Poverty and Hurricane Risk Exposure in Jamaica

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Abstract

This paper investigates the impact of hurricane risk exposure on poverty. To achieve this, we use a small area poverty mapping methodology to simulate our measure of poverty for households in Jamaica, a country that is marked by its experiences with damaging hurricanes. Along with calculated hurricane wind exposure estimates that capture the type of building material which matters for poverty classification, we calculate future risks for household poverty under different general circulation model climate change models. We find that under most models, substantial increases in poverty are likely. The results are indicative of policy instruments needed to counteract the future risk of increases in poverty.

1 Introduction

Tropical cyclones are historically known to be very destructive given the costs they exact on affected geographical locations. Since the year 2000, costs have been estimated to exceed over $33 billon [1] where the Caribbean has borne roughly a third of this cost, amounting to $10 billion. Hurricanes, in particular, have been shown to negatively impact economic welfare, especially that of the most vulnerable households (Thomas et al., 2010; Anttila-Hughes and Hsiang, 2013; Karim and Noy, 2014; Arouri et al., 2015; Baez and Santos, 2007; Henry et al., 2019). Indeed, policymakers are keen to assist with the needs of households that are affected by such negative shocks. However, for proper design and implementation of welfare-protecting policies, it is important to have knowledge of the long-term risk involved in changes in hurricane behavior resulting from climate change. Although there is no definitive conclusion on the future of hurricanes as climate changes (Pielke Jr et al., 2005; Emanuel et al., 2008; Knutson et al., 2008; Knutson et al., 2010), the literature highlights two possible worrying outcomes for economies susceptible to these storms if faced with a warmer climate. First, despite an observed general decline in the frequency of hurricane strikes, the potential of a higher intensity is great (Emanuel et al., 2008). Second, based on other research, both the frequency and intensity of tropical storms will increase (Emanuel, 2005; Saunders and Lea, 2008). Given these possibilities, any policymaker's strategy to combat the welfare ill-effects of hurricanes should consider the future possibilities of these storm under different climate change scenarios.

We study the future implications of hurricanes for poverty in Jamaica by analyzing what obtains under different climate change scenarios. Specifically, we compare expected poverty increases of Jamaican households for current (1981-2000) versus future (2081-2100) climate using the typical greenhouse gas (GHG) emissions projections. These are CCMS5, IPSL5, MICRO5, MPI5 & MRI5 for the climate representative concentration pathway (RCP) 8.5 GHG emission projection where RCP 8.5 is a high emissions pathway to which current emissions are closely

[1] Source: Emergency Events Database (EM-DAT)

aligned. For our measure of poverty we make use of per capita consumption expenditure, the suitability of which has been demonstrated in the welfare literature. For example, by using household surveys for Jamaica and Nepal, Pradhan and Ravallion (2000) show that subjective poverty rates are closely aligned to actual poverty rates. These subjective poverty rates are based on a household survey in which participants indicate whether their consumption of food, clothing and housing were sufficient to satisfy their family's needs.

In this paper, to carry out our analysis we take a number of steps. First, we create a set of hurricanes under each climate setting, that is current and future, for each of the five climate models. Second, we translate hurricanes into household poverty using an estimate derived from survey data [2] which we then use to infer the impact of hurricane damages. Third, to apply our derived estimate to census data, we use small area poverty estimation (Elbers et al., 2003) to obtain a local measure of poverty for all Jamaican households since survey data does not cover all geographical locations. Fourth, we calculate out the local maximum wind speeds (Holland, 1980) for each of the synthetic hurricanes generated in step 1 for each enumeration district in which households are located. Fifth, to obtain expected losses, we find the probability of each storm (Emanuel, 2011) which are used to calculate the annual implied impacts for household poverty under each climate change model.

Jamaica is particularly useful for a case study of this nature for a number of reasons. First, it is very vulnerable to hurricane shocks given its location, size and frequent storm experiences. For instance, since 1988, we identified 18 hurricanes, the most damaging being hurricanes Gilbert and Ivan which struck in 1988 and 2004 respectively. Second, Jamaica is ranked third behind Haiti and Dominican Republic in terms of hurricane strikes between 1990 and 2008 (Economic Commission for Latin America and the Caribbean, 2010). Third, it is considered to be one of the most vulnerable countries in the Caribbean according to the environmental vulnerability index, which is based on 50 indicators including exposure to natural

[2] We use a similar approach to Henry et al. (2019) except that we allow for differences in the damage function according to household wall type.

disasters, human health and climate change (Kaly et al., 2004). Its vulnerability is obvious from the destruction that these storms create. For example, the destruction caused hurricane Gilbert in 1988 amounted to US$4 billion in damages (Pan American Health Organization, 1988) while hurricanes Ivan in 2004 and Dean in 2007 generated US$139 million (Planning Institute of Jamaica, 2004) and roughly US$81 million (Planning Institute of Jamaica, 2007) respectively. Fourth, housing is an important component of the poverty which means that the type of building material used in house construction matters for a hurricane resilience (Agency for International Development, 1981). Based on the most recent (2011) Jamaican census, roughly 30% of households reside in homes that are not resistant to hurricane strikes. Given this background, the welfare of Jamaican households could be at risk considering the future of climate change.

We produce results for four hurricane return periods for each of the five climate change models on the RCP 8.5 high emissions pathway. Though our results vary according to each model, we observe, in general an increase in poverty resulting from hurricanes across the spectrum of event years where this increase is likely to be substantial.

The rest of this paper is organized as follows. Section 2 presents the data and descriptive statistics, which provides details on small area poverty estimates, household survey data, hurricane indexes and other climatic data. Section 3 outlines the estimation model, results and set the stage for poverty analysis. Section 4 engages the hurricane risk modelling and synthetic hurricane generation. Section 5 discusses the future outcomes for poverty and Section 6 concludes the paper.

2 Data and Descriptive Statistics

2.1 Small Area Poverty Estimates

Our objective is to use consumption expenditure data for all Jamaican households. Data that are comprehensive at a national level generally comes from the census. However, the Jamaican census does not collect consumption expenditure data. As a result, we simulated census consumption data for all households using small area poverty estimation methodology.

The small area poverty mapping methodology in general is used to acquire estimates for areas of a population for which data are lacking. Such estimates are generated by models that make use of survey data which are then tied to external data such as from a population census (Elbers et al., 2003). The idea of this methodology is to use the ability of the population census or other national sources of information which are representative of small areas to generate data for poverty estimation from household surveys that do not cover all geographical locations (Molina and Rao, 2015). The usefulness of this method has been seen in the case of Ecuador, where small area poverty estimates were used by the government there after the 2016 earthquake to determine where to channel resources to help rebuild the country (Nguyen et al., 2017). A major application has been seen in the United States (US), where estimates using the Current Population Survey (CPS), administrative and census data were used to allocate financial aid to children of school age living under poverty (Molina and Rao, 2015).

In this study, we "borrow the strength" of the 2011 Jamaican Population Census (JPC), that is, its large sample size or representativeness, to generate consumption expenditure estimates for all small areas that are not covered in the Jamaica Survey of Living Conditions (JSLC).[3] In essence, the poverty indicator, which is consumption expenditure, is not collected by the census. Although this

[3] Data for the JPC and the JSLC are both collected by the Statistical Institute of Jamaica (STATIN) but are distributed by the Sir Arthur Lewis Institute for Social and Economic Studies at the University of the West Indies, Jamaica.

information is collected by the survey, it does not capture small geographical areas in Jamaica. So we use welfare indicators [4] in the household survey that are common to the population census to estimate a reliable indicator for welfare for all households from all areas in the country. We use the small area estimation command in STATA introduced by Nguyen et al. (2017) which includes reliance on the Elbers et al. (2003) methodology, a common approach in the small methods estimation literature. The estimation takes two stages. The first stage estimates a welfare model using household log consumption expenditure per capita and the welfare-influencing household characteristics inclusive of household size, building materials used to construct dwellings, and the share of children in the household. The second stage involves the use of Monte Carlo simulations. Thus, the first stage's parameter estimates obtained and applied to the data from the census to generate reliable consumption expenditure per capita estimates for all areas in Jamaica.

2.2 Household Data

We use the unbalanced panel of 9,553 households created by Henry et al. (2019) which includes their measure of welfare, deflated total consumption expenditure per capita, the share of children in each household and the household size, which is calculated as the number of persons living in the household. These data are from the JSLC, which is an annual survey carried out by STATIN, collecting information on areas such as health, education, consumption and social protection. Importantly, the survey collects data on the material that is used to build the walls of the homes that households reside in. In this regard we note that households live in buildings whose walls are made of one of the following: wood, stone, brick, concrete nog, block and steel and wattle and adobe.

[4]These indicators include household size, share of children in the household and building material of household wall.

2.3 Hurricane Wind Damage Estimates

We construct a hurricane wind damage index similar to Henry et al. (2019). This index is seen as a more comprehensive measure of destruction since it takes into account the physical characteristics of storm events to produce spatial damages at affected localities (see for example, Strobl (2009), Spencer and Polachek (2015), Ishizawa and Miranda (2019)). One drawback of this approach in proxying potential damage at the household level is however that, even though it allows for considerable spatial heterogeneity in exposure across households according to their location, it does not take account of household specific differences in vulnerability due to the type of dwelling they are residing in. In this regard, one important component in terms of a building's resistance to damages due to tropical cyclone winds is the material of the outer walls. As a matter of fact, in an extensive study of common building and wall types and their resistance to hurricane winds – tropical storms of sufficient strengths in the North Atlantic Ocean Basin are generally referred to as hurricanes - in Jamaica the Agency for International Development (1981) identified a number of outer wall types that were substantially more vulnerable to hurricane wind exposure. We thus construct an index that incorporates both a household's physical location as well as its building wind exposure vulnerability. Essentially, we are extending the approach by Henry et al. (2019) but allowing for differences in the damage function according to household wall type. Thus, for a set of households, i=1,. . . , I, located in regions, j=1,. . . ., J, and hurricanes, k=1,. . . , K, with life times of s=1,. . . ,S, we define hurricane destruction for household i during year t as:

$$H_{i,j,t} = \sum_{k=1}^{K} \sum_{s=1}^{S} (W_{i,j,k,s,t})^3 \tag{1}$$

$$W_{i,k,j,s,t} \geq W_{ij}^{*} \tag{2}$$

W represents the wind speed, k captures specific storms, s is the life time of the storm and W* is the household specific threshold for wind damage. There are a few important details that must be noted. First, wind speed is specified to the cubic power because the order of dissipation of the kinetic energy from a storm with respect to wind speed is cubic (Emanuel, 2011). Second, the summation of the values of W over the life time of a storm accounts for the duration of exposure. Third, summation of the cubic value of the W across storms allows for the possibility of having more than one damaging storm occurring in a year. Importantly, one should also note that, in contrast to the previous literature, we here take account of differences in damages in the function in equation 1 across building types as differences in the threshold above which damages are induced. The importance of modeling differences in vulnerabilities across building types in this manner was previously demonstrated by Unanwa et al. (2000) using damage and wind exposure information gathered from a large number of studies for the US. To calculate W, we make use of the wind field modelling methodology by Boose et al. (2004) which is a version of Holland (1980)'s equation. The exact details of the model are provided in Appendix A.

Since the location indicator that we have for households is at the enumeration district level, we use these as our regions, j=1,. . . ., J, shown in Figure 1, where Jamaica is divided into 6,327 enumeration districts, and calculate the maximum wind speed for each storm relative to each district's centroid. The relevant storms over our sample period, 1990 until 2010, produced local wind speeds of at least 63 km/hr, the threshold to be classified as a tropical storm, in one of the enumeration districts are listed in Table B.1. Accordingly, in total there were 16 damaging storms. These storms were not evenly distributed over years, with 2005 and 2008 experiencing the most incidences.

In order for us to estimate W*, importantly the JSLC also collects information on the main material of the outer walls of the buildings that households reside in. More specifically, the JSLC categorizes the outer main walls of a household's building into 7 main types: wood, stone, brick, concrete nog, block and steel, wattle and adobe, and other. In this regard the Agency for International Development

(1981) noted that for Jamaica, housing made of wattle and daub, concrete nog, or wood, or some combination of these types was especially vulnerable to wind damage from hurricanes. We thus consider households as residing in hurricane wind strongly vulnerable housing if the outer walls of their building consists of these types and weakly vulnerable otherwise.[5] [6] Using this classification we find that for our matched panel sample, 37 per cent of households reside in buildings that are strongly vulnerable to hurricane winds. Notably, over our sample period the proportion of households living in strongly vulnerable housing has fallen considerably from 53 to 28 percent.

We next estimate the threshold W* separately for both weakly and strongly vulnerable housing types. To this end we use information on the damages caused by Hurricane Gilbert in 1988. More specifically, the 1989 JSLC collected information regarding the damages incurred after the storm. [7] Households were asked whether there was any damage to their dwelling due to the hurricane and, if yes, whether (a) the house was totally destroyed, (b) the roof and structure was severely damaged, (c) the roof was totally destroyed, (d) there was major roof damage, (e) there was minor roof damage, or (f) there was other roof damage. To use this information to derive a building specific W*, we first created an ordered damage variable where no damage took on the value of 0, and then linearly increased its value starting from damage category (f) down to category (a), providing a maximum of 8 different ordered values. Subsequently, we estimated an ordered probit model where we regressed the damage indicator on the estimated H from (1) given a value of W*, while controlling for the number of rooms, the number of rooms squared, and whether the building was a separate entity. This was done for each housing type – weakly and strongly vulnerable – separately across the range of the values of W* that correspond to the minimum wind speed at which a tropical storm (63 km/hr) is defined up to the maximum hurricane damage

[5] We exclude those households classified as ‘other’. However these constituted only a small percentage (1.6 per cent) of our sample.

[6] Unfortunately, sample size considerations in estimating W* did not allow a more refined breakdown.

[7] Hurricane Gilbert was a category 5 storm that spent 8 hours moving directly over the island, destroying homes, hospitals, agriculture, schools and more. This storm generated US$4 billion in damage (Pan American Health Organization, 1988).

category (252 km/hr) of the Saffir-Simpson Scale (SSS) classification.[8] We depict the obtained t-statistics on H as well the r-squared for the range of values of W* for these two samples in Figures 2 to 5.

As can be seen, for the weakly vulnerable building sample, the r-squared and t-statistic on H for each W*, shown in Figures 3 and 4, clearly fall after wind speeds above SSS 3, i.e., 178 km/hr. [9] We thus chose W* for weakly vulnerable buildings to be SSS 3. In contrast, the point at which the r-squared and t-statistic for the strongly vulnerable building types of the ordered probit regressions fall, as depicted in Figures 5 and 6, is much lower than for the weakly vulnerable ones. More specifically, the maximum is reached around the cut-off point for a storm to be considered SSS 1 (119 km/hr) [10], and we thus chose W* to correspond to this cut-off value. The choice of these damage thresholds points allow us then to use equation 1 to calculate H for any household i located in any enumeration district j exposed to storm k. One should note that H can differ across households both in terms of building outer wall types as well as the fact that the time of interview may differ and thus whether any hurricane occurred before or after the interview.

2.4 Other Data

Henry et al. (2019) also use rainfall and temperature data for their analysis. We also use these data which are calculated for each geographical location in Jamaica. The use of these variables is motivated by Auffhammer et al. (2013) who indicate the possibility of hurricanes being correlated with other weather phenomena. These weather events as noted by Henry et al. (2019) may also affect the welfare of households. These data are sourced from the Climatic Research Unit (CRU) TS v.

[8] The Saffir Simpson Scale is commonly used to roughly categorize likely damages due to hurricanes.

[9] According to the Saffir Simpson Scale category 3 winds correspond to when "...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".

[10] Hurricane damages at Saffir Simpson Scale 1 correspond to "...well-constructed frame homes could have damage to roof, shingles, vinyl sliding and gutters; large branches of trees will snap and shallowly rooted trees may be toppled, extensive damage to power lines and poles likely to result in power outages that could last a few to several days".

3.24 dataset which is housed by the University of East Anglia's CRU.

2.5 Descriptive Statistics

Table B.2 displays the summary statistics. The average consumption expenditure per capita for the household survey and census are rougly J$16,000 and J$17,744 respectively. The average share of children living in each household is 0.20. Finally, the average value of the hurricane index is 0.37 [11], which is used to calculate out the impact of the mean hurricane strike on poverty. Finally, the average rainfall and temperature are roughly 181 millimeters and 26 °Celsius.

3 Method and Estimation

Using the JSLC data, we estimate the impact of hurricane strikes on the log of total consumption expenditure per capita. Our specification is as follows:

$$logC_{ijt} = \alpha + \beta_1 H_{ijt} + \beta_2 X_{ijt} + \delta_{it} + y_t + \phi_i + \mu_{ijt} \tag{3}$$

In equation 3, C is total consumption expenditure per capita, which we have for each household i located in enumeration district j for year t. H represents the hurricane destruction index that is specific to each household and is shown in equation 1. This index as mentioned before differs from that of Henry et al. (2019)'s since it varies according to the building material of household walls, which is very important in accounting for household vulnerability. X is the vector containing rainfall, temperature and share of children.δ are interview month indicators, y are year dummies, and ϕ captures time invariant household specific unobservables that could be correlated with other explanatory variables. Finally, μ is the error term. As it relates to the calculation of standard errors, we follow the approach of Henry et al. (2019) who apply the work of Hsiang (2010) to model

[11] As with Henry et al. (2019)

spatial dependence across households affected by hurricanes.

Table B.3 shows that the estimated impact of hurricanes on consumption expenditure. As can be seen, we estimate a significantly negative coefficient on hurricane. Thus, hurricanes decreases consumption expenditure that implies an increase in poverty. Further analyzing the fixed effects results in Table B.3, we observe that the share of children in the household reduce consumption expenditure per capita, as would be expected. [12] With regard to the climatic variables, one may want to note that rainfall significantly reduces consumption, while there is no effect of temperature. According to Burgess et al. (2015), rainfall captures the impact of floods and so that is perhaps the reason why we are seeing an effect of rainfall. Quantitatively, the average hurricane reduces consumption expenditure by 0.6% with the impact being greater for a more damaging storm (see Table B.4. This indicates that poverty increases and for stronger hurricanes, the impact will be greater.

Now that we have the estimated impact of hurricanes of welfare from the household survey data, we apply it to our simulated census consumption expenditure values for all households across Jamaica to see what the future holds given a changing climate. But first let us discuss how to model hurricane risk and generate synthetic hurricanes for the future to which apply our estimate and damage function described above.

[12] From the perspective of household scale economies, a larger household results in lower expenditure per capita. Explanations supporting this point include the fact that households with more individuals engage in bulk buying which lowers the cost per person spent and can reduce the possible food wastages by utilizing leftovers (Robin, 1985; Deaton and Paxson, 1998). Additionally, since children consume less, one can expect a lowering of consumption expenditure per capita (Kim et al., 2009.

4 Risk Assessment

4.1 Hurricane Risk Modelling

Hurricane risk assessment models can be broadly divided into the traditional single site probability models and the more recent hurricane track modeling using statistical deterministic methods (Vickery et al., 2009). In traditional probabilistic models, location specific statistics of key hurricane parameters are first estimated using historical storm track data. An extreme value distribution is then selected and fitted typically to maximum wind speeds of a hurricane approaching a specific location of interest, allowing the calculation of probabilities of annual occurrence of storms of a given wind speed strength via Monte Carlo methods. Importantly, however, single site probability models are typically only valid for a specific location or a small region given that they use site specific tropical cyclone parameters. Also, since these models use historical hurricane tracks they assume that the intensity evolution of the hurricane is independent of the particular track taken. Moreover, since the historical data contain only a few very strong hurricane strikes, the estimated probabilities can be very sensitive to the tail of the assumed distribution, making direct inference fairly unreliable, particularly for regions that experience infrequent storms (Emanuel et al., 2008).

To address some of the weaknesses of the single site models, Vickery et al. (2009) pioneered the hurricane track modeling method, which models the entire track of a given tropical cyclone from its formation over the sea to its final dissipation as it makes landfall using empirical global distributions of relative intensity in conjunction with climatological values of potential intensity to derive local intensity distributions. This allowed for the modeling of hurricane risk via generating synthetic tracks for large geographic areas, such as the entire coastline of the US. More recently, Emanuel et al. (2008)) built on the approach of Vickery et al. (2009) in generating synthetic tracks, but instead used a random hurricane track model, together with a deterministic approach to model the hurricane intensity over the period of formation to dissipation. More precisely, hurricane tracks are generated from a random draw using a space time probability density function of tropical cyclone formation locations derived from the National Hurricane Centre's (NHC) data from 1970 onward (the year they consider the global satellite detection of tropical cyclones to be complete). Using information such as sea surface temperature and humidity together with historical storms, the model is able to trace the strengthening and weakening of hurricanes as they progress along the modeled tracks, but without using statistical models to model the changes in hurricane intensity as in traditional models. Once the synthetic tracks have been produced, a deterministic numerical simulation of hurricane intensity along each synthetic track is used to determine maximum wind speed and radius of maximum winds using the model developed by Emanuel et al. (2004)). A filter is then applied to the tracks to select those coming within a specified distance of the location of interest. For each location of interest, the intensity model can then produce probabilities as a function of wind speed for that location.[13]

4.2 Synthetic Hurricane Tracks

In this paper we use the synthetic tracks generated with the Emanuel (2011) approach as a basis for the hurricane risk assessment. In this regard, Kerry Emanuel kindly implemented this methodology to generate for us a large set of synthetic tropical cyclone/storm tracks under five different climate models and for two different periods. More specifically, we have synthetic tracks generated using weather from each year of 1985-2000 period and each year the 2085-2100 period for the five different GCMs, namely MICRO5, CCSM4, IPSL5, MPI5, and MRI5. These tracks thus allow us to assess the change in impact of hurricanes on household consumption under five different climate change scenarios. For each of these storms, the model provides for every two hours of the storm's lifetime, the location of the eye, the maximum wind speed, the forward velocity, the central pressure, and the radius of maximum wind speed. Moreover, each storm is attributed to the

[13]The model was validated through comparisons with models which estimated maximum winds with the NHC best track data.

specific year's climate it was generated under. Finally, for each year, under each climate model, we have the average number of storms, similar to the ones in the set that are likely to arise.

We can calculate the local wind speed in each enumeration district for each storm for each point of its life cycle, given the wind field model described above. With our damage function and estimated impact from Section 3, using historical data we can then infer the impact of hurricane damages to a household's consumption due to each storm. Our next step is to generate a distribution of possible years of hurricanes from which we can calculate return period periods of annual consumption impacts. To do so, we assume that each year of weather in each of the ten storm track sets is equally likely to occur. To then generate a set of hurricane events specific to a year's climate, we randomly picked a year and used a Poisson distribution to randomly draw a number of storms of that year's set, according to the expected frequency of events of that year as given by the data. This was done 100,000 times. From this set we can calculate the distribution of implied annual impacts.

5 Poverty and Future Climate

The implied percentage changes in poverty impacts for damaging hurricanes under climate change for the five different climate model for different return periods are in Table B.5. As can be seen, there are likely to be considerable changes. Under the CCMS5 GCM, lower probability event-years are likely to experience decreased impacts on household poverty under both high frequency, but low impact, storms as well under low frequency, but high impact, storms years. For instance, if one considers an event year that is likely to re-occur every 50 years, under the weather, compared to current weather, the likely impact is about 64 per cent lower. In contrast, under the climate models IPSL5, MICRO5 and MPI5, the impact across lower and higher probability event-years is likely to increase across the spectrum of event years. For example, under the MICRO5 GCM increase in poverty due to damaging hurricanes is likely to increase nearly one hundred per cent across the event year probability distribution. Under the IPSL5 model, climate change has a particularly large impact on high frequency, but low impact, event years, whereas for the MPI5 model, as it was with the MICRO5 GCM, the increase is likely to occur across the whole distribution. Finally, for the MRI5, our estimates predict that while high frequency, low impact damaging years are likely to be less damaging, years with low frequency but highly damaging storms are likely to be more substantial in their impact.

6 Conclusion

This paper investigated the poverty impact of hurricane strikes in Jamaica under future climate change scenarios. To achieve, we used hurricane damages that are calculated based on the location and vulnerability of households and the physical characteristics of the storm along with estimated impacts on poverty to understand the future risk of households in the case different climate change scenarios. We find that the future of poverty can be very risky and calls for design and implementation of policies to aid in buffering the expected impacts. Of course, the impact depends on which climate change scenario plays out in the future.

Appendix

A Hurricane Wind Field Modelling

Given hurricane data that incorporates the movement and characteristics of a storm, we calculate out the wind experienced at specific locations during the period of the storm based on the following Boose et al. (2004) equation, a version of Holland (1980)'s equation.

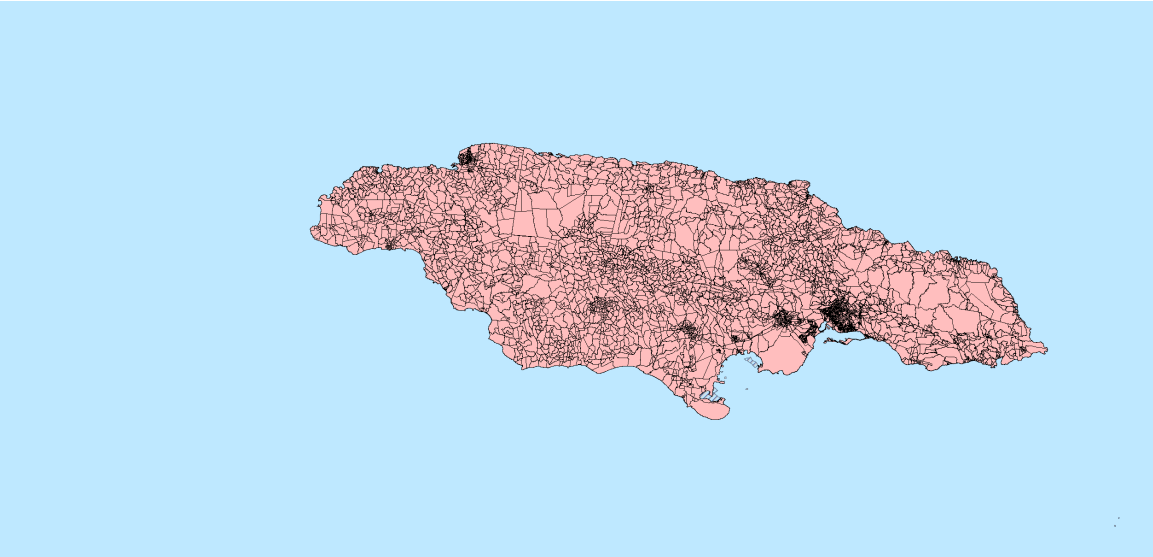
$$\begin{aligned} W_{j,k,t} = GF\left[V_{m,k,t} - S\left(1 - sin(T_{i,k,t})\right)\frac{V_{h,k,t}}{2}\right] \times \\ \left[\left(\frac{R_{m,k,t}}{R_{i,k,t}}\right)^{B_{j,t}} exp\left(1 - \left[\frac{R_{m,k,t}}{R_{i,k,t}}\right]B_{j,t}\right)\right]^{\frac{1}{2}}\Bigg) \end{aligned} \tag{A.1}$$

Note that V_m is the maximum wind speed that is sustained at any point in a hurricane. T is the clockwise angle located between the forward path of the storm and a radial line from the storm center to the location of interest j. V_h is the rate of movement of the eye of the hurricane. R_m represents the radius of maximum hurricane winds. R is the distance from the center of the storm to point of interest j. The other features of equation 3 are, the gust factor, labelled as G, F as the scaling factor for the friction that causes low wind speeds and the changing direction of the wind, S as the asymmetric structure of the storm due to its forward motion, and B as the shape of the wind profile curve.

To calculate W, like Henry et al. (2019), we use HURDAT Best Track Data. This database houses six hourly data on all tropical cyclones in the North Atlantic Basin, in which Jamaica is located. It is important to point out that while V_m, V_h, R and T are either extracted from the database or calculated based on other given data, we have to rely on assumptions for the other parameters of equation 3. Thus, like Henry et al. (2019), we also take 1.5 as the value of G to be 1.5, which has also been used by others, including Paulsen and Schroeder (2005). We also adopt S equal to 1 as did Boose et al. (2004). For F, we combine the approaches of Vickery et al. (2009) and Elliott et al. (2015) that consider the wind speed reduction factor between the coast and the inland which we linearize to determine the scaling factor for surface friction of the hurricane as it approaches land. Finally, for the of B, we make use of Holland (2008)'s approximation method.

B Tables and Figures

Figure 1: Enumeration Districts: Jamaica

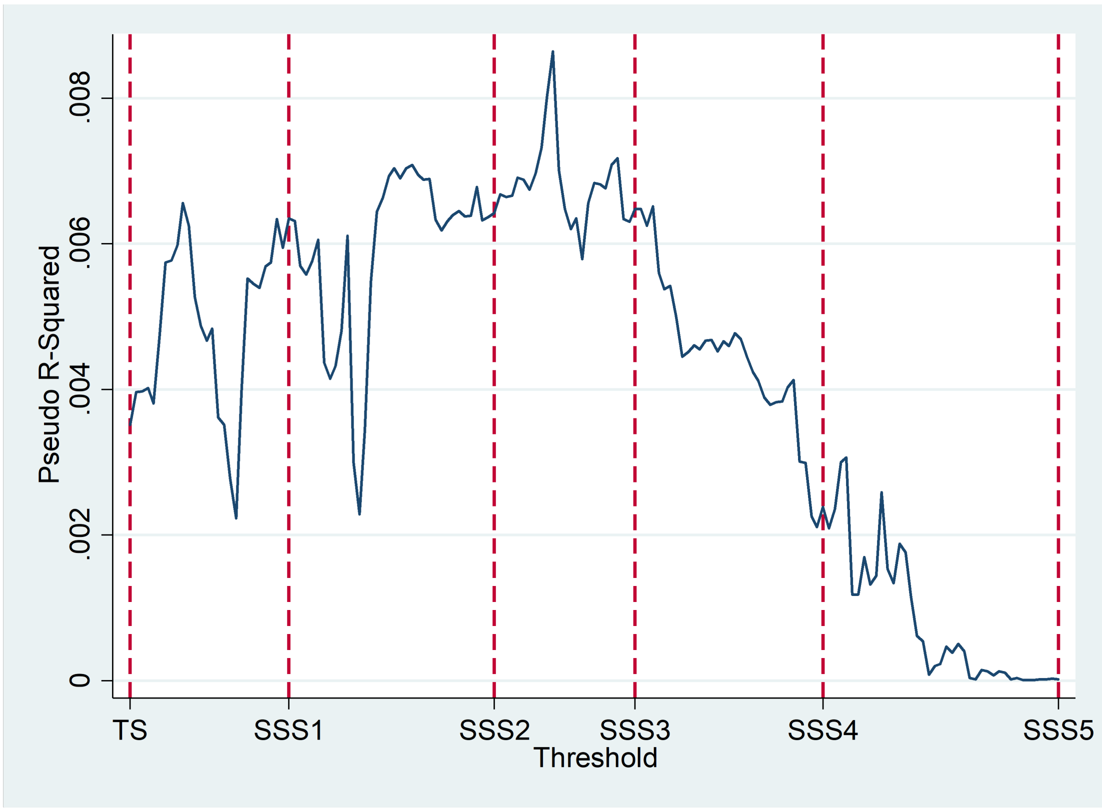


Notes: Figure adopted from Henry et al. (2019). The figure shows 6,327 enumeration districts.

Table B.1: Storms that Affected Jamaica, 1990-2010

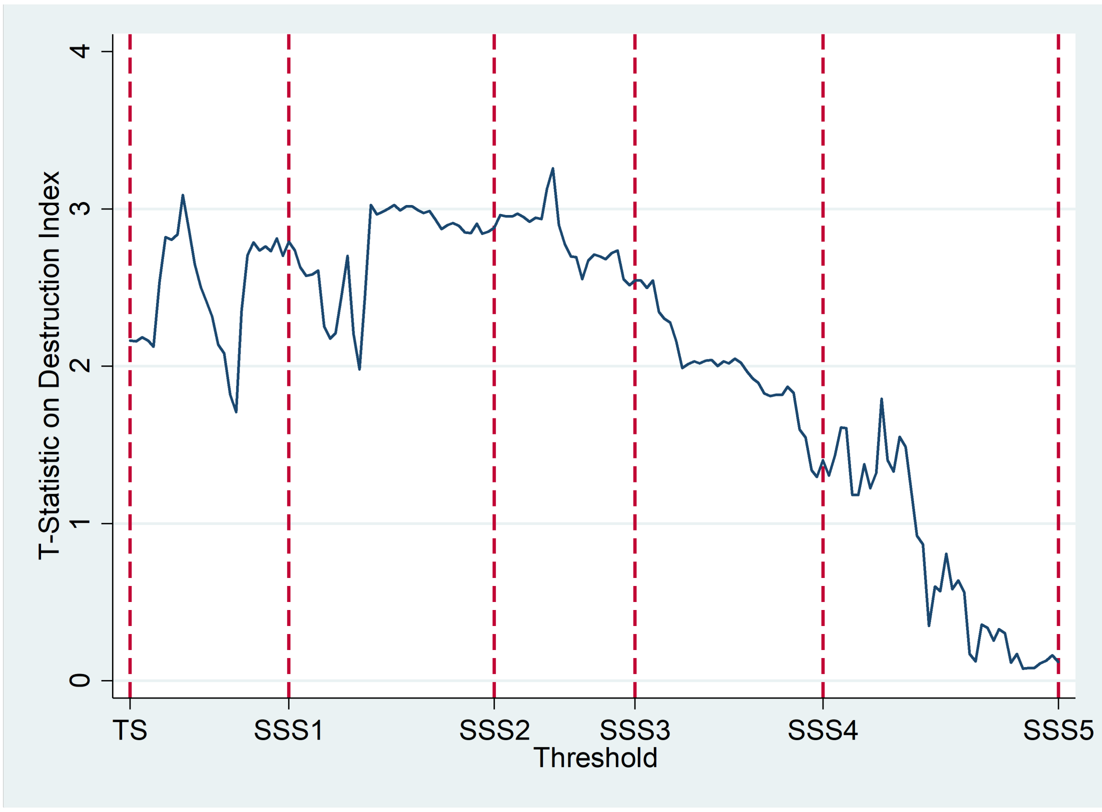
Storm	Year
Gordon	1994
Mitch	1998
Iris	2001
Isidore	2002
Lili	2002
Charley	2004
Ivan	2004
Dennis	2005
Emily	2005
Wilma	2005
Dean	2007
Gustav	2008
Ike	2008
Paloma	2008
Tomas	2010
Sandy	2012

Figure 2: Pseudo-R-Squared for Ordered Probit Regressions for different W thresholds -Weakly Vulnerable Outer Wall Type Household Sample*



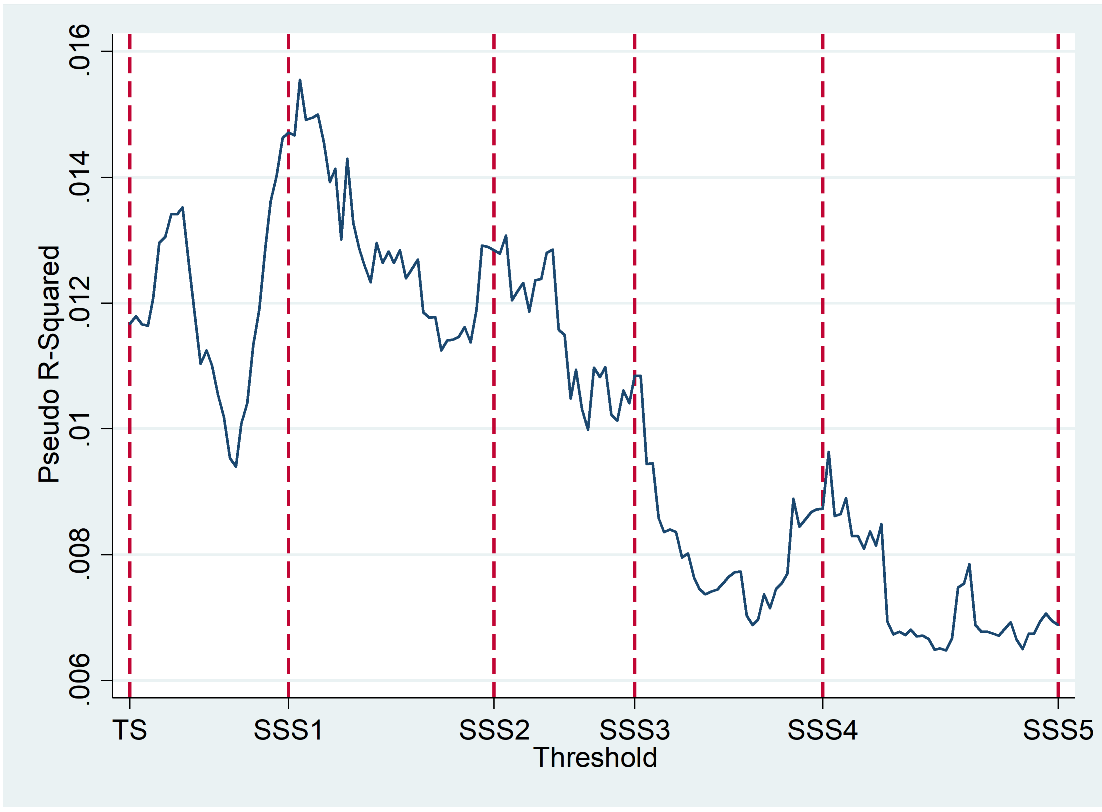
Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) Pseudo R-Squared corresponds to value obtained along different values of W* used to construct H.

Figure 3: T-Statistic on H for Ordered Probit Regressions for different W thresholds -Weakly Vulnerable Outer Wall Type Household Sample*



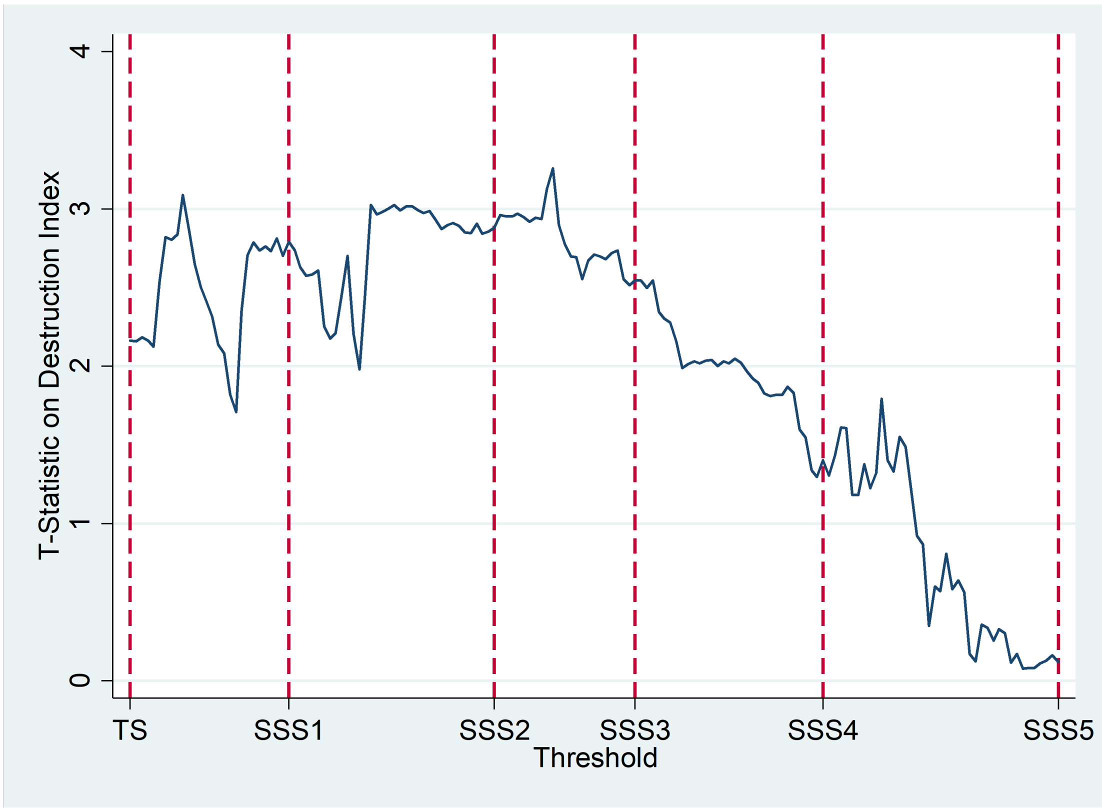
Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) T-Statistic corresponds to value obtained for H for different values of threshold W*.

Figure 4: Pseudo-R-Squared for Ordered Probit Regressions for different W thresholds -Strongly Vulnerable Outer Wall Type Household Sample*



Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) T-Statistic corresponds to value obtained for H for different values of threshold W*.

Figure 5: T-Statistic on H for Ordered Probit Regressions for different W thresholds -Weakly Vulnerable Outer Wall Type Household Sample*



Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) T-Statistic corresponds to value obtained for H for different values of threshold W*.

Table B.2: Descriptive Statistics

Variable	Mean	Std. Dev.
Consumption expenditure per capita:		
Household, JSLC	15776.97	17372.63
Census	17744	19539.05
Share of children	0.20	0.24
Hurricane	0.37	0.98
Rainfall	180.98	285.04
Temperature	25.5	1.03

Table B.3: The impact of hurricanes on consumption expenditure

Variable	Estimate	Std. Error
Hurricane	-0.0083***	(0.0020)
Share of children	-0.2207***	(0.0441)
Rain	-0.0004**	(0.0002)
Temperature	-0.0830	(0.0567)
Observations	22,934	
Number of households	9,546	
Household fixed effects	3.71***	
R-squared within	0.0900	

Notes: (i) The results are from household fixed effects estimation. (ii) Monthly and yearly time dummies are included. (iii) ***, ** - 1%, and 5% levels of significance respectively.

Table B.4: Quantitative impact of hurricanes

	Average Hurricane	Stronger Hurricane
Hurricane	-0.0063***	0.1411***

Notes: (i) Table summarizes quantitative impact of hurricanes using estimated significant coefficient from table B.3. (ii) The estimated coefficients are calculated out using the non-zero average (0.37) and maximum (8.3) values of the hurricane index. (iii) *** - 1% level of significance.

Table B.5: Climate Change in Annual Hurricane Impact (% pts.) on Poverty under 5 different GCMs and different Return Periods

GCM	CCMS5	IPSL5	MICRO5	MPI5	MRI5
20-year	-9.68	100.00	95.23	62.58	-65.27
50-year	-64.25	53.28	95.35	53.51	-98.83
100-year	-73.37	80.47	97.96	57.49	34.32
500-year	-93.23	73.46	98.90	52.99	46.73

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