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Natural Disasters and Scarring Effects

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ABSTRACT: This paper uses a novel empirical approach, following the literature on hysteresis, to explore medium-term scarring of natural disasters for countries vulnerable to climate change. By quantifying the dynamic effects of natural disasters on real GDP per capita for a large number of episodes using a synthetic control approach (SCA) and focusing on severe shocks, we demonstrate that a persistently large deviation of real GDP per capita from *the counterfacutal trend* exists five years after a severe shock in many countries. The findings highlight the importance and urgency of building ex-ante resilience to avoid scarring effects for countries prone to natural disasters, such as those in the Caribbean region.

WORKING PAPERS

Natural Disasters and Scarring Effects

Prepared by Weicheng Lian, Jose Ramon Moran, and Raadhika Vishvesh[1]

I.   Introduction

Natural hazards present significant macroeconomic challenges for small countries, especially for vulnerable developing island states, where *natural disasters* occur frequently and inflict large damage to their economy.[2] To illustrate this, we present in Figure 1 some stylized facts about the Caribbean region. The disaster frequency in the Caribbean, measured as the number of natural disasters every year per billion people, is around 10 times the world average. The economic damage each year in the Caribbean, relative to the GDP size, can be around 20 times higher than the world average in recent decades. The disaster frequency and total disaster cost have had upward trends, which can be intensified by climate change going forward.
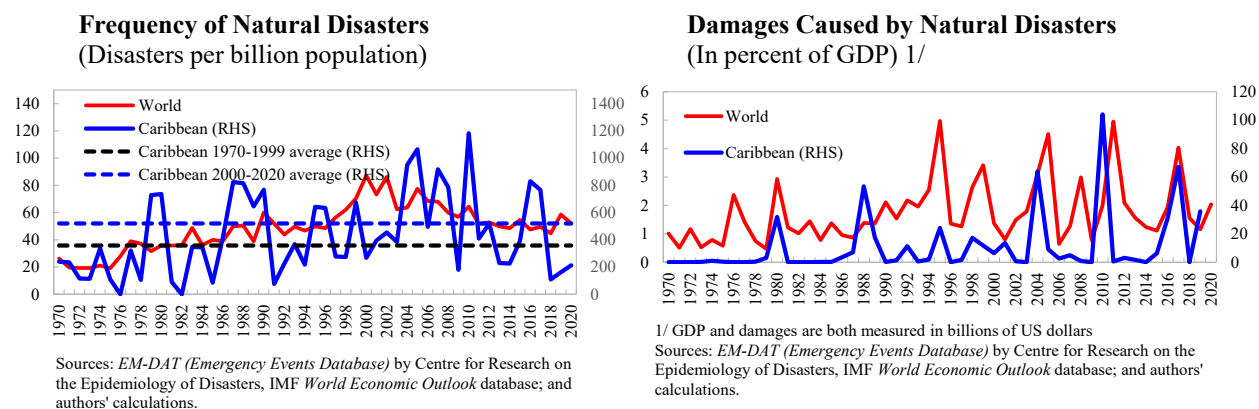
The large total damage of natural disasters in Caribbean countries reflects their high exposure to severe natural disasters, as we document in this paper. Potentially, severe disasters can cause a persistent disruption to aggregate production for these economies—an issue that is, however, not clearly understood in the current literature on the economic impact of natural disaster shocks. Existing studies tend to focus on short-run output effects, an average natural disaster event rather than severe ones, or severe disasters in countries that seem to have a strong capacity to recover from the shock.[3]

This paper has two goals. First, we use a technique to quantify the dynamic impact of severe natural disaster shocks on real GDP per capita that, to the best of our knowledge, has not been applied to small island developing economies.[4] We use the Synthetic Control Approach (SCA), which was developed by Abadie and Gardeazabal (2003) and Abadie et al (2010), and combine this technique with a local

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[2] Severe natural hazards may or may not cause severe natural disasters, depending on the resilience of the economy system. Strobl (2012) uses a wind-filed model to measure the destructiveness of hurricanes.

[3] An incomplete list of recent studies includes Noy (2009), Cavallo et al. (2013), Acevedo (2014), Felbermayr and Goschl (2014), Barone and Mocetti (2014), Tran and Wilson (2020), and Cavallo et al. (2021).

[4] Analytical tools have evolved in quantifying the growth impact of natural disasters. An early attempt was made by Albala-Bertrand (1993), who compares macro indicators before and after natural disaster shocks (Crowards (1999), Charvériat (2003), and Rasmussen (2004)). The panel VARX method is later utilized by several studies to analyze the dynamic impact (Raddatz (2009), Fomby, Ikeda and Loayza (2013), and Acevedo (2014)). These studies tend to find negative impact for a severe shock in developing countries as opposed to in developed countries but no consistent patterns regarding the role of the disaster type. Fomby, Ikeda and Loayza (2013) find that "droughts have a negative effect on both agricultural and non-agricultural growth. In contrast, floods tend to have a positive effect on economic growth in both major sectors. Earthquakes have a negative effect on agricultural growth but a positive one on non-agricultural growth. Storms tend to have a negative effect on gross domestic product growth but the effect is short-lived and small." By contrast, Acevedo (2014) notes that both storms and floods have a negative effect on growth. More recently, several studies make use of the synthetic control approach. Cavallo et al. (2013) analyze severe disasters in a global sample and find no significant impact of natural disasters on economic growth in either the long or short term, except in events succeeded by political instability. Barone and Mocetti (2014) study two earthquakes in Italy and find no significant short-term growth impact but better long-run growth when institutional quality is stronger.

Figure 1 Frequency of Natural Disasters and the Economic Damage in the Caribbean Region

Frequency of Natural Disasters
(Disasters per billion population)

Sources: *EM-DAT (Emergency Events Database)* by Centre for Research on the Epidemiology of Disasters, IMF *World Economic Outlook* database; and authors' calculations.

Damages Caused by Natural Disasters
(In percent of GDP) 1/

1/ GDP and damages are both measured in billions of US dollars
Sources: *EM-DAT (Emergency Events Database)* by Centre for Research on the Epidemiology of Disasters, IMF *World Economic Outlook* database; and authors' calculations.

projection method (LPM) (Jorda (2005)) to do the estimation. Second, we not only estimate the effects, but also try to reveal the underlying channels for persistent effects of natural disaster shocks on real GDP per capita to emerge. We document several patterns to differentiate across competing explanations.

We design our analysis as a two-step approach. In the first step, we apply the SCA to 370 natural disaster episodes that happened in our sample (which mainly consists of small island developing economies) after 1980.[5] For each of these episodes, the SCA allows us to use countries at a similar stage of economic development and with a similar exposure to global shocks to construct a synthetic control unit for the country affected by the disaster in that episode. The high exposure to global shocks of our sample makes such an application of the SCA resemble those that study regions having similar exposure to aggregate shocks at the country level. Despite this similarity, unlike existing regional studies that use the SCA, we find it difficult to get a very good match between the synthetic control and the treated country in terms of the trajectory of real GDP per capita before the natural disaster shock for many episodes—an issue we refer to as that of an imperfect synthetic control later.

In the second step, we mitigate this issue of an imperfect synthetic control using various econometric techniques, especially by utilizing an LPM. We utilize the LPM to obtain an impulse response of real GDP per capita to the natural disaster shock, following the literature on hysteresis in output, and for example, the analysis conducted by Cerra and Saxena (2008) on the persistent effects of financial crises and political conflicts on output. The results from the first step help the LPM exercise in two ways. First, we use the decline in real GDP per capita on impact, which is estimated using the SCA in the first step,

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[5] Our sample also consists of developing countries in Latin America, given they are exposed to similar business cycles as small island developing economies in the Caribbean. Few severe natural disasters, however, happened in these economies.

rather than the immediate economic damage to measure the size of the natural disaster shock. Since the medium-term output effects come from a persistent disruption to production capacity, which should show up also in the initial period, we would argue that our shock measure is a better one than the immediate economic damage in terms of capturing the medium-term output effects. Our estimation results support this argument.

Second, the SCA results from the first step help us control for post-shock noises in the LPM exercise. Instead of using real GDP per capita in different periods after the shock as the dependent variables in the LPM regressions, we use the difference between real GDP per capita of the treated country and that of the synthetic control in corresponding periods as the dependent variables. This helps control for the effects of global shocks on real GDP per capita that happened after the natural disaster shock for which we try to understand its dynamic effects.

We have several findings. First, there is a suggestive pattern to supports the use of the decline in real GDP per capita on impact as the shock size in the LPM exercise: it is significantly and positively correlated with the damage of natural disasters reported by the EM-DAT. For example, the real GDP per capita declines by around 2 percent on impact, for an immediate economic damage of 30 percent of GDP. The relationship seems plausible in economic terms, noting that the decline in real GDP per capita on impact may underestimate the full-year impact as many severe natural disasters in our sample happened in the second half of the year.

Second, we find that severe natural disasters lead to a persistent deviation of real GDP per capita from the counter-factual trend, with little sign of converging back towards the trend even five years after the shock. When a natural disaster shock causes an immediate economic damage of 30 percent of GDP, after the initial decline of real GDP per capita by 2 percent, its deviation from the (counter-factual) trend is estimated to widen in the five-year horizon after the shock, reaching around 8 percent of GDP in the fifth year. One caveat is that we use the intercept of the LPM estimation results and the coefficient of the initial decline in real GDP per capita on impact to reach this finding, but the results are qualitatively the same if we use the coefficient of the initial decline in real GDP per capita only.

We obtain three sets of patterns to help differentiate the underlying channels. First, we find that unlike severe natural disasters, small shocks (i.e. those with small immediate economic damage) do not have persistent effects on real GDP per capita. This pattern suggests that real GDP per capita in our sample does not follow a stochastic trend (otherwise, shocks always cause a persistent deviation of real GDP per capita from the counter-factual trend). Second, we find that if a country's public debt as a share of GDP is

high, the medium-term effects of severe natural disaster shocks on real GDP per capita are amplified.[6] Third, we find that natural disasters of large immediate economic damage tend to drive the value-added of agriculture and tourism sectors to be persistently below the pre-shock trend, which is not the case for other sectors.

These findings have strong policy implications, with three aspects. First, they point to a larger benefit from building resilience ex ante to natural disasters compared with a "counter-factual" world in which even severe natural disasters do not cause persistent output loss. Second, by making severe disasters more frequent and intense, climate change would imply stronger benefits of avoiding scarring effects of natural disasters. Third, other ramifications of scarring effects further add to the benefit of building resilience ex ante. One possibility is that persistent output loss causes a lower tax base, which by exacerbating the indebtedness of the country, can potentially create vicious cycles. Avoiding such vicious cycles is also an important benefit of building resilience ex ante.

Our findings contribute to the literature on hysteresis in output, as is recently summarized by Cerra, Fatás, and Saxena (2020).[7] Existing studies in this literature have not systematically look at the scarring effects of natural disaster shocks, an issue that urgently needs to understand given the challenges presented by climate change. As elaborated later, our findings in this paper reveal interesting issues for future research.

The rest of the paper is organized as follows. Section II presents empirical methodology. Section III describes the data and sample. Section IV reports the findings regarding the dynamic effects of natural disasters on real GDP per capita. Section V explores the underlying channels of medium-term output effects. Section VI concludes.

II.   Empirical Methodology

Quantifying the dynamic effects of natural disaster shocks on real GDP per capita for small island developing countries is challenging. Cavallo et al. (2013) discuss the advantage of the SCA relative to conventional econometric techniques for obtaining such effects. For small island developing economies, one may further argue that they are highly exposed to global shocks and are experiencing economic convergence, the SCA tries to use countries at a similar stage of economic development and having a similar

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[6] We obtain this result by defining a dummy based on whether the public debt exceeds a certain threshold (70 percent of GDP), and from a triple interaction term, defined based on this dummy, a dummy indicating whether the immediate economic damage of the natural disaster is large, and the initial decline in real GDP per capita on impact. The results are not sensitive to this choice of public debt threshold, which is not surprising as they are driven by the comparison between an average episode below the threshold and that above the threshold.

[7] For example, two empirical studies in this literature are Cerra and Saxena (2009, 2017).

exposure to global shocks to form a control unit for the country affected by the natural disaster shock. These features further favor the SCA over conventional econometric tools.

A. The Synthetic Control Approach

Consider a sample that consists of $J + 1$ units. Without loss of generality, the unit $J = 1$ is the treated unit, i.e., affected by a shock at time T_0, and the rest of the sample is referred to as the donor pool.

The SCA tries to estimate the impact of the shock on outcome variable Y for this unit at time t:

$$\tau_{1t} = Y_{1t}^I - Y_{1t}^N,$$

where Y_{1t}^I is the outcome observed at time t and Y_{1t}^N the outcome should the shock have not occurred. The challenge is Y_{1t}^N is not directly available in the data for $t \geq T_0$.

The SCA deals with this challenge by replacing Y_{1t}^N with a weighted average of the outcomes of other units. It estimates $\hat{\tau}_{1t}$ (instead of τ_{1t}):

$$\hat{\tau}_{1t} = Y_{1t}^I - \sum_{j=2}^{J+1} w_j Y_{jt},$$

where the weights $\boldsymbol{W} = (w_2, \ldots, w_{J+1})$ are non-negative and add up to one. They are estimated in two steps.

In the first step, given a set of non-negative constants $\boldsymbol{V} = \{v_1, \ldots, v_k\}$, the SCA minimizes the following objective by choosing $\{w_2(\boldsymbol{V}), \ldots, w_{J+1}(\boldsymbol{V})\}$:

$$\left(\sum_{h=1}^{k} v_h (X_{h1} - w_2(\boldsymbol{V})X_{h2} - \cdots - w_{J+1}(\boldsymbol{V})X_{hJ+1})^2 \right)^{1/2},$$

where $\{X_1, X_2, \ldots, X_k\}$ are referred to as the predictor variables, which are chosen to ensure that the synthetic control and the treated unit share similar characteristics that can affect the outcome Y.

In the second step, the SCA chooses $\boldsymbol{V} = \{v_1, \ldots, v_k\}$ that minimize the following objective:

$$\sum_{\tau \in \tau_0} \left(Y_{1t} - w_2(\boldsymbol{V})Y_{2t} - \cdots - w_{J+1}(\boldsymbol{V})Y_{J+1t} \right)^2$$

for some set $\tau_0 \in \{1, 2, \ldots, T_1\}$ where $T_1 \leq T_0$.

The confidence band of $\hat{\tau}_{1t}$ can be obtained through a permutation method and see Cavallo et al. (2013) for an example.

Our application of the SCA follows closely that of Cavallo et al. (2013), who quantify the dynamic effects of natural disasters also in a cross-country context, but with a focus on the natural disaster episodes of large countries. We follow them in choosing predictor variables, and in a similar spirit, in restricting episodes to be those whose outcome trajectory of the synthetic control matches that of the treated country well.

Predictor variables. We choose the same list of predictor variables: trade openness, capital stock, land, population, schooling, latitude, and a democracy index, as in Cavallo et al. (2013). Moreover, we add tourism sector's share in GDP as an additional one, as several other studies in the SCA literature have sector share as a predictor variable—Table 1 provides a summary for selected studies. Given a data quality issue, we do not have a good coverage of all the predictor variables for our countries.

Donor pools. We construct episode-specific donor pools. For each episode, the donor pool is chosen by restricting the sample countries to those at a similar development stage as the treated country. To deal with a data coverage issue—predictor variables are not available for all countries, which can affect the match between the synthetic control and the treated country (in terms of the trajectory of real GDP per capita)—we construct the donor pool as the combination of potential donor pool countries that has the best match between the synthetic control and the treated country. An algorithm, presented in Annex II, explains the details.

Dropping episodes with a poor match. We exclude episodes whose fifth-year effect $\hat{\tau}_{1,i,T_0^i+5}$ falls into the first or the fourth quartiles of the distribution of $\hat{\tau}_{1,i,T_0^i+5}$. Large medium-term effects are unlikely to be a consequence of natural disaster shocks but reflect a poor fit of the SCA or large post-event episode-specific shocks. By truncating the sample by half, we do not try to get the match to be "perfect" for all the

Table 1 The Design of SCA in Selected Studies

	Intervention	Outcome Variable	Predictor Variables	Donor Pool
Abadie and Gardeazabal (2003)	Terrorism in a Spanish state	Real GDP per capita, 1986 USD thousand	Investment ratio, population density, sectoral shares and human capital measures	Spanish states (positive weights to Madrid and Cataluña)
Cavallo et al. (2013)	Natural disasters	Real GDP per capita, normalized to ND	Trade Openness, Capital Stock, Land, Population, Schooling, Latitude and Democracy Index	Countries in the EM-DAT database (196 countries)
Barone and Mocetti (2014)	Earthquakes in regions of Italy	Real GDP per capita, 1985 euro-equiv. prices	Investment Ratio, Sectoral Shares, Population Density, Schooling, Institutional Quality Measures	Regions in Italy
Abadie et al. (2015)	German reunification	Real GDP per capita, 2002 USD PPP	Inflation, Industry share, investment rate, schooling and trade openness.	Developed countries

episodes in our exercises.[8] By contrast, Cavallo et al. (2013) seem to use a more restrictive selection, to get a very good fit for each episode kept in their exercises.[9]

B. *Quantifying the Dynamic Effects of Natural Disaster Shocks*

The impact of a natural disaster shock on real GDP per capita is assumed to satisfy the following relationship:

$$\tau_{i,k} = \alpha_k + \beta_{k,1_{\{\text{Disaster i is severe}\}}}\tau_{i,0} + \varepsilon_{i,k}, \tag{1}$$

where $\tau_{i,k}$ is the impact of a natural disaster shock on real GDP per capita k*th* period after the shock in the episode i. For small natural disasters, $\beta_{k,0}$ converges to zero when k increases. By contrast, for severe ones, $\beta_{k,1}$ can be persistently large even with k rising.

We estimate the following equation:

$$\hat{\tau}_{1,i,T_0^i+k} = \beta_{0,k} + \beta_{1,k}\hat{\tau}_{1,i,T_0^i} \times (1 - D_i) + \beta_{2,k}\hat{\tau}_{1,i,T_0^i} \times D_i + \beta_{3,k}D_i + \gamma_k Z_i + \varepsilon_i, \tag{2}$$

where $\hat{\tau}_{1,i,T_0^i+k}$ is the estimated impact of the natural disaster on real GDP per capita in country i for the kth year after its occurrence (in period T_0^i), which is estimated using the SCA; D_i is a dummy indicating whether the damage-to-GDP ratio is larger than 10 percent. This threshold implies a significant fraction of the sample whose damage-to-GDP ratio is above the threshold (as is suggested by Figure 2). The results, however, are not sensitive to changing this threshold. Z_i is the damage-to-GDP ratio. Controlling for the damage in the equation helps identify medium-term scarring effects, given that reconstruction activities can boost GDP despite scarring effects and can be captured by the damage to GDP ratio.[10]

We focus on the impulse response of the medium-term output loss to the decline of GDP on impact to measure the scarring effects of natural disaster shocks. This captures better the disruption to production and its propagation over time. By contrast, previous studies use the immediate economic damage as a

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[8] Arguably, the measurement error for the estimated causal effects of natural disasters should make it harder for us to find medium-term output effects, and we may get a lower bound for the true coefficient of the decline in real GDP per capita on impact in our second step.

[9] They keep 4 out of 8 events for disasters above the 99th percentile of the damage, 18 out of 164 for the 90th percentile, and 22 out of 444 for the 75th percentile.

[10] We do not have many controls in equation (2), given a relatively small regression sample, which is significantly smaller than the number of episodes we have due to two factors: (i) we drop those whose medium-term effects fall into the tails of the distribution; (ii) only around half of the episodes report pecuniary damage.

measure for the size of the damage of natural disaster shocks to study their short-term output effects (Noy (2009)).[11] As the immediate economic damage can involve non-productive assets, it is a noisier measure of the disruption to aggregate production capacity.

III.   Data and Sample

A.   Sample Selection and Data Sources

We have three sets of countries in our sample: small island developing states, other countries in the Caribbean, and developing countries in Latin America. For small island developing countries, they all have relatively small GDP size and relatively high dependency on tourism, and for those in Latin America and the Caribbean, they are affected by similar regional business cycle shocks. Having a broad sample helps the construction of the donor pools.

We examine disasters that can be classified at least as being mild. We use a classification similar to Munich Re (2006) where at least one of the following variables—total deaths, total injured, total affected, or total damage—is above the 50th percentile of the empirical distribution of its own region/group of countries according to the *EM-DAT (Emergency Events)* database, a commonly used data source in the literature on natural disasters that is constructed by the Centre for Research on the Epidemiology of Disasters.[12] This gives us a total of 370 natural disasters since 1980, which includes all types of natural disasters (storm, flood, drought, earthquake, and volcanic eruption).

We use the IMF's *World Economic Outlook* dataset, the World Bank's *World Development Indicators* database, and the Penn World Tables (version 10.0) to construct real GDP per capita, the size of population, and land area for the sample countries. We also use data on country's geographic latitudes from Google's Dataset Publishing Language Guide (DSPL). These indicators are used as the predictor variables in the synthetic control approach, as is explained in the next section.

B.   Summary Statistics

Table 2 lists basic characteristics of countries in our sample, including real GDP, real GDP per capita, land area, population, pecuniary damage caused by natural disasters, and damage as share of GDP, versus those of an average country in the world. Our sample countries have a much smaller economic size than

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[11] Noy (2009) adjusts the cost-of-damage using a scaling factor based on the month of year of the event. We don't do so since we study the impact on real GDP per capita after the year of the shock.

[12] Felbermayr et al. (2013) explores severe disaster episodes not covered by the EM-DAT.

Table 2 Summary Statistics

	Our Sample	All countries
Real GDP (USD in billion)	46	2252
Real GDP per capita (USD in thousand)	5.3	12
Land area (in million of square kms)	0.3	2
Population (in million of persons)	8.6	195
Pecuniary damage (USD in billion)	0.2	0.8
Damage ratio (in percent of GDP)	1.8	0.3

Sources: EM-DAT (*Emergency Events database)* , IMF's *World Economic Outlook* database,
World Bank's *World Development Indicators* , and authors' calculations.

the world average, as they are not only poorer but also have a smaller population size (residing in a smaller land area). Specifically, the real GDP is USD 46 billion for the average country in our sample and USD 2,252 billion for the world average. The real GDP per capita is USD 5,300 for the average country in our sample and USD 12,000 for the world average. For the population size, it is 8.6 million vs. 195 million, and for the land area, 0.3 million square kms vs 2 million square kms. The pecuniary damage caused by natural disasters also differs substantially between our sample and the world average. In level terms, the average damage is smaller for our sample (USD 0.2 billion for the average country vs. USD 0.8 billion for the world average) but as share of GDP, it is higher (1.8 percent vs. 0.3 percent).

The larger damage-to-GDP ratio in our sample relative to the global sample reflects two sharply different distributions. Figure 2 plots the distribution of damage-to-GDP ratio for disasters that occurred after 1970 and whose damage exceeded 0.1 percent of GDP and shows that the distributions are different between our sample and the global sample. For the global sample, two-thirds of these events have the ratio below 0.5 percent. For our sample, only around a quarter had their damage falling into this range. Meanwhile, our sample has a much thicker right tail of the distribution. An average country in the global sample rarely experienced a disaster whose damage exceeds 10 percent of GDP, and by contrast, a quarter does so in our sample of the distribution plotted in Figure 2. Therefore, our sample countries not only suffer from larger average damage but also have a large exposure to extremely severe disasters.

We further zoom into the most damaging natural disasters in history when measured based on damage as

share of GDP. Figure 3 plots all the events in the EMDAT with the damage larger than 10 percent of GDP. We highlight two patterns: First, five of the top ten high-damage events and nine of the top twenty between 1970 and 2020 occurred in the Eastern Caribbean Currency Union (ECCU).[13] The most extreme of these occurred recently: Hurricane Maria hit Dominica in 2017, causing an immediate damage around 224 percent of GDP.[14]

IV.   Results

A.   Synthetic Controls for Selected Episodes

Figure 4 shows the performance of the SCA for selected countries and provides suggestive evidence of medium-term scarring effects. ECCU countries are selected as they tend to be much less resilient and have limited resources to recover from a large damage.

We have a good fit of synthetic controls for episodes such as Antigua and Barbuda (1995) and St. Kitts and Nevis (1998), which are shown in the upper panel of Figure 4. The solid and dashed lines match very well before the events. The two lines diverge after the year of the disaster, taking around 5 to 10 years for the solid line to return to the counterfactual dashed line. This pattern is likely driven by scarring effects of the disaster shocks. For both events, there were extremely large damages as share of GDP: 60 percent for Antigua and Barbuda in 1995, and 49 percent for St. Kitts and Nevis in 1998.

Figure 2 Distribution of Damage over GDP: The Caribbean and SIDs v/s the World
(In percent; share in events with damage over GDP exceeding 0.1%)

Note: SIDs are Small Island Developing countries.
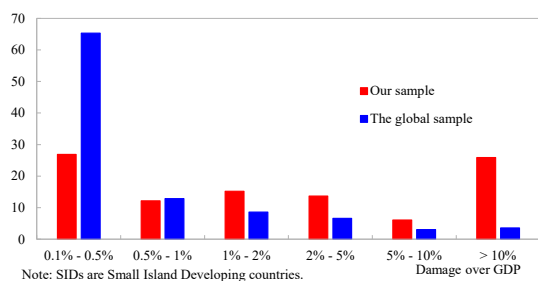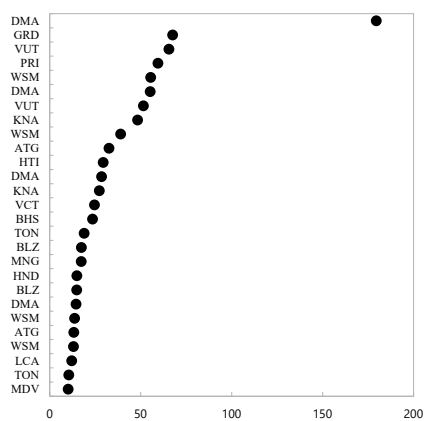
Figure 3 Highly Damaging Natural Disasters
(Disasters with damage over 10 percent of GDP in PPP term)

Note: Except for an episode in Mongolia and in Honduras, all highly damaging disasters occurred either in the Caribbean or small island developing countries.
Sources: EM-DAT, *World Economic Outlook* database, and authors' calculations.

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[13] See Rasmussen (2004) assessment of disasters in the Caribbean, especially those in the ECCU.

[14] Figure 3 shows a smaller number as the denominator is GDP in PPP term.

Interestingly, there are also patterns of long-run scarring. In both episodes, the gap in real GDP per capita between the affected country and the synthetic control widened substantially in the long run. While such patterns may be driven by scarring effects on long-run growth, it may not necessarily be the case. Other shocks may be behind this strong divergence. We leave such issues for future research to investigate but focus on medium-term impact of disaster shocks, i.e., five years after the shocks.[15]
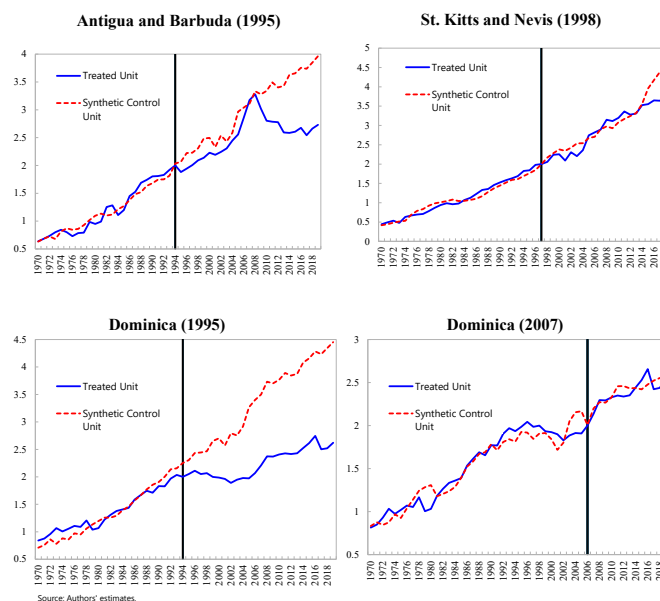
The lower panel of Figure 4 shows the episodes for Dominica in 1995 and 2007 respectively. The damage-to-GDP ratio was

Figure 4 Synthetic Control Estimation Results for Selected Episodes

Source: Authors' estimates.

64 percent in the 1995 episode but only 5 percent in the 2007 episode. Consistent with the dramatic difference in the damage, the 1995 episode has a stronger divergence between the solid line and the dash one.

One may notice that the pre-event fit is not perfect for these episodes, but they should not drive our results, as we explain earlier in describing the DID strategy. We also conduct placebo tests to further mitigate the concern.

B.   Quantifying Medium-Term Effects of Natural Disasters on Real GDP per Capita

Table 3 reports the results of estimating equation (2). The impact on real GDP per capita is transitory for low-damage events, i.e, those whose cost of damage is below 10 percent of GDP. For example, if, on impact, the real GDP per capita declines by 1 percent more relative to the trend, its deviation from the trend will be larger by 0.841 percent one year after the shock, but then decline over time: 0.769 percent in

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[15] The global financial crisis occurred during the post-disaster windows of these episodes. It is possible that Antigua and Barbuda and St. Kitts and Nevis were disproportionately affected by the GFC. The large divergence between Antigua and Barbuda and its synthetic control started after 2010. On the other hand, the disproportionately large exposure to the GFC could stem from the difficulty of recovering fully from its extremely large shocks that happened earlier. A closer look at the tourism and FDI data in Antigua and Barbuda suggests that tourism arrivals did not experience a sharp slowdown after the GFC, but the FDI crashed and was slow to recover.

Table 3 Impulse Response of Real GDP per Capita to A Natural Disaster Shock

	(1)	(2)	(3)	(4)	(5)
	Year 1	Year 2	Year 3	Year 4	Year 5
Change in GDPPC on impact x Low-Damage Dummy	0.841***	0.769***	0.574***	0.478***	0.203**
	(0.0620)	(0.0720)	(0.0906)	(0.103)	(0.0956)
Change in GDPPC on impact x High-Damage Dummy	1.357***	1.049***	0.943***	0.891***	0.911***
	(0.184)	(0.214)	(0.269)	(0.306)	(0.284)
High-Damage Dummy	0.0226	0.00929	0.00513	0.00537	0.0117
	(0.0155)	(0.0180)	(0.0226)	(0.0257)	(0.0239)
Constant	-0.0145*	-0.0253***	-0.0400***	-0.0506***	-0.0577***
	(0.00726)	(0.00845)	(0.0106)	(0.0121)	(0.0112)
Observations	71	71	71	71	71
R-squared	0.786	0.677	0.442	0.311	0.181

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Authors' estimates.

the second year, 0.574 percent the third, 0.478 percent the fourth, and 0.203 percent the fifth. Such a pattern suggests little scarring effects of small disaster shocks.

By contrast, the impact on real GDP per capita is much more persistent for events whose cost of damage exceeds 10 percent of GDP. For a larger decline of 1 percent of real GDP per capita on impact, the effects in the first year to the fifth year after the shock are: 1.357 percent, 1.049 percent, 0.943 percent, 0.891 percent, and 0.911 percent. Moreover, one cannot reject the hypothesis that the effects are constant over time.

To illustrate the magnitude of medium-term output effects, we study a shock that inflicts an economic damage that is around 30 percent of GDP. This is a very severe shock in our sample and causes a 2 percent decline in real GDP per capita in the year of the disaster. We estimate the elasticity by regressing the decline in real GDP per capita on impact on the reported pecuniary damage, without applying the intercept. This decline in real GDP per capita in the year of the disaster, however, should not be interpreted as the full impact of the disaster, because natural disasters tend to occur in the second half of the year in our sample.[16]

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[16] One may further raise concern about why there is no jump in the impulse responses of the first and second years if the disaster only "partially" affects the output in the year of the disaster. One possibility is that reconstruction activities boost GDP in these

We calculate the impulse response to this shock by combining the coefficients of the change in real GDP per capita on impact and the intercepts.[17] We consider the intercept term, as the initial drop in real GDP per capita, $\tau_{i,0}$, may only capture the damage to assets critical for the aggregate production rather than all factors that can influence the speed of post-disaster recovery in real GDP per capita (such as international aid, the size of self-insurance funds accumulated by the government ex ante, and the migration of people out of the affected country affecting the composition of workers). These factors may not be perfectly correlated with the size of the damage to the critical productive assets.

Figure 5 shows that five years after the shock, real GDP per capita is still around 8 percent below the trend, with around 2.3 percent from the contribution of the decline in real GDP per capita on impact, and

Figure 5 The Impulse Response of Real GDP per Capita to a Shock with 2% Decline in Real GDP per Capita on Impact
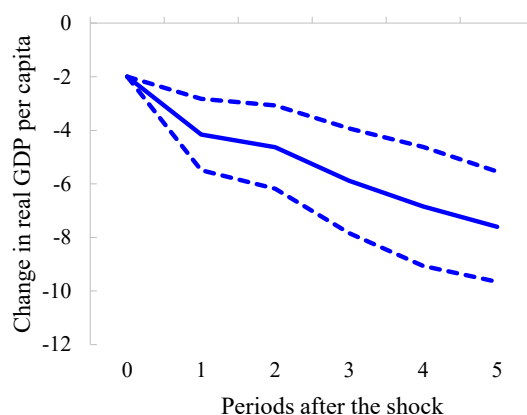
Source: Authors' estimates.

years, which is supported not only by the empirical pattern we document in the appendix D that the construction GDP had a surge after disasters in ECCU countries but also by previous findings in the literature (Crowards (1999) and Charvériat (2003)). Crowards (1999) and Charvériat (2003) do before-after comparisons of macro indicators for natural disaster episodes. Crowards compares the growth rates of key macro variables like GDP, imports, exports, and tourist arrivals before and after 21 major storms in the Caribbean between 1976 and 1996. He finds a rise in GDP growth of approximately 3 percent in the year succeeding a disaster, and attributes this to a surge in construction and rehabilitation activity, and the inflow of external aid. This is then followed by a slowdown of about 2.5 percent in the second year, suggesting that the effects of the temporary boom are short-lived. Charvériat finds similar results when she analyzes 35 disaster cases between 1980 and 1996 in 20 Latin American and Caribbean countries to assess their effects on real GDP growth. Median growth decreases by 2 percent in the year of the disaster and increases sharply by 3 percent in the two years that follow.

[17] The impulse response in the kth year after the shock is calculated as the sum of the intercept and the coefficient of the change in the real GDP per capita on impact in the kth column of Table 1 multiplied by 2 percent.

5.7 percent from the intercept. It is beyond the scope of our current paper to explore what is behind the large intercept, an issue we leave for future research.

C. Placebo Tests

To alleviate any potential concern that our results are driven by poor pre-event fits of synthetic controls, we conduct the following placebo test. We regress the GDP gap in years -5 to -1 on the GDP gap in year -6, with year -k referring to the kth year before the disaster event. We employ the same specification as equation (2), with the only difference being that no natural disasters occurred in these years. If results were driven by a poor fit of the SCA creating a gap between the treated unit and the synthetic control before the shock, we should observe similar results as what we see in Table 3.

Table 4, however, suggests that this is not the case, the only significant effect is on the GDP gap of year -5. It is also useful to recognize that the intercept is insignificantly different from zero in this exercise.[18]

Table 4 Placebo Test: Limited Response in GDP per Capita to a Year -6 Shock

	(1)	(2)	(3)	(4)	(5)
	Year 5	Year 4	Year 3	Year 2	Year 1
Change in GDPPC in Year 6 x	0.691***	0.0309	-0.0153	-0.0711	0.308
Low-damage dummy	(0.197)	(0.223)	(0.232)	(0.208)	(0.227)
Change in GDPPC in Year 6 x	-0.0266	-0.299	0.00288	-0.187	0.227
High-Damage Dummy	(0.244)	(0.276)	(0.287)	(0.258)	(0.280)
High Damage Dummy	0.0496*	0.0611**	0.0388	0.0426	0.0223
	(0.0260)	(0.0295)	(0.0306)	(0.0275)	(0.0299)
Constant	0.00563	-0.00678	-0.0128	-0.0145	-0.0241
	(0.0139)	(0.0157)	(0.0163)	(0.0147)	(0.0160)
Observations	35	35	35	35	35
R-squared	0.366	0.123	0.069	0.074	0.131

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1
Source: Authors' estimates.

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[18] Here, we have a further restriction of the sample based on the SCA fit. If we use a coarser fit, the placebo test results are broadly the same. The results in Table 3 are also robust to having the same sample as those in Table 4.

V. Exploring Underlying Channels

A. Channels for Natural Disasters to Cause Scarring Effects in Small Island Developing Economies

There are multiple reasons why adverse shocks can have persistent negative effects on output (Cerra, Fatás, and Saxena (forthcoming)). For developing countries, a simple mechanism is that real GDP per capita follows a stochastic trend, implying that it declines persistently after any adverse shock. However, this mechanism seems to be inconsistent with our finding that small natural disasters only have transitory effects.

Another channel mentioned in the literature is radical political evolution. Cavallo et al. (2013) analyze large countries and find that "only very large natural disasters, followed by radical political revolution, show long-lasting negative economic effects on economic growth. Even very large natural disasters, when not followed by disruptive political reforms that alter the economic and political system, including the system or property rights, do not display significant effects on economic growth." Given the frequency of severe disasters in our sample, this political revolution channel is, however, unlikely to be a major source of negative medium-term output effects.

A third possibility is lacking resources to recover from the damage inflicted by a severe disaster, which seems to be plausible to explain why such shocks caused no significant effects on economic growth for most episodes studied by Cavallo et al. (2013)—but suppressed output per capita persistently whenever the damage is large in countries of our sample, as they tend to face more binding resource constraints for post-disaster reconstruction.

This channel is supported by the finding of Von Peter, Von Dahlen, and Saxena (2012). They analyze a global sample and find that "major natural catastrophes have large and significant negative effects on economic activity, both on impact and over the longer run." and that "it is mainly the uninsured losses that drive the subsequent macroeconomic cost, whereas sufficiently insured events are inconsequential in terms of foregone output." Countries in our sample tend to have limited insurance protection. For example, Duarte et al. (2022) shows that Caribbean countries, which had the majority of severe natural disaster episodes in our sample, have limited protection from disaster insurance instruments.

There are two testable hypotheses for our sample if the cause of medium-term output effects is a lack of resources to repair damaged infrastructure.

Hypothesis I *High indebtedness of a country can exacerbate the medium-term output loss of a severe natural disaster*

Hypothesis II *During a severe natural disaster episode, tourism and agriculture sectors have stronger medium-term output loss than other sectors.*

An implicit assumption behind Hypothesis II is that the physical assets of tourism and agriculture sectors are more exposed to a severe natural disaster than those of other sectors. This assumption is consistent with the anecdote for our sample countries that these sectors tend to suffer more during hurricanes, floods, and droughts, the type of disaster events causing severe damage in these countries.

B. Testing Hypothesis I: Role of Initial Conditions

To test the Hypothesis I, we estimate the following equation:

$$\hat{\tau}_{1,i,T_0^i+5} = \beta_{0,j} + \beta_{1,j}\hat{\tau}_{1,i,T_0^i} \times D_i \times S_{i,j,T_0^i-1} + \beta_{2,j}\hat{\tau}_{1,i,T_0^i} \times D_i + \beta_{3,j}\hat{\tau}_{1,i,T_0^i} \times S_{i,j,T_0^i-1} + \beta_{4,j}D_i \times S_{i,j,T_0^i-1}$$

$$+ \beta_{5,j}D_i + \beta_{6,j}S_{i,j} + \varepsilon_i, \tag{3}$$

where S_{i,j,T_0^i-1} is the structural indicator j in the year prior to the natural disaster shock in episode i and can be one of four variables: (1) a dummy indicating whether the ratio of public debt over GDP exceeds 70 percent, (2) political stability indicator, (3) the government effectiveness indicator, and (4) tourism dependency. Other variables have the same definitions as those in equation (2).

For the high debt dummy, we choose 70 percent as the threshold to capture the idea that developing countries whose debt exceeds this level may "on average" face tighter borrowing constraints than those whose debt level is below it. The results are not sensitive to the choice of this threshold. It is worth highlighting that this choice does not mean that 70 percent is a level deemed appropriate from other considerations. For example, Greenidge et al. (2012) estimate that gross debt beyond the threshold of 55-56 percent of GDP is associated with lower economic growth for Caribbean countries.[19] Therefore, one should not conflate the debt threshold chosen here with, for example, the medium-term debt target of a fiscal rule.

If resource constraints for repairing assets damaged by natural disasters are the key channel for medium-term output effects of natural disasters to emerge, we should expect the other triple interactions to be statistically insignificant. Here, political stability and the level of governance try to capture the radical political revolution channel by Cavallo et al. (2013). Tourism dependency is captured as the ratio of

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[19] See Guerson (2019) and Lissovolik (2019) for a discussion on the need to build resilience against natural disasters and implications for the fiscal framework in ECCU countries.

tourism receipts over GDP, and we include it to study whether high tourism dependency, a key feature of small island developing economies, can strengthen medium-term output effects of natural disasters.

Table 5 suggests that highly indebted countries have stronger medium-term output loss after a severe natural disaster shock than other countries. The triple interaction term between the high-debt dummy, the high-damage dummy, and the change in real GDP per capita on impact is significant both statistically and economically. For example, for one percent decline in real GDP per capita on impact (caused by a high-damage event, i.e., one with the damage-to-GDP ratio exceeding 10 percent), the fifth-year impact would be stronger by 1.24 percent of GDP for countries whose public debt exceeds 70 percent of GDP than the rest of the sample. By contrast, we do not find a significant role for political stability, government effectiveness, or tourism dependency in affecting medium-term output effects of natural disasters.

C. Testing Hypothesis II: Heterogeneous Natural Disaster Output Effects across Sectors

We test Hypothesis II by analyzing natural disaster output effects at the sector level. Sectoral GDP is available for 15 economies in the Caribbean region: the eight ECCU members plus Haiti, The Bahamas,

Table 5 Role of Structural Indicators in Medium-Term Output Effects of Natural Disasters

	(1)	(2)	(3)	(4)
	Debt exceeding 70 percent of GDP	Tourism dependency	Political stability	Government effectiveness
Δ real GDP per capita	0.403***	0.539***	0.413**	0.422*
	(0.148)	(0.196)	(0.189)	(0.216)
Triple interaction term: Δ real GDP per capita ×	1.147*	0.0628	17.70	-0.991
Dummy_damage × Structural indicator	(0.598)	(0.130)	(54.72)	(18.37)
Δ real GDP per capita × Dummy_damage	0.378	0.402	-18.90	10.98
	(0.316)	(0.961)	(59.84)	(9.735)
Δ real GDP per capita × Structural indicator	-0.913***	-0.0540*	-0.0154	0.125
	(0.254)	(0.0273)	(0.344)	(0.421)
Dummy_damage × Structural indicator	0.0189	0.00246	-1.762	-1.755
	(0.0470)	(0.00775)	(4.404)	(2.315)
Dummy_damage	-0.00129	-0.0101	1.877	-0.161
	(0.0354)	(0.0639)	(4.773)	(0.250)
Structural indicator	0.0227	0.00292	0.0396**	0.0285
	(0.0253)	(0.00202)	(0.0159)	(0.0185)
Constant	-0.0599***	-0.0756***	-0.0505***	-0.0447***
	(0.0123)	(0.0159)	(0.0135)	(0.0147)
Observations	68	53	42	42
R-squared	0.345	0.341	0.393	0.285

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1
Source: Authors' estimates.

Barbados, Jamaica, Belize, Guyana, and Trinidad and Tobago, and five sectors: tourism, agriculture, construction, manufacturing, and high skilled services (which include real estate and financial services sectors). The earliest data available is from 1977 for the ECCU countries, with some regional differences (for example, data for Anguilla is available from 1984 onwards, data for Guyana is available from 1988, and data for Trinidad and Tobago is available from 2000).

Sample selection. As earlier results suggest that medium-term output effects are statistically significant only for severe natural disasters, we only keep natural disasters whose damage-to-GDP ratio exceeds the medium of this ratio within this sectoral exercise sample.

Empirical methodology. We choose the following two-step approach to study the dynamic effect of natural disasters at the sector level. In the first step, we estimate the following equation:

$$Y_{i,t} = \sum_{k=-K}^{K} \beta_k I_{i,k,t} + \delta_i + \varepsilon_{i,t}, \tag{4}$$

where $Y_{i,t}$ is the logarithm of the sectoral GDP, with i indicating an episode-sector pair. $I_{i,k,t}$ is a dummy that is equal to one if year t is the kth year after the shock, and zero otherwise, and δ_i is the episode-sector fixed effect.

In the second step, we estimate a linear trend based on β_k in the 10-year pre-event window and extrapolate the trend to the post-event window. To get the standard error of the extrapolated values, we bootstrap β_k in the 10-year pre-event window based on the standard error of β_k (for simplicity, we ignore the potential correlation between β_i and β_j for $i \neq j$). We use the bootstrapped coefficients to calculate the confidence band.

Figure 6 suggests that natural disasters have significantly negative impact on the GDP of the tourism sector for ECCU countries and countries whose debt-to-GDP ratio is above the median of this sectoral exercise sample. Such patterns, however, do not exist for non-ECCU countries or those whose debt-to-GDP ratio is below the median. Such a pattern is less salient for Agriculture, and even weaker for other sectors.

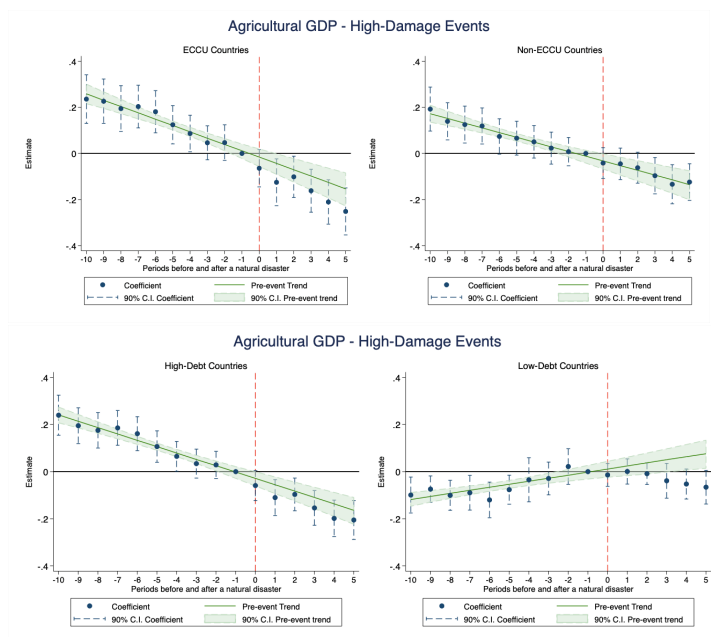### D. The Impact of Natural Disasters on the Import of Machinery and Equipment

We use the same exercise as in the previous section to study the impact of natural disasters on the import of machinery and equipment (M&E). We replace the dependent variable in equation (4) with the import of M&E as share of GDP. This channel can be interesting to study because resource constraints in
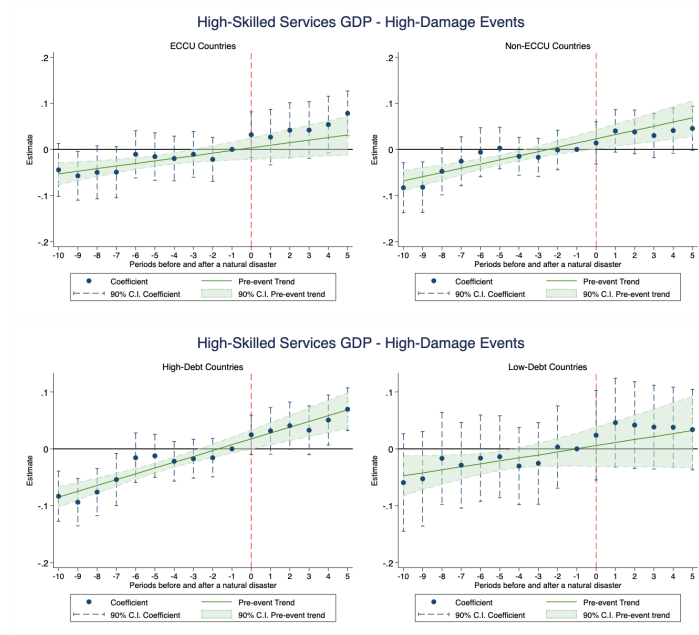
Figure 6 Natural Disaster Impact on Sectoral GDP
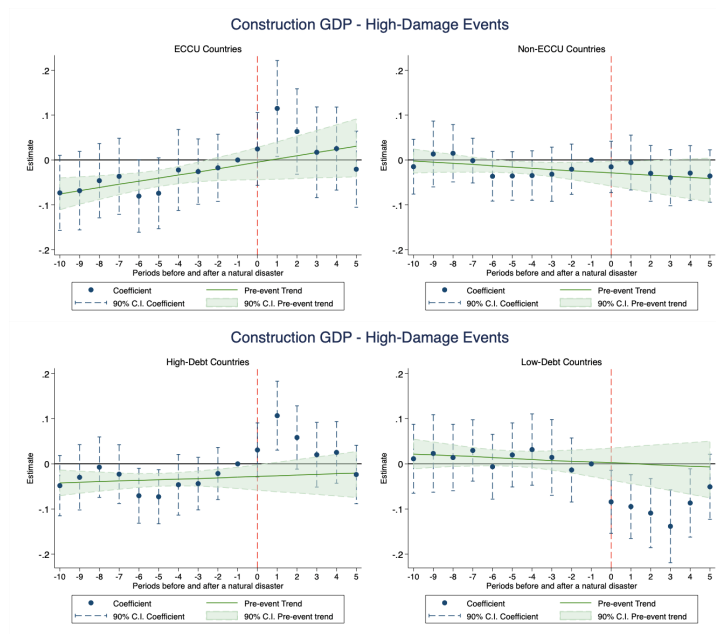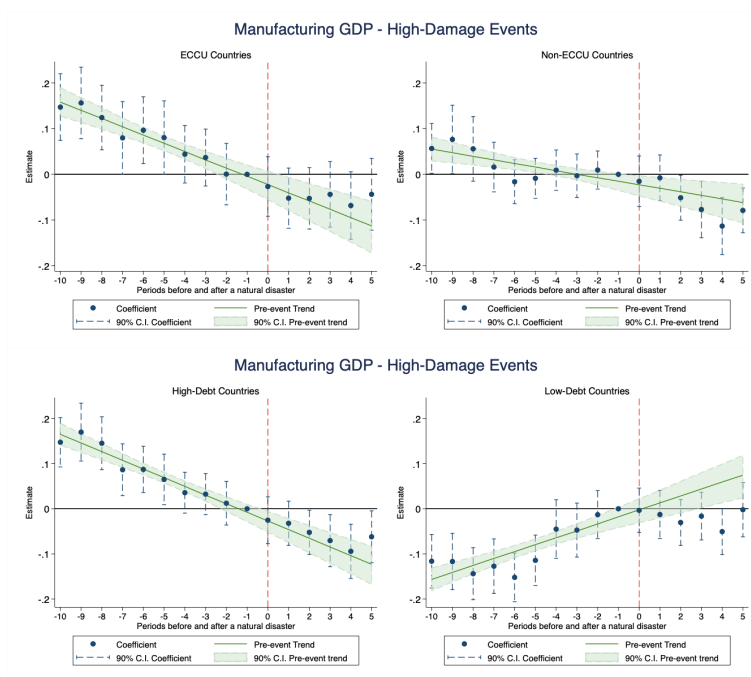
A.   Tourism
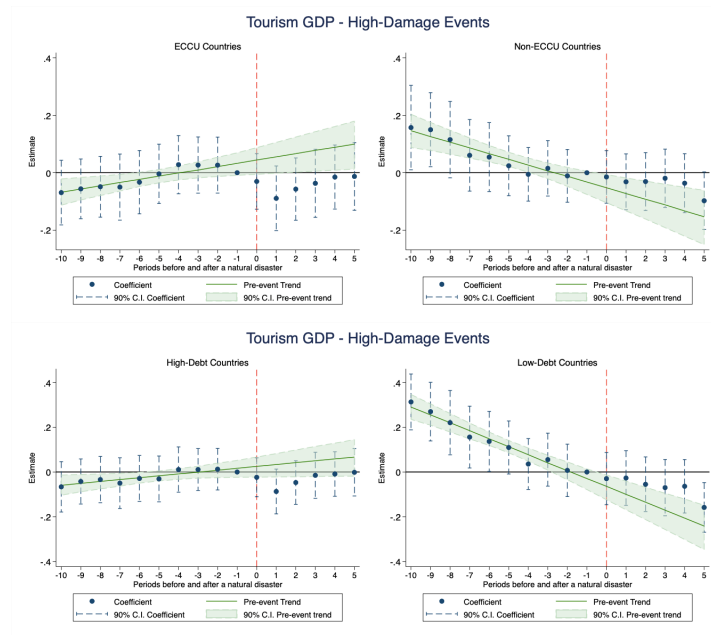
B. Agricultural

C. High-Skilled Services (Real Estate and Finance)

High-Skilled Services GDP - High-Damage Events

High-Skilled Services GDP - High-Damage Events

D. Construction GDP

Construction GDP - High-Damage Events

Construction GDP - High-Damage Events

E. Manufacturing GDP

repairing assets damaged by natural disasters may crowd out the investment in M&E, which can then affect long-term growth through slower capital accumulation and TFP growth. Figure 7 find some weak evidence for ECCU countries.

VI. Conclusion

This paper studies whether natural disasters caused persistent medium-term output loss in small island developing economies, given their high exposure to severe natural disasters—an issue that can be aggravated by climate change, which could make natural disasters more frequent and intense.

We combine the SCA and the LPM to estimate the dynamic effects of natural disaster shocks on real GDP per capita and find that for an extremely severe event, real GDP per capita is persistently lower than the counter-factual trend even five years after the shock. We find suggestive evidence to support a lack of resources to repair damaged assets as the cause of such persistent effects.

Our findings, arguably, provide a strong support for strengthening resilience building ex-ante to reduce scarring effects of severe natural disasters. Future research can further compare the post-disaster economic dynamics of small island developing economies after severe shocks and those of disaster-prone regions in large economies, to further understand these issues.

Figure 7 Natural Disasters Impact on the Import of Capital Goods
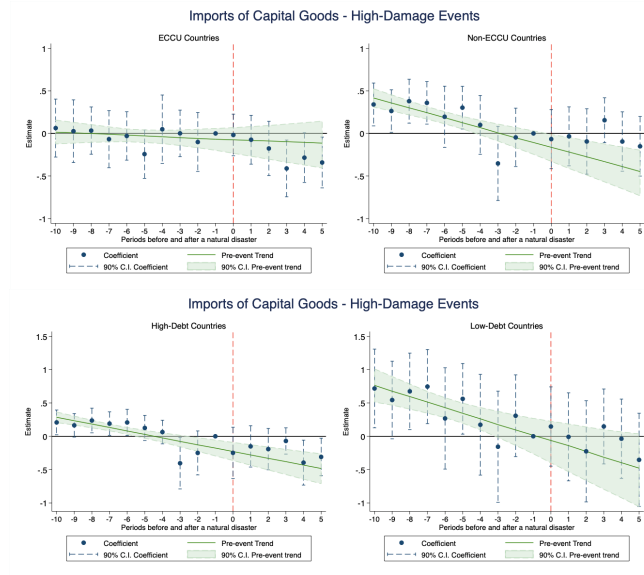
Annex I. Data sources and definitions

Data sources

The primary data sources for this paper are the April 2021 vintage of the IMF World Economic Outlook (WEO) database and the *EM-DAT (Emergency Events)* Database constructed by the Centre for Research on the Epidemiology of Disasters (CRED).

Supplemental datasets used include the Penn World Tables (version 10.0), the World Bank's *World Governance Indicators* and *World Development Indicators,* and Google's Dataset Publishing Language data repository. Additional data on sectoral GDP from the Caribbean country authorities, and detailed import data from the United Nations' COMTRADE database, were also used to study the transmission channels of natural disaster shocks.

Indicators	Sources
Natural disaster data	EM-DAT (Emergency Events Database) created by the Centre for Research on the Epedemiology of Disasters (CRED), Université Catholique de Louvain, Belgium.
Cross country data on GDP, population, inflation, public debt	IMF's *World Economic Outlook* indicators (April 2021 vintage)
Latitude data	Google Dataset Publishing Language (DSPL) Guide
Land area and tourism expenditures data	World Bank's *World Development Indicators* (WDI)
Institutional quality indicators	World Bank's *World Governance Indicators* (WGI)
Missing historical GDP data	*Penn World Tables 10.0*
Sectoral GDP data	Caribbean country authorities
Import data	United Nations' *COMTRADE*

Source: Authors' compilation

Annex II. An algorithm for constructing donor pools

This section explains the algorithm for constructing the donor pool. For an episode i, with country 1 being affected by the natural disaster in time T_0^i:

Step 1. Keep countries that have non-missing values for each of the predictor variables for at least one year between 1970 and year T_0^i;

Step 2. Keep countries whose nominal GDP is between 10 percent and 15 times that of country 1 during the episode. Select ten countries whose real GDP per capita is closest to that of country 1, and whenever possible have five countries that are richer than country 1 and five poorer.

Step 3. Sort the ten countries selected in Step 2 based on the growth rate of real GDP per capita between $T_0^i - 15$ and T_0^i. Select six countries whose growth rate is closest to that of country 1.

Step 4. Define 31 country sets as follows:

- One set consists of six countries selected in Step 3.
- Six sets consist of five countries, with the six countries selected in Step 3 being excluded one at a time.
- Twenty four sets consist of removing each of the six countries selected in Step 3 one at a time, but add each of the four countries eliminated in Step 3.

The donor pool is then defined as the country set that has the lowest pre-event MSPE for the synthetic control corresponding to this country set (i.e. we apply the SCA to it to get the synthetic control). The key results are robust to choosing the country set with the second lowest pre-event MSPE and other variations of our algorithm for the donor pool construction.

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