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Debt, Growth and Natural Disasters: A Caribbean Trilogy

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Debt, Growth and Natural Disasters: A Caribbean Trilogy

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Abstract

This paper seeks to determine the effects that natural disasters have on per capita GDP and on the debt to GDP ratio in the Caribbean. Two types of natural disasters are studied –storms and floods– given their prevalence in the region, while considering the effects of both moderate and severe disasters. I use a vector autoregressive model with exogenous natural disasters shocks, in a panel of 12 Caribbean countries over a period of 40 years. The results show that both storms and floods have a negative effect on growth, and that debt increases with floods but not with storms. However, in a subsample I find that storms significantly increase debt in the short and long run. I also find weak evidence that debt relief contributes to ease the negative effects of storms on debt.

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I. INTRODUCTION

Over the past forty years, the Caribbean has suffered more than 250 natural disasters, most of which were storms. During this period, natural disasters killed over 12,000 people and affected over 12 million more. The economic impact of these disasters has also been substantial with estimated damages of US$19.7 billion in 2010 constant dollars, that is, on average 1 percent of the Caribbean GDP is destroyed every year.[1] All this has happened in a region that is among the most indebted in the world. Hence, the importance of studying the effects of disasters on growth and debt in a disaster prone region like the Caribbean.

The goal of the paper is to determine the effects that natural disasters have on per capita GDP and on the debt to GDP ratio in the Caribbean. To do so, it is necessary to consider the role that official development assistance (ODA) and debt relief play in the aftermath of natural disasters given their importance in the region. There is a growing literature on the economic impact of natural disasters, most of it focused on the effects on output, and the determinants of its economic costs (Noy, 2009; Raddatz, 2009; Skidmore and Toya, 2002; Strobl, 2012; Toya and Skidmore, 2007; and Fomby, Ikeda and Loayza, 2013). However, the impact on public debt has received less attention, and it has not been studied in conjunction with the effects on output.[2]

This paper studies the effects that different types of natural disasters (i.e. storms and floods) have in the Caribbean economies. I use a panel vector autoregressive model with exogenous shocks (VARX) to estimate the mean responses of GDP growth and the debt to GDP ratio growth to different types of natural disasters. Furthermore, I study the effects of both moderate and severe disasters. The panel is estimated using a bootstrap-bias correction of the fixed-effects estimator,[3] covering 12 Caribbean countries over 40 years, from 1970 to 2009.[4] One advantage of using a panel VAR is that it traces the economic response in each year after a natural disaster, while also obtaining the cumulative effect on the economy after a few years, instead of just focusing on the short or long term consequences. Another benefit is that it controls for other

[1]The numbers are for storms and floods only, and for the countries included in this study (see list below).

[2]Noy and Nualsri (2011) study the fiscal consequences of natural disasters, but they do not include Caribbean countries in their sample, and they do not control for other economic variables, which might result in an overestimation of the effects of disasters on debt.

[3]The fixed effects, or least-squares dummy variables (LSDV), estimator is used to capture the country heterogeneity, while the bootstrap algorithm corrects for the inconsistency of the LSDV estimator in dynamic panels when the time dimension is small Nickell (1981).

[4]The countries included in the sample are: Antigua and Barbuda, The Bahamas, Barbados, Dominica, Dominican Republic, Grenada, Haiti, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, and Trinidad and Tobago.

macroeconomic effects (e.g. inflation, investment, government spending, etc.) on output and debt while taking care of the possible endogeneity between these variables.

The results show that both storms and floods have a negative effect on growth, with severe disasters generating larger drops in output. In general, I find that including debt in the model is important because its exclusion overestimates the impact of disasters on output. The results for debt indicate that floods increase debt while storms (in particular severe ones) do not. However, in a subsample of countries, i.e. the Eastern Caribbean Currency Union (ECCU),[5] I also find that storms significantly increase debt in the short and long run.

There is weak evidence that the drop in the debt ratio after storms is partially explained by the role that external debt relief and aid flows play in the recovery after the disasters; where storms seem to benefit from aid flows while floods do not. Furthermore, there is weak evidence that debt relief and humanitarian aid seem to make a difference in the impact of storms on debt. Debt relief appears to attenuate the pressure on debt accumulation to finance the reconstruction activity after storms, but its effect on growth is negligible. However, debt relief seems to have little impact on the effects that floods have on either GDP or debt.

The remainder of the paper is structured as follows; Section II discusses the existing literature, Section III describes the data and sources, Section IV presents the econometric model and the different specifications estimated, and Section V discusses the results of the mean responses and cumulative responses to the disasters shocks. Finally, Section VI concludes and briefly discusses policy implications.

II. Literature Review

There is a growing literature that studies the economic effects of natural disasters. In the Caribbean region there are a few papers that study mainly the effects of hurricanes. Rasmussen (2004) looks at the stylized facts in the region to study the macroeconomic implications of natural disasters in the Caribbean. He finds that in the short run disasters generate an immediate contraction of output, a worsening of external and fiscal balances and an increase in transfers from abroad, while in the long run the effects are inconclusive. Cashin and Sosa (2013) develop country-specific VAR models with block exogeneity restrictions to analyze the effects of

[5] The ECCU is comprised of Antigua and Barbuda, Dominica, Grenada, St. Kitts and Nevis, St. Lucia, and St. Vincent and the Grenadines.

exogenous factors in the ECCU's business cycle. They find that climatic shocks lead to an immediate and significant fall in output, but the effects do not appear to be persistent.[6]

More recently, Strobl (2012) examines the effects of hurricanes in the Caribbean basin constructing an innovative measure of potential local destruction by using a wind field model on hurricane track data, similar to the destruction index proposed by Emanuel (2005). Strobl finds that the average hurricane reduces output by 0.8 percentage points. However, the paper does not control for other economic characteristics such as inflation, investment, government spending, etc., which have an impact on growth. Therefore, it is possible that Strobl is overestimating the effects of hurricanes on growth in the region.

On a broader sample of countries Noy (2009) studies the effects of natural disasters on short term growth. Additionally, Noy examines the economic characteristics that determine the impact of natural disasters on growth; finding that developing and smaller countries are more vulnerable to disasters, and that, countries with better human capital, institutions, and larger governments tend to be less affected by them. Raddatz (2009) estimates the impact of different types of natural disasters on GDP growth. Raddatz also considers the effects of official development assistance (ODA) and external debt levels on the impact of natural disasters on output. He finds that ODA has only a modest and not significant reduction of the effects of natural disasters on output. He also finds that the initial level of debt of a country does not affect the output loss from a natural disaster. In the present paper, I also explore the role that ODA and debt relief play in the aftermath of natural disasters by estimating two alternative specifications introducing these two variables. Additionally, I study the effects that natural disasters have on debt accumulation, but I do not examine the effects that different debt levels have on GDP.

Fomby, Ikeda and Loayza (2013) use a similar methodological approach to Raddatz (2009); they use a VARX to estimate the mean response of growth to natural disasters. However, they build upon Raddatz's model by including additional variables to control for the endogenous effects of inflation, investment and government expenditure, and the exogenous effects of world output. They also study the impact of moderate versus severe disaster in developing countries, while further disaggregating the types of natural disasters. The authors consider four categories of disasters; droughts, floods, storms and earthquakes. They find that (i) not all types of natural disasters have the same impact on growth, e.g. droughts have a more negative effect than floods, storms, or earthquakes; (ii) that severe disasters often have a more negative mean response than moderate disasters do; and (iii) that the timing and growth response varies with the type of natural disaster and the sector of economic activity involved.

[6]The authors do not explicitly define what types of natural disasters are included in the climatic shocks.

I closely follow the methodology employed by Fomby *et al.*, but I focus the analysis in the Caribbean countries.[7] This paper differs from the work of Fomby *et al.* by studying the linkages between debt, growth and natural disasters, and considering the effects that debt relief and aid flows have on debt paths in the aftermath of a disaster. I also include an additional measure of natural disasters to test the robustness of the results. While Fomby *et al.* only focus on measuring the intensity of the natural disasters with respect to the number of people killed or affected by them, I also look at the estimated damages to construct a measure of intensity (see data section below).

III. Data Description

The paper covers 12 Caribbean countries over the 1970 to 2009 period. The economic data for the 12 Caribbean economies come from the Penn World Tables version 7.0 (Heston, Summers, and Aten, 2011), the International Monetary Fund's (IMF) World Economic Outlook (WEO, 2011), the World Bank's World Development Indicators (WDI, 2011), the Organization for Economic Co-operation and Development (OECD), the Paris Club and the Emergency Disaster Database (EM-DAT).

In addition to the natural disasters, I include controls for both domestic and external conditions that determine economic growth and the debt to GDP ratio. The domestic determinants include inflation, trade openness, government consumption, investment and financial depth. All these variables are treated as endogenous. On the external front, I include world GDP growth which affects all countries in the same way, and the change in the terms of trade which have individual country effects. The two external variables are considered to be exogenous, which in the case of the small open economies of the Caribbean is an appropriate assumption.[8] Table 1 details the definitions and sources for each of the variables used in the estimations, Table 2 shows the number of disasters per country, and Table 3 presents summary statistics for each variable.[9]

To fully capture the debt dynamics in the Caribbean, I also include two additional variables; official development assistance (ODA), and a debt relief dummy variable to control for events

[7] Fomby *et al.*'s sample only included four out of the 12 countries covered in this paper (Barbados, Dominican Republic, St. Vincent and the Grenadines, and Trinidad and Tobago). Additionally, Raddatz's finding of a geographic clustering of different types of disasters by region warrants a more in depth study of the effects of storms and floods in the Caribbean.

[8] I use the same exogenous and endogenous variables as Fomby *et al.* with the exception of the debt related variables which they do not consider.

[9] Table 4 presents summary statistics for the ECCU subsample.

of debt forgiveness, debt restructuring and humanitarian aid.[10] When a country's debt is forgiven or a country receives aid in kind (i.e. food, water, blankets, etc.) or cash, these flows immediatly alleviate pressures to issue new debt to finance the rehabilitation and reconstruction work. Also, restructuring the debt of a country so that its repayment schedule is extended and its debt service over the short term is reduced, frees up resources that the government can divert towards post-disaster needs.

To construct the debt relief dummy I collected data from Paris Club Agreements for the Caribbean countries included in the sample, as well as data from the World Bank's Global Development Finance and the OECD's OECD.Stat databases.[11] The dummy accounts for events in which Caribbean countries have benefited from a wide array of aid flows covering debt forgiveness, debt restructuring and/or large humanitarian aid flows, but henceforth I will refer to it as the "debt relief" dummy. To make sure that I only capture debt relief events that are economically meaningful, I construct the dummy such that it is 1 when the debt relief received surpasses 0.01% of GDP.[12]

The data on natural disasters comes from EM-DAT.[13] They collect information on type of disaster, number of people killed (*fatalities*), number of people affected (*total affected*), and (when available) estimated damages caused by the disaster. I consider two categories of natural disasters; storms, and floods and construct the dummy variable for each type of natural disaster by following the measure of intensity proposed by Fomby *et al.*[14] For each type-k natural

[10] It is important to note that debt forgiveness, debt restructuring, and humanitarian aid are part of ODA flows, that is why the two variables are used in separate specifications.

[11] Given that there are two main sources for the debt relief data, the World Bank and the OECD, I create the debt relief dummy from both sources adding debt forgiveness, debt restructuring, and humanitarian aid flows. Then, I combined the two data sets by keeping the data from the source that showed the largest amount in each year for each recipient country. The Paris Club does not report the amounts of debt relief accorded to countries; hence a value of 1 was given to the dummy variable whenever there was an agreement with the Paris Club.

[12] I also construct another dummy variable where the debt relief threshold is higher (at least 1% of GDP); however, the results are very similar to the ones for "moderate" debt relief (at least 0.01% of GDP). I choose the dummy with the lower threshold because it is more relevant in the case of moderate disasters. The results are not presented in the paper but are available upon request.

[13] For a disaster to be included in EM-DAT at least one of the following criteria must be met: i) at least 10 people killed, ii) at least 100 people affected, or iii) a state of emergency was declared or a call for international assistance was made. For a detailed explanation of the classification of disaster types see EM-DAT.

[14] Fomby *et al.* also studied the effects of droughts and earthquakes; however, the small number of these types of disasters (one of each) in the usable observations in the sample precluded their analysis in this paper.

disaster in country i, in year t, I compute;[15]

$$intensity^k_{i,t} = \begin{cases} 1, & \text{if } \frac{fatalities^k_{i,t} + 0.3 \cdot total\ affected^k_{i,t}}{population_{i,t}} > 0.0001 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

that is, any natural disaster that affects more than 0.01% of the population of a country is considered potentially disruptive enough to have an effect on the economy. The affected population is a weighted average of the *fatalities* (with a weight of 1) and the *total affected* (with a weight of 0.3).[16] An alternative to (1) is considered to test the robustness of the results, where the weight of the *total affected* in the index is 1, instead of the 0.3 in equation (1), that is the *fatalities* and *total affected* are given equal weight. Now, to measure the effects of severe disasters a similar index to (1) is constructed where the threshold of the population affected or killed is increased to 1% of the total population of the country.

Unlike Fomby *et al.* where they sum all the cases where a type-k natural disaster affects a country, I simply use the intensity measure as a dummy variable in the estimations. The difference is that Fomby *et al.* study the individual effects of an additional disaster in a given year, whereas this paper studies the effects of having a disastrous year. Fomby *et al.*'s measure is appropriate for their analysis. However, in the context of studying the impact on debt which is usually decided on an annual basis it is better to analyze the impact of a disastrous year than the impact of one additional disaster.[17] The estimation results using Fomby *et al.*'s disasters measure are similar to those presented in here.[18]

An alternative measure of the intensity of the disasters can be obtained by using the data on estimated damages as a percent of GDP

$$intensity^k_{i,t} = \begin{cases} 1, & \text{if } \frac{damages^k_{i,t}}{GDP_{i,t}} > 0.0001 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

This will be used to test the robustness of the results to different measures of the intensity of the disasters.

[15]When more than one type-k natural disaster affects a country in any given year, I aggregate the number of fatalities and people affected to construct the intensity index in that year.
[16]The rationale for the weights is that disasters with fatalities are assumed to be more severe than those without them.
[17]For example, when multiple disasters of the same type afflict a country in one year the government is more likely to respond in a combined manner to the reconstruction needs, rather than to respond on an individual basis.
[18]The results are not included in the paper but are available upon request.

IV. THE ECONOMETRIC MODEL

Following Fomby *et al.* the econometric model to be used is a fixed effects unbalanced panel vector autoregression with exogenous variables (VARX):

$$\mathbf{y}_{i,t} = \alpha_i + \Phi_1 \mathbf{y}_{i,t-1} + \Phi_2 \mathbf{y}_{i,t-2} + \Theta_0 \mathbf{x}_{i,t} + \Theta_1 \mathbf{x}_{i,t-1} + \Theta_2 \mathbf{x}_{i,t-2} + \varepsilon_{i,t} \tag{3}$$

where $\varepsilon_{i,t}$ is a vector of errors, the countries are indexed by $i = 1,2,...,N$, and the time index for each country i is $t = 1,...,T_i$.

The benchmark model includes seven endogenous variables represented by the $\mathbf{y}_{i,t}$ vector, and four exogenous variables given by the $\mathbf{x}_{i,t}$ vector;

$$\mathbf{y}_{i,t} = \begin{bmatrix} \textit{Per capita GDP growth}_{i,t} \\ \textit{Debt to GDP ratio growth}_{i,t} \\ \textit{Investment share of GDP growth}_{i,t} \\ \textit{Government share of GDP growth}_{i,t} \\ \textit{Inflation rate}_{i,t} \\ \textit{Trade openness growth}_{i,t} \\ \textit{Financial depth growth}_{i,t} \end{bmatrix}, \quad \mathbf{x}_{i,t} = \begin{bmatrix} \textit{Storms}_{i,t} \\ \textit{Floods}_{i,t} \\ \textit{Terms of trade}_{i,t} \\ \textit{World growth}_{i,t} \end{bmatrix}.$$

To control for the debt dynamics in the Caribbean, which are influenced by aid flows, debt relief and debt restructurings I estimate two additional specifications; one where *ODA to GDP growth* and another one where a *Debt relief dummy* are included in $\mathbf{x}_{i,t}$. Below there is a discussion of why these two variables are treated as exogenous.

A. The Fixed Effects and Bootstrap Bias-corrected Estimators

The fixed effect coefficient for each country is given by α_i, which captures the unobserved (time-invariant) heterogeneity of the countries in the Caribbean region. The total number of usable observations in the panel is denoted by $T = \sum_{i=1}^{N} T_i$. In equation (3) it is assumed that the errors are homogeneous, $E(\varepsilon_{i,t}\varepsilon'_{i,t}) = \Omega$ for all i and t. The errors are also assumed to be independent within equations $E(\varepsilon_{i,s}\varepsilon'_{i,t}) = \mathbf{0}$, for $s \neq t$, and across equations $E(\varepsilon_{i,s}\varepsilon'_{j,t}) = \mathbf{0}$, for any s and t where $i \neq j$.

Now, I proceed to stack the observations over time and cross-sections, to obtain

$$\begin{aligned}\mathbf{y} &= \mathbf{D}\alpha' + \mathbf{y}_{-1}\Phi_1' + \mathbf{y}_{-2}\Phi_2' + \mathbf{x}\Theta_0' + \mathbf{x}_{-1}\Theta_1' + \mathbf{x}_{-2}\Theta_2' + \varepsilon \\ &= \mathbf{D}\alpha' + \mathbf{Z}\delta' + \varepsilon,\end{aligned} \tag{4}$$

where

$$\mathbf{D} = \begin{pmatrix} \mathbf{i}_{T_1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{i}_{T_2} & \cdots & \mathbf{0} \\ \vdots & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{i}_{T_N} \end{pmatrix}, \tag{5}$$

is a $T \times N$ matrix and $\mathbf{i}$ is a $T_i \times 1$ column of ones.

The fixed-effects vector and the vectors of endogenous and exogenous variables in (4) are defined as follows: $\alpha = (\alpha_1\ \alpha_2 ... \ \alpha_N)'$, $\mathbf{y}_i = (\mathbf{y}_{i,1}\ \mathbf{y}_{i,2} \cdots \mathbf{y}_{i,T_i})'$, $\mathbf{y}_{i(-1)} = (\mathbf{y}_{i,0}\ \mathbf{y}_{i,1} \cdots \mathbf{y}_{i,T_i-1})'$, $\mathbf{y}_{i(-2)} = (\mathbf{y}_{i,-1}\ \mathbf{y}_{i,0} \cdots \mathbf{y}_{i,T_i-2})'$, $\mathbf{y} = (\mathbf{y}'_1\ \mathbf{y}'_2 \cdots \mathbf{y}'_N)'$, $\mathbf{y}_{-1} = (\mathbf{y}'_{1(-1)}\ \mathbf{y}'_{2(-1)} \cdots \mathbf{y}'_{N(-1)})'$, $\mathbf{y}_{-2} = (\mathbf{y}'_{1(-2)}\ \mathbf{y}'_{2(-2)} \cdots \mathbf{y}'_{N(-2)})'$[19] then the fixed-effects estimator or least-squares dummy variable (LSDV) estimator $\hat{\hat{\delta}}$ for δ is given by

$$\hat{\hat{\delta}} = (\mathbf{Z}'\mathbf{A}\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{A}\mathbf{y}, \tag{6}$$

where $\mathbf{Z} = (\mathbf{y}_{-1}\ \mathbf{y}_{-2}\ \mathbf{x}\ \mathbf{x}_{-1}\ \mathbf{x}_{-2})$, $\hat{\hat{\delta}} = (\hat{\Phi}_1\hat{\Phi}_2\hat{\Theta}_0\hat{\Theta}_1\hat{\Theta}_2)$ and where the $T \times T$ matrix $\mathbf{A}$ takes the form

$$\mathbf{A} = \begin{pmatrix} \mathbf{A}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_2 & \cdots & \mathbf{0} \\ \vdots & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}_N \end{pmatrix},$$

with $\mathbf{A}_i = \mathbf{I}_{T_i} - \frac{1}{T_i}\ \mathbf{i}_{T_i}\ \mathbf{i}'_{T_i}$.[20] The fixed effect coefficients can be recovered as $\hat{\alpha} = (\mathbf{D}'\mathbf{D})^{-1}$ $\mathbf{D}'(\mathbf{y} - \mathbf{Z}\hat{\hat{\delta}})$. Now, to obtain the mean response of growth and debt to the exogenous natural disasters, which is what I am ultimately interested in, it is better to rewrite (3) in a more compact way. After controlling for the fixed effects, it is possible to write the multiplier form of the model as:[21]

$$\mathbf{y}_{i,t} = \Phi(L)^{-1}\ \Theta(L)\mathbf{x}_{i,t} + \Phi(L)^{-1}\varepsilon_{i,t}\ , \tag{7}$$

[19]The vectors of exogenous variables $\mathbf{x}_i, \mathbf{x}_{i-1}, \mathbf{x}_{i-2}, \mathbf{x}, \mathbf{x}_{-1}$, and $\mathbf{x}_{-2}$ are similarly constructed.
[20]The $\mathbf{A}$ matrix can be computed as, $\mathbf{A} = \mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'$, Green (2008).
[21]For the VAR to be stable, and invertible, all eigenvalues of the companion matrix $\mathbf{F}$ must have modulus less or equal than 1; $\left|\mathbf{I}_n\lambda^p - \Phi_1\lambda^{p-1} - \Phi_2\right| = 0$, with $|\lambda| < 1$ (Hamilton, 1994). Table 5 shows that the VAR is stable.

where L is the lag operator. Therefore the mean response of $\mathbf{y}$ to $\mathbf{x}$ (the mean response of say, growth, to a natural disaster) is given by the lag polynomial:

$$\hat{\Psi}(L) = \hat{\Phi}(L)^{-1}\hat{\Theta}(L) \, . \tag{8}$$

The mean response is a generalized impulse response function (Pesaran and Shin, 1998), which measures the direct impact of the disasters on each of the endogenous variables. That is, at time zero (when the disaster strikes) the impulse responses measure only the effect from the disaster and not secondary effects from other endogenous variables. Given that there are likely secondary effects, the results could be interpreted as a lower bound of the effects of natural disasters on growth and debt.

To calculate the standard errors of the impulse-response function I use the Monte Carlo method suggested by Hamilton (1994) where the distribution of $\boldsymbol{\psi}_s(\hat{\pi})$ can be inferred by generating a random vector $\pi^{(1)}$ drawn from a $N(\hat{\pi},(1/T)(\hat{\Omega}\otimes\hat{\mathbf{Q}}^{-1}))$, where $\boldsymbol{\psi}_s \equiv \mathrm{vec}(\Psi_s)$ denotes the vector of moving average coefficients associated with lag s, $\hat{\pi} \equiv \mathrm{vec}(\hat{\delta})$ denotes the vector of coefficients from the OLS estimation, and $\hat{\mathbf{Q}}^{-1} = [(1/T)(\mathbf{Z}'\mathbf{Z})]^{-1}$. With $\pi^{(1)}$ I can calculate $\boldsymbol{\psi}_s(\pi^{(1)})$, and then repeat this process 30,000 times. Then, if 90% of the simulations for the first element of $\boldsymbol{\psi}_s$ lie between $(\underline{\psi}_{s1},\overline{\psi}_{s1})$ this interval serves as the 90% confidence interval for the first element of $\hat{\boldsymbol{\psi}}_s$.

Given that the model is dynamic, and the number of periods (T_i) is small and fixed, the LSDV estimator is inconsistent, Nickell (1981).[22] To correct for the bias in the LSDV estimator I use the bootstrap procedure implemented by Fomby *et al.* which follows the work of Pesaran and Zhao (1999), and Everaert and Pozzi (2007). The algorithm to compute the bootstrap bias-corrected (BSBC) estimator is the following:

1. Estimate $\hat{\delta}$ using the LSDV estimator, obtain $\hat{\alpha}$, and calculate the residuals $\hat{\varepsilon} = \mathbf{Ay} - \mathbf{AZ}\hat{\delta}$.
2. Determine the number of bootstrap samples B (here $B = 1{,}000$), with $j = 1,\ldots,B$, and proceed as follows B times:
   (a) Obtain a bootstrap sample $\hat{\varepsilon}^{b(j)}$ of the rescaled residuals $\hat{\varepsilon}^r$, by choosing T integers between 1 and T at random with equal probability. The rescaled residuals are calculated as $\hat{\varepsilon}^r_{i,t} = \sqrt{\frac{T_i}{T_i-1}}\left(\frac{\hat{\varepsilon}_{i,t}}{\sqrt{m_{i,t}}} - \frac{1}{T_i}\sum_{k=1}^{Ti}\frac{\hat{\varepsilon}_{i,k}}{\sqrt{m_{i,k}}}\right)$ for $t = 1,\ldots,T_i$ and $i = 1,2,\ldots,N$; where $m_{i,t}$ is the it-th diagonal element of the projection matrix $\mathbf{M} = (\mathbf{I}_T - \mathbf{AZ}(\mathbf{Z}'\mathbf{AZ})^{-\mathbf{1}}\mathbf{Z}')\mathbf{A}$.

[22] However, the bias decreases as T_i grows.

(b) Calculate a bootstrap sample $\mathbf{y}^{b(j)} = \mathbf{D}\hat{\alpha}' + \mathbf{Z}^{b(j)}\hat{\delta}' + \hat{\varepsilon}^{b(j)}$, where $\mathbf{Z}^{b(j)} = (\mathbf{y}_{-1}^{b(j)}\ \mathbf{y}_{-2}^{b(j)}\ \mathbf{x}\ \mathbf{x}_{-1}\ \mathbf{x}_{-2})$, $\mathbf{y}_{i,-1}^{b(j)} = \mathbf{y}_{i,-1}$ and with initialization $\mathbf{y}_{i,0}^{b(j)} = \mathbf{y}_{i,0}$ for $i = 1, \ldots, N$.

(c) Obtain the LSDV estimator $\hat{\delta}^{b(j)} = (\mathbf{Z}^{b(j)\prime}\mathbf{A}\mathbf{Z}^{b(j)})^{-1}\mathbf{Z}^{b(j)\prime}\mathbf{A}\mathbf{y}^{b(j)}$, and the mean responses $\hat{\Psi}^{b(j)}(L) = \left[\hat{\Phi}^{b(j)}(L)\right]^{-1} \hat{\Theta}^{b(j)}(L)$.

3. Then calculate the bootstrap bias-corrected (BSBC) mean response $\tilde{\Psi}_s$ for the s-lag as

$$\tilde{\Psi}_s = 2\hat{\Psi}_s - \frac{1}{B}\sum_{j=1}^{B}\hat{\Psi}_s^{b(j)}, \text{ for } s = 1, 2, \ldots$$

where $\hat{\Psi}_s$ is the LSDV mean response of Ψ_s.

To calculate the standard errors of the BSBC impulse-responses I follow a procedure similar to the Monte Carlo method used for the LSDV estimator described above. First, I generate B bootstrapped samples for each of the $\hat{\delta}^{b(j)}$ in the above procedure and calculate the BSBC mean response $\tilde{\Psi}^{(j)}$ for each of the samples using the BSBC algorithm to obtain $\{\tilde{\boldsymbol{\psi}}^{(1)}, \ldots, \tilde{\boldsymbol{\psi}}^{(B)}\}$. And again, if 90% of the simulations for the first element of $\boldsymbol{\psi}_s$ lie between $(\underline{\tilde{\psi}}_{s1}, \overline{\tilde{\psi}}_{s1})$ this interval serves as the 90% confidence interval for the first element of $\tilde{\boldsymbol{\psi}}_s$.[23]

B. Diagnostic Tests

Before proceeding with the estimations and presenting the results it is important to test for the stationarity of the time series involved, and choose the lag structure of the model. For the former, I perform panel and individual series unit-root tests, and for the latter I use the likelihood ratio test and the Akaike (AIC) and Schwarz (SBIC) information criteria to select the lag length. Additionally, I do Granger causality tests to determine if *ODA to GDP growth* and the *Debt relief dummy* should be included in the model as endogenous or exogenous variables.

First, I employ the Im, Pesaran, Shin (IPS) panel unit-root tests for each of the series, because the IPS test is appropriate for unbalanced panels such as the one in this paper. The results presented in column 1 of Table 6 indicate that the null hypothesis that all the panels have a unit-root is rejected in all the cases. Similarly, the individual unit root-tests, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP), show that the majority of countries do not exhibit signs of unit-roots in the series. Columns 2 and 3 of Table 6 present the percentage of

[23]The model is estimated in Matlab building on the code developed by Fomby *et al.*

countries that reject the presence of a unit-root for each variable.[24] The evidence suggests that the variables, in log differences, are appropriate to be used in a VARX model.

The lag structure of the VARX is chosen by using the AIC and SBIC information criteria and performing likelihood ratio tests. Table 7 shows the information criteria and likelihood ratio statistics for the benchmark model testing up to three lags for the endogenous and exogenous variables, represented by p and q, respectively.[25] The information criteria point towards a model with $p = q = 1$, while the likelihood ratio tests suggests that the model should include three lags $(p = q = 3)$. As a compromise between the two approaches I choose 2 lags for all the estimations. The likelihood ratio tests suggests that the dynamics are not well captured by a one-lag VARX, while the information criteria suggest that the information loss with 3 lags is higher, hence, 2 lags are used to strike a balance between the two objectives.[26]

Finally, I test the endogeneity/exogeneity of the *ODA to GDP growth* and the *Debt relief dummy* variables by doing Granger causality tests. The tests statistics in Table 8 show that both variables are not Granger caused by the endogenous variables in the model, that is, they can be treated as exogenous.[27] Therefore, in all the simulations both variables are treated as exogenous and are included in the $\mathbf{x}_{i,t}$ vector.

The exogeneity result for debt relief was expected, as there is an argument to be made about its treatment as an exogenous shock. For example the debt initiative for Heavily Indebted Poor Countries (HIPC) launched by the World Bank and the IMF in 1996 relaxed its eligibility requirements in 1999. Hence, countries that benefited after 1999 might have not benefited before. Furthermore, anecdotal evidence suggests that donors are more willing to provide aid for some types of disasters than others. For example, in the case of St. Vincent and the Grenadines that was hit by hurricane Tomas in October 2010, and by floods in April 2011,

[24] *World per capita GDP growth* cannot be tested as a panel because it is a variable that is shared by all countries, so the results presented in Table 6 are the corresponding p-values for the ADF and PP tests.

[25] I use the modified likelihood ratio test suggested by Sims (1980) to take into account the small sample bias, under the null hypothesis that the set of variables was generated from a Gaussian VARX with $p_0 = q_0$ lags against the alternative specification of $p_1 = q_1 = p_0 + 1$ lags. This likelihood ratio test has an asymptotical χ^2 distribution with degrees of freedom equal to the number of restrictions imposed under H_0, which in this case is equal to $K^2(p_1 - p_0) + KD(q_1 - q_0)$, where K and D are the number of endogenous and exogenous variables in the model, respectively.

[26] As an added bonus, choosing two lags makes the comparison with the results of Fomby *et al.* straightforward, since they also use the same lag structure.

[27] I use a likelihood ratio test with an asymptotic χ^2 distribution with degrees of freedom equal to the number of restrictions $(n_1 n_2 p)$, under the null hypothesis that the n_1 variables represented by $\mathbf{y}_1$ are exogenous with respect to the n_2 variables represented by $\mathbf{y}_2$. In this case $\mathbf{y}_1$ is either ODA or debt relief (the variables were tested separately, because they will be used like that in the estimations), and $\mathbf{y}_2$ are all the endogenous variables in the model, $p = 2$ as discussed above.

both with similar estimated damages, the donor response was considerably higher for the hurricane than for the floods (IMF, 2011a,b).[28] Also, Eisensee and Strömberg (2007) find that relief decisions are driven by news coverage of disasters, with disasters that get more coverage receiving more aid.[29]

However, the result showing that ODA is exogenous to the economic conditions (growth, inflation, government spending, investment, debt, etc.) of the recipient countries was surprising. ODA includes a wide array of flows, which not only encompass humanitarian aid after a disaster, or debt relief, but also development projects that one would expect to be partially dependent on the macroeconomic circumstances of the recipient country.

V. Results

This section presents and discusses the results of the effects of natural disasters (i.e. storms and floods) on economic growth and debt. The focus is on the dynamic effects and the adjustment path after a natural disaster. These effects are studied by using the mean impulse response functions and the mean cumulative response of GDP growth and the debt ratio growth to each type of disaster. The results are shown in Figures 1 to 10, where I present the mean and cumulative mean responses for years 0 through 8 (where 0 denotes the year of the disaster) and their corresponding confidence intervals depicting the 10% tails of the distribution.[30] The charts in the figures are organized as follows: the first column shows the effects of storms, while the second column contains the effects of floods; the upper half of the figures depicts the effects on GDP, and the bottom half the effect on the debt ratio. The results presented in this section correspond to the BSBC estimator.

[28]The estimated damages of hurricane Tomas were US$31 million while the ones for the floods were US$26 million. However, the grants and humanitarian aid received for the hurricane were almost three times larger than the ones received for the floods.

[29]A Granger causality test of the debt relief dummy to the exogenous disaster shocks shows that debt relief is not Granger caused by the natural disasters dummies. That is, natural disasters are not a good predictor of debt relief assistance received by affected countries (Table 9). Similarly, Granger causality tests of the debt relief dummy to each type of disaster individually (floods, and storms) show that neither disaster by itself is a good predictor of debt relief (the results are available upon request).

[30]The confidence intervals are constructed using the procedure explained in the previous section.

A. The benchmark model

In the immediate aftermath of natural disasters there are several outcomes that can decelerate growth. Part of the capital stock (including basic infrastructure such as roads, bridges, schools, housing, etc.) is damaged or destroyed, slowing or even halting production activity. Delivery, transportation, and communication systems are disrupted affecting supply chains. And resources that could have been used in the production process need to be devoted to clean-up, rehabilitation, and reconstruction activities.

The results for the benchmark model show that both storms and floods have an immediate negative effect on output growth, albeit none appear to be statistically significant. The benchmark model's results are presented in Figure 1 for moderate disasters and in Figure 2 for severe disasters. The effects of storms appear to be larger than those for floods in the case of moderate disasters; on impact GDP growth falls by more than half a percentage point in the case of moderate storms, and it falls by 0.1 percentage points in the case of moderate floods. As expected, the effects of severe disasters on output growth are larger than those of moderate ones; in particular the immediate effect that severe disasters bring is close to 3 percentage points in the case of floods and above 1 percentage point in the case of storms.

The recovery path after a disaster hits shows that the economy enjoys a small rebound in economic activity in year 1 after storms and year 2 after floods (year 3 after severe floods). However, this is a short lived effect. This suggests that after a natural disaster there is a concentrated effort at reconstruction and rehabilitation that lasts about a year after which a relapse to negative growth follows. After the fifth or sixth year the effects of the disasters are small and tend to disappear. The rebound in economic activity in the years after a natural disaster is associated with higher construction activity to replace or repair basic infrastructure and housing, increased agricultural activity to rehabilitate and replant crops, and a possible productivity boost from replacing low quality capital with high quality one.

In the case of moderate storms the recovery phase is so small that the economy never recovers entirely from the shock and the economy finds itself about 0.5 percent below the level it would have had in the absence of the disaster. But after a moderate flood the economic recovery is large enough to have a slightly positive cumulative effect on the level of output. However, it is important to note that for both storms and floods the cumulative effects are not statistically significant. Interestingly, the cumulative effects after severe disasters are reversed. That is, after a severe storm the economic recovery in the first few years is sufficient to have the economy slightly above its non-disaster output level. However, in the case of severe floods there seems to be only a small rebound in GDP growth linked to a recovery phase and hence the cumulative effect on output is negative.

Different types of government expenditure, and their impact on growth, could explain why moderate storms have a negative cumulative effect on GDP while severe storms have a positive effect. Smaller storms usually have a limited impact on infrastructure, but have large effects on the livelihood of people. In this case the government is expected to increase social assistance programs to help people get back on their feet, but the effect on growth is likely to be small. Severe storms on the other hand have larger effects on infrastructure requiring big investments for reconstruction, which in turn help the economic recovery. The length of the recovery phase also supports this view. Moderate storms have a short recovery of just one year, but severe storms show a longer recovery phase of almost 5 years; after all large reconstruction projects take years to complete.

In the case of floods the results show the opposite cumulative effects; moderate floods have a positive impact on growth and severe floods a negative one. This is consistent with Fomby *et al.*'s finding that moderate floods have a lasting positive effect on growth, while severe ones have a negative effect. They argue that moderate floods have a beneficial effect on growth through higher land productivity. However, I find that moderate floods have an initial negative effect, although not statistically significant, which could be the case given that Caribbean countries have small agricultural sectors and therefore would tend to benefit less from moderate floods.

Before moving to the effects on debt, I replicate in my Caribbean sample the exact model used by Fomby *et al.* by excluding all the debt related variables from the model. The results are presented in Figures A1 and A2 in the Appendix. The results show that excluding debt from the VARX overestimates the negative effect of natural disasters on GDP. When debt is absent from the estimations (Figures A1 and A2) the initial drop in GDP is larger for both types of disasters, and for both moderate and severe intensities. What is more, when debt is excluded, in the case of moderate storms the initial fall in GDP growth is statistically significant (borderline), and there is no recovery phase in the years following the disaster. The recovery phase is also more subdued in the case of severe storms and floods. Excluding debt biases the estimates of the disasters on growth, which capture part of the negative effect of debt on GDP hence showing a larger drop in economic activity after a disaster strikes. The negative effect of debt on growth after a disaster is caused partly by the high opportunity cost of increasing debt to replace damaged capital instead of investing in new capital.

These results clearly point to the need of including public debt as part of the endogenous variables in the model. Both the initial decline in economic activity and the reconstruction that takes place in the aftermath of the disasters have a repercussion in public finances (revenue and expenditure), and create financing needs that increase public debt in the absense of fiscal buffers. Including this variable in the model is crucial to understand the dynamic effects of natural disasters on the economy.

Turning the analysis to debt (bottom half of Figures 1 and 2), the results show that both moderate and severe floods increase the debt ratio growth rate.[31] In the case of severe floods the effect is a significant increase in the growth of the debt ratio of about 16 percentage points. However, the large increase in debt to finance rehabilitation and reconstruction activities after severe floods is not reflected in a pickup of economic activity until the third year of the recovery phase. Given the large opportunity costs involved in increasing debt and mobilizing resources to replace the damaged capital stock instead of investing in new capital, it is not entirely surprising that the increase in government debt is not reflected in a stronger recovery.

Surprisingly, the effect that severe storms have on debt is negative and significant, namely, the debt ratio seems to decline after a storm hits a Caribbean country. The decline in the growth rate of the debt ratio lasts for two periods after a moderate storm, and for three periods after a severe storm. In the latter case the initial decline in the growth rate of the debt to GDP ratio is significant and close to 8 percentage points. An explanation of the decline in the debt ratio growth rate after severe storms is explored in the next subsection.

B. The role of debt relief and ODA

In order to understand the dynamics behind the debt results, I explore the effects that debt forgiveness, debt restructuring, humanitarian aid, and in general ODA play in the aftermath of natural disasters in the Caribbean. To do that, I use two alternative specifications of the model, one with ODA and another one with debt relief as part of the exogenous variables.[32] The results for ODA are presented in Figures 3 and 4, while Figures 5 and 6 cover the case with the debt relief dummy.

[31] The increase in the debt ratio is not only a consequence of lower growth but also of an actual increase in the debt level to finance the recovery and reconstruction activity. The estimations use the debt to GDP ratio because it is a more informative measure of indebtedness than debt levels by themselves. However, estimations for the growth rate of debt levels show very similar results to the ones in Figures 1 through 10 (available upon request).

[32] The debt relief dummy comprises debt forgiveness, debt restructuring and humanitarian aid flows that are larger than 0.01% of the recipient's country GDP.

1. The model with ODA

Here, I study the possibility that the growth of ODA as a percent of GDP has an influence on debt after a natural disaster. Figure 3 presents the results for moderate disasters and Figure 4 the results for severe disasters. Although, a priori this alternative seems an interesting avenue of exploration, the results do not show any material difference compared to the benchmark model (Figures 1 and 2). These results are consistent with the findings of Raddatz (2009) where ODA only has a modest and not significant reduction of the effects of natural disasters. The results are not surprising considering that ODA includes a wide array of flows, which not only encompass humanitarian aid after a disaster, or debt relief, but also long term projects which are not influenced by short term considerations, such as natural disasters.

2. The model with debt relief

Now, we study the model including the debt relief dummy. This is probably a more relevant measure of the development assistance flows that are more closely related to natural disasters and/or debt issues, and might shed light to the role that debt relief plays in the aftermath of natural disasters. However, there is a caveat; the results, although different from what was presented in Figures 1 and 2, are not statistically significant. Therefore, all the results with exogenous debt relief are treated as *weak* evidence of the effects of debt relief in the aftermath of natural disasters (Figures 5 and 6).

The results for growth are very similar to those when debt relief was not included. However, on the debt front, after controlling for debt relief flows we see that on the first 3 years after a moderate storm hits a country there is an initial increase in debt, although still not significant. When including the debt relief dummy the cumulative effect shows an increase in the debt ratio level of about 3 percent, which contrasts with the case without the dummy where the effect on the debt ratio was negligible.[33] This suggests that debt relief helps countries finance the reconstruction activity after a disaster by ameliorating, with external aid funds, the demand to increase public debt. But the evidence is not conclusive, which might be the case if the impact of debt relief is small.

After a severe storm, even after controlling for debt relief, the mean response of the debt ratio growth still shows a significant decline. However, the decline is smaller (7.6 percentage

[33]The exclusion of the debt dummy biases the estimates of the disasters on the debt to GDP ratio that capture part of the negative effect of debt relief on debt; that is, the fact that debt relief is expected to reduce debt.

points) when controlling for debt relief than when not (7.9 percentage points). This indicates that there still are some effects that exert influence over debt that are not captured by the model. The debt results after flood shocks remain unaltered when incorporating the debt relief dummy in the model. The initial mean response, to a severe flood, of the debt to GDP ratio growth is still an increase close to 15 percentage points.

So far, we have seen that different types of natural disasters have a negative effect on output, but they have different effects on debt. While severe floods increase debt, severe storms seem to reduce it, even after controlling for the effects of debt relief. But, as will be shown next there is a subsample of countries in the Caribbean where the effects of storms on debt are quite different.

C. Storms in the Eastern Caribbean Currency Union

This subsection studies the effects of storms in the 6 countries of the ECCU. I only estimate the model with storms because the small number of floods in the sample for the sub-region (only three moderate floods but zero severe ones) precludes their analysis in the model. The model for the ECCU is estimated with just one lag of the endogenous and exogenous variables $(p = q = 1)$ because with the smaller sample size it is not possible to estimate the model with two lags as was done for the broader Caribbean. The results for moderate and severe storms in the ECCU are presented in Figures 7 to 10.[34]

In the ECCU, the immediate effect of a moderate storm (Figure 7) is a decline in GDP growth of about 0.7 percentage points (but not statistically significant), in line with the results for the broader Caribbean. However, unlike the rest of the Caribbean the ECCU countries do not seem to enjoy a strong recovery after moderate storms, instead seeing their economies decline further in the following year. The cumulative impact is a borderline significant lower level of GDP (about 2 percent lower) two years after a storm.

The effect on debt, in this case, is clearly positive and significant. During the year that the ECCU countries are hit by a storm the debt to GDP ratio grows faster by almost 5 percentage points, with a cumulative effect that shows a debt to GDP level that is more than 5 percent higher after 8 years.[35] A possible explanation to why storms significantly increase debt in

[34] The results with ODA as an exogenous variable are not presented because, as shown above, they also have little effect on the results for the ECCU. However, they are available upon request.

[35] Noy and Nualsri (2011) find that a year and a half after a disaster the debt to GDP ratio is higher by more than 8 percent of GDP. However, their results might be upwardly biased since they do not control for other determinants of output and debt in their estimations.

the ECCU but not so in the broader Caribbean could be related to the fact that the ECCU countries are smaller (in population and land size) and more vulnerable to natural disasters (see Table 7.4 in Rasmussen, 2006) than other Caribbean countries. The smaller size not only results in a larger portion of the country being affected when a disaster strikes, but could also suggest limited capacity to respond to the crisis without requiring an increase in debt.

Higher debt and lower growth without a strong recovery phase suggests that the increase in debt is not supporting the economic recovery. These results are consistent with the idea that in the case of moderate storms the government is borrowing to support the affected population with social assistance programs that have little impact on growth.

The results in Figure 8 show that the immediate effect of a severe storm is a decline in growth of close to 2 percentage points, but not significant (borderline), with a negative cumulative effect in the long run due to a very small recovery in the year after the storm strikes. Although, severe storms in the ECCU increase the debt ratio growth by almost 2 percentage points on impact, with a cumulative increase in debt of 5 percent by year 8, the results are not statistically significant. The difference in results with the broader Caribbean where severe storms have a positive cumulative effect on output could be related to the response of debt. While in the broader Caribbean debt declines, in the ECCU debt increases, reconstruction activity is lower, and the cumulative effect on GDP of severe storms is negative.

1. The role of debt relief

The positive effects of debt relief after a natural disaster are similar in the case of the ECCU (Figures 9 and 10). The effects on growth for both moderate and severe storms appear to be small. However, after controlling for the effect of debt relief the impact on debt is larger both in the year of the event and over the long run for moderate and severe storms. Again, we can see that there is *weak* evidence that debt relief helps financing the costs associated with a natural disaster, and reducing the impact on debt. Hence, debt relief seems to play a role in easing the negative consequences of natural disasters in the Caribbean, and in helping the countries in the reconstruction phase.

D. Robustness

All the results presented so far were obtained from the BSBC estimator. Additionally, all the results contained in the paper were also estimated using the LSDV estimator as a robustness check. The LSDV results turned out to be very similar to the BSBC ones, suggesting that given the average time sample of 31 years in the data, the LSDV estimator is a good approximation, that is, the LSDV estimator bias is small. Since the results are very similar they are not included in the paper but are available upon request.

The figures in the Appendix, present robustness checks of the results for the benchmark model and the alternative specification including the debt relief dummy. Figures A3 and A4 use *total affected* as an alternative measure of disaster intensity.[36] Figures A5 and A6 present the results when the estimated damages in U.S. dollars are used to construct the disaster intensity dummy variable. The robustness estimations show that the qualitative response to a disaster at year 0 is robust to the different measures of disaster intensity. However, the cumulative effects seem to depend on the measure used.

VI. Conclusions

This paper studied the effects of natural disasters in the Caribbean economies by using a panel VAR with exogenous variables. Three models have been estimated; a benchmark model that analyzes the effect of moderate and severe storms and floods on debt and growth, and two alternative models that look at the effects that debt relief and ODA play in the aftermath of natural disasters.

In general, the results show that both storms and floods have a negative effect on growth, with severe disasters generating larger drops in output. I find that including debt in the model is important because its exclusion overestimates the impact of disasters on output. When debt is excluded the coefficients for disasters capture part of the negative effect of debt on growth biasing the estimates, and showing a larger drop in economic activity after a disaster strikes. The increase in the debt ratio after a disaster is not only the result of lower GDP, but also an increase in debt levels to finance the recovery and reconstruction activity.

The results indicate that floods increase debt while storms (in particular severe ones) do not. This is partially explained by the role that external debt relief and aid flows play in the recovery after the disasters; where storms seem to benefit from aid flows while floods do not. However, the evidence is weak and far from conclusive. The small effect of debt relief in the response of debt to floods could suggest that floods do not attract as much attention and hence aid as storm do. After all, storms in the Caribbean are usually hurricanes that get global coverage

[36] This is the case where both *fatalities* and *total affected* have a weight of 1 in the intensity measure.

and invite more attention and as Eisensee and Strömberg (2007) show that affects the relief decision of donors. However, neither floods nor storms (separately or combined) are good predictors of a country receiving debt relief, therefore this results should be interpreted carefully.

In the case of the ECCU, the results give a different picture of the effects of storms on debt. Moderate and severe storms increase debt in the short run as in the long run, however, only the effect of moderate storms is statistically significant. The effect of storms on growth is negative; with severe storms initially having a larger negative effect.

Higher debt does not seem to support stronger economic activity during the recovery phase in either moderate or severe disasters. In the case of moderate disasters this might be explained by the type of expenditures that governments incur. I suggest the possibility that moderate disasters likely require more expenditure on social assistance for the affected population while severe ones need a larger component of investment in infrastructure, which is more supportive of an economic rebound in activity. However, even in the case of infrastructure investment, the opportunity cost involved in replacing damaged capital goods instead of investing in new capital results in a weaker recovery than expected *a priori*, especially when it involves increasing debt. More research is needed to fully understand these connections.

The two alternative model specifications considering the effects of aid flows show that general aid flows (ODA) do not have much of an effect in the aftermath of natural disasters. On the other hand, what could be called "targeted aid flows"[37] after a storm, seem to have a role in lessening the negative effects on debt. Particularly, there is weak evidence that debt relief helps to reduce the pressure on debt accumulation to finance the reconstruction activity after storms.

The evidence suggests that debt relief flows are exogenously determined, that is, they do not respond to the economic conditions of the receiving country, and the relief response seems to be uneven among disasters. If that is the case, it suggests that aid recipient countries cannot always count on the good will of their donors. And, this has economic policy implications for Caribbean countries. Disaster prone countries should expect debt to rise in the aftermath of disasters (especially if they don't receive foreign aid), and consequently should attempt to keep sustainable debt levels, and create enough fiscal space to be able to finance their own recovery. Other measures such as establishing disaster funds and increasing insurance coverage for the public and private sector, should also be pursued.[38] Additionally, countries should

[37] These are: debt relief, debt restructuring, and humanitarian aid that are captured in the debt relief dummy.

[38] For an in depth analysis of the different options available to governments in the aftermath of disasters see Cashin and Dyczewski (2006).

seek to build resilience by integrating climate and disaster risk into their policy frameworks both at the macro and micro levels.[39]

[39]For a comprehensive analysis of how to build resilience to disasters see World Bank (2013), and for a detailed description of macro policy options in response to and preparation for disasters see Laframboise and Loko (2012).

Figure 1. Mean Responses of GDP and Debt to Moderate Disasters

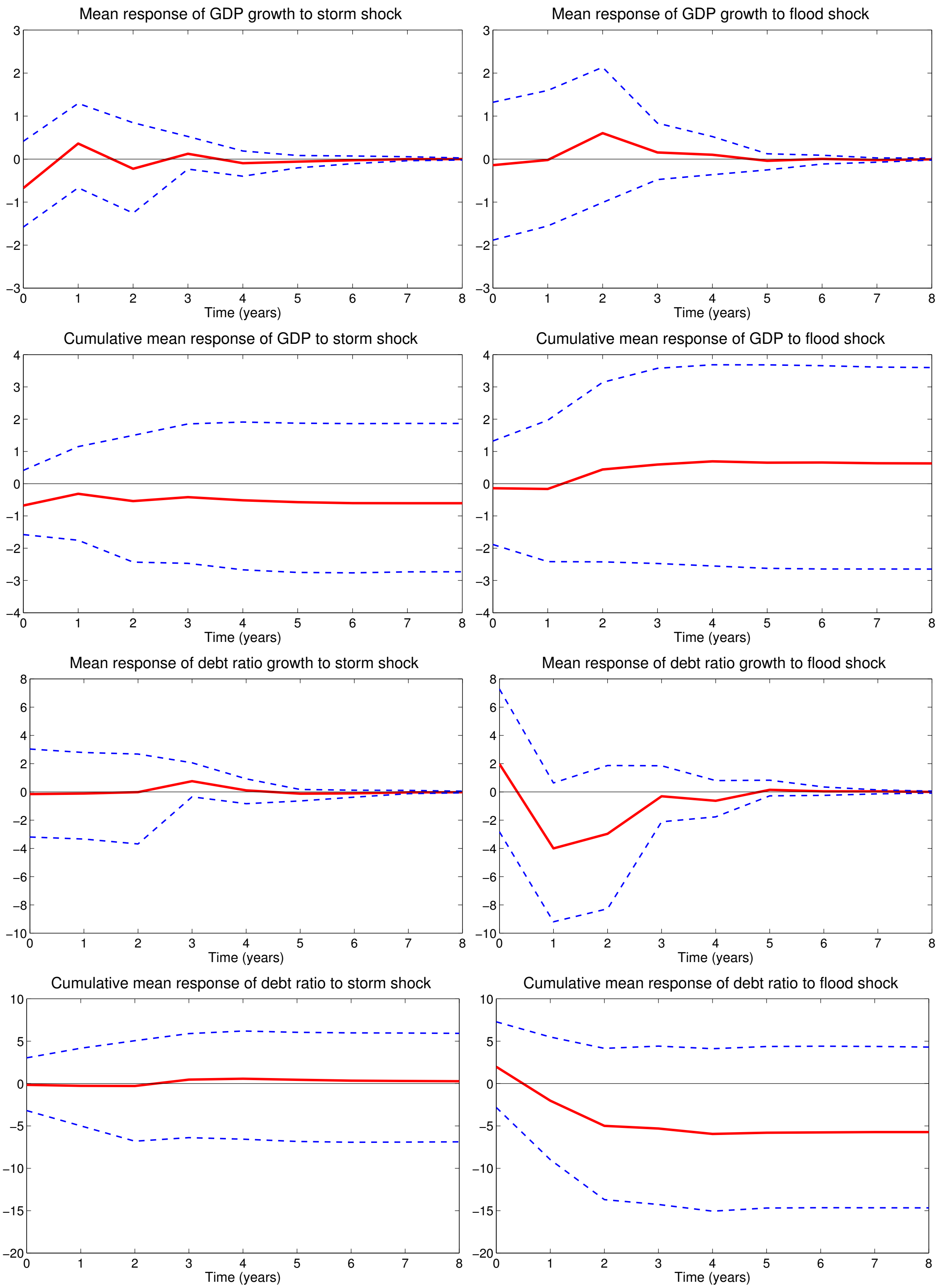

Figure 2. Mean Responses of GDP and Debt to Severe Disasters

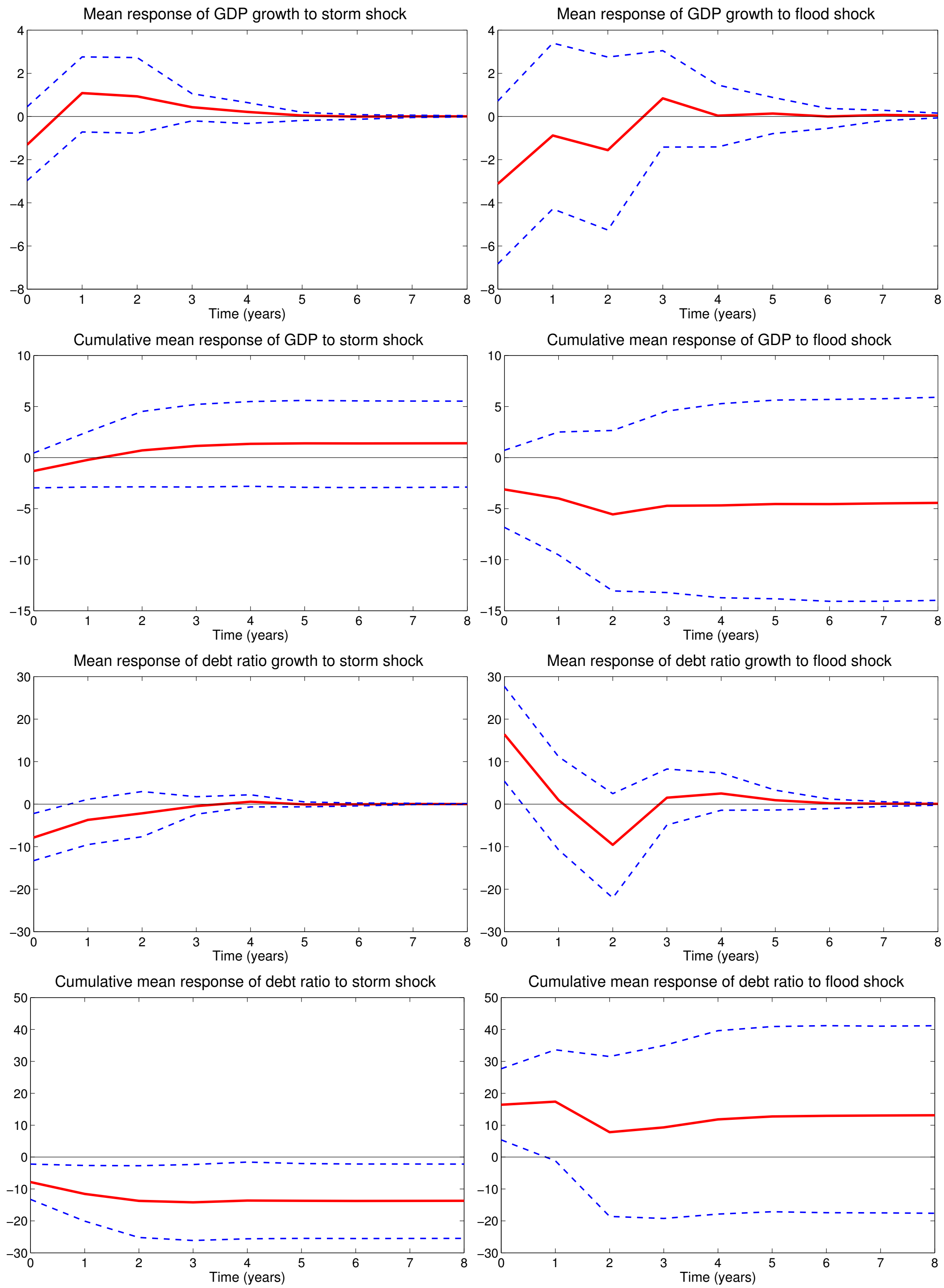

Figure 3. Mean Responses of GDP and Debt to Moderate Disasters Including ODA as an Exogenous Variable

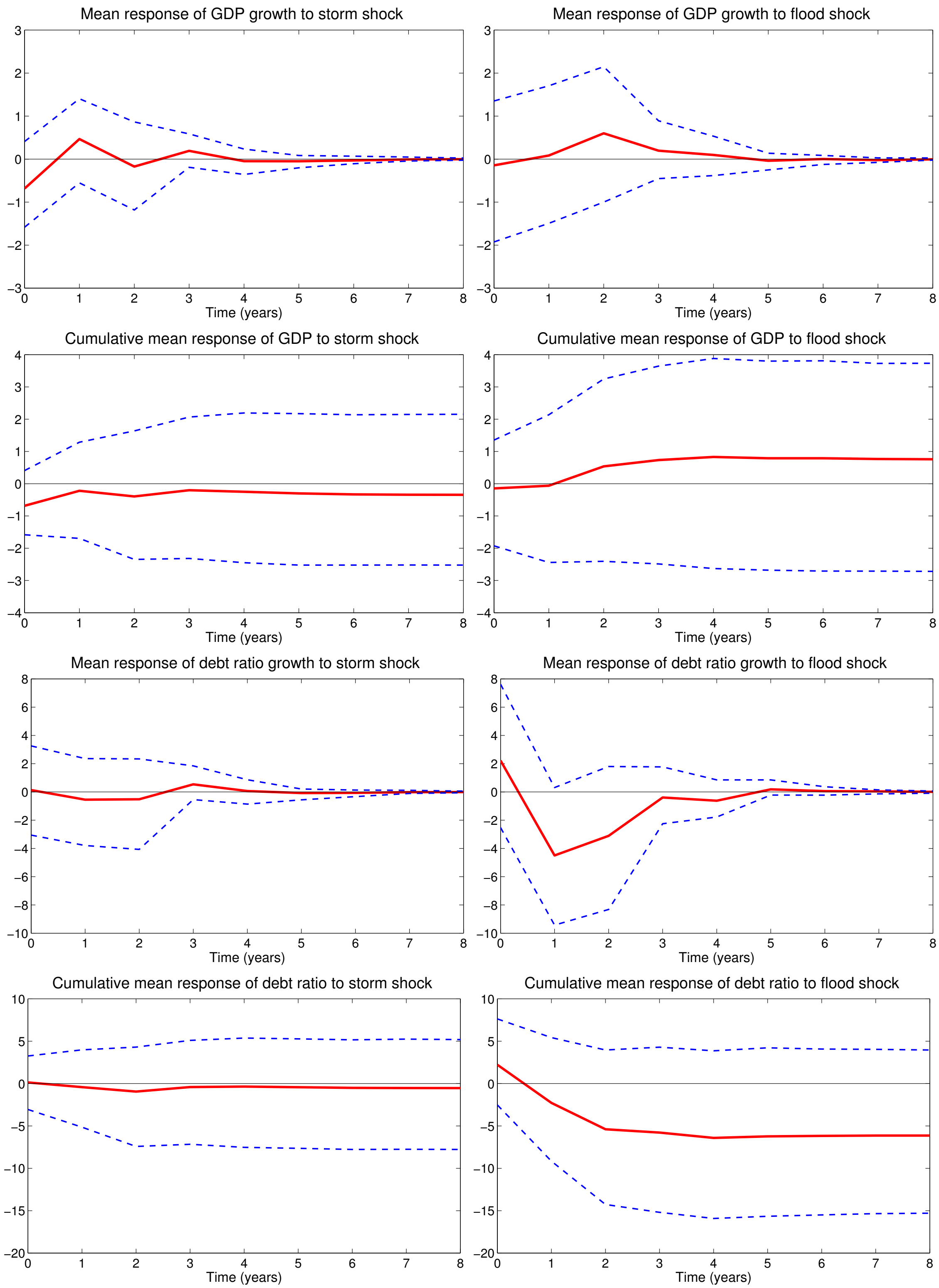

Figure 4. Mean Responses of GDP and Debt to Severe Disasters Including ODA as an Exogenous Variable

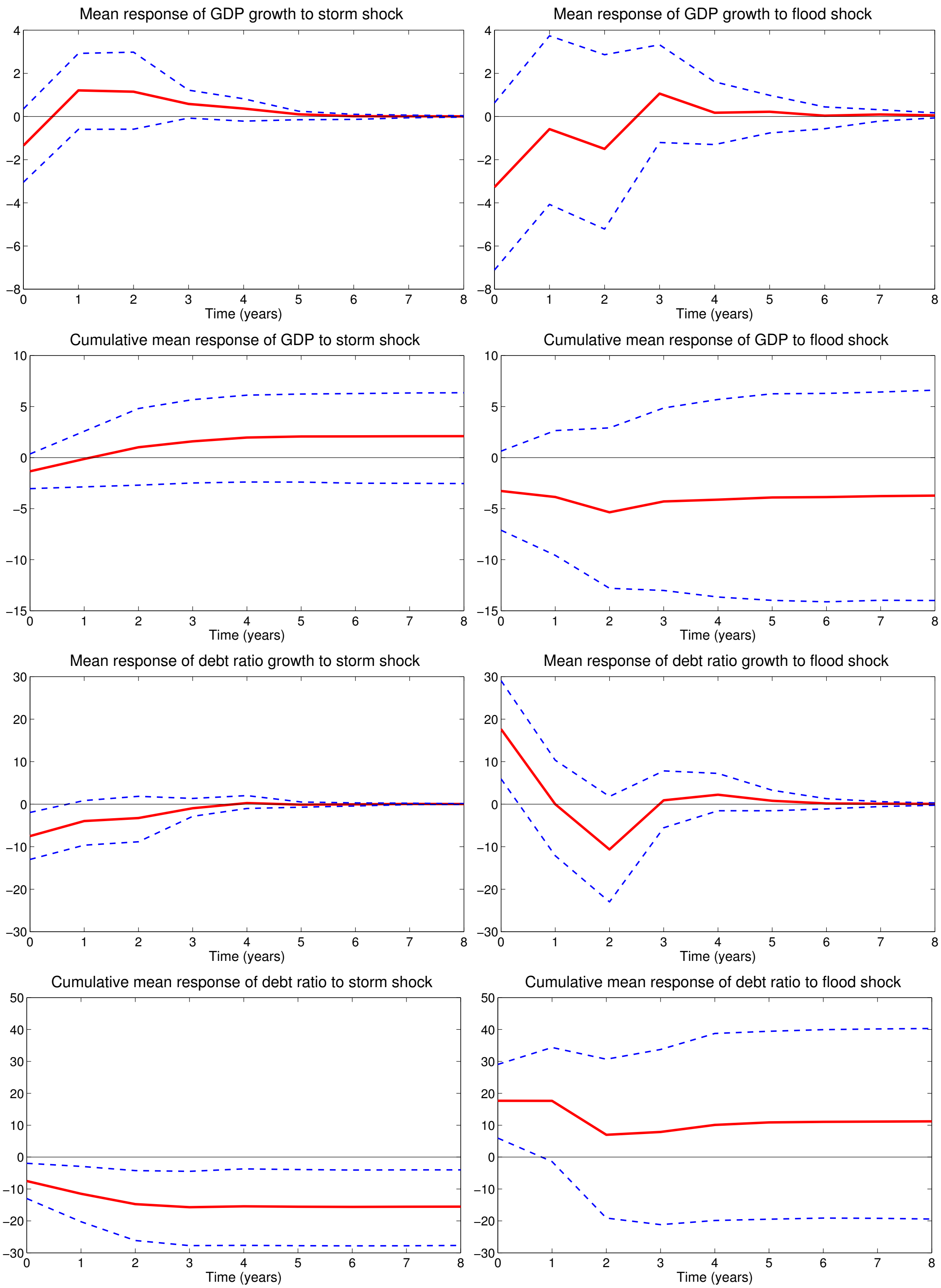

Figure 5. Mean Responses of GDP and Debt to Moderate Disasters Including the Debt Relief Dummy as an Exogenous Variable

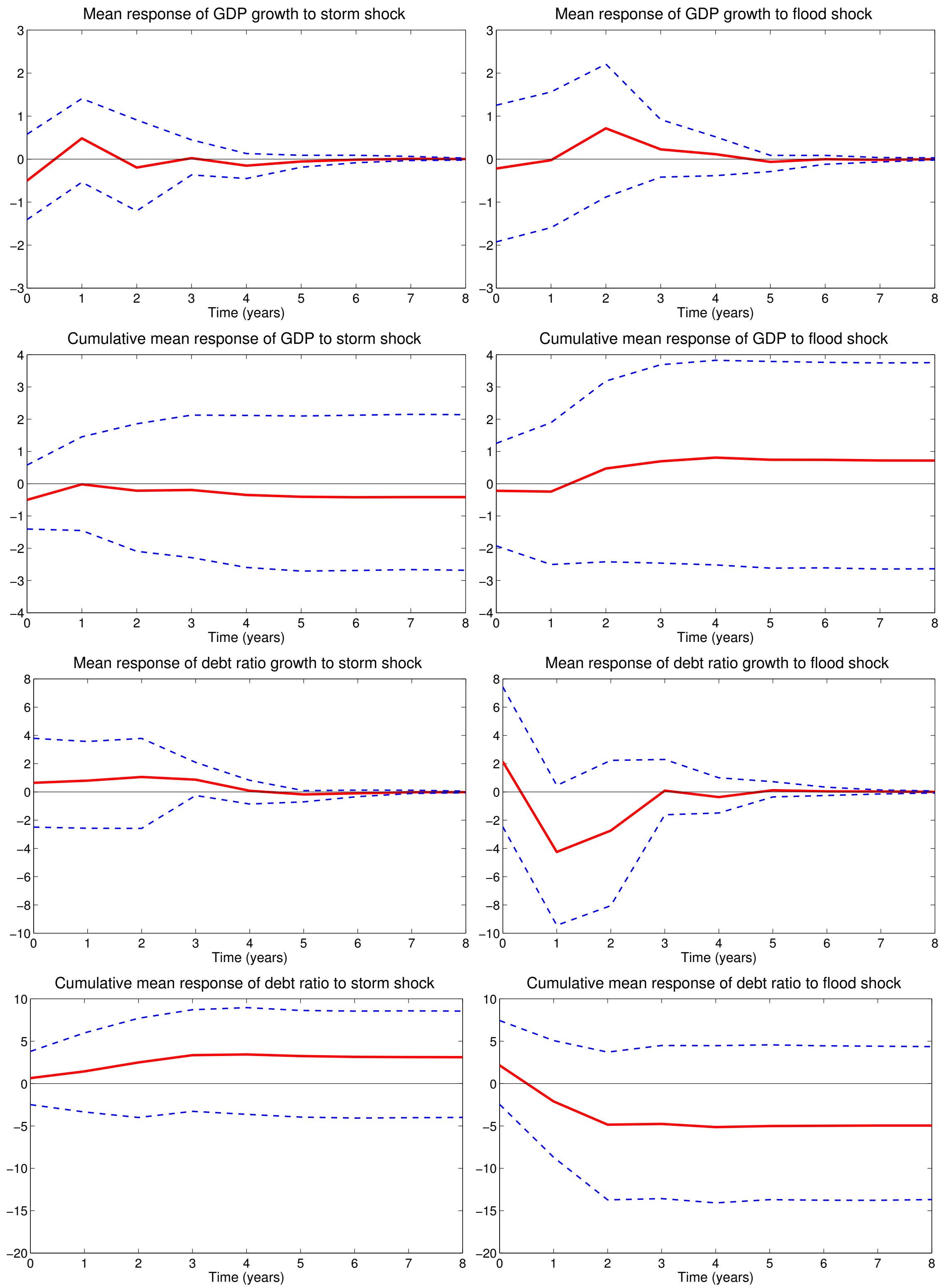

Figure 6. Mean Responses of GDP and Debt to Severe Disasters Including the Debt Relief Dummy as an Exogenous Variable

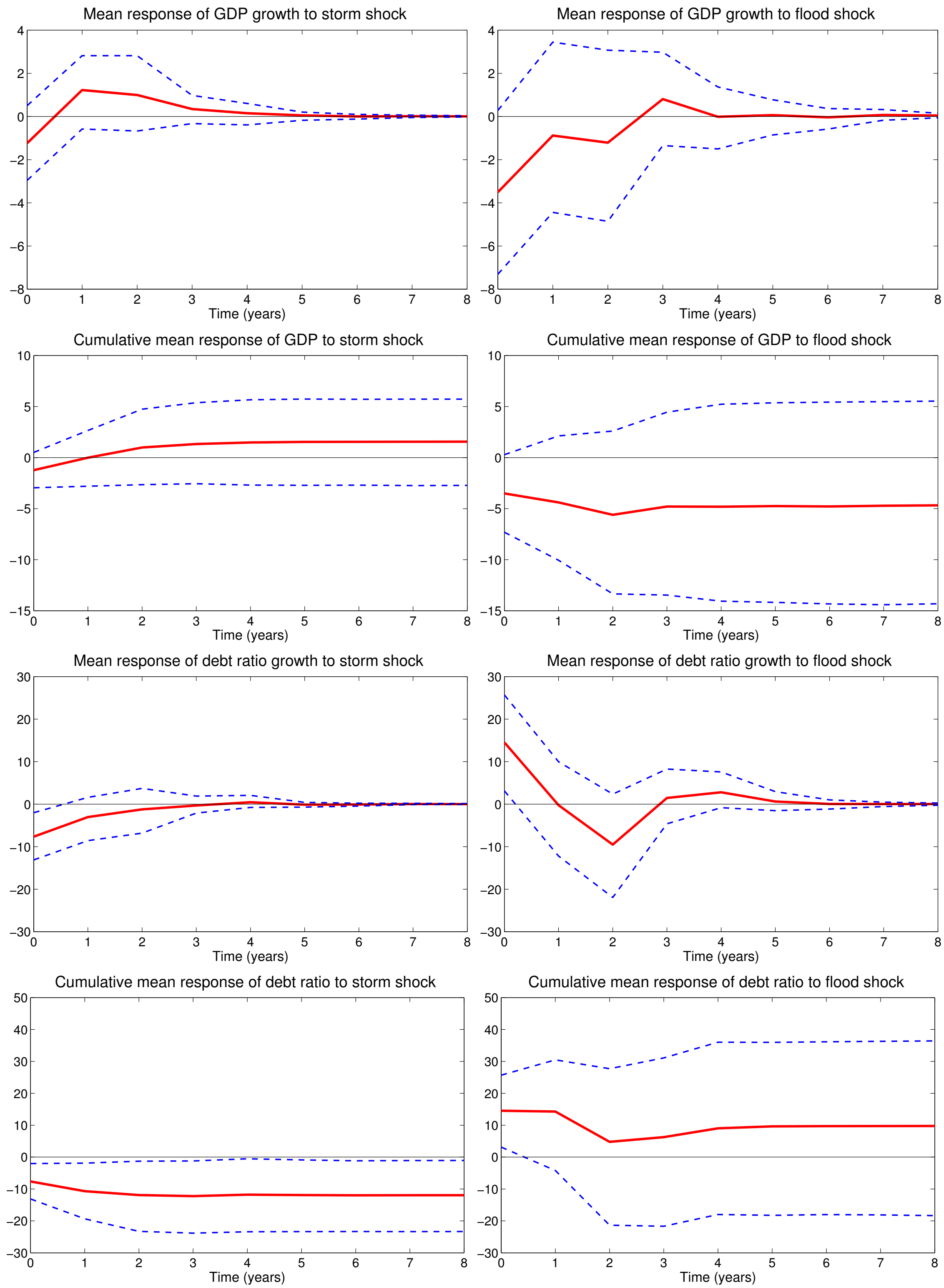

Figure 7. Mean Responses of GDP and Debt to Moderate Disasters (ECCU)

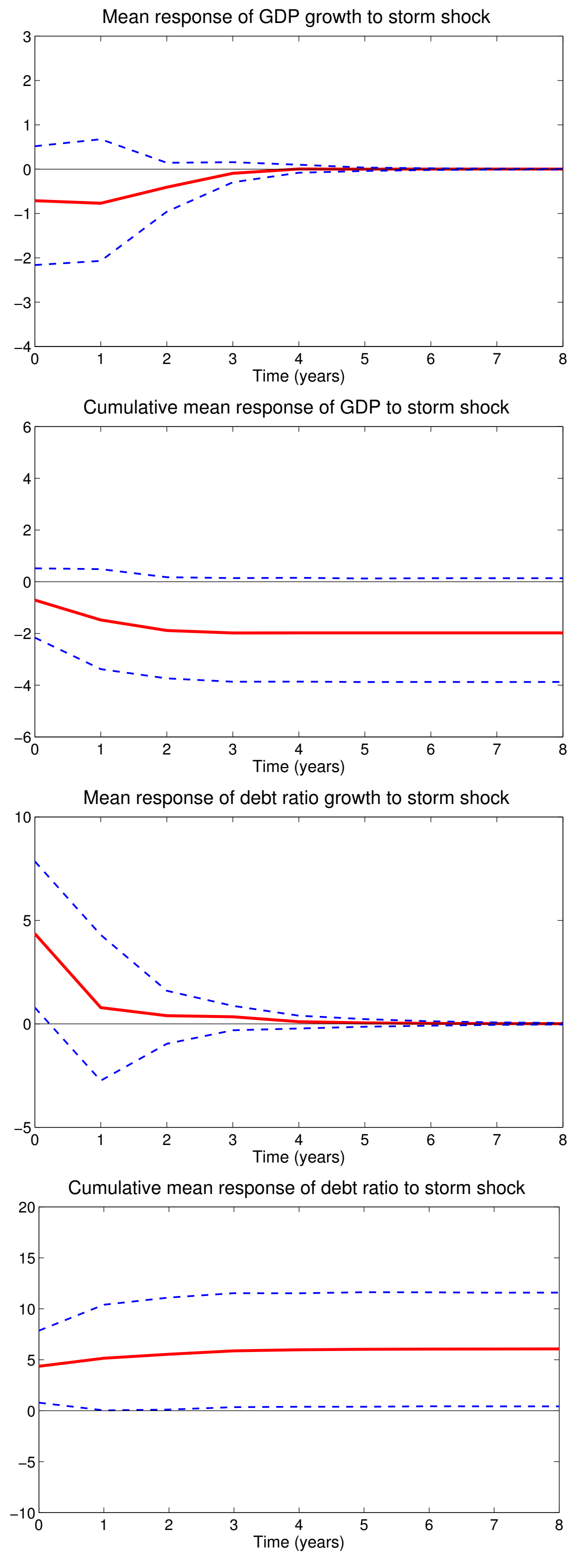

Figure 8. Mean Responses of GDP and Debt to Severe Disasters (ECCU)

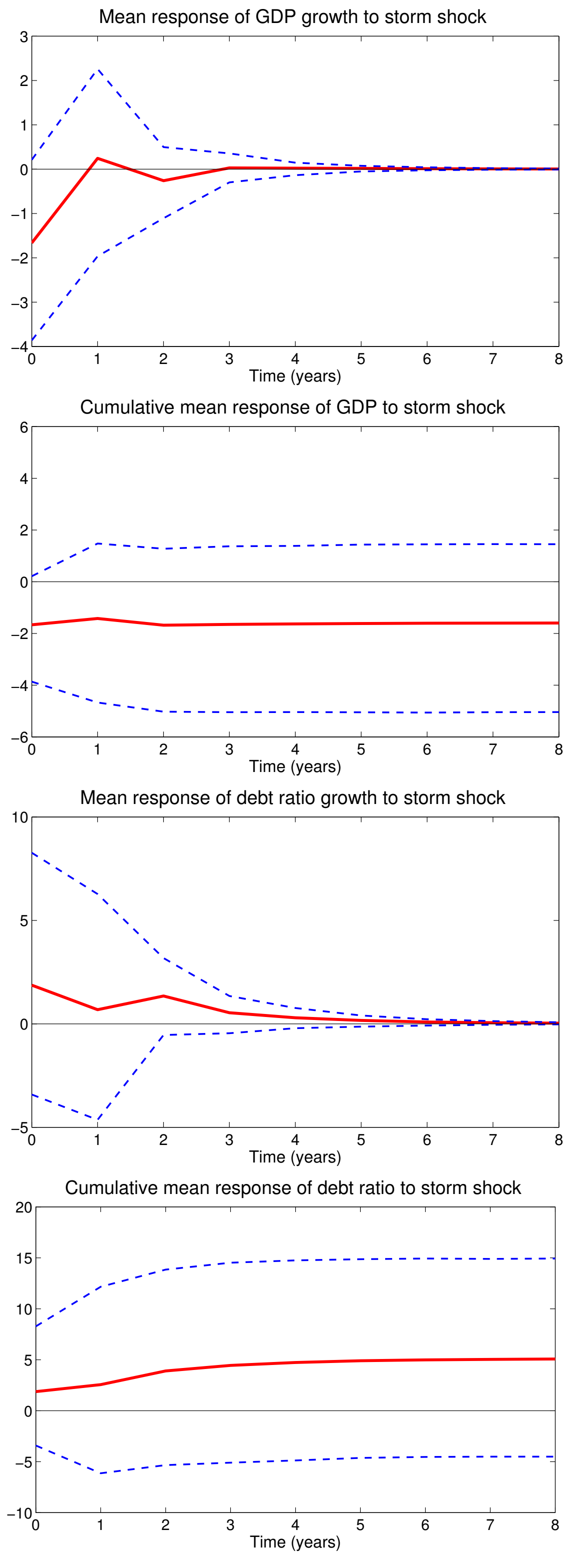

Figure 9. Mean Responses of GDP and Debt to Moderate Disasters Including the Debt Relief Dummy as an Exogenous Variable (ECCU)

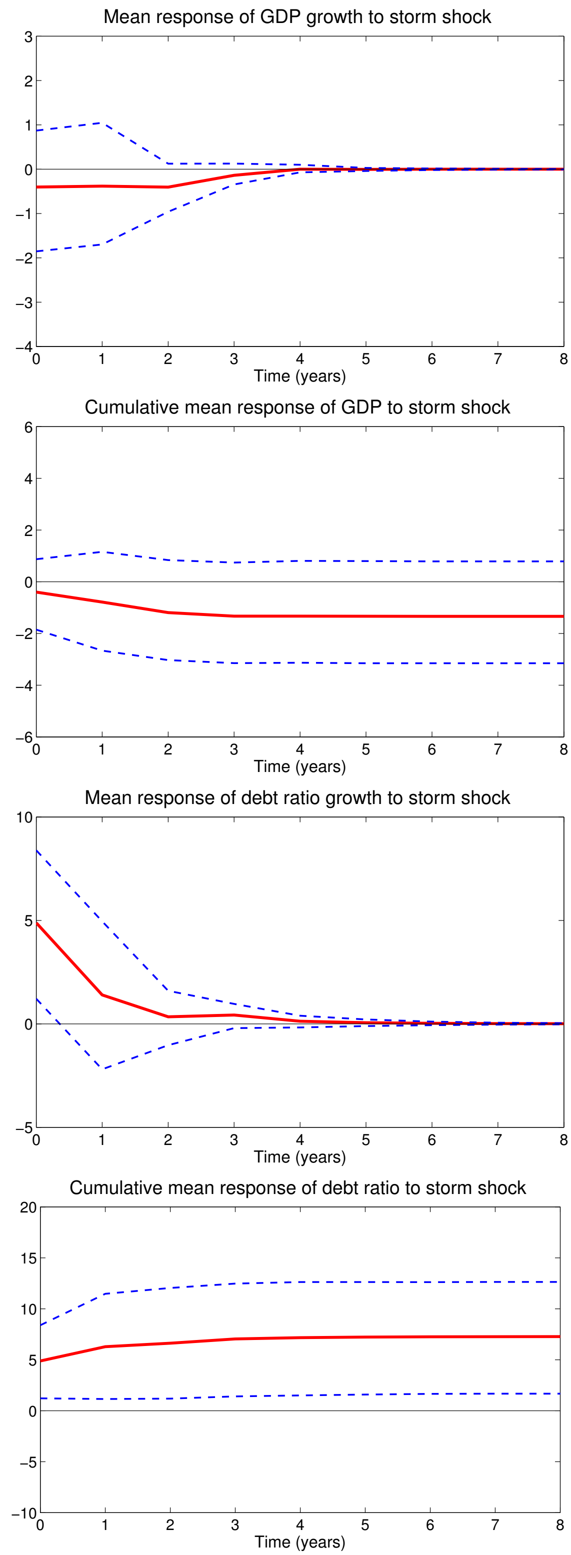

Figure 10. Mean Responses of GDP and Debt to Severe Disasters Including the Debt Relief Dummy as an Exogenous Variable (ECCU)

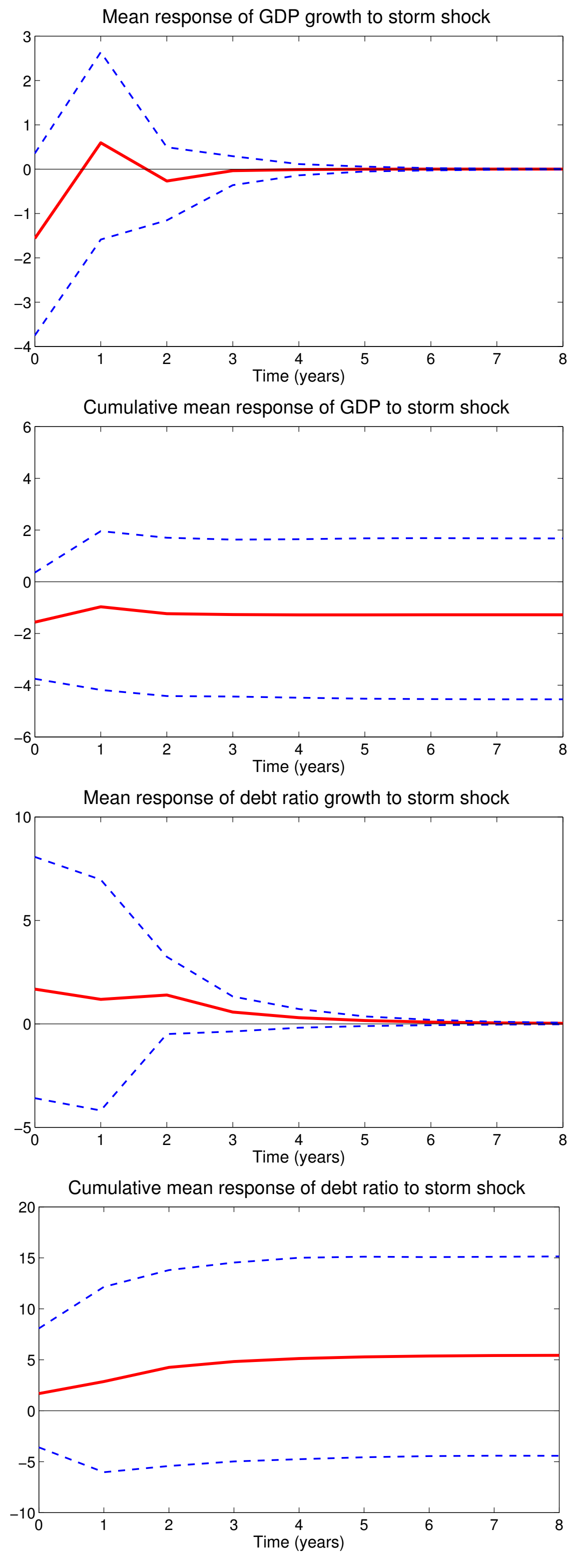

Table 1. Variables and Sources

Variables	Definition	Sources
Per capita GDP growth	Log difference of real per capita GDP	Penn World Tables v.7.0 (variable rgdpch)
Debt ratio growth[1]	Log difference of public debt as percent of GDP	IMF, World Economic Outlook; and Abbas, Belhocine, ElGanainy and Horton (2010)
ODA to GDP growth	Log difference of Official Development Assistance as percent of GDP	OECD.Stat
Investment share of GDP growth	Log difference of investment as a share of real GDP	Penn World Tables v.7.0 (variable ki)
Government share of GDP growth	Log difference of government as a share of real GDP	Penn World Tables v.7.0 (variable kg)
Inflation rate[2]	Inflation rate	World Development Indicators
Trade openness growth	Log difference of the sum of exports and imports as a share of real GDP	Penn World Tables v.7.0 (variable openk)
Financial depth growth	Log difference of domestic credit to private sector as a share of GDP	World Development Indicators
Terms of trade growth	Log difference of the terms of trade of goods and services index	World Economic Outlook
World per capita GDP growth	Log difference of the world's real per capita GDP	Penn World Tables v.7.0 (variable rgdpch)
Debt relief dummy	Defined in the text	Paris Club; OECD.Stat; and World Bank, Global Development Finance
Natural disaster variables	Defined in the text	EM-DAT

[1] The data comes from the World Economic Outlook when available and is complemented with the data of Abbas, Belhocine, ElGanainy and Horton (2010). To fill small gaps in the data a linear interpolation method was used.

[2] The data was complemented with IMF, World Economic Outlook data when it was available and appropriate.

Table 2. Disasters and Debt Relief by Country

Countries	Moderate		Severe		Debt relief
	Storms	Floods	Storms	Floods	
Antigua and Barbuda	4	0	3	0	5
The Bahamas	5	0	0	0	0
Barbados	4	1	0	0	6
Dominica	6	0	3	0	13
Dominican Republic	8	7	2	1	13
Grenada	4	0	1	0	13
Haiti	7	8	2	0	16
Jamaica	8	7	2	2	23
St. Kitts and Nevis	4	0	2	0	5
St. Lucia	3	0	0	0	6
St. Vincent and the Grenadines	5	3	1	0	12
Trinidad and Tobago	3	0	1	0	3
Total	**61**	**26**	**17**	**3**	**115**

Table 3. Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Max.	Dummy[1]
Per capita GDP growth	359	2.39	5.37	−19.82	18.77	...
Debt ratio growth	359	3.01	16.08	−100.48	77.77	...
ODA to GDP growth	359	−0.57	63.45	−281.50	223.10	...
Investment share of GDP growth	359	0.71	16.34	−65.54	73.97	...
Government share of GDP growth	359	−0.11	10.52	−40.42	59.88	...
Inflation rate	359	7.94	9.70	−1.42	77.30	...
Trade openness growth	359	−0.31	9.81	−54.48	67.53	...
Financial depth growth	359	1.59	10.68	−67.63	42.80	...
Terms of trade growth	359	−0.09	9.56	−35.74	76.44	...
World per capita GDP growth	359	2.57	2.64	−3.00	13.50	...
Debt relief dummy	359	0.32	0.47	0	1	115
Storms dummy (moderate)	359	0.17	0.38	0	1	61
Floods dummy (moderate)	359	0.07	0.26	0	1	26
Storms dummy (severe)	359	0.05	0.21	0	1	17
Floods dummy (severe)	359	0.01	0.09	0	1	3

[1] The Dummy column reports the number of cases where the dummy variables take the value of 1.

Table 4. Descriptive Statistics for the ECCU Countries

Variables	Obs.	Mean	Std. Dev.	Min.	Max.	Dummy[1]
Per capita GDP growth	158	3.43	5.05	−13.26	15.88	...
Debt ratio growth	158	3.83	12.79	−25.54	73.92	...
ODA to GDP growth	158	−2.12	73.13	−281.50	223.10	...
Investment share of GDP growth	158	1.06	14.75	−41.87	56.50	...
Government share of GDP growth	158	−0.12	8.52	−40.42	34.49	...
Inflation rate	158	3.50	3.75	−1.42	21.82	...
Trade openness growth	158	−0.99	10.53	−54.48	67.53	...
Financial depth growth	158	2.21	8.01	−17.97	27.50	...
Terms of trade growth	158	−0.41	7.28	−24.50	27.75	...
World per capita GDP growth	158	2.56	2.62	−3.00	13.50	...
Debt relief dummy	158	0.34	0.48	0	1	54
Storms dummy (moderate)	158	0.16	0.37	0	1	26
Storms dummy (severe)	158	0.06	0.24	0	1	10

[1] The Dummy column reports the number of cases where the dummy variables take the value of 1.

Table 5. VAR Stability Condition

Eigenvalues		Modulus
Real	Imaginary	
0.090	0.436*i*	0.446
0.090	−0.436*i*	0.446
−0.132	0.354*i*	0.378
−0.132	−0.354*i*	0.378
−0.343	0.152*i*	0.375
−0.343	−0.152*i*	0.375
−0.256	0.000*i*	0.256
−0.025	0.148*i*	0.151
−0.025	−0.148*i*	0.151
0.174	0.253*i*	0.307
0.174	−0.253*i*	0.307
0.347	0.138*i*	0.373
0.347	−0.138*i*	0.373
0.376	0.000*i*	0.376

Note: All the modulus of the eigenvalues lie inside the unit circle, therefore the VAR satisfies the stability condition.

Table 6. Unit Root Tests

Variables	IPS Panel Unit-root test[1]	Individual Unit-root tests	
		Augmented Dickey-Fuller	Phillips-Perron
Per capita GDP growth	0.0000	25.0	91.7
Debt ratio growth	0.0000	50.0	91.7
Investment share of GDP growth	0.0000	83.3	100.0
Government share of GDP growth	0.0000	75.0	100.0
Inflation rate	0.0000	58.3	58.3
Trade openness growth	0.0000	66.7	91.7
Financial depth growth	0.0000	66.7	100.0
Terms of trade growth	0.0000	83.3	100.0
World per capita GDP growth[2]		0.0092	0.0000
ODA to GDP growth	0.0000	91.7	100.0

Note: The panel unit-root tests show the p-values of the unit-root test with 2 lags, under the null hypothesis that all panels contain a unit root. The individual unit-root tests show the percent of countries that reject the presence of a unit-root with 2 lags, at the 5% significance level.

[1] Im-Pesaran-Shin Panel Unit-root test.

[2] The results for World per capita GDP growth individual unit-root tests (ADF and PP) show the corresponding p-value.

Table 7. Lag Structure Selection

	Number of Lags		
	$p_0 = q_0 = 1$	$p_0 = q_0 = 2$	$p_0 = q_0 = 3$
Information criteria			
Akaike's information criterion	50.93	51.07	51.15
Schwarz bayesian information criterion	52.13	53.14	54.10
Likelihood ratio test			
Log-likelihood[1]	99.89	113.13	90.16
Chi-square critical value	98.48	98.48	98.48
Number of restrictions	11	11	11

Note: For the information criteria the preferred model is the one with the minimum information criteria value. The likelihood ratio test works under the null hypothesis that the set of variables was generated from a Gaussian VAR with $p_0 = q_0$ lags against the alternative specification of $p_1 = q_1 = p_0 + 1$ lags. If log-likelihood $>$ critical value, then reject the null hypothesis at the 5% significance level.

[1] Using the modified likelihood ratio test suggested by Sims (1980) to take into account the small sample bias.

Table 8. Granger Causality Test of ODA and Debt Relief Dummy to the Endogenous Variables

Variable	Log-likelihood	Chi-square critical value	Number of restrictions
Debt relief dummy	16.49	23.68	14
ODA to GDP growth	16.31	23.68	14

Note: Under the null hypothesis that the debt relief dummy and ODA to GDP growth are exogenous with respect to the endogenous variables represented by $\mathbf{y}$. If log-likelihood $>$ critical value, then reject the null hypothesis at the 5% significance level.

Table 9. Granger Causality Test of the Debt Relief Dummy to the Exogenous Shocks

Variable	Log-likelihood	Chi-square critical value	Number of restrictions
Debt relief dummy (moderate disasters)	5.91	9.49	4
Debt relief dummy (severe disasters)	2.79	9.49	4

Note: Under the null hypothesis that the debt relief dummy is exogenous with respect to the disaster variables. If log-likelihood $>$ critical value, then reject the null hypothesis at the 5% significance level.

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Appendix A. Additional Figures

Figure A1. Mean Responses of GDP to Moderate Disasters

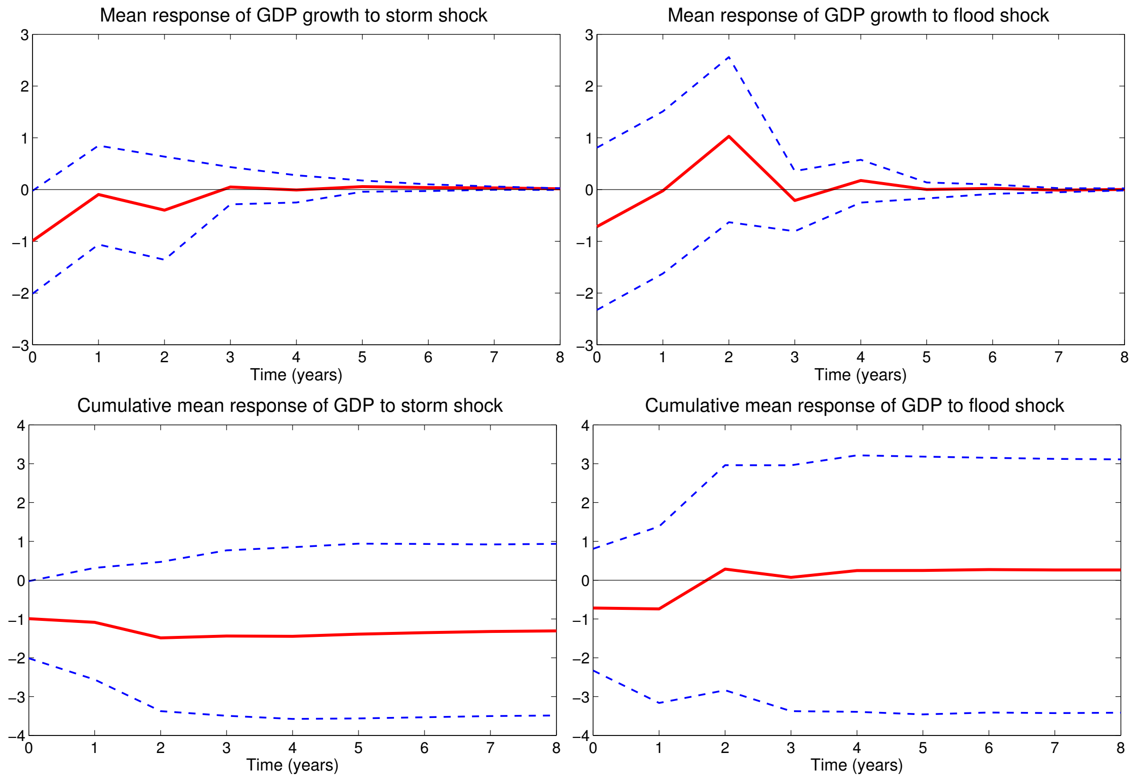

Figure A2. Mean Responses of GDP to Severe Disasters

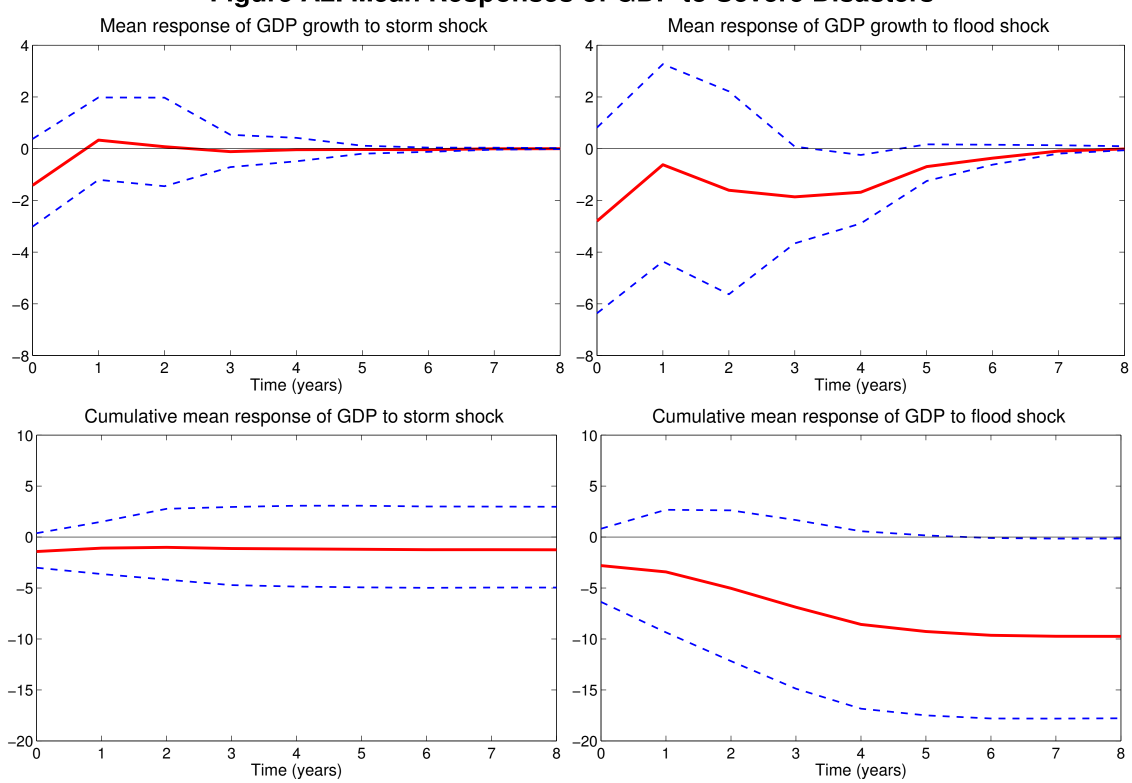

Figure A3. Mean Responses of GDP and Debt to Moderate Disasters (Using Total Affected as an Alternative Measure of Intensity)

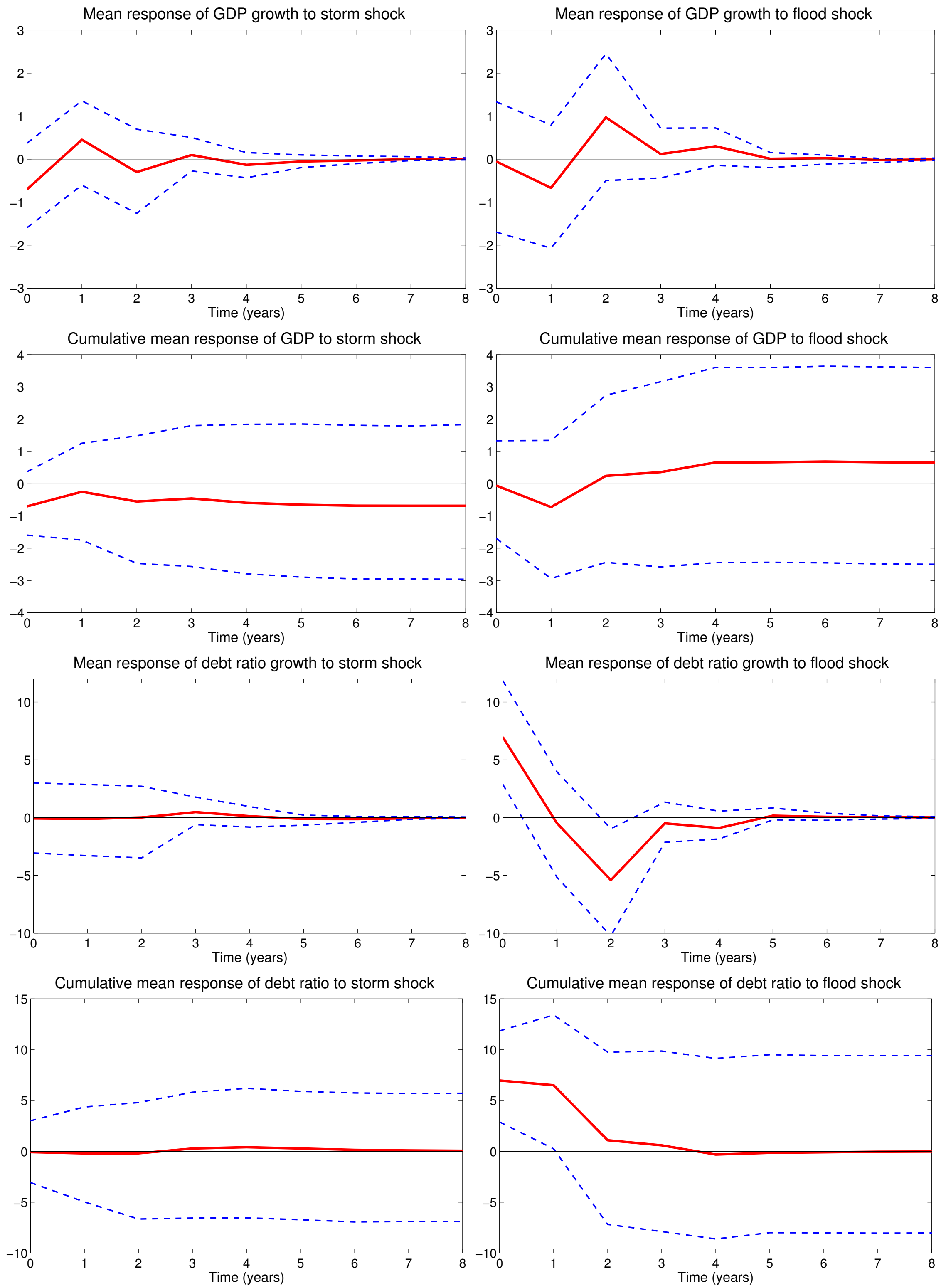

Figure A4. Mean Responses of GDP and Debt to Moderate Disasters Including the Debt Relief Dummy as an Exogenous Variable (Using Total Affected as an Alternative Measure of Intensity)

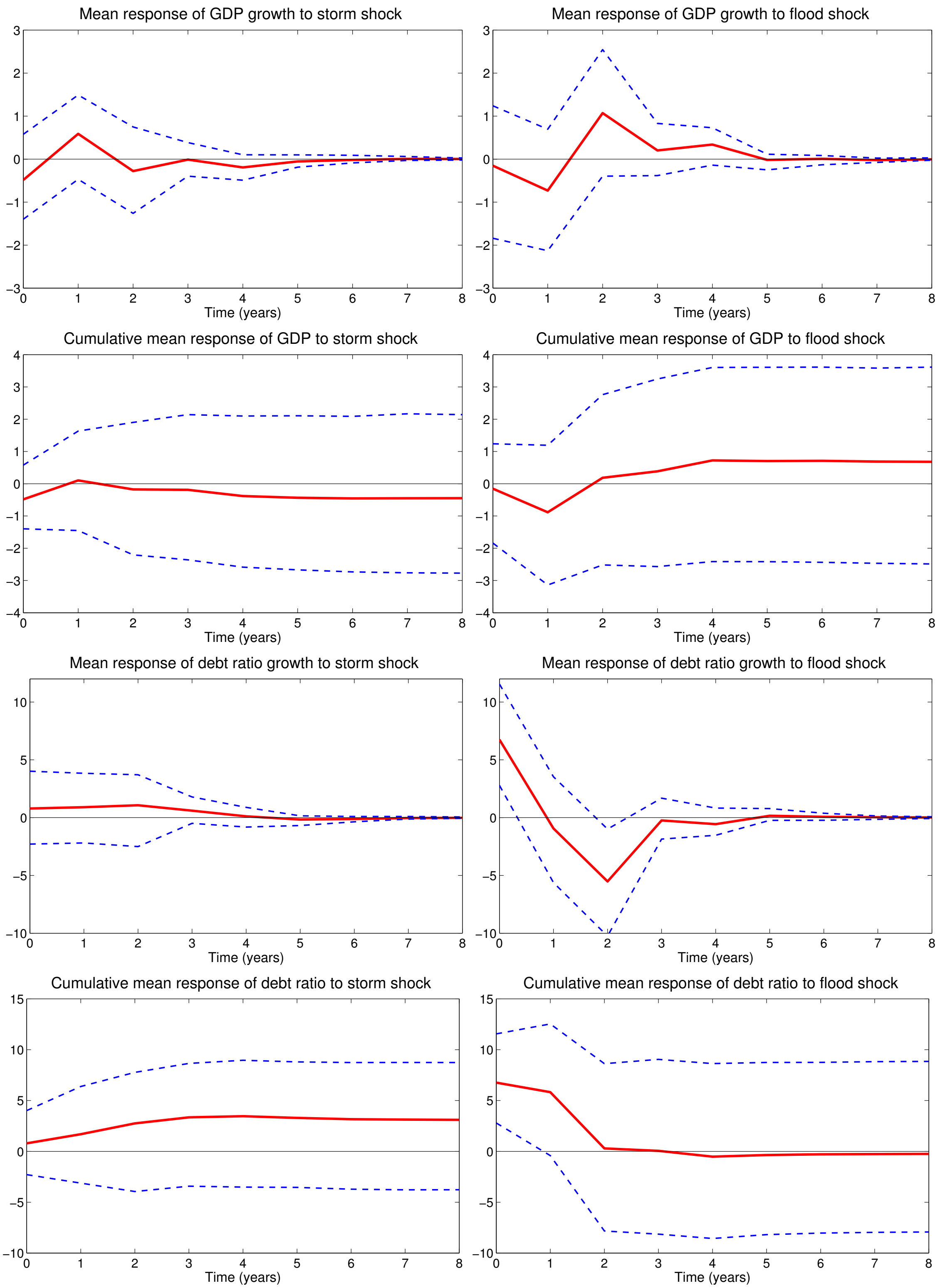

Figure A5. Mean Responses of GDP and Debt to Moderate Disasters (Using Damages as an Alternative Measure of Intensity)

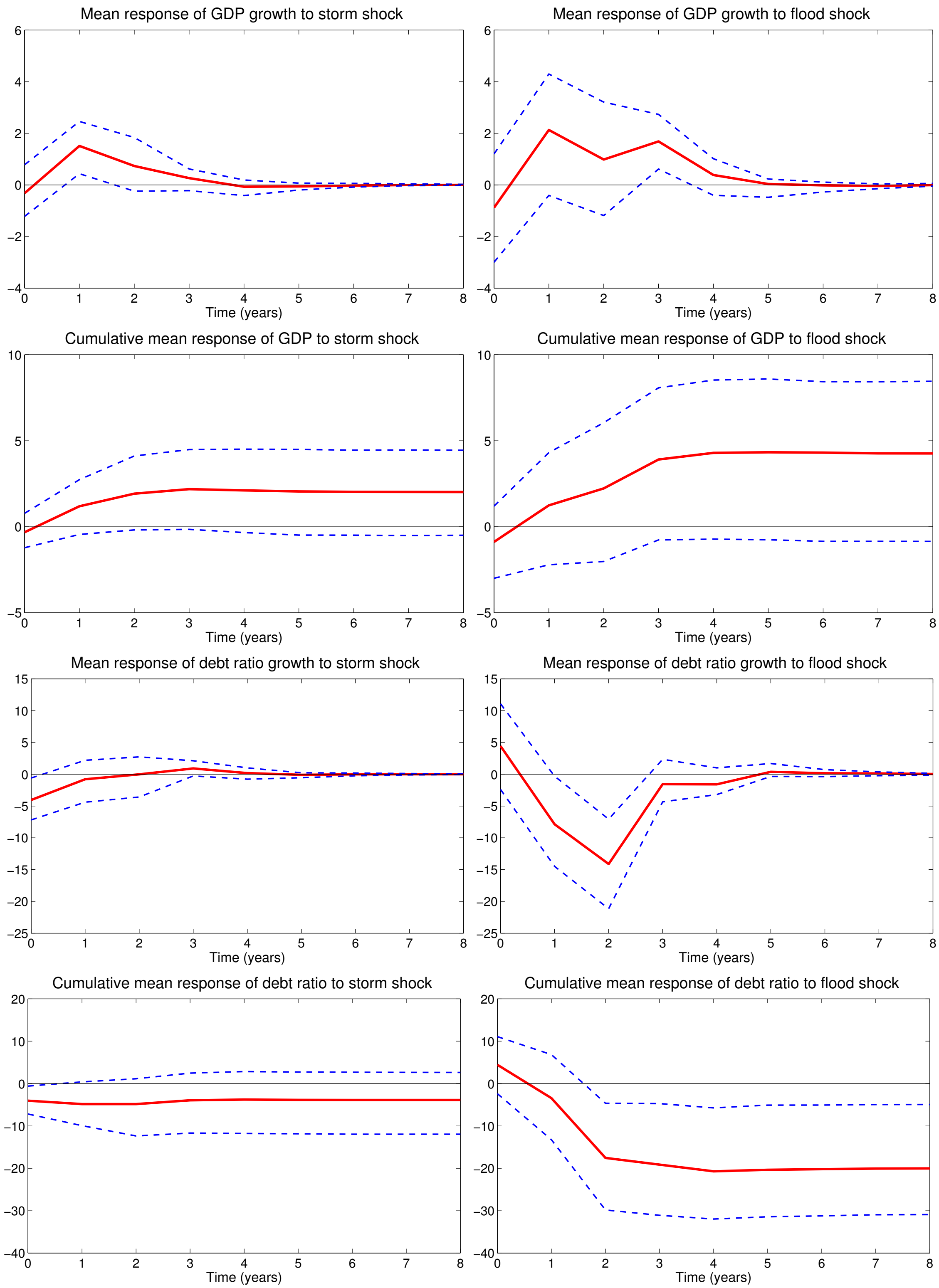

Figure A6. Mean Responses of GDP and Debt to Moderate Disasters Including the Debt Relief Dummy as an Exogenous Variable (Using Damages as an Alternative Measure of Intensity)