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DOI:
10.1111/ecoj.12581

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Document Version
Peer reviewed version

Citation for published version (Harvard):
Heinen, A, Khadan, J & Strobl, E 2019, 'The price impact of extreme weather in developing countries', *The Economic Journal*, vol. 129, no. 619, pp. 1327–1342. https://doi.org/10.1111/ecoj.12581

THE PRICE IMPACT OF EXTREME WEATHER IN DEVELOPING COUNTRIES[1]

Andréas Heinen, Jeetendra Khadan and Eric Strobl

Abstract

We examine the impact of extreme weather on consumer prices in developing countries by constructing a monthly data set of potential hurricane and flood destruction indices and linking these with consumer price data for 15 Caribbean islands. Our econometric model shows that the price 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 price increases.

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 and Noy (2011) and Klomp and 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

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doi: 10.1111/ecoj.12581

further increase the hardship of those already directly affected, as well as result in larger costs for other consumers. Such costs could then further exacerbate any long-term consequences, particularly affecting the poor (see, for instance, Easterly and Fischer, 2001; Dessus *et al.*, 2008).

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 prices tend to increase much faster than in the developed word. However, as to date there is essentially no quantitative assessment of the price impact of natural disasters.[2] The only exception is the study by Cavallo, Cavallo and Rigobon (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% in Chile and 17% in Japan. However, 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.[3] In this paper we thus take a different approach from Cavallo, Cavallo and Rigobon (2014). More precisely, we construct time series of potential destructiveness for two types of extreme weather phenomena - hur-

[2]As a matter of fact, as noted by Cavallo and Noy (2011) in their literature review on the economics of natural disasters, the monetary aspects of disaster dynamics have been generally neglected. Notable exceptions include Keen and Pakko (2011) who evaluate the optimal response of monetary policy in a dynamic stochastic equilibrium model and Ramcharan (2007) who empirically examines the role of exchange rate policy in the degree of damages due to natural disasters.

[3]Internet searches on terms like "prices" or "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/)

ricanes 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 and Gröschl (2014), when building our potential destruction indices we consider not only the physical features of the events, but also take account of their localised nature and the local heterogeneity in exposure to them, which is shown by Strobl (2012) to be important. We combine these indices with country specific monthly time series on prices to construct a large panel data set, allowing us to examine whether econometrically extreme weather affects prices. Using Jamaica as a case study, we then calculate the potential loss in consumer welfare in terms of compensating variation. To do so we estimate price elasticities from a Quadratic Almost Ideal Demand System (QUAIDS) using household budget survey data and model the probabilities of extreme weather events using Peak Over Threshold (POT) models.

Arguably, the Caribbean offers an interesting context within which to study the impact of natural disasters in general, and their price impact 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.[4] 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 *et al.*, 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.

[4]For example, the Eastern Caribbean is considered the most disaster prone region globally, see Acevedo, Cebotari and Turner-Jones (2013)

One should note that hurricanes and floods are the most common and damaging natural shocks in the Caribbean, 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% of Grenada's annual GDP, while the recent 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% 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 by 2030 (see Caribbean Catastrophe Risk Insurance Facility, 2010).

In contrast to Cavallo, Cavallo and Rigobon (2014), our results show that there can be price increases due to natural disasters. This effect is reflected in aggregate consumer price changes, 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 events can result in costs that are multiples of estimated monthly household welfare.

The remainder of the paper is organised 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. In Section 4, we conduct our welfare analysis using the case study of Jamaica. The final section concludes.

1 Data and Summary Statistics

1.1 Potential Hurricane Destruction Index

Hurricanes are tropical cyclones that form in the North Atlantic and the North East Pacific basins and can cause destruction in the form of 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 damages (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 at a very localised level and then uses exposure weights to arrive at an island specific proxy.[5] 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 potential hurricane destruction during month t as:

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

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, K_t is the number of storms that hit in month t, 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. 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.[6] W^* is set equal to 178 km/hr[7], as this threshold is shown by Strobl (2012) to be that above which hurricanes have an economic impact in the Caribbean.

As can be seen from Equation (1), our hurricane destruction index $H_{j,t}$ requires local wind speed $W_{j,i,k,t}$ and exposure weights $w_{i,t-1}$ as inputs. In order to calculate the wind speed, we use the Boose, Serrano and Foster (2004) version of the well-known Holland (1980) wind field model, and hurricane track data from HURDAT. Our exposure weights are based on nightlight imagery provided by the Defense Meteorological Satellite Program (DMSP) satellites, which are now com-

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

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

[7]This corresponds to Saffir-Simpson (SS) Category 3 (178-208km/hr) winds where "...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", see http://www.nhc.noaa.gov/aboutsshws.php.

monly used to proxy local economic activity where no other measures are available, see, for instance, Harari and La Ferrara (2013), Hodler and Raschky (2014) and Michalopoulos and Papaioannou (2014). For further details on the data sources and the construction of Equation (1), see online Appendix A.

1.2 Potential Flood Destruction Index

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). In the absence of a complete flood event database and sufficient data to run a hydrological model for the Caribbean, we perform flood detection based solely on precipitation data.[8]

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:

$$F_{j,t} = \sum_{i=1}^{I} w_{i,j,t-1} \sum_{d=1}^{30} r_{i,j,d,t} \mathbb{1}_{\{r_{i,j,d,t} \geq r^*\}}, \tag{2}$$

where $F_{j,t}$ is the exposure-weighted average excess rainfall of country j in month t, $r_{i,j,d,t}$ is the three-day moving sum of daily rainfall at location i on day d in month t, and $w_{i,j,t-1}$ are exposure weights for location i as defined in Equation (1), see online Appendix B. We assume that potential damages are linearly related to the extent of precipitation during a flood, in congruence with estimated flood fragility curves.[9] r^* is set to 112 mm over a three day window, as determined by an intensity-duration flood model and actual flood event data for Trinidad. Our source for precipitation data are satellite-derived images from TRMM. For further details

[8]This approach has been validated by Montesarchio, Lombardo and Napolitano (2009) for river basins less than 400 km^2, which is essentially the case for all of the Caribbean.

[9]See for instance those used by Federal Emergency Management Authority (FEMA) for damage estimation for the US (see, e.g., Federal Emergency Management Agency, 2006; Scawthorn *et al.*, 2006).

on the data sources and the construction of Equation (2); see online Appendix C.

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 and 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.[10] Thus, in calculating our flood damage index F, we exclude flood events for a cell within an island during a storm if the corresponding estimated wind speed was above the threshold W^*. In this context, our hurricane destruction index H will capture both wind and accompanying rainfall damage for a locality, as long as winds 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 wind damage.[11]

1.3 Consumer Price Data

We construct the difference in the logged monthly consumer price index (CPI) from January 2001 to December 2012 using data from the central banks of 15 island economies in the Caribbean: 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.[12] Our data also allows us to group goods into three broad sub-categories:[13] (i) Food, which includes food goods and non-alcoholic beverages, (ii)

[10]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).

[11]This reduces the correlation between the two potential damage indices from 0.2095 to 0.0128

[12]Our panel is marginally unbalanced, as the data for Bahamas starts only in 2003.

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

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 (iii) Other, which consists of all other goods.

1.4 Summary Statistics

Table 1 displays summary statistics for all variables used in the analysis. Accordingly, the average monthly price change is 0.4%, translating into about 4.8% annually over our time period 2001-2012, although with considerable monthly variation. The rate of change in food prices is higher, but less variable than that of housing and utilities. The variation of both extreme weather proxies is large relative to their mean, due in part to the large number of non-damaging months for each. More precisely, for our total of 2,340 island-months there are only 6.7% or 142 non-zero occurrences of damaging hurricanes, with a corresponding figure of 28.8% or 673 for flooding.

2 Econometric Results

2.1 Econometric Specification

We estimate the impact of extreme weather events on price changes using:

$$\Delta p_{j,t} = \sum_{s=0}^{S} \theta_s^H H_{j,t-s} + \sum_{s=0}^{S} \theta_s^F F_{j,t-s} + \mu_j + \lambda_t + \nu_{j,t}, \qquad (3)$$

where, for country j at time t, $\Delta p_{j,t}$ is the difference in log 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 and Kraay (1998) adjusted standard errors. In all

Table 1: *Summary Statistics of Panel Data Set*

Variable	Mean	Max	Min	St. Dev.	Prob of Event	Mean When Event
Hurricane and flooding						
Hurricane	1609246	1.15e+9	0	3.05e+07	0.029	55.5e+6
Flooding	18.05	416.72	0	49.30	0.288	59.0
Monthly price changes						
All	0.37	12.23	-10.64	0.91	-	0.59
Food	0.50	16.79	-13.02	1.36	-	0.63
Housing & Utilities	0.35	46.47	-47.35	2.20	-	0.57
Other	0.41	11.63	-11.38	0.98	-	0.44
Other variables						
Agricultural tariffs	71.96667	114.6	1	43.00682		
Past hurricanes	0.0000151	0.0000355	0	0.0000109		
Roads	0.0021569	0.0154107	0.0003446	0.0036729		

This table shows descriptive statistics for the 2001-2012 monthly data used to estimate Equation (3). The first panel shows the destruction indices of hurricane and flooding. Prob of Event refers to the probability of a damaging month, and Mean When Event is the mean conditional on the occurrence of a damaging month. The second panel shows monthly price changes for the overall price, as well as for the price of food, housing and utilities, and the remaining consumption goods. Mean when Event refers to the mean when either a damaging hurricane or damaging flood occurs. Agricultural tariffs are from the World Trade Organization. Past hurricanes are average values of our age H variable over the 1950-1999 period. Roads are average roads in km per capita.

estimations we report coefficients as beta coefficients. Importantly, our estimated coefficients capture both the direct and indirect effects of extreme weather, where the latter might include responses via fiscal and monetary policy.[14] Also, since we control for country and time specific fixed effects, the remaining variations in our indices are just random realisations from the spatio-temporal distributions of the weather events, and thus, arguably, they are exogenous. More generally, our coefficients measure the impulse response function of prices to weather, and as long as the number of significant lags is small, our specification is preferable to the inclusion of lags of the dependent variable.

[14]Although beyond the scope of this paper, examining the policy response to extreme events would be an interesting avenue for future research.

2.2 Estimation Results

While we experiment with up to six lag lengths in Equation (3), we only report results including up to two lags of H and F since further lags were consistently insignificant. As can be seen in Column (1) of Table 2, we find that for floods the impact is only contemporaneous, while for hurricanes, it persists up to one month. Our coefficients imply that a standard deviation (std) increase in the hurricane index leads to a 1.33 std contemporaneous price increase, falling to 1.06 after one month. This implies that the average (maximum) hurricane strike over our sample period caused a 0.08 (1.5) percentage point increase in prices with a further 0.06 (1.2) rise a month later. In contrast, for flooding, a one std increase causes a 0.12 standard deviation rise in prices. The average (maximum) effect of a flood event is 0.08 (0.60) percentage points.

For all three CPI sub-categories, shown in Columns (2) through (4), there is a contemporaneous and lagged impact, although their magnitude differs substantially. For instance, the contemporaneous (lagged) impact on food prices is 1.4 (0.5) std higher than on housing and 0.9 (0.5) higher than on other goods. In terms of flooding, decomposition into the sub-categories shows that while there is an effect on the price of food and other goods, housing prices are not affected. As with H, the effect on food is larger (by 0.1 std) than on other goods.

So far we have measured the average impact of extreme weather across all islands. However, the impact of extreme weather may differ across island characteristics. For instance, islands that experienced more extreme weather in the past may take measures to attenuate the impact of future events, such as storing resources, improving structures, and growing crops that are more resistant. To investigate this we construct the average H from 1950 to 1999 and interact it with current values of H and F in the base specification.[15] We follow Balli and Sørensen (2013) and

[15] We set exposure weights w equal to their 1992 value, the first available year. Unfortunately we cannot replicate this analysis for flooding, since our rainfall data is only available back to 1998.

demean the variables before interacting them. The results in Column (5) show that the effect of a one std increase in H for an island with an average past hurricane experience is a 1.135 std increase in prices. The coefficient of the interaction shows that past hurricane experience indeed decreases the impact of current events. Taking the coefficient at face value, would imply, for example, for Jamaica, which has experienced less previous hurricane destruction than the average island (0.0000104 vs. 0.0000151), that the total price impact is 1.525 std.

Local infrastructure, such as roads, could also play a mitigating role in the price impact across islands by allowing goods to be transported quickly to those areas with excess demand. To capture this effect we use interactions of our indices with road density.[16] As our results in Column (6) show, a more extensive road network indeed reduces both the contemporaneous and lagged impact of hurricanes on prices, while there is no such effect for extreme rainfall.

Finally, we also investigate whether heterogeneity across islands in trade policy, in particular tariffs, can play a role. Since most of the tariffs in the Caribbean are on agricultural products, we focus on the impact of agricultural tariffs, taken from the WTO Tariffs database, on food prices. The results in Column (6) show that, as might be expected, a more restrictive trade regime increases the contemporaneous impact of hurricanes on food prices, with no such effect on excessive precipitation.

Our results contrast with those of Cavallo, Cavallo and Rigobon (2014), who find no price increase in response to an earthquake for both Japan and Chile. One possible explanation might be the absence of price gauging laws in the Caribbean. However, while these exist in Japan, there is no such legislation in place in Chile. A more plausible explanation is that small open island developing economies, like the Caribbean, are more sensitive to localised exogenous shocks.

[16]Calculated from the Global Roads Open Access Data Set (gROADS), v1 (1980-2010).

Table 2: *Impact of Hurricane and Flooding on Monthly Price Changes*

	Base results				Interactions		
	All	Food	Housing	Other	All		Food
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
H_t	1.325**	2.801**	1.394**	1.921**	1.135**	1.207**	2.265**
	(0.248)	(0.363)	(0.472)	(0.267)	(0.232)	(0.244)	(0.287)
H_{t-1}	1.060**	1.626**	1.117**	1.163**	0.675**	0.819**	1.378*
	(0.267)	(0.445)	(0.400)	(0.333)	(0.230)	(0.281)	(0.562)
H_{t-2}	0.0618	0.475	0.702	0.242	0.348	0.112	0.306
	(0.253)	(0.586)	(0.401)	(0.382)	(0.380)	(0.244)	(0.502)
F_t	0.122*	0.249**	0.0401	0.149*	0.119	0.123*	0.257**
	(0.0599)	(0.0809)	(0.0849)	(0.0665)	(0.0611)	(0.0595)	(0.0796)
F_{t-1}	0.0295	0.101	-0.0402	0.0342	0.0311	0.0302	0.102
	(0.0686)	(0.0938)	(0.0780)	(0.0710)	(0.0715)	(0.0674)	(0.0947)
F_{t-2}	-0.0454	-0.0366	-0.103	-0.0466	-0.0495	-0.0456	-0.0375
	(0.0624)	(0.0771)	(0.118)	(0.0659)	(0.0625)	(0.0603)	(0.0780)
					Past hurricanes	Roads	Tariffs
H_t					-82,959**	-267.8**	0.0795**
					(31,129)	(77.76)	(0.0181)
H_{t-1}					-165,109	-572.2**	0.0379
					(90,109)	(117.8)	(0.0211)
H_{t-2}					115,318	115.9	0.0276
					(123,713)	(172.8)	(0.0456)
F_t					1,660	5.164	-0.000738
					(3,702)	(8.509)	(0.00160)
F_{t-1}					-275.9	-2.236	0.000415
					(4,314)	(8.091)	(0.00143)
F_{t-2}					2,704	9.134	0.000372
					(3,505)	(7.540)	(0.00163)
F-test($\theta = 0$)	10.43	25.43	5.909	11.37	12.17	13.75	28.99

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

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

For country j at time t, $\Delta p_{j,t}$ is the difference in log CPI, $H_{j,t}$ is the potential hurricane destruction index, $F_{j,t}$ is the potential flood destruction index 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. Columns (1) through (4) show our baseline results, while in Columns (5) through (6), we further interact extreme weather with past hurricane experience, road infrastructure, and agricultural tariffs. F-test(θ=0) is the F-test of the regression, which includes the effect of hurricane and flooding destruction for all lags. Driscoll and Kraay (1998) standard errors are shown in parentheses. ** and * indicate 1% and 5% significance levels, respectively. All regressions are run with 2,145 observations.

3 Potential Welfare Losses: The Case of Jamaica

We next examine the potential welfare implications of the price increases due to extreme weather. To this end we use household data for Jamaica. 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. At the same time Jamaica is also vulnerable to frequent flooding induced by tropical storms, fronts, and troughs.[17]

3.1 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 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, for each household, we consider the compensating variation due to an extreme weather event, defined as the percentage change in expenditure $\Delta ln(C) = ln(\tilde{C}) - ln(C)$ needed to maintain a constant utility after a change in the price vector from $\mathbf{p}$ to $\tilde{\mathbf{p}}$, where $\mathbf{p} = (p_1, \ldots, p_n)$ with p_i the price of good i, and C is the initial level of expenditure. The new level of expenditure, $\tilde{C}$, can be extracted from the indirect utility function $V(C, \mathbf{p})$ by equating the levels of utility before and after the weather-induced price changes: $V(C, \mathbf{p}) = V(\tilde{C}, \tilde{\mathbf{p}})$. This leads

[17] 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. Major damaging floods are known to have occurred in the years 2004, 2007, 2008, 2009, 2010 and 2012 (see Mandal *et al.*, 2014).

to the following expression for compensated variation:

$$\Delta \ln(C) = \ln\left(V^{-1}\left(V(C, \mathbf{p}), \tilde{\mathbf{p}}\right)\right) - ln(C), \tag{4}$$

where $= V^{-1}(., \mathbf{p})$ refers to the inverse of the expenditure function with respect to its first argument. Thus we quantify 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. This approach assumes that there are no laws or customs that prohibit the emergence of undistorted price signals, which is likely for Jamaica where food subsidies were eliminated by the early 1990s (see International Fund for Agricultural Development, and Inter-American Institute for Cooperation on Agriculture, 1994).

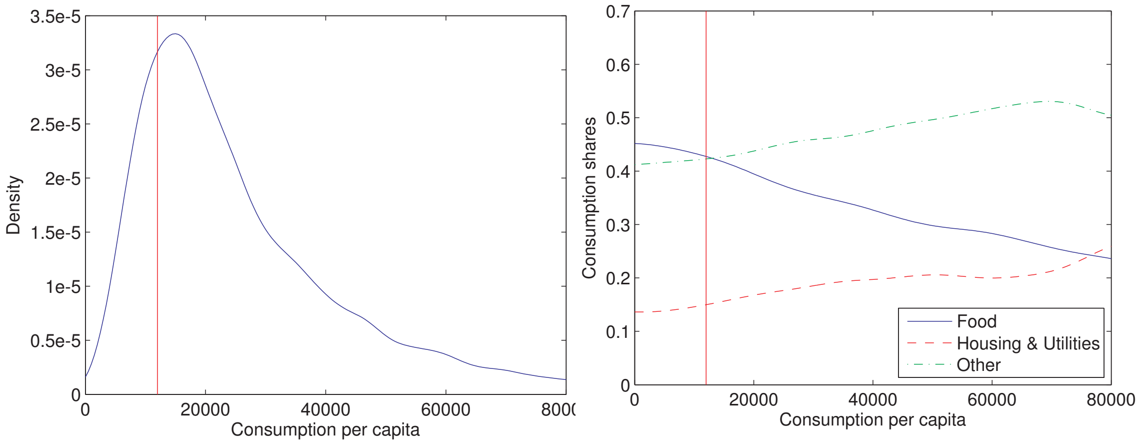
To evaluate the distribution of potential welfare losses implied by extreme weather events we use Equation (4) to calculate the loss in welfare $\Delta \ln(C)^{(\alpha)}$ of a household with budget shares s_i due to a change in the price of goods $\Delta \ln(p_i)^{(\alpha)}$, following a set of possible flood and hurricane events of different strengths, associated with a quantile α likelihood of occurrence. Given that damaging flood and hurricane events are not independent, as similar climate factors are likely to be driving both[18], we look at the distribution of one type of event conditional on the incidence of the other. Since there is an infinite number of possible combination of pairs of events, we focus on the distribution of one type of event conditional on a five year return level of the other, corresponding to a monthly 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 $H_c^{(\alpha)} = F_{H|F}^{-1}(\alpha | F_F^{-1}(0.9833))$, $F_{H|F}$ is the distribution of hurricane, conditional on flooding, F_H and F_F are, respectively, the distributions of hurricane and flooding, and 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

[18]For instance, in our data, 13% of extreme weather damaging months are characterised by both hurricane and flood events.

any conditional quantile of the distribution of each one of these types of events.

3.2 Estimation of Demand System

Figure 1: *Return plots for bivariate POT models*



(a) *Distribution of consumption per capita in Jamaica (2012)*

(b) *Budget Share of different goods, as a function of consumption per capita*

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.

In order to make Equation (4) operational, we follow Attanasio, Di Maro, Lechene and Phillips (2013) and assume a specific functional form of the indirect utility function $V(C, \mathbf{p})$, which leads to the Quadratic Almost Ideal Demand System (QUAIDS) of Banks, Blundell and Lewbel (1997). QUAIDS consists in a system of budget shares equations that is consistent with consumer theory. Its advantage is that it allows elasticities to depend on the level of expenditures, which could be important for the price impact of extreme weather events, given that our broad categories of goods do not allow us to take account of compositional differences across income.

In order to estimate the QUAIDS model, we need household data on budget shares and total expenditures as well as a set of prices that varies across households. For the first, we use 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, so that 1,382 (21.4%) out of the total 6,450 households in our data are classified as poor. The kernel density distribution of per capita consumption per household[19] calculated from the data along with the poverty line threshold is depicted in Figure 1a.

To calculate budget shares from the JSLC, we categorise expenditures into groups of food, housing and utilities, and the remaining items to match our cross-country price data grouping. Figure 1b 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 food decreases with income, standing roughly at around 42% at the poverty threshold. In contrast, expenditure on housing and utilities and on other goods rises with wealth and is about 12 and 41%, respectively, near the poverty line.

Our prices come from the Central Bank of Jamaica for 2012 and we aggregate them to match the prices of our three categories of consumption goods. 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's urban-rural classification and the month it was surveyed. Hence, prices vary over time as well as space across households.

We use the method of Blundell and Robin (1999) to estimate the parameters of the QUAIDS model, including demand shifters and controlling for the potential endogeneity of total expenditures; see online Appendix D for details. The implied compensated (Hicksian) elasticities from our QUAIDS estimation are provided in Table 3. 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

[19] As is standard, we weight children half of adults in the consumption per capita calculation, see Deaton (1997).

coefficients suggest that all three groups of goods are substitutes, although the responsiveness varies considerably.

Table 3: *Compensated (Hicksian) price elasticities from the QUAIDS model*

	Food	Housing & Utilities	Other
Food	-0.607*	0.358*	0.249
	(0.198)	(0.115)	(0.256)
Housing & Utilities	0.780	-1.848**	1.068
	(0.406)	(0.237)	(0.526)
Other	0.210	0.412**	-0.621*
	(0.174)	(0.102)	(0.226)

Elasticities are computed from the QUAIDS estimates in Table D.1 in in online Appendix D, according to Equation D.1 in online Appendix D. Standard errors are shown in parentheses. ** and * indicate 1% and 5% significance levels, respectively.

3.3 Distribution of Hurricane and Flood Events

It is common practice to model the probabilities of rare occurrences, such as weather shocks, using extreme value theory, see, for instance, Jagger and Elsner (2006). A standard approach in this regard is to use Peak Over Threshold (POT) models (see, e.g., Smith, 1987; Davison and Smith, 1990) POT models consist of fitting exceedances above a 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.

As a starting point we model hurricane and flood events independently as univariate POT models; see the estimates given in column (1) of Table E.1 of online Appendix E. For hurricanes, we find a positive but insignificant shape parameter which indicates a slowly decaying power tail, implying a non-negligible probability of extreme events. In contrast, the shape parameter for flooding is 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. In line with our estimations, the return plot for hurricane is convex, while for flooding it is concave and seems to be bounded; see Figure E.1 in online Appendix E.

To account for dependence between hurricanes and floods, we consider six popular bivariate POT models, which combine univariate GPDs into proper bivariate distributions of extremes, characterised 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 E.1 of online Appendix E. which is the most commonly used.[20]

3.4 Potential Welfare Losses

We now have all the 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 use 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. The univariate results are plotted jointly in terms of return periods in Panels (a) and (b) of Figure 2. As expected, given its POT estimates, for floods 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, households just below the poverty line will experience a welfare loss of 0.6%, while the corresponding households in the 95th percentile will be subject to losses of 0.5%. This is due to the fact that poorer households spend a higher share of their income

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

on food, the price of which is more susceptible to extreme events.

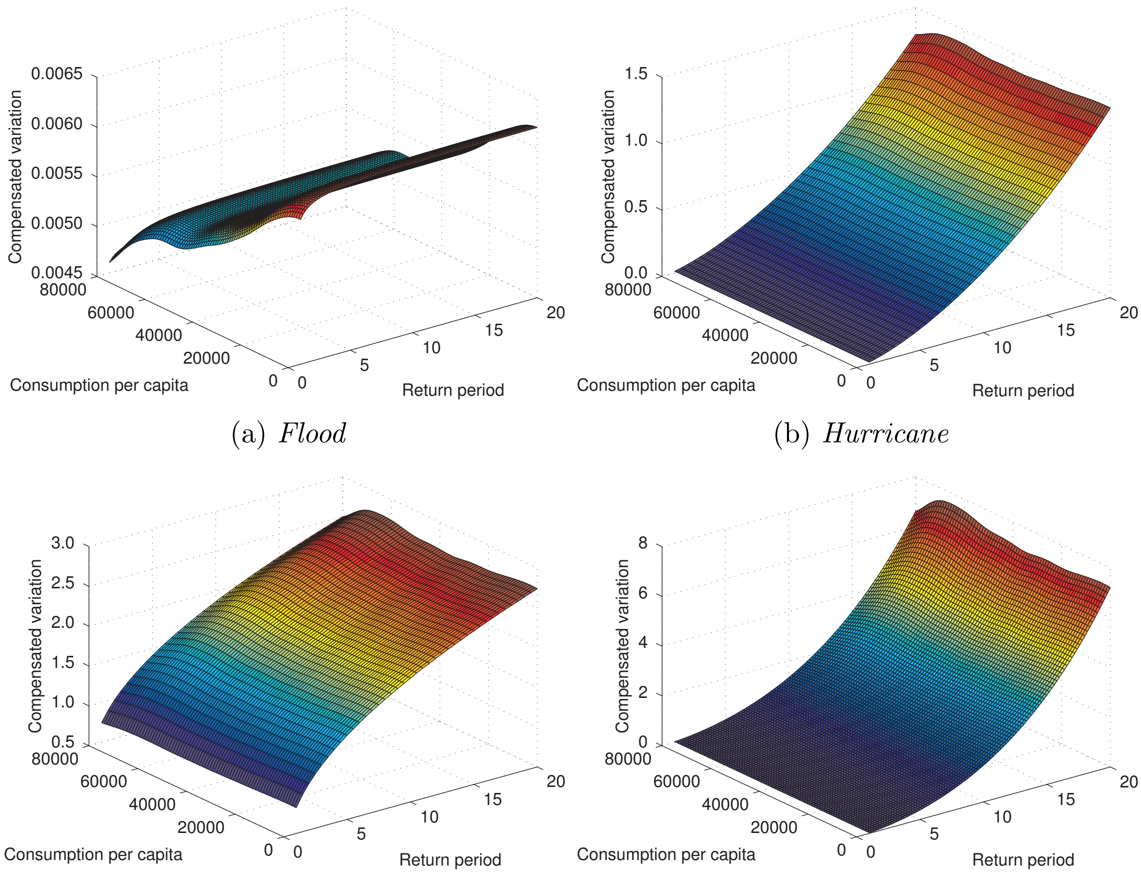
Compensating variation for hurricanes rises substantially in a slightly exponential manner, as one considers more extreme events, as shown in Panel (b) of Figure 2. This implies that a 20 year event results in losses around 9 times larger than for a 5 year event. However, there is little difference across income levels. This is because, while there is a larger price effect on food, which affects the poor more, hurricanes also have an impact on the price of housing, which is more important for richer households.

Panels (c) and (d) of Figure 2 show the compensating variation for conditional flood and hurricane events based on the bivariate estimations. Welfare losses rise relatively sharply but then flatten out for more extreme events. For example, while a 10 year conditional flood decreases welfare by about 200%, the corresponding figure for a 20 year conditional event is about 267%. There is now little difference across income, which is driven by the conditional hurricane event. For hurricanes, the shapes of the bivariate and univariate distributions are similar, with losses rising sharply as events become more extreme. For instance a 20 year hurricane event causes on average a 710% loss in consumer welfare.

4 Conclusion

In this paper we investigate how extreme weather can drive short-term price increases in the Caribbean. Our results show that while the expected price increase is on average small every month, when this does occur the impact can be multifold of average price changes. In this regard the expected monthly impact is larger and occurs more often for floods, but when a hurricane strikes the resulting rise is considerably larger. Looking at broad sub-categories of goods, we find that both hurricanes and floods have the largest impact on food prices, but only hurricanes affect the price of housing goods. Our results indicate that greater previous hur-

Figure 2: *Return plots for univariate and bivariate POT models*



(a) *Flood*

(b) *Hurricane*

(c) *Flood Conditional on Hurricane (bivariate)*

(d) *Hurricane Conditional on Flood (bivariate)*

This figure shows estimates of a series of kernel regressions of compensated variation on consumption per capita. Panel (a) and (b) shows results for flooding and hurricanes derived from univariate POT models. Panel (c) shows results for flood events, conditional on 5 year return period hurricane events, interpolated over a grid of return periods between 1 and 20 years. Panel (d) shows results for hurricane events, conditional on 5 year return period flooding events, interpolated over a grid of return periods between 1 and 20 years. Kernel regressions use a Gaussian kernel and a plug-in bandwidth. Compensating variation is measured in percentage changes.

ricane exposure, a more open trade policy, and better infrastructure may mitigate the price impact of extreme weather events. However, one should note that these findings may not necessarily be generalisable to larger landlocked countries.

Using the case study of Jamaica we also investigate the welfare implications due to the price impact of extreme weather events. We find that losses in welfare can be large for the rarer events. If we consider hurricanes and floods as independent events, floods have a disproportionately larger impact on the poor due to their higher spending on food. This effect disappears when we allow for dependence due to the impact of hurricanes on the price of housing goods and the propensity of richer households to spend more on these goods.

More generally our analysis suggests that the potential short-term costs of price pressure due to shortages of goods after an extreme weather event should not be ignored. In this regard, some governments in developing countries have already been employing targeted policies for many years. For example, the Philippines National Food Authority keeps stocks of rice and corn in order to buffer the price hike due to droughts, floods, and typhoons.

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Additional Supporting Information may be found in the online version of this article:

Appendix A. Wind Field Model

Appendix B. Exposure Weights

Appendix C. Flood Detection

Appendix D. Quadratic AIDS Model

Appendix E. Peak Over Threshold Models

Data S1.

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