Crime Watch

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Crime Watch: Hurricanes and Illegal Activities

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Abstract

We investigate the relationship between hurricane strikes and crime for Jamaica. To this end we construct hurricane damages and daily recorded criminal activity. Hurricanes are found to significantly increase crime by 35%, where the impact is stronger for more damaging storms, but this only lasts for the duration of the storm. Decomposing crime into its various subtypes, one finds that while aggravated assault, break-ins and shooting increases during a hurricane, murders, rapes, and robberies actually decline. The greatest increase is with shootings, while the greatest decline is with rape. Crucially, the impact of crime depends on the existence of a storm warning. Our results also show that high frequency data more accurately estimates the impact of hurricanes on crime.

Keywords: crime, hurricanes, storm warning, Jamaica

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Section I: Introduction

One of the potential negative consequences of natural disasters is the increase in criminal activities. This can have serious implications for policy since it likely places a strain on the allocation of public resources in order to mitigate the impact of crimes emanating from natural disasters. As a matter of fact, a large amount of the literature seems to provide evidence that the likelihood and intensity of criminal acts will increase with natural disasters, which underscores the importance of addressing disaster-generated crimes; see, for instance, Spencer (2017), Leitner and Helbich (2010), and Zahran et al. (2009). While most of the studies on the topic focus on changes in temperature and rainfall, other climatic factors, such as tropical cyclones, also play a role. For tropical cyclones, pro-social behavior is often observed, although there is also a common perception that anti-social behavior, such as crime, may be important in the aftermath. In this paper we specifically investigate how tropical cyclones have affected daily crime rates, using the case study of Jamaica.

To date there are only a handful of papers that have investigated the crime and natural disaster relationship. For these, the evidence is rather mixed, and there may be a number of reasons for this. One reason may be the existence of evacuation orders. However, while Leitner and Helbich (2010) find increases in criminal activities in Texas resulting from Hurricane Rita, possibly due to the fact that the evacuation order was not observed by some residents, they find no impact on crime for hurricane Katrina as there was no compulsory evacuation mandate. Another possible factor behind the contrasting results in the literature may be the modeling of the natural disasters in their impact. For example, Zahran et al. (2009) focus on the impact of a number of major disasters, i.e., hurricanes, floods, wildfires, and drought, on crime in Florida but these are grouped together and are aggregated at the annual level. Moreover, crime in current studies is often also aggregated in total or fairly broad sub-groups, not allowing for heterogeneous effects, such as violent or domestic crimes. However, violent or domestic crimes each encompass a number of potentially very different activities, such as aggravated assault, larceny, theft, burglaries, robberies, forcible rapes, and aggravated stalking. Finally, the crime data used are generally of fairly low frequency, being either annual, monthly, or weekly. Spencer (2017), for example, aggregates monthly panel data on crime for Florida to obtain semi-annual counts, and finds both positive and negative impacts of hurricanes on these, while Wetherley (2014) employing annual data finds no effect of typhoons on criminal acts, except for property crimes a year after the event. Others, such as Varano et al. (2010) who investigated the impact of Hurricane Katrina on Texas, New Orleans, and Phoenix, have utilized weekly time-series crime data and discovered only a modest effect. Finally, Leitner and Helbich's (2010) study of hurricanes Katrina and Rita on Texas use three months of daily crime totals. The results show only hurricane Rita having an impact on burglaries and auto thefts.

One may also want to note that with the exception of Roy's (2010) study on India and Wetherley's (2014) study on the Philippines, the general focus of the natural-disaster-crime literature appears to be on developed countries. However, a priori, one would not expect the relationship between the two factors to be the same for developing countries. Firstly, these nations tend to be less resilient to the impacts of natural disasters. Furthermore, they are often less stable in terms of law and order. Thus, our case study of Jamaica may arguably be particularly suitable for the question at hand. That is, Jamaica has long struggled with high levels of crime and was the first Caribbean country to experience rising crime rates, especially in the 1990s (Inter-American Development Bank (IADB), 2016). Although recent trends in Jamaica for violent crimes have been trending downwards, they are still seen as being high relative to the rest of the world (Harriott and Jones, 2016; Seepersad, 2016; IADB, 2016).[2] At the same time, the island is also subject to many natural disasters, most notably hurricanes. As a matter of fact, these storms have been shown to cause considerable economic damage in various forms; see, for instance, Planning Institute of Jamaica (PIOJ) (2007) and Spencer and Polachek (2015).

The data set we compiled has a number of attractive features relevant for our study. Firstly, we unlike previous studies on the topic construct a hurricane wind field model based measure of destruction that takes account of the local heterogeneity in the effects of the storm itself, as well as the assets and population exposed to it. This lies in contrast to previous studies that have either used hurricane incidence variables to capture disaster effects (Leitner and Helbich, 2010; Varano et al., 2010; Spencer, 2017) or disaster frequency variables (Zahran et al., 2009). Secondly, we not only have access to high frequency, i.e., daily crime data, but these are disaggregated by several crime types. Many other studies instead used lower frequency data, such as annual (Zahran et al., 2009; Spencer, 2017) and/or aggregated crime (Zahran et al., 2009). Importantly, over our long time period of 13 years, Jamaica experienced a large number of damaging storms (13), providing us with enough variation to identify effect of hurricanes on crime.

The rest of this paper is organized as follows. Section II describes the data and summary statistics, Section III presents the econometric model and discussion of the results and Section III concludes with policy implications.

Section II: Data and Summary Statistics

[2] This probably explains why crime expenditure is recorded to be one of the highest in the Caribbean, accounting for approximately 4% of GDP which equates to about J$62 billion in 2014 (Inter-American Development Bank, 2016; Jamaica Observer, 2017).

A. Crime Data

Our source for crime data is the Jamaica Constabulary Force (JFC) statistical database. The data provided are daily totals reported at the parish level from 2002 to 2014, and break down the crimes committed in terms of aggravated assaults, break-ins, murders, rapes, robberies and shootings (see Table 1). There are 14 parishes in Jamaica, providing us with 66,712 observations over our thirteen year sample period.

The data consist of reported crimes to the police stations, most of which are often verified by police visits to the crime scenes. However, some potential for measurement error may still exist due to a lack of reporting. One may want to note in this regard that the incentive to report is greater if reporting is required for victims to claim insurance (for death, robberies, or break-ins), to recover lost documents, or are adamant that criminals should be punished for their actions. These factors that influence reporting holds also in the case of a hurricane since without a record of a police report, insurance claims, for example, cannot be processed. However, while the JCF does not provide information on this, we believe that due to the disruption that hurricanes cause, it is possible that all crimes do not get reported, or at least not immediately.[3]

B. Hurricane Destruction Index

In estimating the impact of hurricanes on crime, earlier studies generally used incidence dummies or frequency counts as proxies of storm destruction. Here, in line with the recent disaster literature – see, for instance, Strobl (2012) - we construct a proxy of hurricane damages based on the physical characteristics of each storm that allows for heterogeneous impacts across space. To translate wind speed into potential damage, one should note that property damage due to a tropical storm should vary with the cubic power of the wind speed experienced on physical grounds (Emanuel, 2005), and it is for this reason that previous studies have simply used the

[3] If it is the latter, then allowing for lagged impacts is likely to pick up these delayed effects.

cubic power of wind speed as a destruction proxy.[4] However, there is likely to be a threshold below which there is unlikely to be any substantial physical damage (Emanuel, 2011). Moreover, the fraction of property damaged should approach unity at very high wind speeds. To capture these features we employ the index:

$$H_{ijt} = \frac{v_{n,ijt}^3}{1+v_{n,ijt}^3} \tag{1}$$

where,

$$v_{n,ijt} = \frac{MAX[(V_{ijt} - V_{thresh}),0]}{V_{half} - V_{thresh}} \tag{2}$$

and v_{ijt} is the wind experienced at point *i*, time *t* due to storm *j* as calculated in (1), V_{thresh} is the threshold below which no damage occurs, and V_{half} is the threshold at which half of the property is damaged. Following Emanuel (2011) we use a value of 93 km (i.e. 50kts) for V_{thresh} and a value of 278 km (i.e. 150kts) for V_{half}. The level of wind at a location during the passage of a hurricane is crucially dependent on that location's position relative to the storm and its movement and features, thus requiring explicit wind field modeling. In order to calculate the local wind speed (*v*) experienced due to a hurricane, we use Boose et al.'s (2004) version of the well-known Holland (1980) wind field model, which, given hurricane track data, can estimate the wind experienced at any local point relative to the storm during its life span. Details of this wind field model are described in detail in Appendix B. Over the sample period, 2002 until 2014,

[4] Other papers that have modeled the damage-wind speed relationship in a cubit manner include Strobl (2011), Strobl (2012), Antilla-Hughes (2012), Hsiang and Jina (2014), and Ishizawa and Miranda (2018). Specifically, Strobl (2012) shows for the Caribbean that not allowing for a cubit relationship can induce considerable attenuation bias.

there were 13 damaging storms producing local wind speeds of at least 92 km/hr. Table 2, Appendix A gives a list of the storms that affected Jamaica during the period of study.

C. Exposure

In order to derive parish specific aggregate time varying measures of destruction we also want to take exposure into account. Ideally, we would like to have time varying information on the degree of dispersion of economic activity within parishes at the most spatially disaggregated level as 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. One may want to note that nightlights have now found widespread use in proxying local economic activity where no other measures are available; see, for instance, Harari and La Ferrara (2013), Holder and Raschky (2014) and Michalopoulos and Papaioannou (2014). In terms of coverage, each DMSP satellite has a 101 minute near-polar orbit at an altitude of about 800km above the surface of the earth, providing global coverage twice per day, at the same local time each day, with a spatial resolution of about $1km^2$ near the equator. The resulting images provide the intensity of nightlight for each pixel per year, normalized to a scale ranging from 0 (no light) to 63 (maximum light).[5] We use the stable, cloud-free series; see Elvidge et al. (1997). These grid cell values have then two purposes: (1) they define the set of points used to calculate out local wind speed, and (2) they are used to create weights to generate exposure weighted parish level variables proxies of hurricane destruction. One should note that the weights are defined for the year prior to the day in question, so as to ensure that they are not affected by the hurricane events themselves.

[5] 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 almost quantitatively and qualitatively identical.

D. Alternative Hurricane Nightlight Exposure Indices

We also experiment with a number of other hurricane destruction proxies based on local wind speed. More specifically, we created a parish level incidence dummy of hurricane destruction. In a similar manner we calculated an incidence dummy at the parish capital rather than at the centroid. Another proxy that we construct is where we calculate the local wind speed at the constituency – which is an administrative unit below a parish – weight these with the share of constituency population in the parish the year before and then sum these to obtain constituency population weighted hurricane destruction indices. Finally, we estimated the local wind speed within parishes at the centroid of our nightlight cells, but then simply averaged these, over all cells (rather than taking local light intensity into account).

E. Climatic Control Variables

As a result of a global complex climate system, hurricane activity is likely to be correlated with other weather phenomena, such as rainfall and temperature; see Auffhammer et al. (2013). In order to ensure that our hurricane destruction index is not picking up these other climatic factors, we also construct a number of other weather control variables at the parish level. This is arguably particularly important in our context since there are a number of crime-weather studies that find an impact of temperature and rainfall on crime (Horrocks and Menclova, 2011; Mares, 2013; Ranson, 2014; Wetherley, 2014).

To construct parish level rainfall, we use the satellite derived Tropical Rainfall Measuring Mission (TRMM)-adjusted merged-infrared precipitation (3B42 V7) product. These 3 hourly precipitation estimates were generated by first using the TRMM, Visible and Infrared Scanner (VIRS) and TRMM Microwave Imager (TMI) orbit data (TRMM products 1B01 and 2A12) and the TMI/TRMM Combined Instrument (TCI) calibration parameters (from TRMM product 3B31) to produce Infrared (IR) calibration parameters. The derived IR calibration parameters were then employed to adjust the merged-IR precipitation data, which consists of Geostationary Meteorological Satellite (GMS), Geostationary Operational Environmental Satellites (GOES)-East, GOES-West, Meteosat-7, Meteosat-5, and National Oceanic and Atmospheric Administration (NOAA)-12 data. The final gridded, adjusted merged-IR precipitation (mm/hr) data have a 3 hourly temporal resolution and a 0.25-degree by 0.25-degree spatial resolution. Since the TRMM grid cells are of greater size than the location points, we use the value of the TRMM cell whose centroid is closest to our nightlight exposure cells to proxy the local rainfall. Similarly to the hurricane destruction index, we use the shares of parish level nightlight intensity as weights to derive an exposure weighted parish level daily rainfall series.

For obtaining proxies of parish level daily temperature, we use the daily local weather station values available from the two stations in Jamaica with consistent daily information, namely the Sangster and Norman Manley International Airport Stations. In order to spatially interpolate these series to local values across our points i, we use the method of Harlow et al. (2004) to allow for the fact that temperature will fall and rise according to the level of elevation. To this end, we employed the moist adiabatic lapse rates for Dominica, as available from Smith et al. (2009). To derive elevations at each nightlight cell value we used the United States Geological Survey (USGS) GTOPO30 global (Digital Elevation Model) DEM. As with the other climatic variables, we then calculated nightlight cell exposure weighted parish level daily temperature series.

F. Other Variables

We also use information provided by the Meteorological Service of Jamaica (MSJ) to generate a storm warning dummy variable, which captures whether or not and when (exact date) storm warnings were issued for impending storms. Storm warnings are issued by the MSJ when a storm is within a certain grid area relative to the location of the island within a 24-hr period. The expected conditions include storm winds up to at least 119km/hr. Based on the data provided by the MSJ for the time period of this study, a warning can be issued when a storm is within 40km to 425km of the island. Figure 1 in Appendix A demonstrates the storm-warning-crime relationship. It shows how crime changes with and without crime warnings 14 days before and 14 days after a hurricane strikes. Accordingly, crime without storm warnings generally remains higher than if there are no warnings and consistently so before and after a hurricane. So it appears that storm warnings may play a role in mitigating crime.

While the literature highlights the importance of evacuation orders, we are unable to incorporate it into our analysis for two reasons. First, evacuation orders are issued to residential locations that are in low-lying areas, near gullies and close to the shores, and there are no official maps of these. More importantly, such orders are always issued when there are official storm warnings, so it is perfectly correlated with these. Further, even without these two preceding reasons, residents typically do not obey evacuation orders (Jamaica Gleaner, 2017) despite the threat that violators of these orders will be negatively sanctioned (Jamaica Gleaner, 2016).

G. Summary Statistics

Table 3 provides statistics for all variables used in our regression analyses. The table shows the number of observations, mean, and standard deviation for all our crime categories. As can be seen, the daily crime incidences differs substantially across aggravated assault (0.05), break-in (0.47), murder (0.26), rape (0.16), robbery (0.46), and shooting (0.27). The average daily non-zero value of our hurricane index is 0.05, suggesting that on average during a hurricane the average rate of destruction is 5 per cent. Daily rainfall averages around 4.9 millimeters while the average daily temperature is around 26.5 degrees Celsius. Finally, holiday and weekend days constitute 0.026 and 0.286 per cent of our sample, respectively.

Section III: Econometric Estimation and Results

A. Econometric Model

We investigate the impact of hurricanes on criminal activities using the following benchmark specification:

$$log(Crime_{it}) = \alpha + \beta_1 \sum_{d=0}^{7} H_{it-dy} + \beta_2 X_{it} + \beta_3 D_{it} + \eta_i + d_t + m_m + y_y + u_{it} \tag{3}$$

where $Crime_{it}$, is crime for each parish i and day t, H_{it} is the parish specific hurricane destruction index which we calculated from (1), dy captures our inclusion of lagged hurricane which we consider up to day 7, X is a vector of climatic control variables, namely, rainfall and temperature. D is a vector of other controls, which are storm warning as well as holiday and weekend indicators. d, m, y are daily, monthly[6] and yearly dummies. To take account of parish fixed effects η, we employ a panel fixed effects estimator. We use Driscoll and Kraay's (1998) hetereoskedastic consistent standard errors to account for all possible cross-sectional and serial dependence among the error terms u.

Importantly, our identifying assumption is that after we control for parish fixed effects, time effects, climatic controls, and storm warnings, variations in H are just random realizations from the distribution of storms. In other words, we are assuming that there are no other omitted variables that may be correlated with hurricane damages and affect crime. One possible violation of this assumption that deserves further discussion are population movements before, after, and

[6] We use day of the week for daily and monthly dummies.

during hurricanes. With regards to H, one worry might be that affected people and criminals move in response to hurricanes. Given that our destruction index is constructed from the physical characteristics of the storm and from population weights a year prior to the storm, such population movements are unlikely to be correlated with our H. They may, however, be important in terms of storms warnings, in that storm warnings may induce population (or criminal) movements away from (or to) an affected area before, during or after a storm. Alternatively they may induce affected individuals or criminals to temporarily stay at (or leave) their home. Unfortunately, we have no further data to disentangle these different forces. Our storm warnings variable should thus be interpreted rather generally, without being able to identify the exact channel with which it affects crime during a hurricane, although we do provide some speculative reasons where appropriate.

B. Total Crime

We first estimate the impact of hurricanes on aggregate crime numbers, which is just the sum of the total number of criminal activities in each of the categories listed in part A, Section II. As can be seen from Table 4, while temperature in general significantly increases crime, there is no effect of rainfall or storm warnings. The positive relationship between temperature and crime is well supported in the weather-crime literature; see for instance, Jacob et al. (2007), who show a 5% increase in crime as a result of a rise in average weekly temperature. One can also see from our estimates that during holidays crime falls while it rises during weekends.

We further investigated whether hurricanes have non-contemporaneous effects on total crime by including lags in our analysis. Figure 2 shows the plot of the lagged coefficients which all turned out to be insignificant. Thus, there are no non-contemporaneous effects of hurricanes on criminal activities. Similar conclusions can be found in Wetherley et al. (2014). One may want to note that this lack of a lagged impact was also true for all our remaining crime regressions, and we thus refrain from reporting these any further.

In order to see whether our lack of impact of hurricanes on crime is due to some anticipation, we conducted a placebo experiment for total crime by re-estimating the model with the assumption that hurricane strikes took place seven days earlier. Since the strikes would have taken place before the actual hurricane occurrences, the estimated effect should be statistically insignificant. As column two shows, an anticipation effect is not driving our lack of significance on the hurricane destruction proxy.

As modeled, the storm warnings proxy captures a simple direct effect on crime regardless of whether a storm strikes or not in the end. However, feasibly storm warnings may have an indirect effect by reducing the impact of a storm by allowing for people to prepare for the storm, including reducing the likelihood of being a victim to a crime. To capture this, we next proceeded to include an interaction term of the storm warning dummy with the hurricane index, shown in the last column of Table 4. Accordingly, both the destruction index on its own as well as the interaction term are significant predictors of total crime. More specifically, their signs suggest that while hurricanes increase total crime, this is buffered when a storm warning is issued. This buffering effect may raise the concern that there may be a high correlation between warnings and the hurricanes themselves. However, Pearson's statistical value of 0.1064 indicates a positive but low correlation between warnings and hurricanes. While not downplaying this positive relationship, this low correlation outcome helps to dissipate the concern of a strong correlation between non-random warnings and storm characteristics. Quantitatively, the average hurricane seen over the sample period increased total crime by roughly 35% whereas a more damaging hurricane contributed to a significantly larger increase, 288% (see Table 6). However, once a storm warning is issued the effect disappears, as one cannot reject the null hypothesis of the sum of the coefficients being zero. One may also want to note that, although not reported here, there was only a contemporary impact of hurricanes on crime, that is, once a storm ceases to be damaging the spike in crime disappears.

C. Crime Decomposition

As has been already demonstrated in the literature, natural disasters can have heterogeneous impacts across specific crimes. Thus, we re-ran equation (3) for each of our six crime categories, the results of which are shown in Table 5. Since the model with the interaction term seems the most appropriate specification to tease out the effect of hurricanes on crime, we use this for all crime categories as well. According to Table 6, hurricanes positively impacts aggravated assault, indicating that crimes involving bodily harm inflicted upon a person for the average (maximum) storm increases by 0.5% (4.4%). Such significant increases have also been noted by Spencer (2017) for Florida. Despite the absence of the joint significance with our hurricane variable, we see that individually, storm warnings do play a role in reducing aggravated assault when an average hurricane strikes, an amount equal to about 3%. Likewise, there is a significant positive coefficient for the break-in category implying that the unlawful entry of homes or other buildings with the intent to commit a wrongdoing increases with hurricane strikes (Leitner and Helbich, 2010; Spencer, 2017). Quantitatively, the average hurricane strike increases break-ins by approximately 33% with the most damaging storm observed over our sample period causing increases by more than 270% (see Table 6). One possible reason for this increase is that often times people tend to come together during storms, whether it is a single person moving to be with family and friends or those vulnerable temporarily relocating for safety reasons, thus leaving their dwellings behind unguarded. Criminals being aware of this may use these situations as the opportune time to break-in into homes. However, we note that when a storm warning is issued, break-ins are reduced on average by 29%. This interaction variable is jointly significant with H so that the overall average impact on break-ins is only 3.7% with the maximum impact being 30% when a storm warning is issued.

Turning our attention to murders, one discovers that these significantly decrease by approximately 6% for the average strike with a 50% reduction for the strongest hurricane. In contrast, using weekly crime counts, Varano et al. (2010) find no increases in murders during the passage of hurricane Katrina in New Orleans. Table 6 also shows that sexual crime against females decline by on average by 4%, which stands in contrast to the findings by Thornton and Voigt (2007) where women were more likely to become rape victims during Hurricane Katrina in New Orleans. However, one should note in this regard that Thornton and Voigt's (2007) data were based mainly on qualitative information gathered from several different sources, including the media and victims' report in September 2005. Like murders, storm warnings issued for hurricanes increases the number of sexual offences. A possible explanation for this increase may be attributed to the level of personal disaster preparedness or lack of protection (see Thornton and Voigt, 2007). Thus, criminals may view storm warnings as an opportunity to attack the vulnerable who might be living alone, who choose not to leave their homes in the event of a hurricane or even if they leave return to their homes immediately after the storm.

For robberies we find that these fall by about 7% during an average storm but these reduction are roughly 8 times larger reduction for strongest storm (Table 6). This finding lies in contrast to Spencer (2017) who discovered an increase in robbery of 1550 per 100,000 inhabitants for Florida after hurricanes. The overall reduction in robberies has to do with the effect of storm warnings issued. Quantitatively, storm warnings for hurricanes account for roughly a 5% increase in robberies for the average strike. Perhaps due to a lack of adequate security or social order, there are more individuals facing unwanted acts against their personal property. Finally, we see that the average storm increases shooting by 29%. Thus, unlawful shootings significantly increase in the face of a hurricane, which is especially true for larger hurricanes. Notably, for this criminal act, though there is no evidence of joint significance with our hurricane variable, we see that storm warnings can play a role in reducing shootings by 28% on average.

The change in crime as well as the heterogeneous estimated results could be driven by different factors. For example, hurricanes create opportunities for crime against property (break-ins) because they soften the target even if evacuation orders were followed. In general, families and friends might choose to stay together leaving their properties behind. Thus, by this cohesion, less vigilance is exercised which opens up avenues for criminals especially if homes or businesses are not protected by grills or hurricane shutters. Further, if hurricanes destroy buildings, then it becomes much easier for criminals to enter. In addition, the usual means of survival (employment) for some individuals are disrupted, for instance, through construction and agriculture. Thus, crime can potentially serve as a survival mechanism that smooths out the loss in income until life returns to normality. Aggravated assault might play out when criminals attack a seemingly defenseless house but find occupants who would sustain bodily harm if, for example, there is resistance against giving up goods that are demanded by criminals. Such resistance could also lead to shootings. As it relates to reductions in crime, natural disasters potentially intensify human solidarity, as they provide a bonding experience for humans when it comes to survival and recovery. Thus, people are less inclined to hurt each other, so we observe declines, for example, for rape, robbery and murder. The influence of human solidarity and the resulting reductions in crime has been marked in the literature (Fritz, 1961; Morrow & Peacock, Quarantelli, 1989; 1997; Siegel et al., 1999). Fritz (1961). For example, Fritz (1961) argues that the behavior following a disaster is pro-social and has the effect of protecting others. The existence of this type of behavior emanates from the common suffering and losses experienced which encourages altruistic actions. Quarantelli (1989) points out that pro-social behavior is a general characteristic of natural disasters and so crime turns out to be lower than normal. Others such as including Goltz et al. (1992) show that previous experience with natural disasters result in individuals protecting not only themselves but also others.

Overall, one may want to note that compared to the results on aggregate crime, the decomposition by crime type exposes very heterogeneous responses. More precisely, some crime types (aggravated assault, break-ins, and shootings) increase, while others (murder, rape and robbery) fall. Storm warnings in all cases act to buffer the relative increase or decrease, but for some fully (aggravated assault, rape and shootings) and for others only partially (break-ins, murder, and robbery). The overall finding of an increase in total crime, mitigated by storm warnings thus seems to be an artifact of very different underlying criminal forces.

D. Robustness Checks

We conduct a number of robustness checks. First, we conducted additional placebo experiments for our total crime variable. More specifically, we re-estimated the model assuming that hurricane strikes took place on the same calendar day, but 1 to 3 years into the future. As Table 7 shows, our estimated effects on total crime are insignificant, which points to the same conclusion as does our previous placebo experiment which focused on storms striking 7 days earlier than actual occurrences. Second, we explored alternative transformations and specification of total crime, namely, crime per capita, inverse hyperbolic sine transformation and Poisson fixed effects estimation. Similar to the original results in Table 4, Table 8 shows that hurricanes do impact crime positively and confirms the reducing effect of storm warnings once they are issued. Third, we used alternative hurricane exposure nightlight indices as described in Section II, part D above to estimate the impact on total crime. We present these results in Table 9. As can be seen, all indices produce a positive effect on crime and as before, we observe a similar role that storm warnings play in reducing the effect of hurricanes on crime. Note that the estimated impact using our parish centroid index is more or less the same as what our original index produces, while others, namely, constituency/sub-parish, parish capital centroid, parish equal weighted indices estimate smaller results. The lower results than our benchmark measure suggest that these alternative indices may suffer from attenuation bias by not capturing potential hurricane damages as accurately.

Fourth, we aggregated our crime data to lower frequencies, namely, monthly and annual, to ascertain how our results using high frequency daily data compare to these other frequencies. The advantage of high frequency crime data is the smaller time interval within which unlawful activities occur. This allows for a more precise determination of the impact of hurricanes since there is likely to be less variations in the data due to other events that might potentially influence the various types of crimes. To examine whether the use of lower frequency data may explain some of contrasting findings in the current literature we re-ran equation (3) after aggregating our variables to monthly and annual frequencies, the results of which are presented in Tables 10 and 11, respectively. Examining Table 10 we note positive coefficients for total crime, break-ins, and shooting, as is the case with daily data. However the estimated impacts are 36, 14 and 9 times smaller, respectively, while the effect on rape, though negative, is two times smaller. Additionally, monthly aggregates do not produce any significant effects on aggravated assault, murder, or robbery. Table 11 shows that there are no significant effects, in total or by crime type, when using annual data. Similarly, Wetherley (2014) using annual frequency finds no impact on rape, murder, robbery, and physical injury. Overall, our results thus suggest that using lower frequency data might possibly be disguising the realities of the effects of hurricanes. Finally, we spatially aggregate our data to the country level to check for any possible nationwide effects. As the results in Table 12 show, no impacts are found at the country level for total crime and all subcategories.

Section IV: Conclusion and Policy Implications

We find that hurricanes do impact criminal activities, a conclusion which is in line with some of the current disaster-crime literature. Our study not only contributes to the current literature on natural disasters and crime, and more generally possibly on climate and conflict, but also fortifies it in two main ways. First, we use daily data, which has not been fully exploited in the literature, to pinpoint a more precise impact of hurricanes on criminal activities. Importantly, we find noticeably larger effects on crime with daily rather than monthly data, and no effects using annual data.

Second, our analysis utilizes an index of hurricane damages which incorporates the physical characteristics of each storm relative to specific location where the crimes took place. This stands largely in contrast to the disaster-crime literature which generally makes use of the frequency of hurricanes or their mere occurrences. These approaches to capturing hurricane effects might not be entirely accurate since the nature and magnitude of storms do matter, as our findings show. Thirdly, the explicit consideration of storm warnings when hurricanes are imminent plays a role in influencing crime. In our case, this turns out to be true for all types of crime considered.

With Jamaica being a high-crime society, costing the economy billions of dollars, our results point to the need for public policy to address the short-term increases in crime, namely, aggravated assault, break-in and shooting during natural disasters such as hurricanes. In this regard, some crimes against people, namely, murder, rape, and robbery actually decline in the face of hurricanes leaving assaults and shootings as the main criminal activity for policy makers to address and allocate more resources to when a natural disaster is imminent or immediately once it occurs. Noteworthy is the fact that crime against property, captured by break-ins, has the largest increase among all crime categories. This could help in educating the public, at least those who have to or choose to leave their homes behind, of break-ins, and the need to secure one's property possibly through household-disaster insurance schemes.

Appendix A

Table 1 Definitions of Crime

	Violent Crimes
Aggravated Assault	An attack greater than normal violence that is inflicted upon a person by another causing severe bodily harm
Break-In	The unlawful entry of a dwelling house or any building to commit a felony
Murder	The unlawful killing of one person by another
Rape	Having unlawful carnal knowledge of a female by force, fear or fraud against her will
Robbery	The unlawful possession of the property of another person from his person, taken by force or violence or putting him in fear with the intention of permanently possessing his property
Shooting	The unlawful discharge of a firearm by a person with the intent to injure of kill another

Note: Definitions are compiled from the Jamaica Constabulary Force and The National Police College of Jamaica.

Table 2 Storms that affected Jamaica, 2002-2014

Storm	Year(Month)	Saffir-Simpson Scale
Isidore	2002 (September)	3
Lili	2002 (September)	3
Charley	2004 (August)	3
Ivan	2004 (September)	5
Dennis	2005 (July)	3
Emily	2005 (July)	5
Wilma	2005 (November)	5
Dean	2007 (August)	5
Gustav	2008 (August)	4
Ike	2008 (September)	3
Paloma	2008 (November)	3
Tomas	2010 (November)	1
Sandy	2012 (October)	1

Table 3 Descriptive Statistics

Variable	Observation	Mean	Std. Dev.
Crime			
Aggravated Assault	66,712	0.051	0.334
Break-In	66,712	0.470	0.834
Murder	66,712	0.258	0.643
Rape	66,712	0.155	0.443
Robbery	66,712	0.462	0.924
Shooting	66,712	0.273	0.661
Weather			
Hurricane	66,712	0.047	0.082
Daily Rainfall	66,712	4.950	13.459
Temperature	66,712	26.498	1.570
Dummy			
Storm Warning	66,712	0.069	0.254
Holiday	66,712	0.026	0.158
Weekend	66,712	0.286	0.452

Notes: Table reports the number of observations, mean and standard deviation for each variable. Panel 1 presents the crime variables which are our dependent variables in six separate regressions. Panel 2 presents our first set of controls, the weather variables, including the variable of interest, hurricane. Panel 3 shows additional controls used in the analysis. Units of measurements for the variables are as follows: (i) all crime variables – number of crime incidences (ii) hurricane – percentage damage (iii) rainfall– millimeters (iv) temperature – degrees Celsius.

Table 4 Impact of Hurricanes on Total Crime

	Dependent Variable: Log (Crime)		
	(1)	(2)	(3)
Hurricane	0.5020	-0.3858	7.4855***
	(0.4347)	(0.2943)	(0.2678)
Hurricane*Storm Warning			-7.5909***
			(0.4261)
Total Hurricane Effect	0.5020	-0.3858	-0.1054
	(0.4347)	(0.2943)	(0.5033)
Rainfall	1.23E-05	0.0001	-0.0000124
	(0.0002)	(0.0002)	(0.0002)
Temperature	0.0111***	0.0113***	0.0116***
	(0.0024)	(0.0024)	(0.0024)
Storm Warning	0.0163	0.0175	0.0187
	(0.0104)	(0.0102)	(0.0102)
Holiday	-0.0439***	-0.0436***	-0.0435***
	(0.0127)	(0.0127)	(0.0126)
Weekend	0.0618***	0.0623***	0.0621***
	(0.0074)	(0.0074)	(0.0074)
Observations	66,712	66,614	66,712
R-squared within	0.0538	0.0538	0.0545

Notes: (i) (2) reports the results from the placebo regression for a hurricane one week later (t+7). (ii) Day, monthly and yearly dummies are included in (1)-(3). (iii) Driscoll-Kraay standard errors in parentheses. (iv) In (3), hurricane and hurricane*storm warning are jointly insignificant. (v) ***, ** - 1%, and 5% levels of significance respectively.

Table 5 Impact of Hurricanes on Types of Crime

	Dependent Variable: Log (Crime)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Aggravated Assault	Break-In	Murder	Rape	Robbery	Shooting
Hurricane	0.1147***	7.0855***	-1.3098***	-0.8503***	-1.4285***	6.2179***
	(0.0432)	(0.1430)	(0.1123)	(0.1015)	(0.2196)	(0.5018)
Hurricane*Storm Warning	-0.0987**	-6.2953***	0.9797***	0.7296***	1.0043***	-6.0422***
	(0.0390)	(0.3309)	(0.1421)	(0.1336)	(0.2349)	(0.5404)
Total Hurricane Effect	0.0160	0.7902***	-0.3301***	-0.1207	0.4242***	0.1757
	(0.0582)	(0.3605)	0.1811	(0.3216)	0.3125	(0.7375)
Rainfall	-4.13E-06	0.0003	-0.0003***	3.04E-05	-0.0001	-0.0002
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Temperature	0.0029***	-0.0006	0.0064***	0.0031**	0.0013	0.0030**
	(0.0007)	(0.0018)	(0.0014)	(0.0012)	(0.0018)	(0.0014)
Storm Warning	0.0008	0.0194**	0.0007	0.0054	-0.0057	0.0127**
	(0.0022)	(0.0078)	(0.0054)	(0.0050)	(0.0072)	(0.0056)
Holiday	0.0016	-0.0563***	-0.0001	0.0351***	-0.0599***	0.0004
	(0.0032)	(0.0089)	(0.0080)	(0.0085)	(0.0088)	(0.0079)
Weekend	0.0023	-0.0062	0.0193***	0.0206***	0.0588***	0.0199***
	(0.0027)	(0.0057)	(0.0045)	(0.0039)	(0.0055)	(0.0044)
Observations	66,712	66,712	66,712	66,712	66,712	66,712
R-squared within	0.0772	0.0528	0.009	0.0036	0.028	0.0079

Notes: (i) Day, monthly and yearly dummies are included. (ii) Driscoll-Kraay standard errors in parentheses. (iii) Hurricane and hurricane*storm warning are jointly insignificant in (1), (4) and (6). (iv) Hurricane and hurricane*storm warning are jointly significant in (2), F=8.64***; (3), F=11.08***; and (5), F=5.82***. (v) The Z-tests of equality of coefficients indicate that the outcomes for aggravated assault, break-in and murder are significantly different (p-values for the tests on assault and break-in; aggravated assault and shooting; break-in and shooting are all zero). This is also true for murder, rape and robbery (p-values for the tests on murder and rape; murder and robbery; rape and robbery are all zero). (vi) ***, ** - 1%, and 5% levels of significance respectively.

Table 6 Summary: Economic Impact of Hurricanes

	Summary: Economic Impact						
	Total Crime	Aggravated Assault	Break-In	Murder	Rape	Robbery	Shooting
Hurricane	**0.3481**	**0.0053**	**0.3295**	**-0.0609**	**-0.0395**	**-0.0664**	**0.2892**
	2.8838	0.0441	2.7224	-0.5033	-0.3267	-0.5489	2.3891
Hurricane*Storm Warning	***-0.3530***	***-0.0046***	**-0.2928**	**0.0456**	***0.0339***	**0.0467**	***-0.2810***
	-2.9166	*-0.0379*	-2.4188	0.3764	*0.2803*	0.3859	*-2.3216*
Total Average Impact	**0.3481**	**0.0053**	**0.0368**	**-0.0154**	**-0.0395**	**-0.0197**	**0.2892**
Total Maximum Impact	2.8838	0.0441	0.3036	-0.1268	-0.3267	-0.1630	2.3891

Notes: (i) Table summarizes quantitative impact of hurricanes using estimated significant coefficients from tables 3-9. (ii) The estimated coefficients are calculated out using the average (0.047) and maximum (0.384) values of the hurricane index. (iii) The coefficients in bold are the values capturing the average hurricane strike and those not bolded represent the impact from more damaging hurricanes. (iv) *Values in italics* represent coefficients not jointly significant with *Hurricane*.

Table 7 Additional Placebo Experiments: Impact of Hurricanes on Total Crime

	Dependent Variable: Log (Crime)		
	(1)	(2)	(3)
	1 year	2 years	3 years
Hurricane	0.3992	0.1488	0.1803
	(0.2815)	(0.2564)	(0.2461)
Hurricane*Storm Warning	-0.2582	-0.7718	-1.077
	(0.5678)	(0.6751)	(0.6325)
Rainfall	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Temperature	0.0113***	0.0114***	0.0114***
	(0.0024)	(0.0024)	(0.0025)
Storm Warning	0.0179	0.0173	0.0165
	(0.0103)	(0.0103)	(0.0104)
Holiday	-0.0456***	-0.0454***	-0.0428***
	(0.0128)	(0.0127)	(0.0127)
Weekend	-0.0679***	0.0607***	-0.0676***
	(0.0075)	(0.0074)	(0.0075)
Observations	66,309	65,906	65,503
R-squared within	0.0536	0.0536	0.0532

Notes: (i) The table reports the results from the placebo regressions for 1, 2 and 3 years into the future for the corresponding calendar day for hurricane strikes. (ii) Day, monthly and yearly dummies are included in (1)-(3). (iii) Driscoll-Kraay standard errors in parentheses. (iv) *** - 1% level of significance respectively.

Table 8 Impact of Hurricanes on Crime: Alternative Transformations for Total Crime

	Dependent Variable: Log (Crime)		
	(1)	(2)	(3)
	Crime Per Capita	Poisson FE	Inverse Hyperbolic Sine Transformation
Hurricane	8.62e-05***	9.8490***	7.5050***
	(7.32E-06)	(0.7330)	(0.5490)
Hurricane*Storm Warning	-7.02e-05***	-10.02***	-7.589***
	(1.06E-05)	(1.3780)	(0.9500)
Rainfall	-3.18E-09	0.0001	-1.80e-05
	(4.76E-09)	(0.0003)	(0.0002)
Temperature	6.53E-08	0.0222***	0.0117**
	(6.65E-08)	(0.0053)	(0.0050)
Storm Warning	4.44E-07	0.0231**	0.0163
	(2.58E-07)	(0.0113)	(0.0080)
Holiday	-4.47E-07	-0.0615***	-0.0434**
	(3.99E-07)	(0.0205)	(0.0193)
Weekend	8.23e-07***	-0.0247***	-0.0188
	(2.88E-07)	(0.0091)	(0.0087)
Observations	66,712	66,712	66,712
R-squared within	0.0161	0.0122	0.6778

Notes: (i) Table shows the estimated impacts of hurricane on crime for different transformations/specifications of total crime: crime per capita, column 1; Poisson fixed effect specification, column 2; inverse hyperbolic sine transformation. (iii) The results here corresponds to model (3) in table 4. (iv) With the Poisson fixed effect specification and the inverse hyperbolic sine transformation, hurricane and its interaction with storm warning are insignificant. (v)) ***, ** - 1%, and 5% levels of significance respectively.

Table 9 Impact of Hurricanes on Crime: Alternative Hurricane Indices

	Dependent Variable: Log (Crime)			
	Constituency Index	Parish Capital Incidence	Parish Incidence	Parish Equal Weight Index
Hurricane	4.1800***	4.7274***	7.5109***	0.0013***
	(0.2140)	(0.1890)	(0.2343)	(0.0001)
Hurricane*Storm Warning	-4.2277***	-4.7681***	-7.7058***	-0.0018***
	(0.3948)	(0.3920)	(0.3898)	(0.0003)
Rainfall	4.90E-05	2.05E-04	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Temperature	0.0114***	0.0114***	0.0114***	0.0115***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Storm Warning	0.0152	0.0152	0.0156	0.0187*
	(0.0102)	(0.0102)	(0.0102)	(0.0101)
Holiday	-0.0440***	-0.0440***	-0.0440***	-0.0442***
	(0.0127)	(0.0127)	(0.0127)	(0.0127)
Weekend	0.0619***	0.0619***	0.0619***	0.0621***
	(0.0074)	(0.0074)	(0.0074)	(0.0074)
Observations	66,712	66,712	66,712	66,712
R-squared within	0.0539	0.0539	0.0539	0.0539

Notes: (i) Table shows the estimated impacts if the hurricane data were calculated for exposure in constituency/sub-parish, parish capital/city, parish centroid and equal weighted centroid locations. (ii) The results here corresponds to model (3) in table 4. (iii) Monthly and yearly dummies are included. (iv) Driscoll-Kraay standard errors in parentheses. (v) The same controls used in tables 4 are also used for these regressions. These results as well as for all crime sub-categories are available upon request. (vi) The hurricane-storm-warning variable is not jointly significant with the hurricane variable. (vii) ***, ** - 1%, and 5% levels of significance respectively.

Table 10 Impact of Hurricanes on Crime: Monthly Data

	Total Crime	Aggravated Assault	Break In	Murder	Rape	Roberry	Shooting
Hurricane	0.2105**	-0.0475	0.4953***	0.0685	-0.4051**	-0.4099	0.6983***
	(0.0974)	(0.1347)	(0.1159)	(0.1095)	(0.1726)	(0.2165)	(0.1281)
Hurricane*Storm Warning	-0.0074	0.0067	-0.0140	0.0001	0.0134	0.0036	-0.0233***
	(0.0064)	(0.0060)	(0.0085)	(0.0084)	(0.0090)	(0.0073)	(0.0067)
Observations	2,184	2184	2184	2,184	2,184	2,184	2,184
R-squared within	0.3629	0.7285	0.379	0.0869	0.0443	0.1549	0.0611

Notes: (i) Table shows the estimated impacts if the data were monthly instead of daily. (ii) The results here corresponds to model (3) in table 4 and all results in table 5. (iii) Monthly and yearly dummies are included. (iv) Driscoll-Kraay standard errors in parentheses. (v) The same controls used in tables 4 and 5 are also used for these regressions. The results are available upon request. (vi) ***, ** - 1%, and 5% levels of significance respectively.

Table 11 Impact of Hurricanes on Crime: Annual Data

	Total Crime	Aggravated Assault	Break In	Murder	Rape	Roberry	Shooting
Hurricane	-0.0120	0.0454	0.1800	0.0355	-0.0706	-0.1643	-0.0989
	(0.2049)	(0.3928)	(0.2316)	(0.3266)	(0.3594)	(0.1736)	(0.2987)
Hurricane*Storm Warning	-0.0079	-0.0124	-0.0110	-0.0041	-0.0170	-0.0071	0.0081
	(0.0069)	(0.0120)	(0.0103)	(0.0105)	(0.0122)	(0.0073)	(0.0084)
Observations	182	182	182	182	182	182	182
R-squared within	0.635	0.927	0.703	0.3483	0.2698	0.5271	0.2499

Notes: (i) Table shows the estimated impacts if the data were annualized instead at the daily level. (ii) The results here corresponds to model (3) in table 4 and all the results in table 5. (iii) Yearly dummies are included. (iv) Driscoll-Kraay standard errors in parentheses. (v) The same controls used in tables 4 and 5 are also used for these regressions. The results are available upon request.

Table 12 Impact of Hurricanes on Crime: Country Level Data

	Total Crime	Aggravated Assault	Break In	Murder	Rape	Roberry	Shooting
Hurricane	-0.0371	-1.8653	-0.1425	0.1144	-0.0169	-0.0046	0.0918
	(0.1854)	(1.3083)	(0.2698)	(0.1266)	(0.0830)	(0.1799)	(0.1123)
Hurricane*Storm Warning	-0.0001	0.0010	-7.78E-06	-0.0002	-4.10E-05	-0.0001	-0.0001
	(0.0002)	(0.0016)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Observations	13	13	13	13	13	13	13
R-squared	0.9848	0.5099	0.9569	0.9887	0.9944	0.9806	0.9913

Notes: (i) Table shows the estimated impacts if the data were aggregated to the country level. (ii) The results here corresponds to model (3) in table 4 and all the results in table 5. (iii) Robust standard errors are in parentheses. (iv) The same controls used in tables 3 and 4 are also used for these regressions. The results are available upon request.

Figure 1 How Crime Changes With and Without Storm Warnings

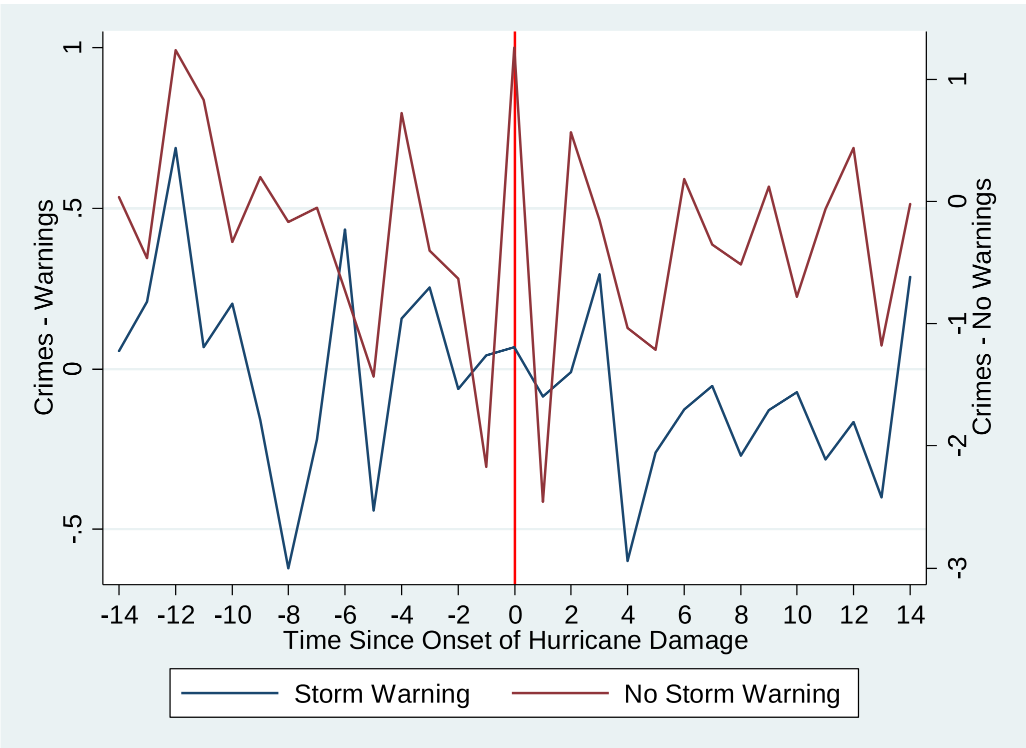
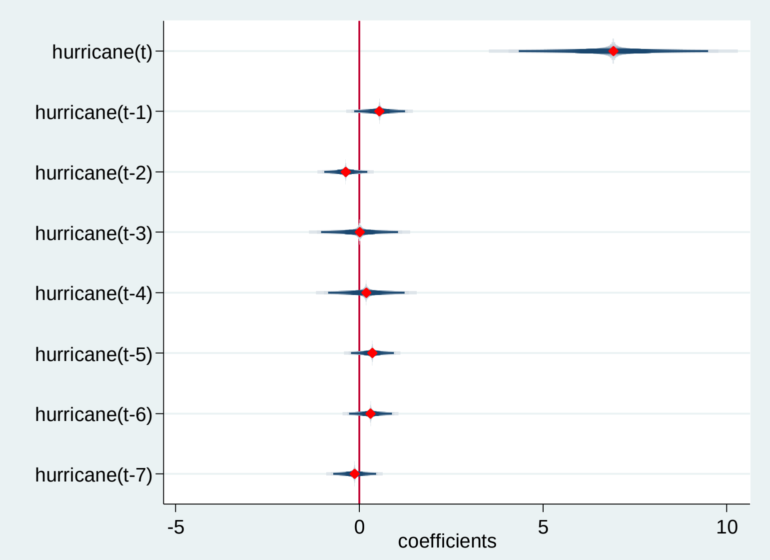


Figure 2 Total Crime: Coefficient Plot



Note: All lags are insignificant.

Appendix B: Wind Field Model

We use Boose et al.'s (2004) version of the well-known Holland (1980) wind field model. More specifically, the wind experienced at time t due to hurricane k at any point P=i, i.e., V_{ik} is given by:

$$V_{i,k,t} = GF\left[V_{m,k,t} - S\left(1-\sin\left(T_{i,k,t}\right)\right)\frac{V_{h,k,t}}{2}\right]\left[\left(\frac{R_{m,k,t}}{R_{i,k,t}}\right)^{B_{jt}} \exp\left(1-\left[\frac{R_{m,k,t}}{R_{i,k,t}}\right]^{B_{jt}}\right)\right]^{\frac{1}{2}} \quad \text{(B1)}$$

where V_m is the maximum sustained wind velocity anywhere in the hurricane, T is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the pixel of interest, P=i, V_h is the forward velocity of the hurricane, R_m is the radius of maximum winds, and R is the radial distance from the center of the hurricane to point P. The remaining ingredients in (B1) consist of the gust factor G and the scaling parameters F, S, and B, for surface friction, asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively.

In terms of implementing (B1), one should note that V_m is given by the storm track data described below, V_h can be directly calculated by following the storm's movements between locations along its track, and R and T are calculated relative to the point of interest P=i. All other parameters have to be estimated or assumed. For instance, we have no information on the gust wind factor G, but a number of studies (e.g. Paulsen and 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 to directly determine F, Vickery et al. (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 linearly decreases within this range as we consider points i further inland from the coast. Finally, to determine B we employ Holland's (2008) approximation method, whereas we use the parametric model estimated by Xiao et al. (2009) to estimate R_{max}.

Our source for hurricane data is the Hurricane Database (HURDAT) Best Track Data, which provides six hourly data on all tropical cyclones in the North Atlantic Basin, including the position of the eye of the storm and the maximum wind speed. We linearly interpolate these to 3 hourly positions in order to be in congruence with our rainfall data in Section II, part D. We also restrict the set of storms to those that came within 500 km of Jamaica and that achieved hurricane strength (at least 119 km/hr) at some stage.[7]

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

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