IDB WORKING PAPER SERIES Nº IDB-WP-1551

Climate Change, Hurricanes, and Sovereign Debt in the Caribbean Basin

Eduardo Cavallo
Santiago Gómez
Ilan Noy
Eric Strobl

Inter-American Development Bank
Department of Research and Chief Economist

January 2024

Climate Change, Hurricanes, and Sovereign Debt in the Caribbean Basin

Eduardo Cavallo*
Santiago Gómez*
Ilan Noy**
Eric Strobl***

* Inter-American Development Bank
** Victoria University of Wellington
*** University of Bern

January 2024

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Climate change, hurricanes, and sovereign debt in the Caribbean Basin / Eduardo Cavallo, Santiago Gomez, Ilan Noy, Eric Strobl.
p. cm. — (IDB Working Paper Series ; 1551)
Includes bibliographical references.
1. Debts, Public-Caribbean Area. 2. Climatic changes-Economic aspects-Caribbean Area. 3. Hurricanes-Caribbean Area. I. Cavallo, Eduardo A. II. Gomez, Santiago. III. Noy, Ilan. IV. Strobl, Eric, 1969 - V. Inter-American Development Bank. Department of Research and Chief Economist. VI. Series.
IDB-WP-1551

http://www.iadb.org

Abstract

Caribbean Islands are exposed to hurricanes, the damages of which are projected to intensify due to anthropogenic climate change. The region is also highly indebted. We focus on the interaction between climate change, hurricanes, and public debt. We investigate what the typical impact of Caribbean hurricanes on public debt in the region has been and how anthropogenic climate change has shaped this impact. Our findings show that for the 10 most severe storms, the average increase in debt, measured as the difference between post and pre-storm trends, is about 10 percent. Three years after such a storm, debt levels are 18 percent higher than what would have been expected otherwise. Based on findings from Extreme Weather Event Attribution (EEA) research, we calculate that the impact of a severe hurricane on public debt that is attributable to climate change amounts to an increase of 3.8 percent of the debt stock relative to the level of debt at the time of the event.

JEL classifications: Q54

Keywords: Caribbean, Public debt, Hurricanes, Attribution, Climate change

1. Introduction

The Caribbean is very exposed to hurricanes, and these hurricanes constitute possibly the single most significant disaster risk for the region. This high risk is mainly because of the prevalence of intense hurricanes in the Caribbean basin, the hurricanes' projected intensification because of anthropogenic climate change, the population's concentration along the coasts, and the Caribbean's reliance on agriculture and tourism—two sectors that are particularly vulnerable to damage from hurricanes. In the parlance of disaster professionals, the region is characterized by high hazard, high exposure, and high vulnerability.

At the same time, the region is heavily indebted, with public debt for the average country having risen from 41 percent to 59 percent of GDP from 1980 to 2020. It is this interaction between hurricanes, changing risk because of climate change, and public debt that is the focus of this paper. We ultimately aim to answer two questions. First, what has been the impact of Caribbean hurricanes on public debt in the region? Second, what has been the role of anthropogenic climate change in determining this impact?

We answer these two questions using economic data from the past four decades in the region. To answer the first question, we estimate an econometric model whose purpose is to identify the average dynamic development of public debt in the aftermath of a hurricane event, an approach developed in Cavallo et al. (2022). For the second answer, we use insights from the impact attribution literature (Noy et al., 2023) to provide an estimate of the contribution of climate change to this risk and to its consequences.

Generally, the impact of a hurricane can be measured in terms of its immediate destruction of the stock of economic assets. These include residential, commercial, and public buildings, roads, other transportation infrastructure such as ports, and utility networks (e.g., electricity and sewage systems). The impact of a hurricane can also include its effect on the flow of economic activity in the immediate aftermath of the event, as a direct result of damage to assets, or later and indirectly through its flow-on effects on supply chains, consumer demand, or as a result of the ensuing macroeconomic shifts in fiscal accounts, relative prices, and exchange rates.

A significant body of research examines the economic impacts of hurricanes, much of it focusing on the Caribbean, Central America, and the Gulf of Mexico (especially Florida, Louisiana, Mississippi, and Texas), as this region experiences the most destructive hurricanes. For example, the 2017 Hurricane Maria destroyed assets on the island of Dominica valued at more than 200 percent of Dominica's annual GDP (Thomas et al., 2020).[1] Events like this, where the damage is more than the annual GDP of an affected country, are, unfortunately, not that rare in the Caribbean region. Several recent studies explore the implications of this damage to various aspects of economic activity. This includes Caribbean hurricanes' impacts on incomes and GDP (e.g., Strobl, 2012; Ishizawa and Miranda, 2019; and Campbell and Spencer, 2021) on proxies for GDP such as nightlights (Bertinelli and Strobl, 2013; Ishizawa et al., 2019); their historical impact on trade, particularly sugar trade, and trade flows more generally (Mohan and Strobl, 2013; Mohan, 2023; Bensassi et al., 2017); their impact on households' incomes and asset holdings (Jakobsen, 2012; Henry et al., 2020); their impact on important economic sectors such as agriculture (Mohan, 2017; Gassebner et al., 2010; Spencer and Polachek, 2015; Mohan and Strobl, 2017), and tourism (Carballo et al., 2023); their impact on financial indicators such as international reserves (Strobl et al., 2020), prices (Heinen et al., 2019), and banking sector stability (Brei et al., 2019); and their effect on fiscal accounts (Ouattara et al., 2018; Mohan and Strobl, 2021). Nevertheless, Mohan et al. (2018) report that there is significant heterogeneity in the impact of storms on some of the various macroeconomic aggregates identified above, even within the relatively narrow context of the Caribbean Island countries.

Most of the damage from hurricanes is associated with the rainfall occurring during a hurricane rather than the locally measured wind the storm generates.[2] The damage originates from both fluvial and pluvial flooding arising out of the excessive rainfall (including flash floods). Other damage from hurricanes is sometimes associated with storm surges. These usually are more damaging in areas that have a smaller tidal range (and thus less protection against abnormally large waves), and where the bathymetry of the coast is conducive to the generation of large waves. That is generally less the case in the Caribbean islands than it is, for example, on the Louisiana coast. Wind damage is also a possibility, but in most cases wind damage is connected with rainfall (through a combination of rainfall and wind destabilizing slopes by increasing moisture and reducing plant cover).

[1] For comparison, the costliest disaster event in the last century, the 2011 earthquake/tsunami in Japan, damaged assets valued at about 4 percent of Japan's GDP.

[2] Collalti and Strobl (2022) report this for Jamaica. Yonson et al. (2018) reached a similar conclusion in their investigation of tropical cyclones in the Philippines, and Smiley et al. (2022) reported a similar observation for Hurricane Harvey in 2017 in Texas.

From our perspective, the centrality of excessive rainfall as a source of damage allows us to estimate the impact of climate change on the damage from these storms, as much of the research on the attribution of hurricanes tended to focus on the role of anthropogenic increase in Greenhouse Gases (GHG) in increasing the amount of rainfall associated with hurricanes rather than in climate change's role in changing the storms' (average or maximum) windspeed. This focus on precipitation in the attribution literature is mainly because the anthropogenic increase in windspeed is significantly more challenging to model than the anthropogenic increase in rainfall.

The Caribbean countries and territories have always experienced hurricanes, and their intensity may be increasing because of anthropogenic climate change (Knutson et al., 2021). Some studies attempt to investigate the connection between hurricanes and climate change within the context of specific events in the Caribbean, while others analyze the North-West Atlantic hurricane seasons and specifically, the emergence and detection of a climate change signal in aggregate trends.

For the 2017 hurricane season, a particularly damaging one that included Hurricane Irma, Maria, and Harvey, Murakami et al. (2018) found that the occurrence of powerful hurricanes during that year was mainly caused by high sea surface temperatures, indicating a potential causal link to climate change. Similarly, for the 2020 Atlantic hurricane season, Reed et al. (2022) use hindcast simulations to investigate the link between climate change and hurricane extreme rainfall. They find that climate change had already, by 2020, likely increased hurricane extreme hourly rainfall rates by 11 percent and extreme 3-day accumulated rainfall by 8 percent. This result suggests it may be the case that the climate-change-induced increases in rainfall quantified for individual storms like Irma, Maria, and Dorian—detailed below—also apply to full hurricane seasons, including during weaker storms. This would be consistent with the results of Knutson et al. (2020), who project that 2°C global warming would cause a 15 percent increase in hurricane precipitation rates in the North Atlantic.

Another study by Li and Chakraborty (2020) focuses on the rate (time) it takes hurricanes to weaken once they make landfall. Their study shows that this rate decreases with ocean warming, thus making hurricanes more damaging in coastal areas where they release most of their rainfall.

Two hindcast simulation studies suggest climate change increased precipitation associated with specific Caribbean hurricanes. Patricola and Wehner (2018) estimated that climate change increased the rainfall associated with Hurricanes Irma (2017) and Maria (2017) in the area close to the storm center by 6 percent and 9 percent, respectively. Reed et al. (2021) found that climate change may have increased Hurricane Dorian's (2019) total accumulated rainfall and the probability of extreme 3-hourly rainfall amounts by 7 percent and 16 percent, respectively. Similarly, several papers have arrived at similar conclusions for Hurricane Harvey in 2017 (e.g., Trenberth et al., 2018, and Wehner and Sampson 2021).

Two other attribution studies looked specifically at hurricanes that passed through the Caribbean region. A statistical analysis of rainfall in Puerto Rico between 1956-2016 indicates that long-term climate trends likely increased the probability of precipitation of Hurricane Maria's magnitude in the most affected regions by a factor larger than one, with the best estimate of 4.85 (Keelings and Ayala, 2019). However, Puerto Rico's high climate variability and the data limitations of this specific study prevented the authors from drawing a statistically definitive conclusion regarding the link between climate change and hurricanes' associated rainfall.

Studies that examined the attribution of Atlantic hurricane trends suggest that climate change may have increased intensification rates – as measured by windspeeds (Bhatia et al., 2019, 2022) or the probability of highly active hurricane seasons (Pfleiderer et al., 2022). However, linking these trend analyses to increased intensity for specific events has yet to be reliably done, given the infrequent occurrence of these events.

Overall, we conclude a conservative estimate of the additional rainfall during hurricanes in the Caribbean basin is around 10 percent. The basic Clausius-Clapyeron relationship posits a 7 percent increase in the vapor-holding capacity of air with every 1°C rise in temperature. As the world has already warmed by around 1.2°C since pre-industrial times, and since there are several other mechanisms through which anthropogenic climate change is hypothesized to increase rainfall during tropical cyclone events, 10 percent is probably a lower bound on the possible actual increase in rainfall that can already be attributed to climate change. We will use this in our quantifications of the increase in debt, as detailed below.

Globally, total debt (including both public and private) has increased rapidly between 2008 and 2020. This increase has been especially pronounced for emerging and developing economies (EMDEs). Their cumulative debt, as a share of their cumulative GDP, has doubled in this time period—from about 100 percent to more than 200 percent (Kose et al., 2022a). In Latin America and the Caribbean, total debt has risen to US$5.8 trillion, or 117 percent of gross domestic product (Powell and Valencia, 2022). Government debt in the Emerging Markets and Developing Econies

(EMDEs) has reached 63 percent of GDP in 2021, i.e., the highest level since the 1980s (Kose et al., 2022a), and in Latin America and the Caribbean public debt soared to 72 percent of GDP during the pandemic (Powell and Valencia, 2022). External debt in the EMDEs reached 31 percent of GDP in 2020, a high level for a group of countries that still suffer from the "original sin" of borrowing in foreign currency (Eichengreen et al., 2023). The EMDEs of the Caribbean basin have also experienced a large increase in indebtedness in the past decade, rising from 46 percent of GDP in 2010 to 59 percent of GDP in 2020.

Beginning with Lis and Nickel (2010) and Noy and Nualsri (2011), several studies have examined the impacts of disasters (caused by hurricanes, earthquakes, or other types of natural hazards) on fiscal accounts, focusing on either expenditures and revenue separately, or on the net surplus/deficit (e.g., Melecky and Raddatz, 2014; Klomp, 2019; Noy et al., 2023; Alejos, 2018). These papers conclude that government accounts generally worsen after disasters, as expenditures increase during the emergency, recovery, and reconstruction phases, and as specific tax revenue streams decline because of temporary assistance in the form of "tax holiday" policies (e.g., for imports of construction materials, or temporary decreases in income tax rates in affected regions) and decline in taxable economic activities (e.g., imports of luxury goods, or corporate profits). In fewer cases, papers have also examined public borrowing and the evolution of the debt stock after disasters (e.g., Mohan et al., 2018).[3]

The significant impact of disasters on public debt is partly explained by the limited impact of alternative financing options like foreign aid and risk insurance. Despite the surge in foreign aid that is typically observed in the aftermath of such disasters, this aid proves to be insufficient. Becerra, Cavallo, and Noy (2014) find that, on average, aid flows increase by 18 percent in the year a natural disaster occurs. However, this increase amounts to only 0.25 percent of a country's GDP and less than 3 percent of the total estimated damages. Moreover, a significant portion of this aid is not additional funding but is reallocated from other sectors, such as infrastructure development to humanitarian assistance (Becerra, Cavallo, and Noy, 2015). Insurance options are also limited, especially in developing countries. These countries face challenges like underdeveloped insurance markets, political resistance to investing in risk mitigation for events

[3] Relatedly, Klomp (2015) examined the impact of disasters on sovereign risk and found that the likelihood of a sovereign rating downgrade or even default rises in the aftermath of disaster events.

that may not occur, and inadequate institutional frameworks for risk assessment and contract enforcement (see Borensztein, Cavallo and Valenzuela, 2009).

The governments, facing immediate and substantial financial demands for response and reconstruction find themselves with few alternatives but to increase public debt to manage these crises. This paper provides new evidence on the link between climate change, hurricanes, and debt levels on the Caribbean basin.

The remainder of the paper is organized as follows. After describing the data (in Section 2) and the methodological approach (in Section 3), we estimate the impact of hurricanes on the burden of debt for countries in the Caribbean basin (in Section 4). Then, in Section 5, we perform calculations of the likely role of anthropogenic climate change in the additional debt that we identify to have resulted from these hurricanes. We end with some discussion of the policy implications of our findings.

2. Data

Our primary data source is the records of extreme weather events drawn from EM-DAT; a publicly available database of disaster impact data curated by the Center for Research on the Epidemiology of Disasters (CRED). Aiming to cover all disaster incidents globally, the EM-DAT database documents the occurrences and impacts of diverse disaster categories from 1900 to the present.

In line with EM-DAT's operational definition, a disaster pertains to a scenario or incident surpassing local response capacities, thus necessitating external assistance. To warrant inclusion within the database, a disaster must satisfy at least one of the subsequent criteria: i) a death toll of 10 individuals or more; ii) 100 individuals or more being affected; iii) a proclamation of a state of emergency; or iv) an appeal for international assistance.

We focus on storms in the Caribbean basin, i.e., countries with a coast facing the Caribbean Sea.[4] The EM-DAT database records 152 storms in this region during 1970-2020 that caused disasters, as satisfied by its inclusion criteria, although only 145 include damage data (see Appendix A). This represents approximately 11.7 percent of that period's global storm count. Mexico is the country within the Caribbean basin that has experienced the most storms, with 18

[4] The Caribbean basin countries included in our analysis are the Bahamas, Barbados, Belize, Colombia, Costa Rica, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Trinidad and Tobago, and Venezuela. We exclude the overseas territories in the region, given the absence of independent economic data on many of them and their dependence on the countries that own them (e.g., the British Virgin Islands or Curaçao).

storms hitting it during these five decades (also positioning it within the global top 10 for storm-affected countries). The smaller countries of the Dominican Republic (16 storms), the Bahamas (15), and Jamaica (15) have also been hard-hit by these events. The last two decades (2001-2020) have been characterized by 61 percent of storms in the Caribbean Basin over the last 50 years (see Table 1).[5]

The higher incidence of hurricane disasters in recent decades can possibly be attributed to the influence of climate change on the frequency of extreme weather events, and/or to increased exposure and vulnerability to the impact of these storms, and/or enhanced data reporting practices (especially with the advent of the internet in the mid-1990s). Data presented by Cavallo et al. (2022) and Cavallo et al. (2023) show that the increase in the incidence of disasters is higher for events that can be (partially) attributed to climate change (like storms) than for other types of disasters that are unrelated to climate change (e.g., earthquakes). While a much longer time series is required to arrive at any definite conclusions, this observation is commensurate with the view that climate change is a factor in this observed increase, even if not the only one.

Table 1. Number of Storms by Country and Decade

Country	1971-1980	1981-1990	1991-2000	2001-2010	2011-2020	Total
The Bahamas	0	1	3	5	6	15
Barbados	1	1	1	3	1	7
Belize	2	0	2	5	2	11
Colombia	0	1	0	1	1	3
Costa Rica	0	0	1	1	3	5
Dominican Republic	2	3	3	4	4	16
El Salvador	0	0	3	3	3	9
Guatemala	0	0	0	3	4	7

[5] Cavallo, Becerra, and Acevedo (2022) show an increasing trend in the incidence of extreme weather events reported in EM-DAT. This can be related to climate change, increased exposure to natural hazards, and improved reporting in the dataset. There has been a significant increase in the incidence of hydrological (x5.9), meteorological (x4.7), and climatological events (x6) since 1970. There has also been an increase in the number of geophysical events, but smaller (x3 since 1970). Earthquakes and volcanic eruptions are not influenced by climate change. Therefore, this evidence suggests that at least part of the increasing trend of extreme weather events is due to increased exposure and improved reporting, but not all of it.

Haiti	2	2	2	4	4	14
Honduras	3	0	2	2	3	10
Jamaica	2	2	2	6	3	15
Mexico	5	2	0	4	7	18
Nicaragua	0	2	3	3	3	11
Panama	0	1	2	0	2	5
Trinidad and Tobago	1	1	0	2	0	4
Venezuela	0	0	1	1	0	2
Total	18	16	25	47	46	152

Source: Authors' compilation based on EM-DAT.

Taking the 145 episodes in the sample listed in Appendix A, we consider three impacts reported in EM-DAT: the mortality rate, the affected population (as a share of the country's population), and the estimated direct economic damage to property and physical assets as a percentage of GDP.[6] Table 2 shows the intensity of the episodes on each dimension by decade. On the three dimensions, except for mortality in the 1990s, the relative impacts have been decreasing over these intervening decades despite the increase in the number of storm disaster events, suggesting that there has been progress in adaptation to the risk posed by these storms. However, this study does not focus on these changes over time. Instead, we focus on studying the impact of storms of a given intensity range on debt levels, as is explained below.

[6] For the mortality and affected rates, the country's population one year before the disaster was employed. Similarly, the GDP of the previous year is used to scale the economic damage.

Table 2. Average Intensity of the Storms by Decade

	Number of Episodes	**Mortality** (per million population)	**Affected** (per million population)	**Damages** (percentage of the GDP)
1971-1980	18	213.4	107833.9	9.5
1981-1990	16	11.8	50048.2	6.9
1991-2000	25	168.7	73979.2	7.8
2001-2010	47	31.9	20403.6	2.6
2011-2020	46	30.2	36723.2	2.0

Source: Authors' compilation based on EM-DAT.

From the sample of 145 storms in the database, a synthetic ranking is formulated to rank each storm according to its intensity by combining the information on mortality, people affected, and damages from EM-DAT. The first step towards constructing a synthetic ranking involves standardizing each damage variable to make these comparable. To do so, we subtract the mean and divide each by its standard deviation. Subsequently, the simple average of the three standardized variables is calculated for every storm.[7] Detailed information about the resulting ranking and position of each storm can be found in Appendix B.

The data on debt comes from the *Historical Inter-American Development Bank Debt Database*, which contains information on debt for 26 Latin American and the Caribbean countries from 1980 until 2021. This information includes total government debt by legislation where the debt was issued (domestic or external), and other descriptors of this debt. We use the information on total debt and debt by legislation. This database is compiled by the IDB from the ministries of finance of each country. Appendix C reports the stocks of total, external, and domestic debt for all the Caribbean basin countries in the sample since 1980.

[7] The database may not contain a record of every storm's mortality, affected, and damage. When data are missing for one or two variables, the average is computed using the available data only.

3. Methodology

We employ a comparative case study approach. In the first step, we collect data on the trajectory of government debt in the affected economies across a window centered on the year the storm hits. For this analysis, we consider a window of 3 years before and after the occurrence of the storm. This implies that for each episode, we consider a 7-year window centered on the year when the storm hits.

The second step is to pool across multiple episodes. To do so, we adopt the methodology of Cerra and Saxena (2008). This approach involves computing indices that trace debt stocks in each country over the time window of the event study. For each country/episode, the base year T is defined as the year of the storm (i.e., for the storm that hit Jamaica in 1988, T is 1988).

We undertake a series of data transformations to mitigate potential comparability issues arising from cross-country and temporal variations in debt stocks. First, the database's debt series denominated in current nominal USD are converted to real USD of 1980. Additionally, the debt stock for each episode is indexed to 100 for the base year. Subsequently, each series corresponding to a country/episode is adjusted backward for years T-3 through T-1 and forward for T+1 through T+3 using the actual growth rates of debt stocks for that country over the specific period of study. This procedure subsequently allows aggregating episodes across countries by taking simple averages of the indexed series.

The next step is to calculate the simple averages of the adjusted (indexed) series for the selected storms in a group (groups to be defined below). The average is calculated as follows:

$$\bar{d}_s = \frac{1}{n_s}\sum_{i=1}^{n} y_{i,s}\,; \qquad s = T-3, \dots, T, \dots, T+3 \tag{1}$$

where n_s is the number of countries/episodes in the group, and s represents the time index. Note that, by construction, the result is a *synthetic* index of the average debt stock for a group of countries/episodes that is equal to 100 in period T. For the rest of the years around T, the index is the simple average that traces the evolution of debt stocks across the countries in the group.

When presenting the results, we focus on the average values across selected groups of storms, i.e., top-10, top-20, and so on, based on the intensity ranking from the table in Appendix B. For each group, we distinguish between the short-term effects, defined as the average effect of storms in that group at the year of the disaster T. Short-term effects are calculated as the difference between the counterfactual debt stock if the storms had not materialized (which is the projection of what the average debt stock in T would have been if debt followed the pre-episode trend) and the actual debt stocks observed in T (which by construction is set to 100). The medium-term effect is the arithmetic difference between the pre-and post-disaster debt stock averages.

More specifically, we run the following regression:

$$d_{i,s} = \beta_0 + \beta_1 \times s + \beta_2 \times storms_T + \beta_3 \times after_T + \beta_4 \times s \times after_T + v_{i,s} \qquad (2)$$

for the normalized debt stock level ($d_{i,s}$), where i corresponds to a country/episode in a group of interest, and s denotes a time index over the 7-year window centered around T; $storm_T$ is an indicator variable that is equal to one for the period the storm occurred ($s = T$); $after_T$ is an indicator variable that is equal to one for all the periods after the disaster ($s > T$). While in the graphical representation of the results we focus on the average results, in the regressions we include all the episodes in a group to gain degrees of freedom. Therefore, when we focus on the top-10 storms, for example, we include 10 episodes in the regression. When we focus on the top 20 storms, we include 20 episodes in the regression, and so on for the top 30 and top 40 groups. Each episode will have a window of 7 years centered on T.

The methodology is enhanced through two refinements. Episodes lacking debt data within the 7-year window are excluded from the sample to avoid distorting the estimates. Also, to mitigate potential distortions caused by outliers, we calculate studentized residuals for debt stock across all remaining episodes.[8] After deleting the set of episodes identified as outliers, or for which there is missing data on debt for any year in the event window, we end up with the set of 90 storms (see Appendix B).[9] From this pool of episodes we rank from the highest rate (i.e., highest synthetic indicator using mortality, affected, and damages) to the lowest. We then estimate the short and medium-term effect of storms for groups of the top 10, 20, 30 and 40 storms based on intensity.

[8] Specifically, we consider all 152 storms in the sample (see Appendix A), and we take the residual variation for the regression:

$$d_{i,s} = \beta_s + e_{i,s}; \quad s = T-3, \dots, T-1, T+1, \dots, T+3, \qquad (3)$$

where $d_{i,s}$ is the debt stock index, for country i in period s, for each one of the country / episodes in the list. We then run a separate regression for every period s and compute the studentized residuals as $\hat{e}_{i,s} = \frac{d_{i,s} - \hat{\beta}_s}{\hat{\sigma}_{e,s}}$, where $\hat{\sigma}_{e,s}$ is an estimate the standard deviation of $e_{i,s}$ (estimated from a separate regression in which we exclude the country / episode i). Thus, for every country / episode, there are 6 studentized residuals (one for each s). Finally, we drop countries/episodes for which residuals are larger than 2.5 in at least one period.

[9] Appendix B shows the list of the 90 episodes with the information about mortality, the number of people affected and the value of damages according to EM-DAT.

Table 3 presents the summary statistics of the intensity of the storms in each group based on the synthetic ranking. As expected, the intensity decreases as we include episodes with lower rank order.

Table 3. Summary Statistics Storms Synthetic Ranking

	Mortality (per million population)	**Affected** (per million population)	**Damages** (percentage of the GDP)
Top 10	179	168,161	13.7
Top 20	114	114,478	9.3
Top 30	85	88,468	7.8
Top 40	63	70,651	5.7

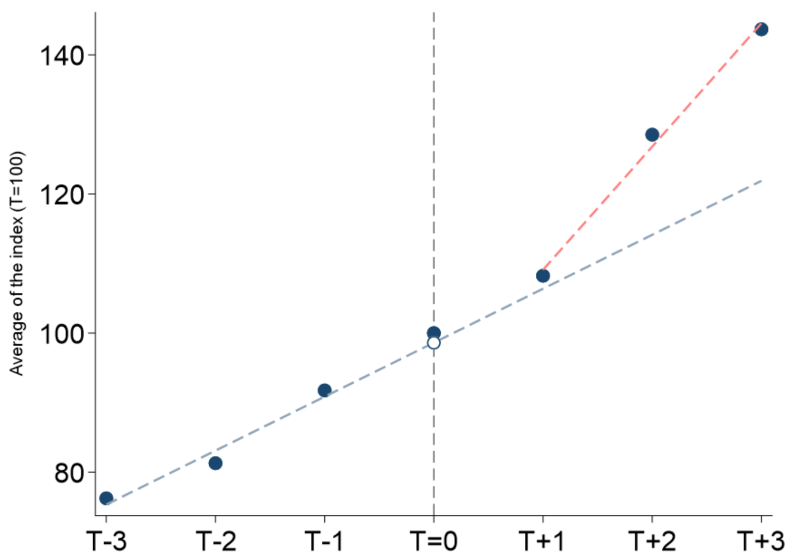
Source: Authors' compilation based on EM-DAT.

4. Results

Using the top 10, 20, 30, and 40 storms with the highest intensity, we estimate the storms' short-term and medium-term effects on debt stocks in each group. Full regression results are reported in Table 4. Figure 1 illustrates the results for the top 10 storms. In the figure, "T" is the storm year, with each dot showing the average across the 10 episodes for three years before and after "T," respectively. The figure depicts pre- and post-trend lines and the pre-trend line projection up to "T+3." The short-term effect at "T" is the difference between the actual debt levels (set equal to 100 by construction) and the counterfactual (which is calculated from equation (2) as $\beta_0 - \beta_1 * 4$). The medium-term effect captures the difference between post and pre-trend debt stocks (coefficient estimate β_4 in equation (2)). The third statistic of interest is the ratio of the dot at "T+3" (actual debt stock at T+3) to the corresponding point on the dashed line at "T+3" (counterfactual debt stock at T+3 is if debt had continued with the pre-disaster trend). It is the ratio of the estimated value of the regression in T+3 over the counterfactual value in T+3 if the storm had not materialized.

The findings presented in Figure 1 and in Table 4 are that the top 10 storms based on a synthetic ranking of damages do not significantly impact debt levels among the examined group in the short run. However, there is a significant acceleration in debt accumulation of 9.96 percent, which is the difference between post and pre-storm trends. Three years post-storm, debt levels are 17.9 percent higher than what would have been expected if the disaster had not occurred. These results are even more statistically significant if we rank storms by their economic damage (rather than using the synthetic index). This may be because economic damage is expected to exert a bigger pressure on the fiscal accounts than, for example, mortality or morbidity.[10]

Figure 1. Increase in Debt Levels before and after Storms:
Results for Top 10 Storms Based on Synthetic Ranking of Damages
(debt levels indexed to 100 on year storm strikes)

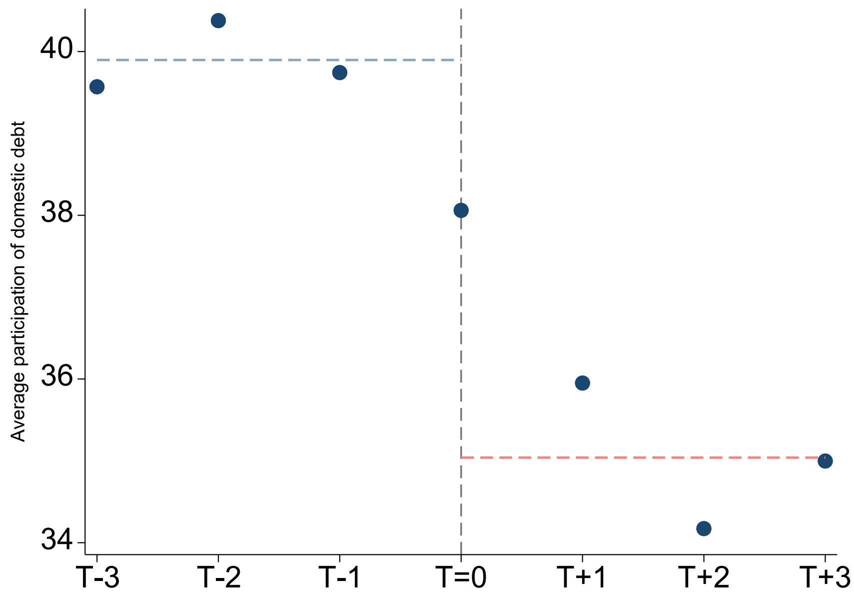


Note: The sample comprises the 10 storms with the highest direct damage in the Caribbean basin according to a synthetic measure capturing mortality, affected population and economic damages. T=0 is the year that the storm hit. Debt levels at T=0 are indexed to 100. For the rest of the years around T, the index is the simple average that traces the evolution of debt stocks across the countries in each group. Each blue dot corresponds to the (simple) average of the indexed debt level on that period for the 10 storms included. The dashed blue line is the trend before the onset of the storm. The red dashed line is the trend after the storm.
Source: Authors' compilation based on EM-DAT and HIDB – IDB.

[10] We prefer to use the synthetic ranking as the basis for our benchmark estimates, as there is significant discussion in the literature about the accuracy of the economic damage from EM-DAT, and specifically its uniformity across events, as the data are obtained from many diverse sources (see Jones et al., 2022).

We also examine the dynamics of debt, post-hurricane, separately for domestic and external debt. A priori, we see no reason to expect the impact to be more concentrated in one type of debt. What we find is that both domestic and external debts increase. Domestic debt stock increased by 31 percent on average, and external debt stock increased by 83 percent on average in the three years following the onset of the storm for the top 10 storms. This implies a steady growth in the share of external debt relative to total debt after storms (see Figure 2). This trend is likely due to these countries needing to obtain resources from international markets to rebuild infrastructure damaged by disasters and fund social programs and other initiatives and for domestic markets to be more constrained by the post-hurricane decline in economic activity. The rise in multilateral credit provided to these affected countries further underscores this pattern.

Figure 2. Change in Share of Domestic Debt to Total Public Debt: Results for Top 10 Storms Based on Synthetic Ranking of Damages



Note: Each blue dot is the average share of domestic debt in total debt on that period. The blue line is the pre-disaster average, and the red line is the post-disaster average.
Source: Authors' compilation based on EM-DAT and HIDB – IDB.

Regarding storms in the top 20 to top 40 categories, the short-term effects remain insignificant across specifications, and the estimated medium-term effects tend to decrease in magnitude and statistical significance as milder storms are considered in the synthetic ranking. According to these estimates, storms have a statistically significant medium-term impact (at the 10 percent level) for the top 10 (+9.96 percent) and 20 storms (+6.53 percent) (Table D). The estimated effects at T+3 range from +17.9 percent of the initial debt stock for the top 10 storms to +4.8 percent of the initial debt stock for the storms in the top 40.

Different patterns emerge in the medium term when analyzing storms ranked by mortality. In this context, there is a significant positive effect on debt for the top 20 and top 40 storm groups. Debt levels increased by 8.8 percent and 6.3 percent, respectively, three years after the storm. By year T+3, debt levels rise by 15.4 percent and 9.4 percent compared to what they would have been if they had continued their prior trajectory (see column "Effect T+3" in table D).

For rankings based on the affected population, there is a discernible and statistically significant increase in debt for the top 10 and top 40 storms only. After these storms, debt levels outpace their prior trends by 9.3 percent and 5.8 percent, respectively. This implies an overall impact at T+3 that is equivalent to 20.3 percent and 8.5 percent higher debt stock, respectively, than what would have been expected following the pre-event trend.

In the damages ranking, the results are that storms lead to higher public debt in the medium term across all intensity categories. Still, events with higher intensity exhibit quantitatively bigger estimated effects at T+3. For a detailed view of these results by group and across raking methods, see Table 4.

Table 4. Estimation Results: Effects of Storms on Government Debt (in %)

	Storm ranking based on a synthetic measure			**Storm ranking based on mortality**			**Storm ranking based on the affected population**			**Storm ranking based on damages over GDP**		
	Short Term	**Medium Term**	**Effect T+3**	**Short Term**	**Medium Term**	**Effect T+3**	**Short Term**	**Medium Term**	**Effect T+3**	**Short Term**	**Medium Term**	**Effect T+3**
Top 10	1.38 (12.07)	9.96** (4.79)	17.9	1.62 (11.68)	6.91 (5.72)	11.8	4.46 (10.94)	9.30* (5.12)	20.3	7.65 (10.63)	9.48** (4.01)	26.2
Top 20	-1.31 (12.77)	6.53* (4.01)	11.5	-2.12 (15.10)	8.83* (4.94)	15.4	-3.94 (13.20)	5.54 (4.15)	7.6	2.22 (7.69)	6.15* (3.53)	13.2
Top 30	0.44 (9.23)	4.73 (3.23)	9.8	-2.60 (10.45)	6.57 (4.28)	9.1	-2.09 (9.40)	5.34 (3.50)	6.7	1.00 (6.13)	5.14* (2.72)	9.5
Top 40	-1.21 (7.74)	3.60 (2.89)	4.8	-2.13 (8.38)	6.33* (3.42)	9.4	-1.91 (7.51)	5.83** (3.05)	8.5	-1.30 (8.79)	6.96** (2.95)	12.8

Note: The short-term effect is calculated as: $100 - \beta_0 - \beta_1 * 4$, the medium-term effect is β_4, and the effect at T+3 is equal to $(\beta_0 + (\beta_1 + \beta_4) * 7 + \beta_2 + \beta_3)/(\beta_0 + \beta_1 * 7)$. *** (**) [*] denotes significance at the 1 (5) [10] % level. Standard errors are reported below the point estimates in parentheses.
Source: Authors' compilation based on EM-DAT and HIDB – IDB.

Fisher Randomization Tests

One concern may be that the storm impact estimates are, by pure chance, capturing other shocks that may have occurred coincidentally at the same time as the storms. Another concern is that as debt levels have been rising in the region during years with and without storms (see Appendix C), the storm impact estimates may simply be picking up the trend. To investigate these, we randomly identified (fictional) storms across countries and time period 1,000 times and then compared the distribution of the resultant t-statistic with that estimated for the true sample of actual storms. The percentage of t-statistics from the randomly drawn samples above the actual t-statistics for the four storm categories are shown in Table 5. As can be seen for both the top 10 (0.5 percent) and top 40 storms (4.3 percent), the results suggest that the estimated impact for the true sample is not random. For the top 20 and top 30 storms, the corresponding percentage is just below and above 10 percent, a result not surprising given that the original test statistics were only significant at the 10 percent level. Thus, overall, the Fisher randomization tests do not indicate that the findings are driven by chance.

Table 5. Fisher Randomization Tests

	Actual t-statistic (Medium-term effects, storms ranking based on damages over GDP)	% of random simulations with t-statistics larger than the actual estimate
Top 10	2.36	0.5%
Top 20	1.74	9.6%
Top 30	1.89	11.9%
Top 40	2.36	4.3%

Note: We conducted 1000 simulations of country-year events without excluding the country-year of the actual storms. Random rankings were assigned to the simulated storms. For each group of storms, which includes various group sizes (e.g., 10 storms, 20 storms, and so on), and for each simulation, we performed the regression analysis in equation (2). The t-statistic of the "medium-term coefficient" (coefficient estimate β_4 in equation 2) was then calculated for each group in all simulations following the methodology employed in the regressions using actual storms. The null hypothesis of the test assumes that $\beta_4$is different from zero. We compared the t-statistic of the actual set of storms ("Actual t-statistic") of the medium-term effects for storms ranking based on damages over GDP in Table 4 with the distribution of t-statistics derived from the simulations and report the % of random simulations with t-statistics larger than the actual estimate.

5. Attribution

Having identified the average impact of hurricanes on the stock and composition of public debt, we consider the evidence with respect to the role of anthropogenic climate change in these dynamics. As we detailed earlier, the scientific literature indicates that the rainfall from these storms has increased because of climate change. Furthermore, the literature has also provided evidence that rainfall is one of the primary drivers of damage from storms in the Caribbean (e.g., Collalti and Strobl, 2022).

The climate attribution literature suggests that the minimum increase of rainfall that can be confidently attributed to anthropogenic climate change is determined by the Clausius–Clapeyron relationship, which implies a 7 percent increase in the amount of water in the air for every 1ºC increase in temperature. We therefore use a 10 percent increase in rainfall and damages attributable to anthropogenic climate change. Given our findings that more severe storms impose an increasing impact on the stock of debt, we conclude that the 10 percent figure is most likely a minimum threshold for the impact of anthropogenic increasing storm intensity (attributable to climate change) on debt.

Table 6 shows the results of the median storm in each group. For storms in the top 10 of the intensity ranking, the impact on debt that is attributable to climate change amounts to an increase of 3.8 percent of the debt stock relative to the level of debt at T=0 (Table 6). In the case of the median storm—in terms of the rank order within the top-10 group—that is, the hurricane that hit Belize in 1998, the storm implied an additional USD 22.2 million (US dollars of 2022) of incremental debt that can be attributed to anthropogenic climate change. For storms with lower intensity ranking, the estimated impacts on debt are quantitatively lower but economically substantial. Storms in the top-20 group experience a 2.3 percent increase in debt stocks on average, storms in the top 30 list experience a 1.7 percent increase in debt stocks on average, and storms in the top 40, a 1.3 percent increase in debt stocks on average, compared to initial debt stocks (see Table 6).

For specific hurricane events, we can see, for example, that for the storm experienced by the Bahamas in 2016 (which is the median storm by intensity in the top-20 group), the increase in debt that is attributable to climate change was USD 180 million (USD of 2022) out of a much larger increase in borrowing. More details about each storm in each of the groups, their estimated impact on debt, and the estimated attributable impact to climate change are available in Appendix 6.

Table 6. Attribution Results for the Median Storm in each Group

	Year	**Country**	**Effects of storms on debt** (millions of 2022 USD)	**Effects attributed to Climate Change** (millions of 2022 USD)	**Attributed effects as a percentage of debt stock in T=0**
Top 10	1998	Belize	221.8	22.2	3.8
Top 20	2016	Bahamas	1,800.9	180.1	2.3
Top 30	2007	Belize	252.8	25.3	1.7
Top 40	2007	Nicaragua	458.3	45.8	1.3

Note: The "effects of storms on debt" is calculated as the difference between total minus counterfactual debt stocks. The "total debt stock" at T=3 is the estimated debt level at T=3, assuming that the debt stock at T=0 grows after the storm at the estimated average post-storm growth rate of the debt stock for the top-X storms. The counterfactual debt stock at T=3 is the estimated debt level at T=3 if the debt stock at T=0 had grown at the growth rate of debt stock pre-storm for the top-10 storms.

6. Conclusion

Twenty-nine Caribbean region countries and territories are associated with the United Nations' Small Island Developing States (SIDS) group. SIDS have been frequently identified as facing the brunt of climate change impacts. We document that hurricanes significantly increase public debt for affected countries, as their need to pay for emergencies and for recovery and reconstruction leads them to take on more debt. This debt increase is, at least in part, attributable to climate change. We estimate that, on average, for a severe storm, the increase in debt that is attributable to climate change is valued at approximately 3.8 percent of the pre-hurricane debt stock.

There are many caveats to these estimates. First, they are based on averages, but of course, the exact pattern of destruction, the required spending for recovery and reconstruction, and the funding available from other sources before public borrowing becomes necessary are different for each event. Second, the counterfactual debt trajectories we estimate are based on the pre-hurricane trajectory of the growth of debt, but there might be other changes that have an impact and are not easily factored out given the relatively smaller datasets we have (using more data from more countries will only exacerbate the first concern). Thirdly, the attribution research we use is incomplete, so our conclusion that about 10 percent is associated with attributable impact should be viewed as tentative. As is documented elsewhere, attribution studies tend to focus on high-income countries, and much more such research on the impact of hurricanes on the less wealthy parts of the Caribbean is necessary before more definite conclusions can be reached about impact attribution.

Nevertheless, this quantification is important from a policy perspective, as it allows the development of international mechanisms that could potentially provide support to those vulnerable developing countries that are facing extreme and worsening weather shocks. In particular, these estimates could provide useful evidence for the formulation of the Loss and Damage Fund as it is being designed in successive United Nations Framework Convention on Climate Change (UNFCCC) meetings.

References

Alejos, L. 2018. "Estimating the Fiscal Impact of Extreme Weather Events." Ann Arbor, United States: University of Michigan. Working Paper. Available at: http://www-personal.umich.edu/~lalejos/pdf/FiscalImpact.pdf

Becerra, O., E.A. Cavallo, and I. Noy. 2014. "Foreign Aid in the Aftermath of Large Natural Disasters." *Review of Development Economics* 18(3): 445-460.

Becerra, O., E.A. Cavallo, and I. Noy. 2015. "Where is the Money? Post-disaster Foreign Aid Flows." *Environment and Development Economics* 20(5): 561-586..

Bensassi, S., P. Mohan, and E. Strobl. 2017. "A Storm in a Teacup? Hurricanes and Sugar Prices in the First Half of the Nineteenth Century." *Weather, Climate, and Society* 9(4): 753-768.

Bertinelli, L., and E. Strobl. 2013. "Quantifying the Local Economic Growth Impact of Hurricane Strikes: An Analysis from Outer Space for the Caribbean." *Journal of Applied Meteorolgy and Climatology* 52: 1688–1697.

Borensztein, E., E. Cavallo, and P. Valenzuela. 2009. "Debt Sustainability under Catastrophic Risk: The Case for Government Budget Insurance." *Risk Management and Insurance Review* 12(2): 273–94.

Bhatia, K. T., G. Vecchi, T.R. Knutson, H. Murakami, J. Kossin, K.W. Dixon, and C.E. Whitlock. 2019. "Recent Increases in Tropical Cyclone Intensification Rates." *Nature Communications* 10(1): 635.

Bhatia, K., A. Baker, W. Yang, G. Vecchi, T. Knutson, H. Murakami, and ... C. Whitlock. 2022. "A Potential Explanation for the Global Increase in Tropical Cyclone Rapid Intensification." *Nature Communications* 13(1): 6626.

Brei, M., P. Mohan, E. Strobl. 2019. "The Impact of Natural Disasters on the Banking Sector: Evidence from Hurricane Strikes in the Caribbean." *Quarterly Review of Economics and Finance* 72: 232-239.

Campbell, A., and N. Spencer. 2021. "The Macroeconomic Impact of Extreme Weather: Evidence from Jamaica." *International Journal of Disaster Risk Reduction* 61: 102336.

Carballo Chanfón, P., P. Mohan, E. Strobl, and T. Tveit. 2023. "The Impact of Hurricane Strikes on Cruise Ship and Airplane Tourist Arrivals in the Caribbean." *Tourism Economics* 29(1): 68-91.

Cavallo, E., O. Oscar Becerra, and L. Acevedo. 2022. "The Impact of Natural Disasters on Economic Growth." In: M. Skidmore, editor. *Handbook on the Economics of Disasters*. Cheltenham, United Kingdom: Edward Elgar Publishing.

Cavallo, E. B. Hoffmann, and I. Noy. 2023. "Disasters and Climate Change in Latin America and the Caribbean: An Introduction to the Special Issue. *Economics of Disasters and Climate Change* 7(2).

Cavallo, E., A. Powell, and O. Becerra. 2010. "Estimating the Direct Economic Damages of the Earthquake in Haiti." *Economic Journal* 120(546): F298–F312.

Collalti, D., and E. Strobl. 2022. "Economic Damages Due to Extreme Precipitation during Tropical Storms: Evidence from Jamaica." *Natural Hazards* 110(3): 2059-2086.

Eichengreen, B., R. Hausmann, and U. Panizza. 2023. "Yet it Endures: The Persistence of Original Sin." *Open Economies Review* 34: 1–42.

Gassebner, M., A. Keck, and R. Teh. 2010. "Shaken, Not Stirred: The Impact of Disasters on International Trade." *Review of International Economics* 18(2): 351-368.

Heinen, A., J. Khadan, and E. Strobl. 2019. "The Price Impact of Extreme Weather in Developing Countries." *Economic Journal* 129(619): 1327–1342.

Henry, M., N. Spencer, and E. Strobl. 2020. "The Impact of Tropical Storms on Households: Evidence from Panel Data on Consumption." *Oxford Bulletin of Economics and Statistics* 82(1): 1-22.

Ishizawa, O., and J. Miranda. 2019. "Weathering Storms: Understanding the Impact of Natural Disasters in Central America." *Environmental and Resource Economics* 73: 181-211.

Ishizawa, O.A., J.J. Miranda, and E. Strobl. 2019. "The Impact of Hurricane Strikes on Short-term Local Economic Activity: Evidence from Nightlight Images in the Dominican Republic." *International Journal of Disaster Risk Science* 10: 362-370.

Jakobsen, K. 2012. "In the Eye of the Storm—The Welfare Impacts of a Hurricane." *World Development* 40: 2578-2589.

Jones, R.L., D. Guha-Sapir, and S. Tubeuf. 2022. "Human and Economic Impacts of Natural Disasters: Can We Trust the Global Data?" *Scientific Data* 9: 572. Available at: https://doi.org/10.1038/s41597-022-01667-x

Keellings, D., and J.J. Hernández Ayala. 2019. "Extreme Rainfall Associated with Hurricane Maria over Puerto Rico and Its Connections to Climate Variability and Change." *Geophysical Research Letters* 46(5): 2964-2973.

Klomp, J. 2015. "Sovereign Risk and Natural Disasters in Emerging Markets." *Emerging Markets Finance and Trade* 51(6): 1326-41.

Klomp, J. 2019. "Does Government Ideology Shake or Shape the Public Finances? Empirical Evidence of Disaster Assistance." *World Development* 118: 118-127.

Knutson, T., S.J. Camargo, J.C. Chan, K. Emanuel, C.H. Ho, J. Kossin, and L. Wu. 2020. "Tropical Cyclones and Climate Change Assessment: Part II: Projected Response to Anthropogenic Warming." *Bulletin of the American Meteorological Society* 101(3): E303-E322.

Knutson, T.R., M.V. Chung, G. Vecchi, J. Sun, T.L. Hsieh, and A.J. Smith. 2021. "Climate Change Is Probably Increasing the Intensity of Tropical Cyclones." *Critical Issues in Climate Change Science, Science Brief Review*. https://doi. org/10.5281/zenodo, 4570334(4).

Kose, A.M., F.L. Ohnsorge, C.M. Reinhart, and K.S. Rogoff. 2022a. «The Aftermath of Debt Surges." *Annual Review of Economics* 14(1): 637-663.

Kose, A.M., S. Kurlat, F. Ohnsorge, and N. Sugawara. 2022b. "A Cross-country Database of Fiscal Space." *Journal of International Money and Finance* 128: 102682.

Li, L., and P. Chakraborty. 2020. "Slower Decay of Landfalling Hurricanes in a Warming World." *Nature* 587: 230-234.

Lis, E., and C. Nickel. 2010. "The Impact of Extreme Weather Events on Budget Balances." I*nternational Tax and Public Finance* 17: 378–399.

Melecky, M., and C. Raddatz. 2014. "Fiscal Responses after Catastrophes and the Enabling Role of Financial Development." *World Bank Economic Review* 29(1): 129-149.

Mohan, P. 2017. "Impact of Hurricanes on Agriculture: Evidence from the Caribbean." *Natural Hazards Review* 18(3): 04016012.

Mohan, P. 2023. "The Impact of Tropical Storms on International Trade: Evidence from Eastern Caribbean Small Island Developing States." *Economics of Disasters and Climate Change*, 7(2).

Mohan, P.S., B. Ouattara, and E. Strobl. 2018. "Decomposing the Macroeconomic Effects of Natural Disasters: A National Income Accounting Perspective." *Ecological Economics* 146: 1-9.

Mohan, P., and E. Strobl. 2013. "The Economic Impact of Hurricanes in History: Evidence from Sugar Exports in the Caribbean from 1700 to 1960." *Weather, Climate, and Society* 5: 5-13.

Mohan, P., and E. Strobl. 2017. "A Hurricane Wind Risk and Loss Assessment of Caribbean Agriculture." *Environment and Development Economics* 22(1): 84-106.

Mohan, P., and E. Strobl. 2021. "The Impact of Tropical Storms on the Accumulation and Composition of Government Debt. *International Tax and Public Finance* 28(3): 483-496.

Murakami, H., E. Levin, T.L. Delworth, R. Gudgel, and P.C. Hsu. 2018. "Dominant Effect of Relative Tropical Atlantic Warming on Major Hurricane Occurrence." *Science* 362(6416): 794-799.

Noy, I., and A. Nualsri. 2011. "Fiscal Storms: Public Spending and Revenues in the Aftermath of Natural Disasters. *Environment and Development Economics* 16(1): 113–128.

Noy, I., T. Okubo, E. Strobl, and T. Tveit. 2023. "The Fiscal Costs of Earthquakes in Japan." *International Tax and Public Finance* 30: 1225-1250.

Noy, I., D. Stone, and T. Uher. 2023. "Extreme Events Impact Attribution: A State of the Art." Manuscript.

Ouattara, B., E. Strobl, J. Vermeiren, and S. Yearwood. 2018. "Fiscal Shortage Risk and the Potential Role for Tropical Storm Insurance: Evidence from the Caribbean." *Environment and Development Economics* 23(6): 702-720.

Patricola, C.M., and M.F. Wehner. 2018. "Anthropogenic Influences on Major Tropical Cyclone Events." *Nature* 563(7731): 339-346.

Pfleiderer, P., S. Nath, and C.F. Schleussner. 2022. "Extreme Atlantic Hurricane Seasons Are Made Twice as Likely by Ocean Warming." *Weather and Climate Dynamics* 3(2): 471-482.

Powell, A., and O. Valencia, editors. 2022. *Dealing with Debt: Less Risk for More Growth in Latin America and the Caribbean*. 2022 Development in the Americas (DIA) report. Washington, DC, United States: Inter-American Development Bank.

Reed, K.A., M.F. Wehner, A.M. Stansfield, and C.M. Zarzycki. 2021. "Anthropogenic Influence on Hurricane Dorian's Extreme Rainfall." *Bulletin of the American Meteorological Society* 102(1): S9-S15.

Reed, K.A., M.F. Wehner, and C.M. Zarzycki. 2022. "Attribution of 2020 Hurricane Season Extreme Rainfall to Human-induced Climate Change." *Nature Communications* 13(1): 1905.

Spencer, N., and S. Polachek. 2015. "Hurricane Watch: Battening Down the Effects of the Storm on Local Crop Production." *Ecological Economics* 120: 234-240.

Strobl, E. 2012. "The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions." *Journal of Development Economics* 97: 130-141.

Strobl, E., B. Ouattara, and S. Kablan. 2020. "Impact of Hurricane Strikes on International Reserves in the Caribbean." *Applied Economics* 52(6): 1-11. Available at: DOI:10.1080/00036846.2020.1731411

Thomas, A., A. Baptiste, R. Martyr-Koller, P. Pringle, and K. Rhiney. 2020. "Climate Change and Small Island Developing States." *Annual Review of Environment and Resources*, 45: 1-27.

Trenberth, K., L. Cheng, P. Jacobs, Y. Zhang, and J. Fasullo. 2018. "Hurricane Harvey Links to Ocean Heat Content and Climate Change Adaptation." *Earth's Future* 6: 730 - 744.

Wehner, M., and C. Sampson. 2021. "Attributable Human-induced Changes in the Magnitude of Flooding in the Houston, Texas Region during Hurricane Harvey." *Climatic Change* 166: 20.

Yonson, R., J.C. Gaillard, and I. Noy. 2018. "The Measurement of Disaster Risk: An Example from Tropical Cyclones in the Philippines." *Review of Development Economics* 22(2): 736-765.

Appendix A. List of Storms in the Caribbean Basin

Year	Country	Ranking Synthetic	Ranking Mortality	Ranking Affected	Ranking Damages
1998	Honduras	1	2	4	1
1974	Honduras	2	1	10	2
1974	Belize	3		1	21
2020	Honduras	4	34	2	
2019	Bahamas (the)	5	3	32	6
1998	Nicaragua	6	4	11	7
1988	Jamaica	7	26	3	4
1980	Haiti	8	18	8	3
2000	Belize	9	14	7	5
1979	Dominican Republic (the)	10	6	5	27
2004	Haiti	11	5	29	36
2020	Belize	12		14	
1994	Haiti	13	7	9	29
2001	Belize	14	9	21	8
1998	Belize	15	17	6	90
1998	Dominican Republic (the)	16	16	18	12
2004	Jamaica	17	45	17	13
2020	Nicaragua	18	61	15	15
1988	Nicaragua	19	22	20	11
2020	Guatemala	20	40	12	49
2008	Belize	21	24	13	47
1988	Haiti	22	36	16	24
2004	Bahamas (the)	23	20	38	9
2005	Guatemala	24	8	31	25
1982	Nicaragua	25	27	46	10
2016	Bahamas (the)	26			23
1978	Belize	27	19	28	22
2014	Guatemala	28	109	19	61

1998	El Salvador	29	11	47	18
1999	Bahamas (the)	30	58		16
2008	Haiti	31	13	39	
2007	Belize	32		23	38
2001	Bahamas (the)	33			26
2007	Nicaragua	34	21	30	
2009	El Salvador	35	15	45	20
2012	Jamaica	36	112	22	65
2016	Jamaica	37		27	
2015	Bahamas (the)	38	10	44	43
1992	Bahamas (the)	39	32	63	14
2016	Honduras	40	101	25	
2005	Belize	41	39		
2010	Guatemala	42	30	33	28
2004	Dominican Republic (the)	43	12	86	33
1998	Haiti	44	25	99	19
2017	Barbados	45	53		
1974	Trinidad and Tobago	46	75	24	53
2012	Bahamas (the)	47	66		
2008	Costa Rica	48	69	26	70
2012	Haiti	49	28	40	32
1975	Mexico	50	106		
1971	Mexico	51	115		
1974	Mexico	52	120		
1987	Barbados	53		111	17
1993	Nicaragua	54	43	36	
1980	Dominican Republic (the)	55	95		40
2020	El Salvador	56	38	41	42
1980	Jamaica	57	63	49	30
2011	Mexico	58	97	34	75
1987	Dominican Republic (the)	59	108		52

2007	Jamaica	60	78	52	31
1996	El Salvador	61	74		94
1994	Jamaica	62	86		82
2016	Belize	63		35	
2001	Dominican Republic (the)	64	114		95
2005	Honduras	65	44	50	34
2007	Bahamas (the)	66	64	42	
2011	Bahamas (the)	67		37	51
2010	Mexico	68	85	48	44
2015	Haiti	69	29	62	
1996	Honduras	70	90	51	46
1976	Mexico	71	37	54	66
1988	Panama	72	35	77	39
1983	Colombia	73	31	105	37
2010	Dominican Republic (the)	74	33	60	
1992	Panama	75	23	129	64
2005	Haiti	76	41	70	41
2010	Jamaica	77	46	110	35
2016	Costa Rica	78	79	53	
2017	Bahamas (the)	79			83
1995	Bahamas (the)	80			84
2017	Haiti	81	57	56	
2017	Nicaragua	82	55	58	
1996	Nicaragua	83	42	92	56
1980	Barbados	84		43	57
2008	Jamaica	85	49	101	48
2020	Colombia	86	91	61	78
2005	Jamaica	87	70	76	54
2011	Dominican Republic (the)	88	96	64	76
2004	Barbados	89	52	81	63
2017	Costa Rica	90	67	91	55

2013	Mexico	91	76	100	50
2007	Honduras	92	99	69	72
1988	Mexico	93	51	98	58
2008	Mexico	94	116	68	87
2017	Dominican Republic (the)	95	107	73	69
1983	Mexico	96	50	74	
2010	Venezuela (Bolivarian Republic of)	97	83	79	77
2001	Jamaica	98	111	128	45
2010	El Salvador	99	65	94	67
2017	Honduras	100	71	66	
2005	Bahamas (the)	101	62	71	
2020	Haiti	102	54	75	
1973	Jamaica	103	59	106	68
2019	Guatemala	104	93	65	
1985	Jamaica	105	60	125	59
1998	Panama	106	98	88	92
1993	Venezuela (Bolivarian Republic of)	107	48	122	86
2020	Dominican Republic (the)	108	105	104	62
2014	Mexico	109	121	102	60
2009	Mexico	110	119	87	91
2006	Haiti	111	81	72	
2006	Mexico	112	110	89	93
1996	Dominican Republic (the)	113	56	80	
2004	Trinidad and Tobago	114	72	107	85
2020	Mexico	115	104	109	81
2015	El Salvador	116	73	82	
2004	Nicaragua	117	47	108	
2016	Mexico	118	102	114	89
2016	Panama	119	80	83	

2015	Mexico	120	113	124	71
2017	Panama	121	82	84	
2018	Mexico	122	118	126	79
2017	Guatemala	123	94	85	
2005	Nicaragua	124	92	90	
2008	Dominican Republic (the)	125	89	95	
2001	Colombia	126	68	118	
1995	Dominican Republic (the)	127	84	116	
1986	Dominican Republic (the)	128	77	121	
1979	Haiti	129	88	123	
2017	El Salvador	130	87	127	
2007	Guatemala	131	100	117	
1977	Mexico	132	122	112	
1997	El Salvador	133	103	119	
2007	El Salvador	134	117	115	
2002	Barbados	135		59	88
1995	Costa Rica	136		78	73
1978	Honduras	137		93	74
1996	Jamaica	138		120	80
2010	Barbados	139		55	
2008	Bahamas (the)	140		57	
2020	Costa Rica	141		67	
2017	Jamaica	142		96	
2016	Nicaragua	143		97	
2018	Dominican Republic (the)	144		103	
1990	Trinidad and Tobago	145		113	

Note: The list excludes seven storms for which there is no data on mortality, affected and damages in EM-DAT. Bahamas-1990, Barbados-1995, Belize-2010, Dominican Republic-1989, Haiti-1990, Honduras-1971, Trinidad and Tobago-2005.

Appendix B. Summary Statistics Storms in the Caribbean Basin
(Excluding outliers and episodes with missing data)

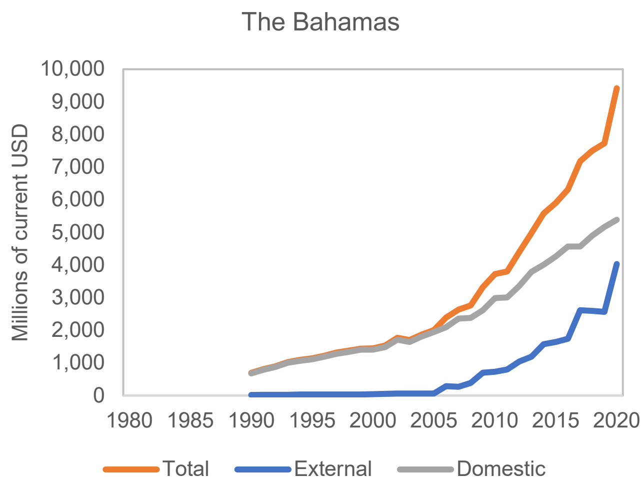
Ranking	**Country**	**Year**	**Mortality** (per million population)	**Affected** (per million population)	**Damages** (percentage of the GDP)
1	Jamaica	1988	21.00	346,710.20	30.40
2	Belize	2000	60.20	268,848.80	28.50
3	Nicaragua	1998	682.00	178,069.60	22.50
4	Belize	2001	124.80	83,192.60	22.40
5	Belize	1998	41.50	276,348.70	0.00
6	Jamaica	2004	6.00	132,071.80	9.50
7	The Bahamas	2004	35.50	26,588.70	17.50
8	Haiti	2004	615.30	40,100.70	1.10
9	Belize	2008	26.90	161,522.10	0.60
10	The Bahamas	2016			5.10
11	The Bahamas	1999	3.20		6.60
12	Guatemala	2014	0.40	99,902.00	0.20
13	The Bahamas	2001			3.70
14	Guatemala	2005	124.80	37,679.00	4.20
15	Belize	2007		69,269.10	0.90
16	Jamaica	2016		44,731.60	
17	Jamaica	2012	0.40	78,600.40	0.10
18	El Salvador	2009	46.50	15,589.40	5.40
19	Honduras	2016	0.80	48,432.00	
20	Nicaragua	2007	33.80	38,469.00	
21	Barbados	1987		890.20	6.50
22	Guatemala	2010	16.20	32,564.40	3.10
23	Haiti	2008	74.10	26,141.70	

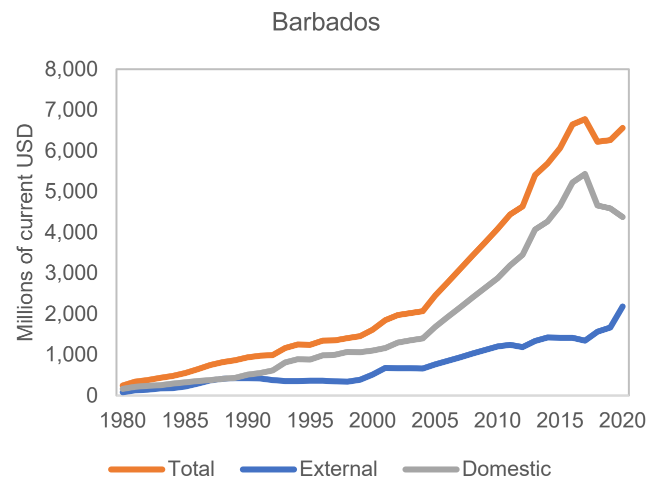
24	Costa Rica	2008	2.50	47,184.00	0.10
25	Belize	2005	11.00		
26	Haiti	2012	18.10	24,325.00	2.00
27	Barbados	2017	3.60		
28	The Bahamas	2015	84.80	17,243.60	0.80
29	The Bahamas	2012	2.60		
30	Belize	2016		28,774.20	
31	Jamaica	2007	1.90	12,339.10	2.50
32	Mexico	2011	1.10	32,440.50	0.10
33	The Bahamas	2007	2.80	19,848.90	
34	Honduras	2005	8.30	14,176.30	1.30
35	The Bahamas	2011		26,790.10	0.40
36	Jamaica	1994	1.60		0.00
37	El Salvador	1996	2.10		0.00
38	Mexico	2010	1.60	14,410.80	0.80
39	Honduras	1996	1.40	12,902.50	0.60
40	Haiti	2005	9.80	4,693.50	0.80
41	Costa Rica	2016	1.80	10,214.00	
42	Jamaica	2010	5.50	920.50	1.20
43	Haiti	2015	17.40	6,431.40	
44	Dominican Republic	2010	14.20	6,687.50	
45	Haiti	2017	3.30	8,440.90	
46	Nicaragua	2017	3.40	8,281.90	
47	Jamaica	2005	2.30	3,902.40	0.30
48	Jamaica	2008	4.80	1,480.80	0.50
49	Dominican Republic	2011	1.20	5,669.10	0.10
50	Nicaragua	1996	9.30	2,271.10	0.20
51	The Bahamas	2017			0.00
52	The Bahamas	1995			0.00

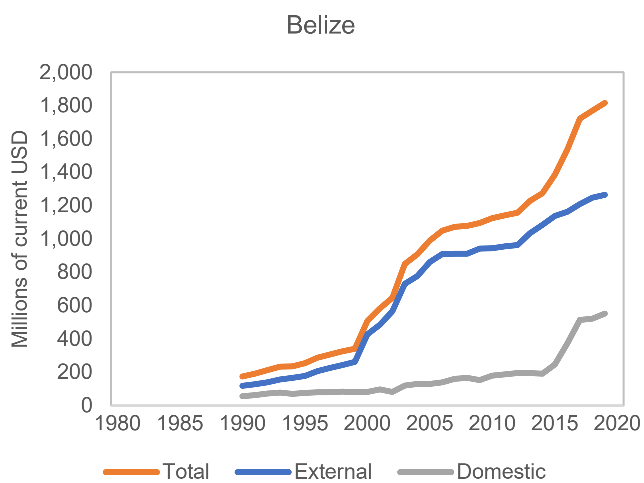
53	Mexico	2013	1.90	1,485.90	0.50
54	Costa Rica	2017	2.60	2,325.50	0.30
55	Honduras	2017	2.20	5,088.40	
56	Honduras	2007	0.90	4,762.00	0.10
57	Barbados	2004	3.70	3,289.70	0.20
58	Jamaica	2001	0.40	76.60	0.60
59	Mexico	2008	0.30	4,801.30	0.00
60	Dominican Republic	2017	0.50	4,045.30	0.10
61	The Bahamas	2005	2.90	4,372.00	
62	Haiti	2006	1.80	4,356.90	
63	El Salvador	2010	2.80	1,973.30	0.10
64	Mexico	2014	0.20	1,462.30	0.20
65	Panama	1998	1.10	2,652.10	0.00
66	Mexico	2009	0.30	2,679.20	0.00
67	El Salvador	2015	2.10	3,220.90	
68	Mexico	2006	0.40	2,567.30	0.00
69	Panama	2016	1.80	3,032.50	
70	Panama	2017	1.70	2,980.40	
71	Guatemala	2017	1.30	2,942.50	
72	Trinidad and Tobago	2004	2.20	1,300.30	0.00
73	Nicaragua	2005	1.30	2,532.90	
74	Mexico	2016	0.70	620.10	0.00
75	Mexico	2015	0.40	183.50	0.10
76	Nicaragua	2004	5.40	1,121.30	
77	Dominican Republic	2008	1.40	1,808.30	
78	Colombia	2001	2.50	350.20	
79	Guatemala	2007	0.80	454.20	
80	El Salvador	2007	0.30	546.90	

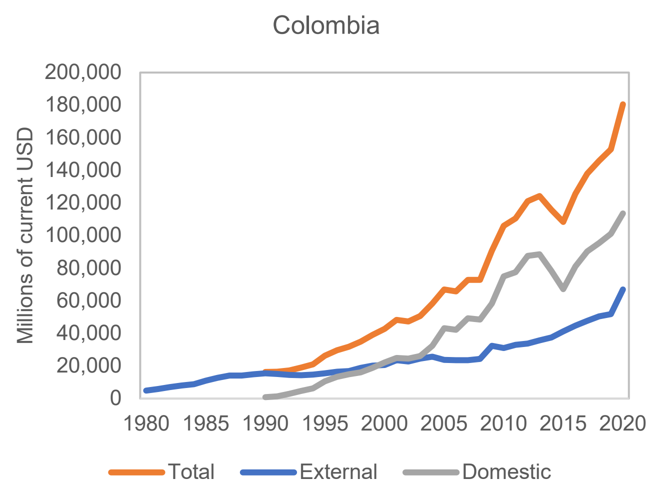
81	El Salvador	1997	0.70	345.00	
82	El Salvador	2017	1.60	93.40	
83	Barbados	2002		7,536.40	0.00
84	Costa Rica	1995		3,682.30	0.10
85	Barbados	2010		9,131.10	
86	Jamaica	1996		318.80	0.00
87	The Bahamas	2008		8,387.70	
88	Jamaica	2017		1,784.00	
89	Nicaragua	2016		1,678.20	
90	Trinidad and Tobago	1990		796.00	

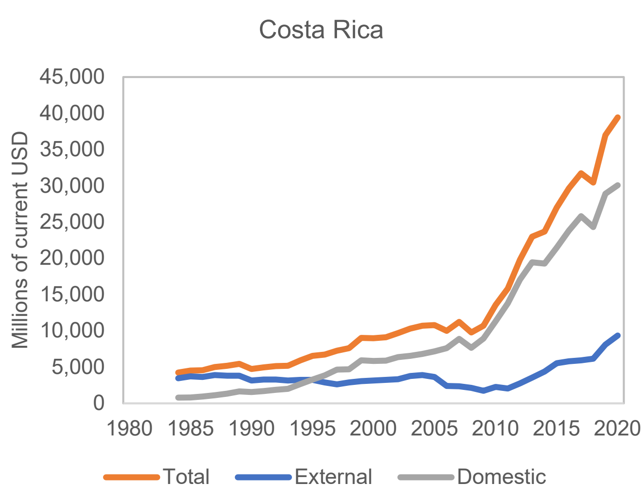
Appendix C. Total, Domestic and External Debt Stocks by Country

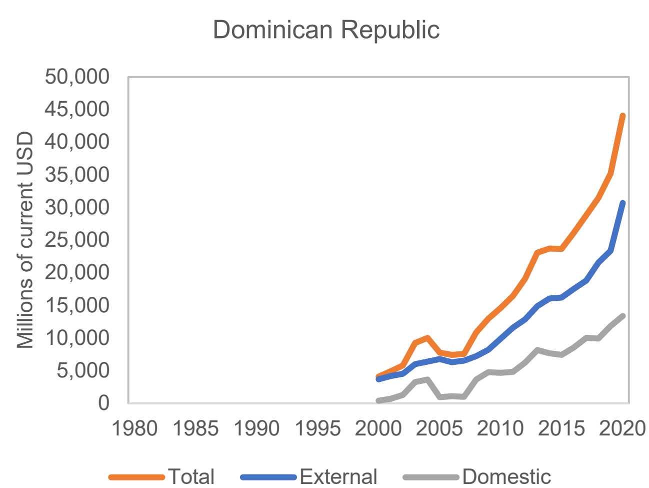


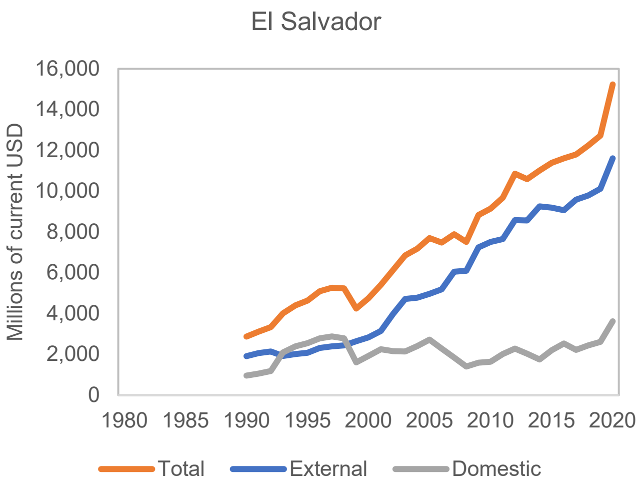


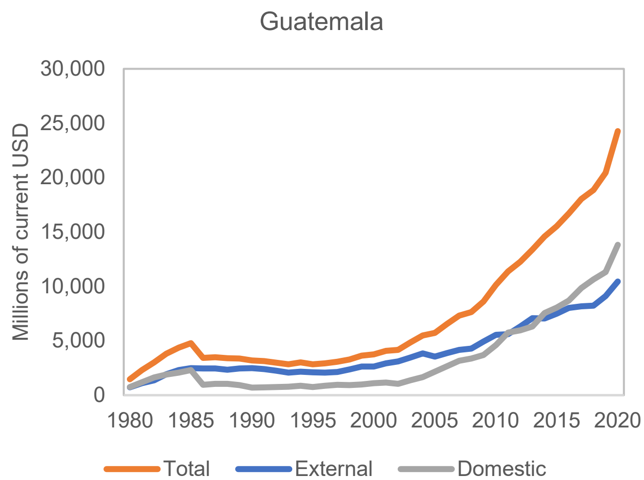


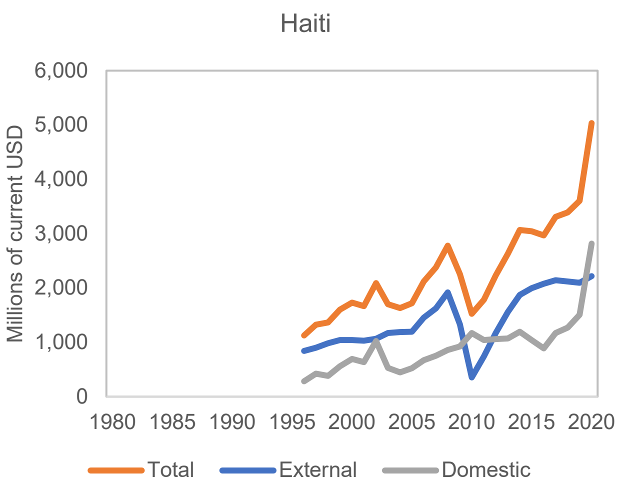


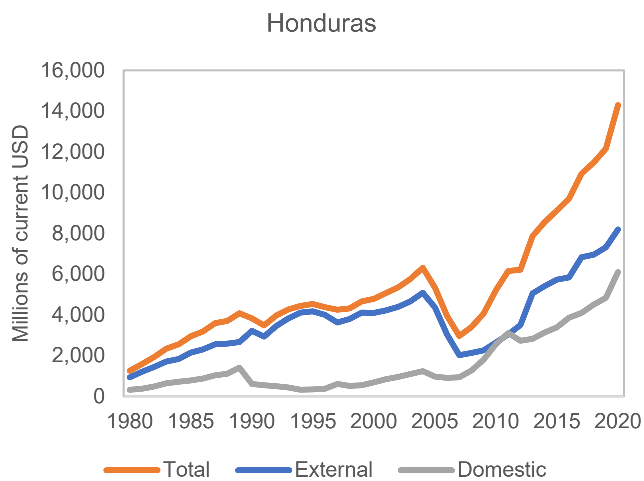


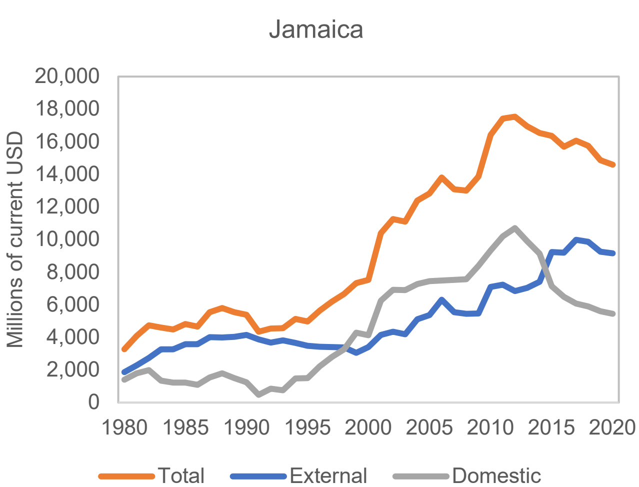


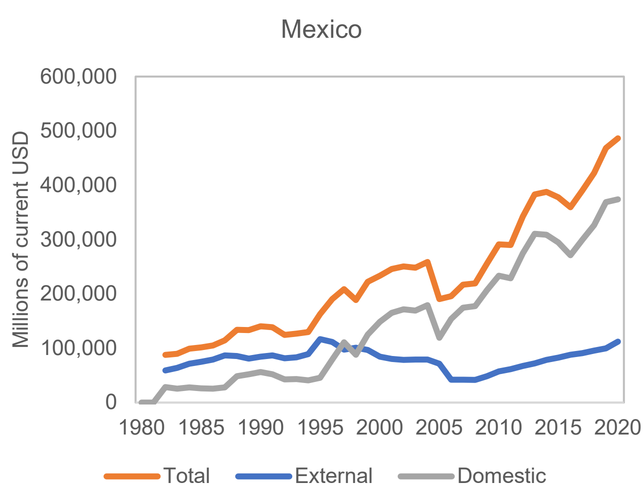

El Salvador
Millions of current USD
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
1980 1985 1990 1995 2000 2005 2010 2015 2020
Total
External
Domestic

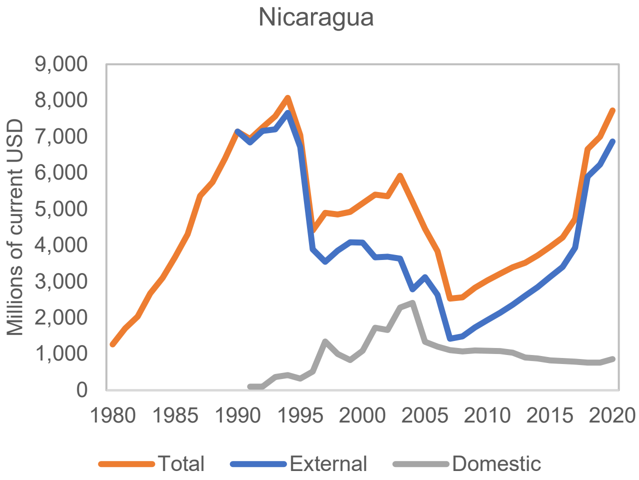

Guatemala
Millions of current USD
30,000
25,000
20,000
15,000
10,000
5,000
0
1980 1985 1990 1995 2000 2005 2010 2015 2020
Total
External
Domestic

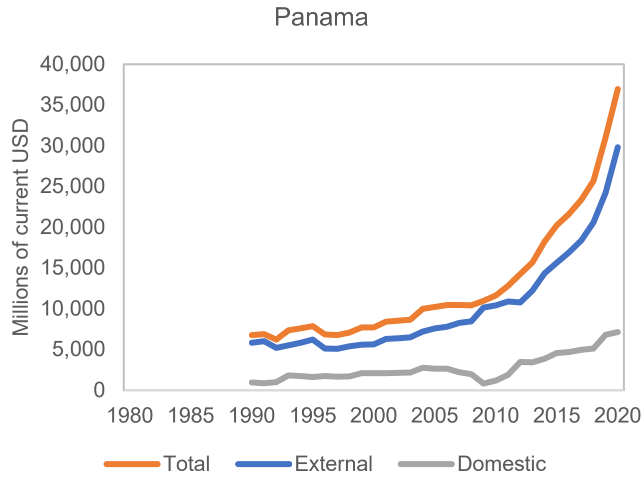

Haiti
Millions of current USD
6,000
5,000
4,000
3,000
2,000
1,000
0
1980 1985 1990 1995 2000 2005 2010 2015 2020
Total
External
Domestic

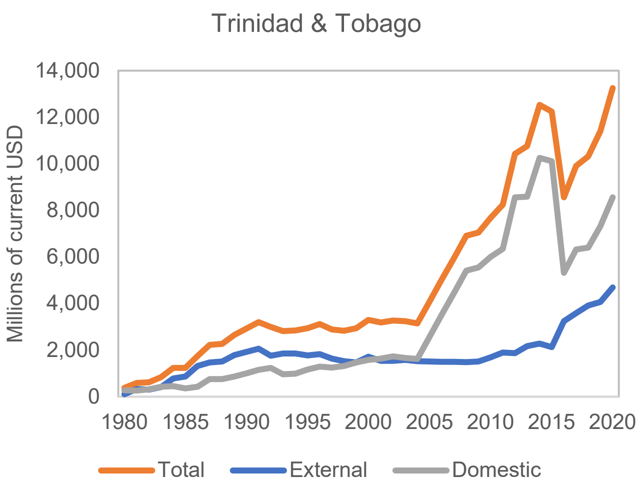

Honduras
Millions of current USD
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
1980 1985 1990 1995 2000 2005 2010 2015 2020
Total
External
Domestic


Jamaica
Millions of current USD
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
1980 1985 1990 1995 2000 2005 2010 2015 2020
Total
External
Domestic


Mexico
Millions of current USD
600,000
500,000
400,000
300,000
200,000
100,000
0
1980 1985 1990 1995 2000 2005 2010 2015 2020
Total
External
Domestic


Nicaragua
Millions of current USD
9,000
8,000
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
1980
1985
1990
1995
2000
2005
2010
2015
2020
Total
External
Domestic


Panama
Millions of current USD
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
1980
1985
1990
1995
2000
2005
2010
2015
2020
Total
External
Domestic


Trinidad & Tobago
Millions of current USD
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
1980
1985
1990
1995
2000
2005
2010
2015
2020
Total
External
Domestic

Appendix D. Top Storms and Their Estimated Impacts on Debt Stocks

A. Top 10

Year	Country	Total Debt Stock T=0 (in Current USD)	Total Debt Stock T=0 (in 2022 USD)	Total Debt Stock T+3[11] (in 2022 USD)	Counterfactual total Stock T+3[12] (in 2022 USD)	Total minus counterfactual debt stock (in 2022 USD)
1988	Jamaica	5,803.8	14,358.7	23,422.8	17,966.7	5,456.2
2000	Belize	508.0	863.3	1,408.2	1,080.2	328.0
1998	Nicaragua	4,856.9	8,718.5	14,222.1	10,909.2	3,312.9
2001	Belize	582.5	962.8	1,570.6	1,204.7	365.8
1998	Belize	325.2	583.7	952.2	730.4	221.8
2004	Jamaica	12,394.0	19,197.8	31,316.7	24,021.7	7,295.0
2004	Bahamas	1,872.9	2,901.0	4,732.3	3,630.0	1,102.4
2004	Haiti	1,633.2	2,529.7	4,126.6	3,165.4	961.3
2008	Belize	1,077.5	1,464.7	2,389.4	1,832.8	556.6
2016	Bahamas	6,315.6	7,699.9	12,560.6	9,634.7	2,925.9

[11] The total debt stock at T=3 is the estimated debt level at T=3, assuming that the debt stock at T=0 grows after the storm at the estimated average post-storm growth rate of the debt stock for the top-10 storms.

[12] The counterfactual debt stock at T=3 is the estimated debt level at T=3 if the debt stock at T=0 had grown at the growth rate of debt stock pre-storm for the top-10 storms.

B. Top 20

Year	Country	Total Debt Stock T=0 (in Current USD)	Total Debt Stock T=0 (in 2022 USD)	Total Debt Stock T+3[13] (in 2022 USD)	Counterfactual total Stock T+3[14] (in 2022 USD)	Total minus counterfactual debt stock (in 2022 USD)
1988	Jamaica	5,803.8	14,358.7	20,430.7	17,072.5	3,358.2
2000	Belize	508.0	863.3	1,228.3	1,026.4	201.9
1998	Nicaragua	4,856.9	8,718.5	12,405.3	10,366.2	2,039.1
2001	Belize	582.5	962.8	1,369.9	1,144.7	225.2
1998	Belize	325.2	583.7	830.6	694.1	136.5
2004	Jamaica	12,394.0	19,197.8	27,316.2	22,826.2	4,490.0
2004	Bahamas	1,872.9	2,901.0	4,127.8	3,449.3	678.5
2004	Haiti	1,633.2	2,529.7	3,599.5	3,007.8	591.7
2008	Belize	1,077.5	1,464.7	2,084.1	1,741.6	342.6
2016	Bahamas	6,315.6	7,699.9	10,956.1	9,155.2	1,800.9
1999	Bahamas	1,438.4	2,526.7	3,595.2	3,004.2	590.9
2014	Guatemala	14,598.9	18,046.3	25,677.7	21,457.1	4,220.7
2001	Bahamas	1,538.1	2,542.1	3,617.1	3,022.6	594.6
2005	Guatemala	5,714.3	8,563.1	12,184.2	10,181.5	2,002.7
2007	Belize	1,072.8	1,514.0	2,154.2	1,800.1	354.1
2016	Jamaica	15,686.0	19,124.3	27,211.6	22,738.8	4,472.8
2012	Jamaica	17,539.8	22,354.9	31,808.4	26,580.0	5,228.4
2009	El Salvador	8,831.9	12,044.5	17,137.9	14,320.9	2,817.0
2016	Honduras	9,702.0	11,828.7	16,830.8	14,064.3	2,766.5
2007	Nicaragua	2,532.1	3,573.4	5,084.5	4,248.8	835.8

[13] The total debt stock at T=3 is the estimated debt level at T=3, assuming that the debt stock at T=0 grows after the storm at the estimated average post-storm growth rate of the debt stock for the top 20 storms.
[14] The counterfactual debt stock at T=3 is the estimated debt level at T=3 if the debt stock at T=0 had grown at the growth rate of debt stock pre-storm for the top-20 storms.

C. Top 30

Year	Country	Total Debt Stock T=0 (in Current USD)	Total Debt Stock T=0 (in 2022 USD)	Total Debt Stock T+3[15] (in 2022 USD)	Counterfactual total Stock T+3[16] (in 2022 USD)	Total minus counterfactual debt stock (in 2022 USD)
1988	Jamaica	5,803.8	14,358.7	19,553.1	17,155.5	2,397.6
2000	Belize	508.0	863.3	1,175.6	1,031.4	144.2
1998	Nicaragua	4,856.9	8,718.5	11,872.4	10,416.6	1,455.8
2001	Belize	582.5	962.8	1,311.1	1,150.3	160.8
1998	Belize	325.2	583.7	794.9	697.4	97.5
2004	Jamaica	12,394.0	19,197.8	26,142.8	22,937.1	3,205.7
2004	Bahamas	1,872.9	2,901.0	3,950.5	3,466.1	484.4
2004	Haiti	1,633.2	2,529.7	3,444.9	3,022.5	422.4
2008	Belize	1,077.5	1,464.7	1,994.6	1,750.0	244.6
2016	Bahamas	6,315.6	7,699.9	10,485.5	9,199.7	1,285.7
1999	Bahamas	1,438.4	2,526.7	3,440.7	3,018.8	421.9
2014	Guatemala	14,598.9	18,046.3	24,574.7	21,561.4	3,013.4
2001	Bahamas	1,538.1	2,542.1	3,461.7	3,037.3	424.5
2005	Guatemala	5,714.3	8,563.1	11,660.8	10,231.0	1,429.9
2007	Belize	1,072.8	1,514.0	2,061.7	1,808.9	252.8
2016	Jamaica	15,686.0	19,124.3	26,042.7	22,849.3	3,193.4
2012	Jamaica	17,539.8	22,354.9	30,442.0	26,709.2	3,732.8
2009	El Salvador	8,831.9	12,044.5	16,401.7	14,390.5	2,011.2

[15] The total debt stock at T=3 is the estimated debt level at T=3, assuming that the debt stock at T=0 grows after the storm at the estimated average post-storm growth rate of the debt stock for the top 30 storms.
[16] The counterfactual debt stock at T=3 is the estimated debt level at T=3 if the debt stock at T=0 had grown at the growth rate of debt stock pre-storm for the top-30 storms.

2016	Honduras	9,702.0	11,828.7	16,107.8	14,132.7	1,975.2
2007	Nicaragua	2,532.1	3,573.4	4,866.1	4,269.4	596.7
1987	Barbados	745.7	1,920.5	2,615.2	2,294.6	320.7
2010	Guate-mala	10,154.7	13,625.5	18,554.6	16,279.4	2,275.2
2008	Haiti	2,782.0	3,781.9	5,150.0	4,518.5	631.5
2008	Costa Rica	9,787.5	13,305.0	18,118.2	15,896.5	2,221.7
2005	Belize	990.0	1,483.5	2,020.2	1,772.5	247.7
2012	Haiti	2,233.0	2,846.0	3,875.5	3,400.3	475.2
2017	Barbados	6,776.2	8,089.2	11,015.5	9,664.7	1,350.7
2015	Bahamas	5,904.6	7,290.0	9,927.3	8,710.0	1,217.3
2012	Bahamas	4,399.9	5,607.8	7,636.5	6,700.1	936.4
2016	Belize	1,536.7	1,873.5	2,551.3	2,238.5	312.8

D. Top 40

Year	Country	Total Debt Stock T=0 (in Current USD)	Total Debt Stock T=0 (in 2022 USD)	Total Debt Stock T+3[17] (in 2022 USD)	Counter-factual total Stock T+3[18] (in 2022 USD)	Total minus counter-factual debt stock (in 2022 USD)
1988	Jamaica	5,803.8	14,358.7	19,525.8	17,684.2	1,841.6
2000	Belize	508.0	863.3	1,173.9	1,063.2	110.7
1998	Nicaragua	4,856.9	8,718.5	11,855.9	10,737.7	1,118.2
2001	Belize	582.5	962.8	1,309.2	1,185.8	123.5
1998	Belize	325.2	583.7	793.8	718.9	74.9
2004	Jamaica	12,394.0	19,197.8	26,106.3	23,644.1	2,462.2
2004	Bahamas	1,872.9	2,901.0	3,945.0	3,572.9	372.1
2004	Haiti	1,633.2	2,529.7	3,440.1	3,115.6	324.5
2008	Belize	1,077.5	1,464.7	1,991.8	1,804.0	187.9
2016	Bahamas	6,315.6	7,699.9	10,470.8	9,483.2	987.6
1999	Bahamas	1,438.4	2,526.7	3,435.9	3,111.9	324.1
2014	Guatemala	14,598.9	18,046.3	24,540.4	22,225.9	2,314.6
2001	Bahamas	1,538.1	2,542.1	3,456.9	3,130.9	326.0
2005	Guatemala	5,714.3	8,563.1	11,644.6	10,546.3	1,098.3
2007	Belize	1,072.8	1,514.0	2,058.8	1,864.6	194.2
2016	Jamaica	15,686.0	19,124.3	26,006.4	23,553.6	2,452.8
2012	Jamaica	17,539.8	22,354.9	30,399.5	27,532.4	2,867.2
2009	El Salvador	8,831.9	12,044.5	16,378.8	14,834.0	1,544.8
2016	Honduras	9,702.0	11,828.7	16,085.3	14,568.2	1,517.1
2007	Nicaragua	2,532.1	3,573.4	4,859.3	4,401.0	458.3

[17] The total debt stock at T=3 is the estimated debt level at T=3 assuming that the debt stock at T=0 grows after the storm at the estimated average post-storm growth rate of the debt stock for the top-40 storms.
[18] The counterfactual debt stock at T=3 is the estimated debt level at T=3 if the debt stock at T=0 had grown at the growth rate of debt stock pre-storm for the top-40 storms.

1987	Barbados	745.7	1,920.5	2,611.6	2,365.3	246.3
2010	Guatemala	10,154.7	13,625.5	18,528.7	16,781.2	1,747.6
2008	Haiti	2,782.0	3,781.9	5,142.8	4,657.7	485.0
2008	Costa Rica	9,787.5	13,305.0	18,092.9	16,386.4	1,706.4
2005	Belize	990.0	1,483.5	2,017.4	1,827.1	190.3
2012	Haiti	2,233.0	2,846.0	3,870.1	3,505.1	365.0
2017	Barbados	6,776.2	8,089.2	11,000.1	9,962.6	1,037.5
2015	Bahamas	5,904.6	7,290.0	9,913.4	8,978.4	935.0
2012	Bahamas	4,399.9	5,607.8	7,625.8	6,906.6	719.2
2016	Belize	1,536.7	1,873.5	2,547.7	2,307.5	240.3
2007	Jamaica	13,083.0	18,463.2	25,107.4	22,739.4	2,368.0
2011	Mexico	289,915.6	377,164.0	512,889.3	464,515.6	48,373.7
2007	Bahamas	2,636.0	3,720.1	5,058.8	4,581.6	477.1
2005	Honduras	5,334.8	7,994.4	10,871.2	9,845.9	1,025.3
2011	Bahamas	3,805.6	4,950.9	6,732.5	6,097.5	635.0
1994	Jamaica	5,131.3	10,129.8	13,775.1	12,475.9	1,299.2
1996	El Salvador	5,099.3	9,512.5	12,935.6	11,715.6	1,220.0
2010	Mexico	290,921.2	390,353.7	530,825.4	480,760.1	50,065.4
1996	Honduras	4,376.7	8,164.5	11,102.5	10,055.4	1,047.1
2005	Haiti	1,719.4	2,576.5	3,503.7	3,173.3	330.5