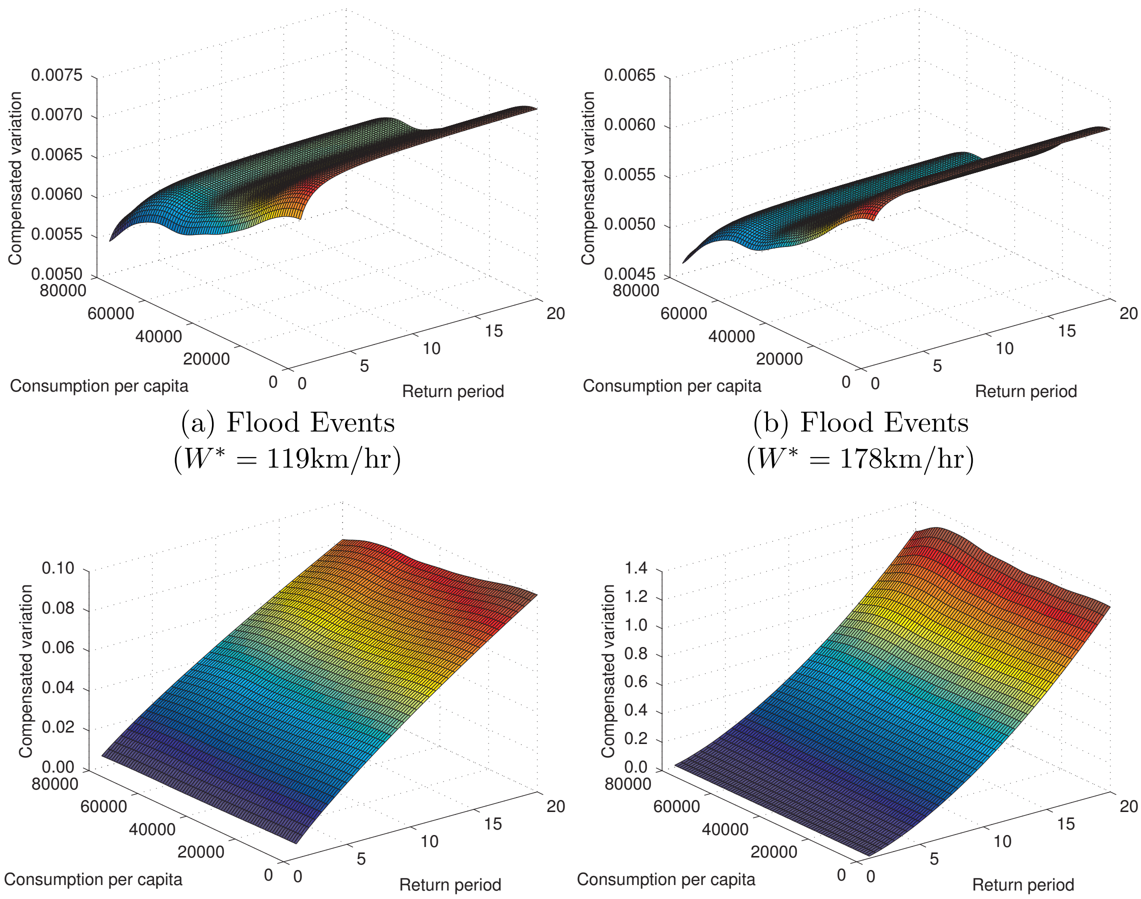
[18]See e.g. Ledford & Tawn (1996), who develop estimation of the model, Longin & Solnik (2001), who use the model to study extreme dependence between financial returns, and Bonazzi, Cusack, Mitas & Jewson (2012), who use the model to analyze the spatial dependence in wind storms.

4.4 Potential Welfare Losses

We now have all parameters to calculate the welfare loss $\Delta \ln(C)^{(\alpha)}$ of any household in our Jamaican data set for any quantile α of the weather distribution. In order to demonstrate how these losses vary across income levels we used a Nadaraya-Watson non-parametric regression estimate of the effect of income on compensating variation, calculated as a percentage of initial household consumption, for each of a range of α's. These kernel estimates are plotted jointly across the range of α's, depicted in terms of return periods, for flood events using each the two hurricane thresholds for inclusion during tropical storms in Panels (a) and (b) of Figure 4. As expected, given our univariate POT estimates, for both series welfare losses rise up to a 5 year return period and then remain fairly stable for a given income group. However, clearly welfare losses are larger for poorer households across the full range of depicted events. For example, for a 10 year event using the $W^* = 119$ km/hr ($W^* = 178$ km/hr), households just below the poverty line will experience a welfare loss of 0.7 (0.6) per cent, while the corresponding households in the 95th percentile will be subject to losses of 0.6 (0.5) per cent.

In contrast to floods, compensating variation for hurricanes rises substantially as one considers more extreme events, in a roughly linear fashion under the $W^* = 119$ km/hr and in a slightly exponential manner under the $W^* = 178$ km/hr threshold - as shown in Panels (a) and (b) of Figure 4. This implies that for the lower threshold, a 20 year event produces 5 times greater losses than a 5 year event, while for the higher threshold, a 20 year event results in losses 7 times larger than for a 5 year event. One may also want to note the stark differences in losses under the two threshold definitions for equal probability events, ranging from multiples of 10 to 14 across the range that we depict. This arises because, as shown by our econometric analysis, limiting damage to stronger winds suggested not only lagged effects but also an impact on prices of housing goods. Perhaps most importantly, in examining

Figure 4: Return plots for univariate POT models



(a) Flood Events ($W^* = 119$km/hr)

(b) Flood Events ($W^* = 178$km/hr)

(c) Hurricane Events ($W^* = 119$km/hr)

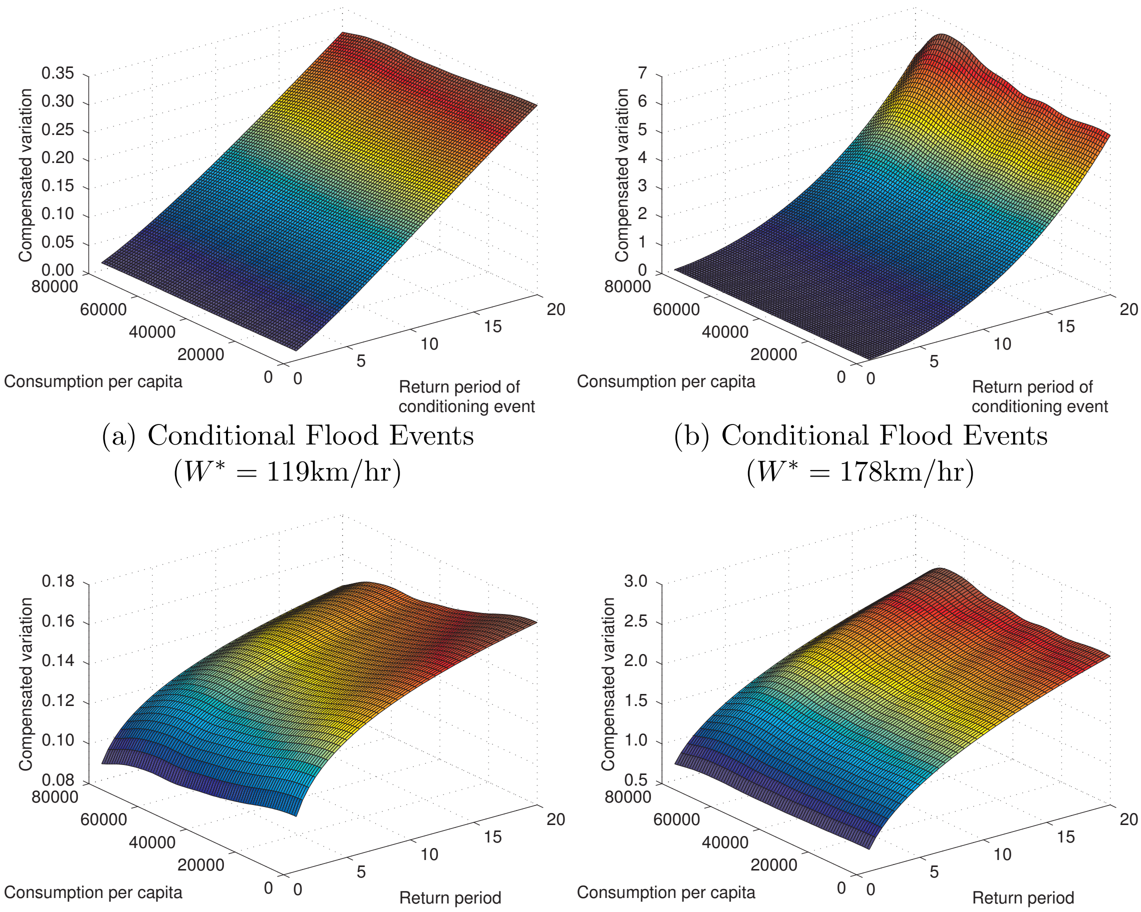
(d) Hurricane Events ($W^* = 178$km/hr)

This figure shows estimates of a series of kernel regressions of compensated variation on consumption per capita, plotted over a grid of tail events with 1 to 20 year return periods of hurricanes with a 119 km/hr threshold in Panel (a), hurricanes with a 178 km/hr threshold in Panel (b), flooding with a 119 km/hr threshold in Panel (c), and flooding with a 178 km/hr threshold in Panel (d). Kernel regressions use a Gaussian kernel and a plug-in bandwidth. Compensating variation is measured in percentage changes.

welfare losses across income levels, one finds that, for the 119 km/hr threshold, poorer households experience greater losses than richer ones, whereas one finds the reverse when assuming that damages occur at wind speeds greater than the Saffir-Simpson scale of 3. This is due to the fact that, on average, richer households spend a substantially larger fraction of their total income on housing and utilities, the price of which reacts only to more extreme storm months. Nevertheless, these differences are not particularly pronounced given the total level of losses, particularly for the most extreme event months. For example, a 20 year event month under the $W^* = 178$ km/hr definition, would suggest losses of about 128 per cent of initial expenditure for households at the 95th percentile of the income distribution, whereas the equivalent figure is about 125 per cent for households just below the poverty level.

We next recompute compensating variation using the probabilities derived from the bivariate estimations to allow for dependence among hurricane and flood events. From the large number of possible combinations of conditioning events, we choose two as illustrative examples. Firstly, in terms of floods, we compute the welfare losses of 5 year flood events, conditional on 1 to 20 year hurricane events, since the severity of floods does not change much for events of lesser probability. Using a similar line of reasoning for hurricanes, we use the range between 1 and 20 year return period events conditioned on a 5 year flood event. Panels (a) and (b) of Figure 5 show the flood events for the two thresholds. Unsurprisingly, they have the same qualitative shape and features as their univariate counterparts. More specifically, welfare losses rise sharply as events become more extreme. Given that the inflationary pressures of hurricanes dominate those of floods, we again find that for the lower threshold, losses are relatively larger for poorer households and the contrary for the greater threshold. If we take for instance a 5 year flood event, conditioned on a 20 year hurricane event for $W^* = 178$ km/hr, then welfare losses for the richest households will be around 700 per cent and a little under 600 per cent for poorer households,

Figure 5: Return plots for bivariate POT models



(a) Conditional Flood Events ($W^* = 119$km/hr)

(b) Conditional Flood Events ($W^* = 178$km/hr)

(c) Conditional Hurricane Events ($W^* = 119$km/hr)

(d) Conditional Hurricane Events ($W^* = 178$km/hr)

This figure shows estimates of a series of kernel regressions of compensated variation on consumption per capita. Results for 5 year return period flood events, interpolated over a grid of conditional hurricane events occurring with a return period between 1 and 20 years, for hurricanes are shown with a 119 km/hr threshold in Panel (a) and hurricanes with a 178 km/hr threshold in Panel (b). The regression shows results for 5 year return period hurricane events, interpolated over a grid of conditional flood events occurring with a return period between 1 and 20 years, are shown for flooding with a 119 km/hr threshold in Panel (c) and flooding with a 178 km/hr threshold in Panel (d). Kernel regressions use a Gaussian kernel and a plug-in bandwidth. Compensating variation is measured in percentage changes.

while corresponding figures for the lower threshold are about 30 and 33 per cent, respectively.

Examining our conditional hurricane events in Figure 5, one finds that both thresholds produce fairly similar shapes over the return periods, rising relatively sharply but then flattening out as we consider the more extreme conditionals. Again, the welfare losses for similar return periods differ markedly across these. For example, while a 10 year conditional hurricane decreases welfare by about 12 per cent for the $W^* = 119$ km/hr, considering only winds above $W^* = 178$ km/hr suggests an average loss of about 150 per cent. The corresponding figures for 20 year conditional events are 16 and 235 per cent, respectively. As before, there are some marginal differences across income, depending on what level of wind speed is assumed to be damaging. For instance, a conditional 20 year hurricane event under the $W^* = 119$ km/hr, would imply a welfare loss 2 percentage points greater for poorer households, while setting the threshold higher implies that richer households would expect a loss 10 percentage points higher than poorer ones.

5 Conclusion

In this paper we investigate how extreme weather can drive short-term inflation. To this end we construct hurricane and flood destruction indices from weather and exposure data and combine these with monthly price data for 15 Caribbean islands. Our econometric results suggest that while the expected inflationary rise due to extreme weather is on average small every month, when this does occur the impact can be multifold of monthly average inflation. In this regard the monthly impact is larger on average and occurs more often for floods, but when a hurricane strikes the resultant rise is considerably larger. Using the case study of Jamaica we also investigate the welfare implications of the inflationary costs of such negative shocks. We find that losses in welfare can be large for the rarer events. Moreover, because of different consumption patterns, depending on the strength of a damaging hurricane the welfare decline of poorer can be smaller or larger than those of wealthier households, although the differences are not substantial either way.

More generally our analysis suggests that the potential short-term costs of inflationary pressure due to shortages of goods after an extreme weather event should not be ignored. In this regard, there are some governments in developing countries that already have been employing deflationary policies for many years. For example, the Philippines National Food Authority keeps stocks of rice and corn to buffer price hikes due to droughts, floods, and typhoons. Our results suggest that other countries with significant exposure to extreme weather may benefit from implementing similar policies. Specifically with regard to monetary policy, Ananda, Prasad & Zhang (2015) note that headline inflation targeting, taking acount of supply-driven shocks, is likely to be the optimal strategy to keep inflation low and stable in developing countries. Our finding that food prices are the most severely affected by extreme weather provides further support for the use of headline inflation targeting for nations afflicted with such events.

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Appendices

A Wind field model

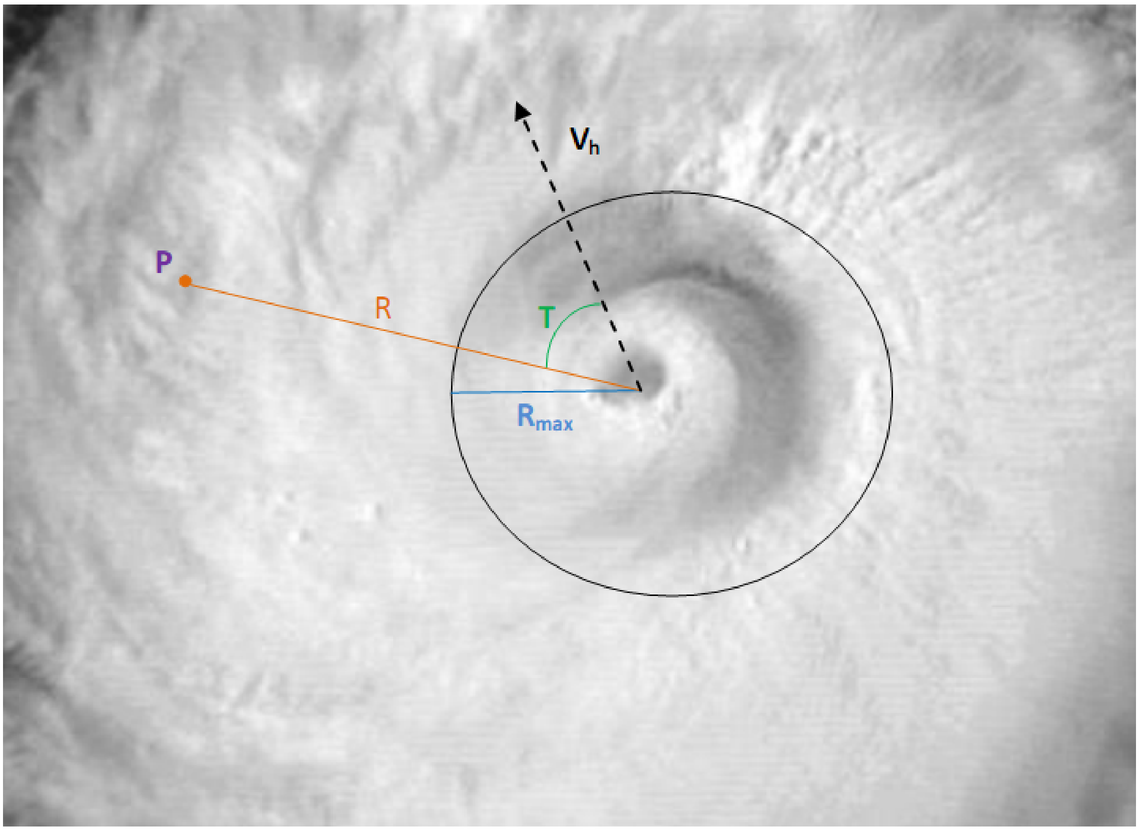
In order to calculate local wind exposure during a storm we use the Boose et al.'s (2004) version of the well-known Holland (1980) wind field model. More specifically, $W_{i,k,t}$, the wind experienced at any point i, during hurricane k at time t is given by:

$$W_{i,k,t} = GD\left[V_{m,k,t} - S\left(1 - \sin(T_{i,k,t})\right)\frac{V_{h,k,t}}{2}\right]\left[\left(\frac{R_{m,k,t}}{R_{i,k,t}}\right)^{B_{jt}} \exp\left\{1 - \left[\frac{R_{m,k,t}}{R_{i,k,t}}\right]^{B_{jt}}\right\}\right]^{1/2}, \quad \text{(A.1)}$$

where, for hurricane k, at time t, $V_{m,k,t}$ is the maximum sustained wind velocity anywhere in the hurricane, $T_{i,k,t}$ is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the i-th pixel of interest, $V_{h,k,t}$ is the forward velocity of the hurricane, $R_{m,k,t}$ is the radius of maximum winds, and $R_{i,k,t}$ is the radial distance from the center of the hurricane to the i-th point P. The relationship between these parameters and point P are depicted in Figure A.1. The remaining ingredients in Equation (A.1) consist of the gust factor G and the scaling parameters D for surface friction, S for the asymmetry due to the forward motion of the storm, and B, for the shape of the wind profile curve.

In terms of implementing Equation (A.1) one should note that $V_{m,k,t}$ is given by the storm track data described below, $V_{h,k,t}$ can be directly calculated by following the storm's movements between successive locations along its track, and $R_{i,k,t}$ and $T_{i,k,t}$ are calculated relative to the i-th point of interest P. All other parameters have to be estimated or values assumed. For instance, we have no information on the gust wind factor G, but a number of studies (see e.g. Paulsen & Schroeder 2005) have measured G to be around 1.5, and we also use this value. For S we follow Boose et al. (2004) and assume it to be 1. While we also do not know the surface friction

Figure A.1: Hurricane Wind Field Model



Notes: (1) Sample diagram of input parameters into typhoon wind field model; (2) P: point of interest, R: distance from storm eye to point of interest, R_{max}: radius of maximum wind speed, T: angle of point relative to direction of storm; V_h: forward speed of storm.

to directly determine D, Vickery, Masters, Powell & Wadhera (2009) note that in open water the reduction factor is about 0.7 and reduces by 14% on the coast and 28% further 50 km inland. We thus adopt a reduction factor that decreases linearly within this range as we consider points i further inland from the coast. Finally, to determine B we employ Holland's (1980) approximation method, whereas we use the parametric model estimated by Xiao, Xiao & Duan (2009) to estimate $R_{m,k,t}$.

B Flood detection

Since Caine (1980), there have been a large number of studies that use intensity-duration precipitation thresholds for flood induced landslides and debris flow (see e.g. Guzzetti, Peruccacci, Rossi & Stark 2008, Cannon, Boldt, Laber, Kean & Staley 2011, Turkington, Ettema, van Weste & Breinl 2014). More recently, this approach has also been employed to identify floods more generally, see for example Hurford, Parker & Priest (2012), on the grounds that for other types of floods, such as urban, river, or flash floods, the concept of an intensity-duration threshold is similar: a surface has a maximum water storage capacity above which surface runoff will occur, see Gumbricht (1996). The intensity-duration approach entails taking information on the duration and intensity of rainfall for known landslide events and estimating a power law relationship between the two:

$$Intensity = aDuration^b, \tag{B.1}$$

where a and b are parameters to be estimated and can be used to identify the threshold rainfall intensity that will induce landslides for a given rainfall duration. With regard to the Caribbean, Pathirana, Aliasgar, & Baban (2010) collected duration and intensity data for flood events in Trinidad over the period 2004-2008 and in estimating Equation (B.1) found a to be 4.064 and b -0.267. We use these estimates to infer flood events in the Caribbean more generally. To this end we set duration equal to 3 days, so that the resultant implied intensity threshold is a cumulative 3-day sum of rainfall of 112 mm. We choose to identify flood events over three day windows rather than some shorter or longer horizon since Wu, Adler, Tian, Huffman, Li & Wang (2014) note that the data of precipitation that we use, namely Tropical Rainfall Measuring Mission (TRMM) satellite derived rainfall, is much better suited to identifying flood occurrences for 3-day windows than incidences of a shorter nature.[19]

C Peaks over threshold models

Peaks Over Threshold (POT) models (see e.g. Smith 1987, Davison & Smith 1990) rely on the Pickands Balkema de Haan theorem, which states that for a large class of distributions exceedances over a large threshold m are well approximated by a Generalized Pareto Distribution (GPD), which is characterized by a scale parameter σ and by a shape parameter ζ. We thus consider that the distribution of our natural disaster variable $X = F, H$, can be approximated as follows:

$$P(X \leq x) = \begin{cases} (1 - F_n(m)) \left(1 - \left(1 + \zeta \frac{x-m}{\sigma}\right)_+^{-1/\zeta}\right) & \text{whenever } x \geq m \\ F_n(m) & \text{whenever } x < m, \end{cases} \tag{C.1}$$

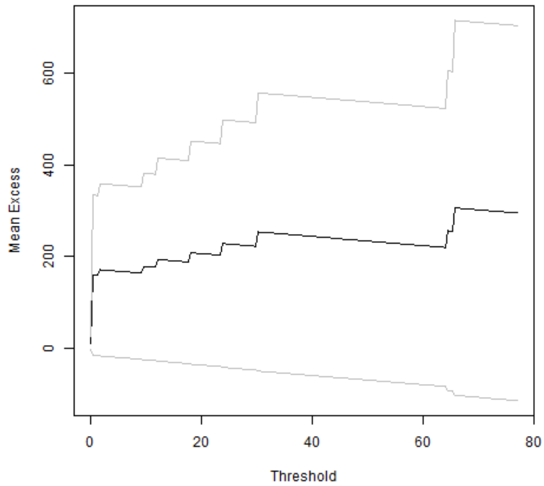
where $z_+ = \max(0, z)$, and $F_n(x) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}_{\{X_i \leq x\}}$ is the empirical distribution, based on the sample $(X_1, \ldots, X_n)$. The shape parameter captures the fatness of the tails of the distribution, which indicates how likely it is to observe extreme weather events. In particular a positive shape parameter implies a power law, which corresponds to the case where extreme events are prevalent. More specifically, a negative value of the shape parameter ζ implies that the distribution has an upper

[19] Similarly, Mathew, Babu, Kundu, Kumar & Pant (2014) find that 3-day cumulative rainfall derived from TRMM data can be a significant predictor of landslides.

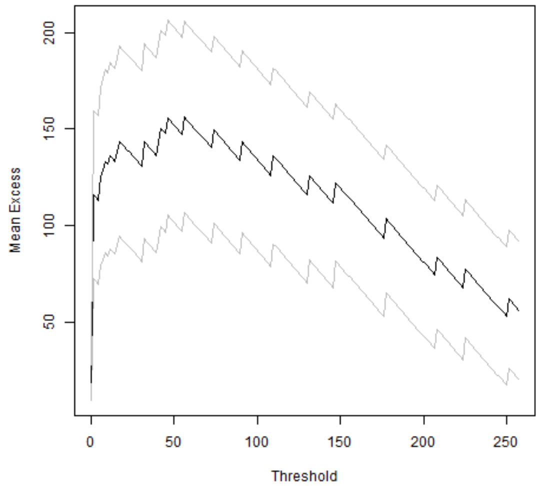
bound of $-1/\zeta$, while, when $\zeta = 0$, the distribution has a thin tail with exponential decay (like e.g. the normal distribution), and when $\zeta > 0$, the distribution has a fat tail, with power decay (like, e.g., the Student t distribution).

We first need to determine the appropriate threshold for each one of our four extreme weather series for Jamaica, i.e., for the hurricane and flood events, defined alternatively according to the 119 km/hr or 178 km/hr hurricane threshold. To do so, we follow standard practice and examine mean residual plots, where the different thresholds are plotted against the empirical estimates of tail expectations, as shown in Figure C.1. The idea underlying the use of the MRL plot is to find the threshold beyond which the plot is linear. This is because the tail expectation of a GPD is linear in the threshold, i.e., $E[Y - m_1|Y > m_1] = E[Y - m_0|Y > m_0] + m_1\frac{\zeta}{1-\zeta}$ where $Y \sim GDP(m_0, \sigma_0, \zeta)$, and $m_1 > m_0$ are thresholds. Given that there are only relatively few hurricane events (13 and 28 out of a total of 180 months for the 119 and 178 km/hr series, respectively), we include all extreme events by selecting a threshold of 1 for both hurricane series. This is roughly in agreement with the MRL plots in Figures C.1a and C.1b, which look reasonably linear from the very start. The flood series have more events (11 and 79, out of 180 months for the 119 and 178 km/hr series, respectively), not all of which are extreme, and thus we select thresholds of 50 and 180, after which the plots become approximately linear, as can be seen in Figures C.1c and C.1d.

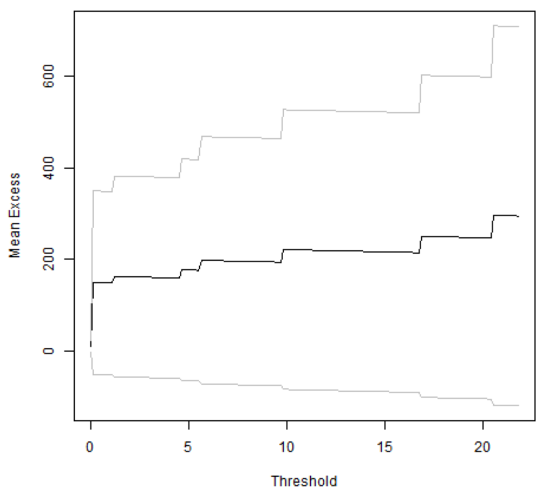
Figure C.1: Mean Residual Plots



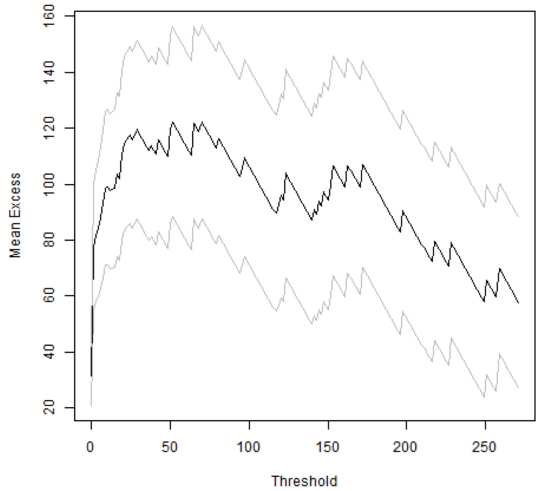
(a) Hurricane (119 km/hr threshold)



(b) Hurricane (178 km/hr threshold)



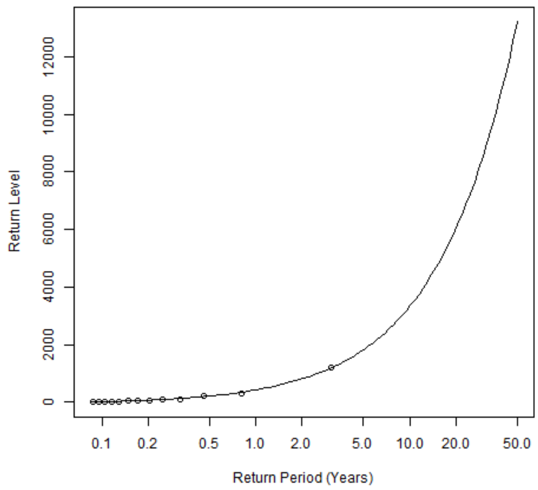
(c) Flooding (119 km/hr threshold)



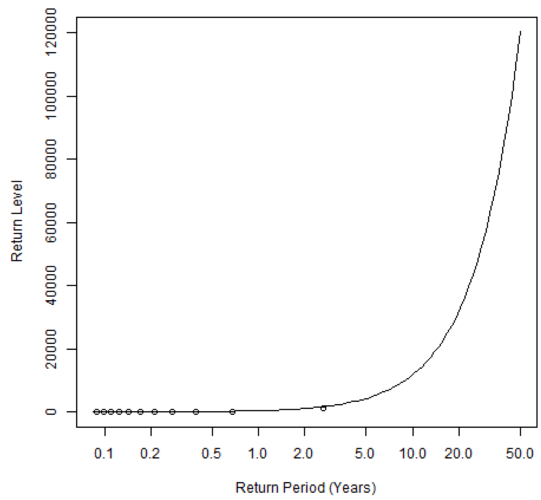
(d) Flooding (178 km/hr threshold)

This table shows Mean Residual (MRL) plots for hurricane with a 119 km/hr threshold in Panel (a), hurricane with a 178 km/hr threshold in Panel (b), flooding with a 119 km/hr threshold in Panel (c), and flooding with a 178 km/hr threshold in Panel (d). The plots show tail expectation $E[Y - m|X > m]$ for different values of the threshold m. The idea underlying the use of the MRL plot is to find the threshold after which the plot is linear, since a defining feature of the GPD is that its tail expectation is linear in the threshold: $E[Y - m_1|Y > m_1] = E[Y - m_0|Y > m_0] + m_1\frac{\zeta}{1-\zeta}$ where $Y \sim GDP(m_0, \sigma_0, \zeta)$, and $m_1 > m_0$ are thresholds.

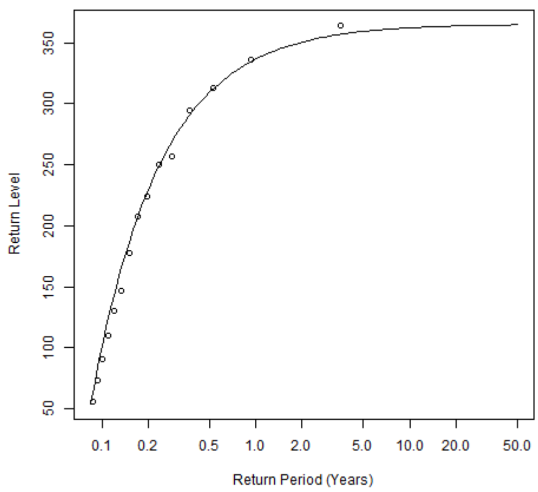
Figure C.2: Univariate Peaks Over Threshold models



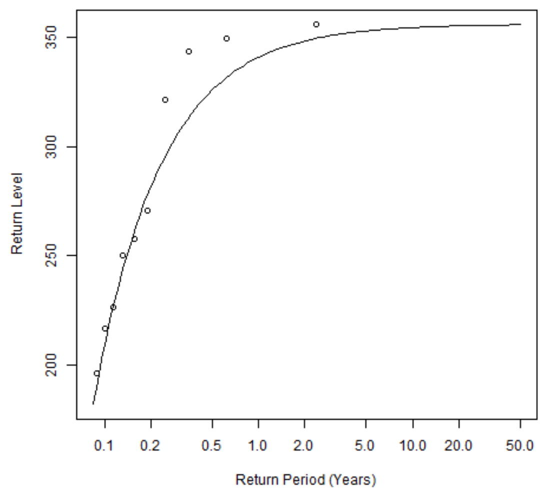
(a) Hurricane (119 km/hr threshold)



(b) Hurricane (178 km/hr threshold)



(c) Flooding (119 km/hr threshold)



(d) Flooding (178 km/hr threshold)

This figure shows the fit of the GPD model for hurricane with a 119 km/hr threshold in Panel (a), hurricane with a 178 km/hr threshold in Panel (b), flooding with a 119 km/hr threshold in Panel (c), and flooding with a 178 km/hr threshold in Panel (d). Dots indicate observed extreme events, while the line represents the fitted POT model.

Table C.1: Univariate and bivariate peaks over threshold (POT) models for hurricane and flooding

	Univariate POT Independence (1)	Gumbel (2)	Asymmetric Gumbel (3)	Galambos (4)	Asymmetric Galambos (5)	Mixed (6)	Asymmetric mixed (7)
	Panel A: Speed greater than 119km/h						
Hurricane							
Scale	49.02	32.14	30.00	36.85	45.01	44.89	45.01
	(26.8)	(17.00)	(16.59)	(20.25)	(27.40)	(27.09)	(25.13)
Shape	0.85		1.29	1.27	1.07	1.06	0.96
	(0.52)		(0.60)	(0.58)	(0.52)	(0.48)	(0.41)
Asymmetry			0.94**		0.96*		
			(0.26)		(0.30)		
Logl	-74.58						
Flooding							
Scale	303.87**	244.95*	246.40*	278.32*	237.31	237.34*	237.31*
	(9.00)	(79.00)	(80.55)	(91.88)	(105.85)	(75.65)	(80.10)
Shape	-0.96**	−0.67	−0.66	−0.80	−0.61	−0.65	−0.64
	(0.02)	(0.34)	(0.36)	(0.36)	(0.56)	(0.34)	(0.37)
Asymmetry			0.87*		1.00**		
			(0.28)		(0.00)		
Logl	-86.39						
Joint asymmetry							0.01***
							(0.00)
Dependence		0.55**	0.49*	1.14**	0.97*	1.00**	0.97**
		(0.10)	(0.19)	(0.34)	(0.30)	(0.00)	(0.00)
AIC		493.88	497.73	493.66	499.16	494.63	496.73
Chi		0.54	0.54	0.54	0.48	0.50	0.50
	Panel B: Speed greater than 178km/h						
Hurricane							
Scale	16.65	12.38	11.94	13.19	21.59	21.57	21.57
	11.43)	(8.55)	(1182.54)	(9.28)	(2137.18)	(2135.54)	(2135.84)
Shape	1.45	1.77	1.40	1.87*	0.90	0.96	0.93
	(0.75)	(0.83)	(138.67)	(0.85)	(88.64)	(94.98)	(92.23)
Asymmetry			0.87		0.71		
			(85.75)		(70.30)		
Logl	-57.83						
Flooding							
Scale	173.45**	200.32	183.35	251.70*	178.41	178.44	178.42
	(1.48)	(101.93)	(18151.94)	(91.91)	(17663.08)	(17665.10)	(17663.96)
Shape	-0.98**	−1.11	−1.04	−1.42	−1.01	−1.01	−1.01
	(0.00)	(0.70)	(−103.00)	(0.55)	(−100.24)	(−100.23)	(−100.26)
Asymmetry			0.67		0.67		
			(66.46)		(66.62)		
Logl	-51.83						
Joint asymmetry							−0.09
							(−9.33)
Dependence		0.68**	0.54	0.78*	0.94	0.77	0.86
		(0.11)	(53.12)	(0.26)	(92.84)	(76.71)	(84.67)
AIC		370.31	374.07	369.43	375.89	371.65	373.53
Chi		0.40	0.41	0.41	0.33	0.39	0.36

This table displays results for univariate POT models in Column (1), and for bivariate POT models with a Gumbel model in Column (2), an asymmetric Gumbel in Column (3), a Galambos model in Column (4), and asymmetric Galambos model in Column (5), a mixed model in Column (6), and an asymmetric mixed model in Column (7). Panel A shows results with a 119km/hr threshold, results with a 178km/hr threshold are in Panel B. All models are estimated with maximum likelihood. The scale and shape parameters are marginal parameters of the POT model, and they correspond to parameters σ and ζ in Equation (C.1). Asymmetry, joint asymmetry and dependence are parameters characterizing the dependence of the bivariate POT models. Dependence is the dependence parameter of the bivariate POT model. AIC refers to the Akaike Information Criterion. Chi is the tail dependence of the bivariate POT models, which represents the probability that one series is extreme, conditional on the fact that the other series is also extreme.