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Abstract[1]

This paper estimates the impact of catastrophic natural disasters on economic growth using an event study methodology on a country panel dataset from 1970 to 2019. The severity of the events is determined by the associated mortality. We find that affected economies—which, given the way natural disasters are ranked, comprise mainly developing countries—suffer an average loss between 2.1 and 3.7 percentage points (p.p.). The estimated loss is not offset by above-average growth rates in the disaster's aftermath. In contrast, when the severity of the events is determined by physical intensity rather than by mortality—which implies a more balanced estimating sample of developed and developing economies—the estimated effects on growth are negligible. Thus, the negative impacts of natural disasters on economic growth are larger for poorer countries, suggesting that the impact of natural disasters on growth is an economic development issue.

JEL classifications: Q54; O47

Keywords: Natural disasters, Economic growth, Event study

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1. Introduction

Natural disasters can have severe economic and human consequences, depriving people of livelihoods and assets, and taking lives. Yet despite their potentially enormous costs, an understanding of the economic effects of natural disasters—their frequency, their duration, their severity—remains a work in progress. This paper focuses on the impacts of natural disasters on economic growth.

Economic theory offers competing hypotheses as to the possible impacts of natural disasters on growth. Models rooted in a Schumpeterian tradition would predict output falling in the aftermath of a shock that depletes labor and capital, subsequently unleashing the forces of creative destruction in the economy, leading to higher productivity and growth.[2] The Solow (1956) model, with production functions that exhibit diminishing marginal productivity of capital, would predict higher growth rates in the aftermath of a shock that reduces the capital to labor ratio below the steady state level. In contrast, in learning-by-doing models, a shock that destroys human and physical capital has negative effects on productivity and growth.[3]

The competing theoretical predictions suggest that assessing the impact of natural disasters on economic growth is ultimately an empirical question. However, the task of providing conclusive empirical evidence is elusive. A main challenge is that this assessment requires a counterfactual that is not observable: what would have happened absent the shock. The empirical work relies on two alternative approaches: cross-country regressions and comparative case studies. Both approaches provide useful insights to understand dimensions of the size and direction of the effect of natural disasters on growth, and they have their own advantages and limitations.

Cross-country analyses typically follow the growth regressions tradition (Barro, 1991). The effect of natural disasters on growth is estimated in a regression in which the dependent variable is the annual growth rate of GDP (or GDP per capita), and the explanatory variables include an indicator of the occurrence, or a measure of intensity of the natural disaster, and other determinants of economic growth (Cavallo and Noy, 2011).[4] An advantage of this approach is that the estimated effect can be interpreted as the impact of a disaster on growth for the average country. Using the

[2] See, for example, Caballero and Hammour (1994).

[3] See for example, Martin and Rogers (1997).

[4] The estimated effect can be a short-run effect (if the growth rate is on the period that the disaster occurred), a long-run effect (if the growth rate is defined over a longer interval), or a dynamic effect (combining short and long-term effects). Salient examples of this approach are Skidmore and Toya (2002), Noy (2009), and Strobl (2012).

terminology of the treatment effects literature, the estimate is the *average treatment effect* of a natural disaster on economic growth.[5]

The use of this approach generates a tradeoff between the gains of generality in the interpretation and weak identification due to possible endogeneity issues that arise, for example, from the definition of natural disasters. This is so because not all natural disasters are the same, nor is there a convention or clear definition of what constitutes a natural disaster. One consideration is the "hazard"—who and what geographic areas are at risk—and another is the "incidence"—whether the hazard materializes, when and where. Yet another consideration is the "impact"—who is affected, and how, when the disaster strikes. To become a disaster, a hazard must generate destruction of human and physical capital. While many countries are exposed to natural hazards, the incidence of the disaster depends on the capacity of a society to mitigate them, making those impacts endogenous to economic development and growth. Even though these considerations can be mitigated by including control variables, the estimates may be biased unless all factors are controlled for.[6]

The second methodological approach is comparative case studies. In them, the analysis focuses on the effect of one or more large and catastrophic disasters. The analysis is typically carried out on longitudinal datasets. The effects on economic growth are measured by using event studies, in which the effects are estimated by comparing the average growth rates before and after disasters.[7] The loss in generality of this approach is offset by gains in identification because it requires less stringent assumptions. Following the analogy to the treatment effects literature, the estimated effect of natural disasters on economic growth in the comparative studies approach

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[5] The identifying variation in this setup comes from comparing growth rates between the group of countries affected by a disaster and the group of unaffected countries, after controlling for other determinants. Under the assumption that the occurrence of the disaster is orthogonal to unobservable determinants of economic growth, the coefficient associated with the disaster variable is the causal effect of natural disasters on economic growth.

[6] Unlike purely cross-sectional studies, longitudinal (panel) studies can control for time-invariant, unobservable factors. The identification of the effect of natural disasters on economic growth in longitudinal studies relies on the comparison of GDP growth rates using countries that were unaffected by a natural disaster as a control group. Thus, the identification of the causal effect requires that there be no differential trends in the GDP growth between the affected and unaffected countries, which is a difficult condition to hold. Adding country-specific time trends can account for those differences, yet it implies that the estimation extrapolates the pre-shock trend to the post-shock period, which can be problematic over long periods of time (see Cavallo et al., 2013).

[7] The identifying assumption in this setup is that the distribution of the economic growth would have evolved smoothly around the time of the shock absent the disaster. Thus, the differences on average growth rates before and after the disaster are estimates of the effect of natural disasters on economic growth for the affected economies. Examples of this literature are Albala-Bertrand (1993) and Borensztein et al. (2017). Alternatively, Cavallo et. al. (2013) use a synthetic control method approach, in which the counterfactual is constructed by generating a synthetic control group based on countries unaffected by a natural disaster.

emulates an average treatment effect *for the treatment group*; that is, it is the estimated effect of the natural disaster on economic growth for the group of countries severely affected by a disaster.

This paper adds to the literature by providing new estimates of the impacts of large, catastrophic natural disasters on economic growth at the country level in the short term (i.e., in the year of the disaster) and the medium term (i.e., a few years after the disaster) using comparative case studies. The methodology builds on Borensztein et al. (2017), who study the behavior of the average level and growth rate of real GDP per capita six years before and six years after the 50 natural disasters with highest mortality in a sample going up to 2008. They find that, in the year of the disaster, output drops between 2 and 4 percentage points on average. In this paper we update their results, extending the sample 11 years to 2019 and considering additional disasters. Extending the sample permits including all catastrophic events that materialized post 2008, such as the 2010 earthquake that struck Haiti, which has the highest mortality rate on record (222,170 deaths according to EM-DAT). Considering other types of events permits drawing broader conclusions regarding the impacts of natural disasters.

In adopting Borensztein et al (2017) methodology, we opted for a simple but transparent event study approach pooling across different types of natural disaster episodes. We build counterfactuals using pre-disaster trends and use them to assess the impact of natural disasters on real GDP per capita growth and levels. We find that during the year of the disaster, real GDP per capita growth declines by between 2.1 and 3.7 percentage points (p.p.) on average, vis-à-vis the average pre-disaster growth for the most catastrophic disasters in the sample, where the severity of the disasters is determined based on the number of fatalities per million people. The estimated negative impacts decline as less severe disasters, and/or disasters materializing in more advanced economies, are included in the samples. The pre- and post-disaster average growth rates are not statistically different, suggesting that the occurrence of the natural disaster does not affect real GDP per capita growth in the medium term. However, the fact that the post-disaster growth rate is not higher than the pre-disaster average suggests that the output lost during the disaster is never fully recovered.

To identify natural disasters with the potential of having aggregate impacts on the economy, we follow Borensztein et al. (2017) and select episodes based on their associated mortality rate. This in turn implies that the resulting sample for the event studies includes predominantly developing countries, where the mortality associated with disasters is higher.

Although the sample is ultimately determined by the selection criterion chosen, using mortality as a selection criterion guarantees that the resulting sample includes countries with similar institutions, financial markets, and insurance markets, thereby making it possible to draw policy conclusions that are generalizable to countries that share these characteristics. Developing economies tend to have a lower capacity to mitigate the effects of natural disasters and, even worse, conditions in developing countries can even amplify those effects (for instance, by having lenient building codes or by building in high-risk areas, or having shallower credit and insurance markets, weaker institutional capabilities, and poor health care systems). In additional analyses, we use monetary damages as the measure of the severity of a natural disaster (that include more developed economies) and found neither short nor long-term effects of the disaster on economic growth. Taken together, our results suggest that the incidence of natural disasters on growth is mostly an economic development issue.

Section 2 provides a brief and selective overview of the related literature to ascertain how this chapter fits into the broader picture. Section 3 is devoted to defining the shock, beginning with information on natural disasters at the level of individual events, then aggregating them up to the country/year dimension, such that the defined unit of observation can be then used to shed light on the empirical question of the paper. Section 4 presents the empirical strategy, the main results and sensitivity analyses. Finally, Section 5 presents some final remarks and policy implications.

2. Related Literature

The literature analyzing the effects of natural disasters on economic growth is diverse, yet there is no consensus about the effects of a natural disaster on economic growth. From a theoretical standpoint, the path to recovery from the output lost amidst the disaster could yield differential effects in the medium and long run (Cavallo et al., 2013). Thus, the empirical literature has focused on assessing the effects of natural disasters on economic growth in the short or the long run, trying to disentangle which factors may amplify or mitigate those effects.

The variation in the estimated effects of natural disasters on economic growth is sizable. In a meta-study comparing 750 estimates reported in 22 studies for the early 2000s, Klomp and Valckx (2014) find that most of the studies tend to find negative effects of natural disasters on economic growth in the short run (in the year of the disaster), yet an important share of those estimates are not significant. The negative effects of disasters on economic growth are concentrated on developing countries and related to disasters triggered by hydro-meteorological and climatic events. Recent advances using new sources of data (for both disasters and economic development) suggest that very large natural hazards have a negative contemporaneous effect on economic growth and highlight the fact that a natural hazard can have devastating effects on a subnational level, which is particularly difficult to cope with in smaller economies (Bertinelli and Strobl, 2012; Felbermayr and Gröschl, 2014; Klomp, 2016).

The approach used in this paper—as well as in most papers that use either cross-country regressions or comparative studies—relies on the occurrence of natural disasters. However, some papers use information on the hazard. Because the timing, location, and intensity of a hazard can be considered orthogonal to the determinants of the economic growth, the estimated effect of the natural hazard on economic growth is less likely to be affected by endogeneity issues. Moreover, as Cavallo et al. (2013) and Felbermayr and Gröschl (2014) show, there is a positive correlation between the physical magnitude of a disaster and the direct impacts of a natural disaster in terms of number of people killed and pecuniary damages to structures. Thus, the estimated effect of natural hazards is an *indirect* estimate of the effect of natural disasters on economic growth. But using information on hazards rather than on disasters has two limitations from an empirical point of view. First, because different types of hazards are measured in different scale units (e.g., magnitude for earthquakes, windspeed for storms and so on), the analysis is required to focus on only one type of disaster or to use an aggregation method that may compromise on the interpretation. Second, since not all hazards materialize in natural disasters, the interpretation of the estimated effect is different. Using the terminology of the treatment effects literature, the estimated effect resembles an *intention to treat*, that is, the average effect that a natural hazard has on economic growth, considering that not all hazards become natural disasters. A promising avenue of research in this field is to explore the factors that explain why natural hazard becomes a natural disaster and use this information to estimate the overall effect of natural disasters on economic growth.

An additional dimension in the related analyses is the locational impact of natural disasters. Hazard, incidence, and impacts vary according to the unit of analysis: whether it is individuals, a neighborhood or a community, a province within a country, or the country itself. When assessing the impacts of natural disasters on economic growth, the unit of analysis is usually the country. Focusing on the country level may, however, lead to missing significant events. Disasters tend to occur at a subnational level, which means that some natural hazards materialize over smaller units, creating significant impacts on those affected, yet minimal impacts on the aggregate economy (this is especially true in large countries). The fact that those events do not show up in GDP figures does not mean that they do not matter. They may matter greatly—and they may even be fatal—to those directly impacted, but they do not have significant aggregate effects, especially in large countries. The main challenge to exploiting subnational level variation of disasters is the lack of systematic information on economic activity at the subnational level, especially for low-income countries. Nonetheless, some papers have analyzed the effects of natural disasters on economic growth at the subnational level in the United States and other advanced economies, where the information is available. Thanks to this approach, results have uncovered mechanisms used by populations to self-protect from the negative effects of disasters that usually are not observable at the country level, such as internal migration (Boustan et al., 2012; Boustan et al., 2020). In developing economies, though, the information at the subnational level is scarcer and, in many cases, unreliable. New approaches to overcome this limitation have used satellite data on night-time light intensity as an indirect measure of economic activity (Bertinelli and Strobl, 2013; Klomp, 2016). The increasing availability of high-frequency data and the use of new techniques can shed light on relevant factors that make some regions resilient to the force of nature, thus providing another promising avenue for research.

Considering the available evidence, the emerging consensus in the literature—which is still evolving—is that natural disasters have, on average, a negative impact on short-term economic growth, while the medium to long-run effects remain elusive. This paper provides new estimates of the short and medium-term effects focusing on catastrophic natural disasters. In what follows, we characterize the dataset used to define natural disasters and to implement the empirical strategy.

3. Stylized Facts about Natural Disasters

The source of data for natural disasters used in this paper is EM-DAT, an online emergency disaster database of the Center for Research on the Epidemiology of Disasters (CRED).[8] The EM-

[8] EM-DAT was created with the initial support of the World Health Organization (WHO) and the Belgian Government. Current sponsors include the International Federation of Red Cross and Red Crescent Societies (IFRC), the United Nations International Strategy for Disaster Reduction (ISDR), and the United States Agency for International Development (USAID) among others Available online at https://www.emdat.be/.

DAT database has worldwide coverage and reports data on the occurrence and effects of different types of disasters from 1900 to the present.[9]

EM-DAT defines a natural disaster as a situation or event which overwhelms local capacity, necessitating a request for external assistance. For a disaster to be entered into the database, at least one of the following criteria must be fulfilled: (1) 10 or more people reported killed; (2) 100 people reported affected; (3) declaration of a state of emergency; or (4) call for international assistance.

Among the group labeled "Natural disasters,"[10] we focus on four subgroups which are the most common and for which there is more information available:[11]

- *Geophysical*: a hazard originating from solid earth, such as volcanic eruptions and earthquakes.
- *Meteorological*: a hazard caused by short-lived, extreme weather and atmospheric conditions that last from minutes to days, such as extreme temperatures and storms.
- *Hydrological*: a hazard caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater, such as landslides and floods.
- *Climatological:* a hazard caused by long-lived, atmospheric processes ranging from intra-seasonal to multi-decadal climate variability, such as wildfires and droughts.

The left panel of Table 1 presents the frequency distribution of the four types of natural disasters since 1970.[12] There are a total of 12,377 unique events in the sample between 1970 and 2019. About 45 percent of them are *hydrological* (mainly floods and landslides), 35 percent are *meteorological* (mainly storms and extreme temperatures), and 11 percent are *geophysical* (earthquakes, tsunamis, volcanic activity, and mass movements usually associated with soil

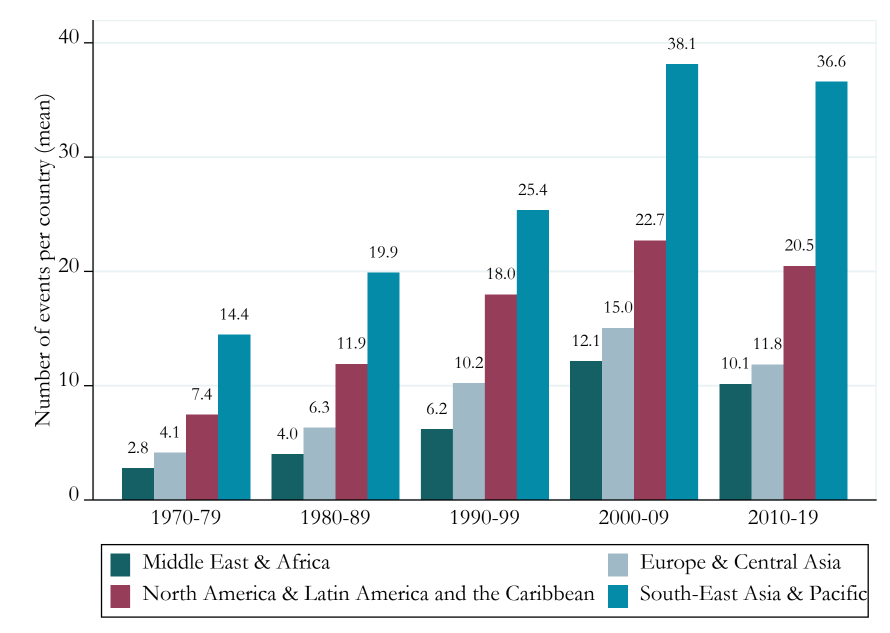
[9] The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutions and the press.
[10] The second group of disasters in the database are "Technological," which includes for example, chemical spills.
[11] The group natural disasters in the database also contains information on Biological (including pandemics) and Extraterrestrial events, which we omit from the sample because they are different in nature, and there is less information available.
[12] We narrow the period of analysis starting in 1970 because there is more information available in the database.

erosion). These three types of disasters account for 91 percent of the events in the sample. All three can cause great damage in a short period of time (typically less than 10 days) and the timing, location and duration are not exactly predictable, making them shock-like events for the affected communities. The rest are climatological events comprising droughts and wildfires. Droughts account for 5.3 percent of the episodes in the sample; they last significantly longer than any of the other types of events (232 days on average). The longer duration makes them less shock-like and slower-moving processes than the other types of natural disasters.

The central panel of Table 1 provides the same information for the subset of events that have data on their associated mortality. The total number of natural disasters is reduced by about one third to 8,500 unique events. Of those, 97 percent are hydrological, meteorological, or geophysical. There are only 52 droughts (0.6 percent of total events) with information on fatalities.

Figure 1 shows the average number of natural disasters in each country by region, using the World Bank country classification (World Bank, 2021). In every decade, South-East Asia and the Pacific is the region with the highest average incidence of disasters per country. The worst decade on record was 2000-09, when the average number of events per country was 38 in South-East Asia and the Pacific, and 12 in Middle East and Africa.

Figure 1. Average Number of Natural Disasters in Each Country by Region

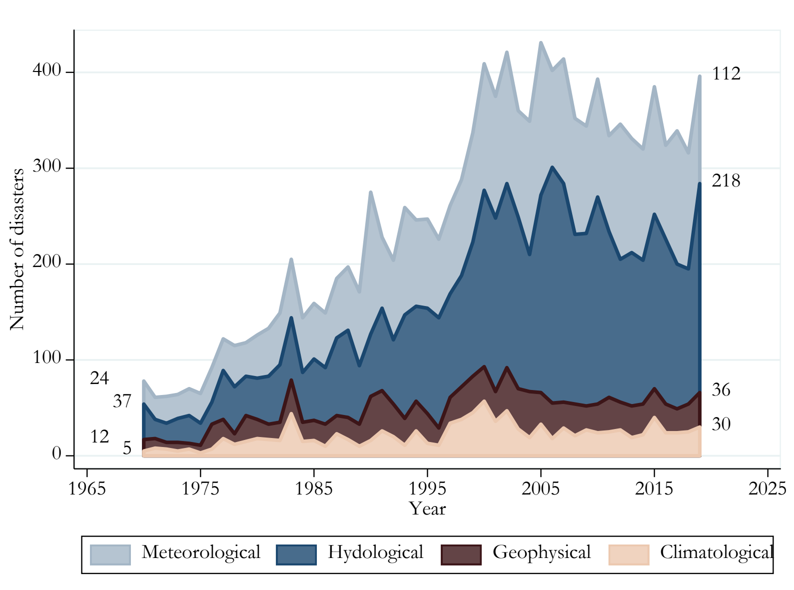


Source: Authors' calculations based on EM-DAT.

Figure 1 also shows that there seems to be an increasing trend in the incidence of natural disasters reported in EM-DAT, which may be related to climate change and/or to improved reporting in the dataset. Figure 2, panel A, shows the total number of events over time by type pooling across regions. There was a significant increase in hydrological (x5.9 since 1970), meteorological (x4.7) and climatological events (x6), all of which may be influenced by climate change.[13] However, there was also a significant increase (x3 since 1970) in the number of geophysical events which are not influenced by climate change, which suggests that at least part of the increasing trend of natural disasters is due to improved reporting.

Figure 2. Reported Natural Disasters, 1970-2020

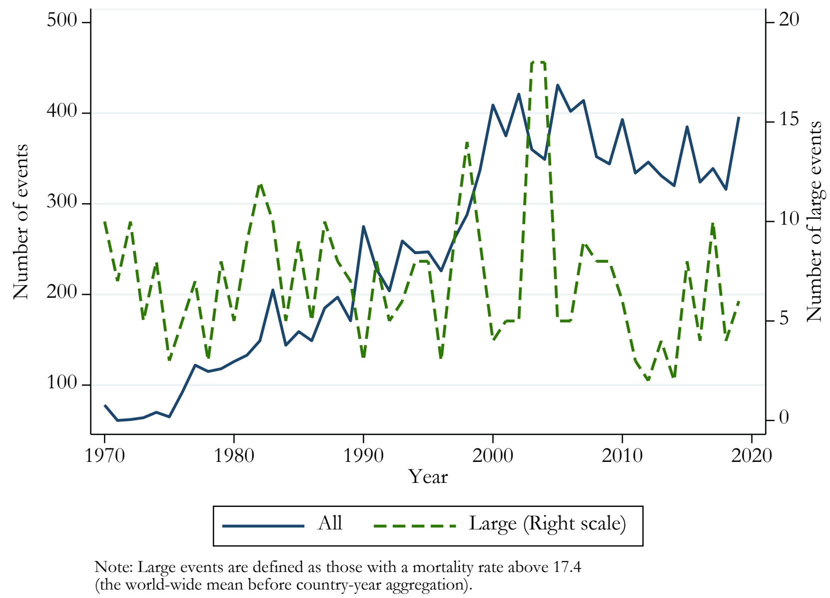
A. Number of Natural Disasters by Subgroup



[13] While it is impossible to link one hurricane to climate change, scientists agree that as the waters warm, pumping more moisture into the atmosphere, and seas rise, hurricanes and storms become more lethal (See Intergovernmental Panel on Climate Change)

Figure 2., continued

B. Increasing Prevalence of Natural Disaster (1970 – 2019)



Source: Authors' calculations based on EM-DAT.

Table 1. Distribution of Natural Disaster by Type – Disaster Level (1970 – 2019)

Disaster Type	All disasters			Disasters with number of deaths				Large disasters[1]			
	Occurrence		Duration in days[2]	Occurrence		Duration in days[2]	Mortality Rate	Occurrence		Duration in days[2]	Mortality Rate
	Observations	(%)		Observations	(%)			Observations	(%)		
Climatological											
Wildfire	427	3.5	12.8	75	2.1	17.5	0.7	0	0		
Drought	61	5.3	232.4	52	0.6	341.9	740.6	12	3.4	721.7	3,201.9
Geophysical											
Volcanic Activity	209	1.7	8.4	54	0.6	3.5	84.6	5	1.42	0.2	903.0
Mass Movement (Dry)	41	0.3	0.9	39	0.5	0.9	3.1	2	0.6	< 1	20.9
Earthquake	1,101	8.9	<1	758	8.9	<1	75.8	77	21.8	<1	735.1
Hydrological											
Landslide	682	5.5	1.2	647	7.6	1.3	4.3	24	6.8	2	78.7
Flood	4,904	39.6	9.0	3,564	41.9	9.9	2.7	73	20.7	13.4	81.2
Meteorological											
Extreme Temperature	575	4.7	13.3	66	5.5	14.1	9.2	31	8.8	18.5	120.1
Storm	3,777	30.5	1.8	2,745	32.3	2.0	11.0	129	36.5	3.2	215.7
Total	**12,377**	**100**	**17.8**	**8,500**	**100**	**8.1**	**17.4**	**353**	**100**	**30.3**	**395.3**

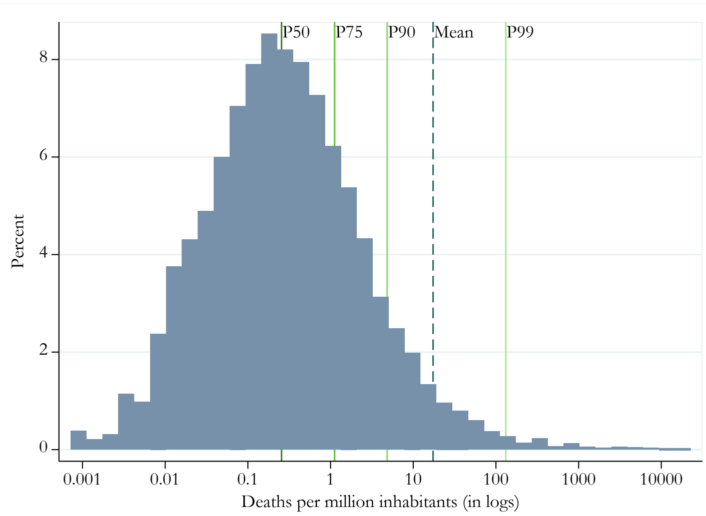
Source: Authors' calculations based on EM-DAT and population data from World Development Indicators (WDI).
Notes:
[1] We define a large disaster as a disaster with a mortality rate over the mean across all disasters (before aggregation).
[2] Duration is the average duration in days of each type of disaster.

To probe the latter point in greater depth, we check whether the increasing trend in the number of disasters also holds for large disasters, which, due to their magnitude, are more likely to be reported. We determine the magnitude of the disasters based on the human mortality rate rather than on the estimated direct economic damages because the latter is more likely to be biased towards advanced economies in the database.[14] Panel B shows the total number of events (left axis) over time pooling across regions, and the number of events above a mortality threshold (right axis). The mortality threshold set is equal to the average mortality rate (per million people) in the sample, covering all episodes since 1970 (which is 17.4 deaths per million inhabitants; see Table A1 in the Appendix). The figure shows that while there is an increasing trend in the overall number of events, there is no trend for "above-the-mean mortality" events, providing confirmation that the increasing trend in the former may be driven in part by improved reporting. Once the smaller—and conceivably less catastrophic events—are filtered out of the sample, there does not seem to be an increasing trend for remaining events; instead, there are years with peaks and troughs in the number of events around a mean of about 7.1 occurrences per year.

The combination of more and less catastrophic events in the sample begs the question of what the distribution of mortality is. Figure 3 shows that the distribution of (log) mortality is skewed to the right: the average mortality rate for events in the sample (17.4) falls in between the 90th and the 99th percentile of the distribution. This in turn implies that the subset of "above-the-mean-mortality" events is much smaller than the full sample (see also Table A1). Figure 3 also shows that, relative to the size of a country, the typical disaster tends to exhibit a low mortality rate, yet the distribution has a heavy right tail. The median disaster recorded in the EM-DAT dataset has a mortality rate of 0.2553 deaths per million inhabitants. Nonetheless, the most catastrophic disasters reach up to 22,716 deaths per million inhabitants (the 2010 Haiti Earthquake).

[14] Estimates of monetary damages reported by EM-DAT tend to be biased towards advanced countries because they typically have more developed insurance sectors and better data quality than low-income countries (Felbermayr and Gröschl, 2014).

Figure 3. Distribution of (log) Mortality Rate, 1970-2019



Source: Authors' calculations based on EM-DAT and World Development Indicators (WDI).

The right panel in Table 1 shows the subset of "above-the-mean-mortality" events (large or more catastrophic disasters). The total number of disasters then falls to 353. Those events are more likely to have aggregate (macro) effects, and the frequency distribution of events in the reduced sample of "above-the-mean-mortality" episodes is different from the full sample. The largest number of occurrences in the reduced sample are *meteorological* (storms and extreme temperatures, 45 percent), followed by *hydrological* (floods and landslides, 27.5 percent) and by *geophysical* (earthquakes, tsunamis, and others, 24 percent). Climatological events (droughts) are less than 4 percent of the total.[15]

Table 2 shows the percentage of people affected by each type of disaster across types and regions. People affected excludes fatalities; it is defined in EM-DAT as those requiring immediate assistance during a period of emergency, i.e., requiring basic survival needs such as food, water, shelter, sanitation, and immediate medical assistance. Due to their geographical location and population density, different types of hazards have differential effects around the globe. The largest share of people (48 percent) are affected by hydrological events (mainly floods and landslides)—especially in Southeast Asia and the Pacific. They are followed by climatological events (droughts), especially in the Middle East and Africa, and meteorological events (mainly storms

[15] Also note that the average duration of the subset of droughts with "above-the-mean" mortality is more than twice that of the broader sample of droughts.

and extreme temperatures), especially in North America. In Latin America and the Caribbean and in Europe and Central Asia the percentage of people affected is more evenly split among climatological, hydrological, and meteorological events. Geophysical events affect the smallest number of people in all regions.

Table 2. Distribution of Persons Affected by Type of Event and Region, 1970-2019

	Affected	Climatological	Geophysical	Hydrological	Meteorological
	(% of total)	(% within region)			
Europe & Central Asia	0.8	29.6	19.6	30.4	20.5
Middle East & Africa	7.7	77.8	0.9	16.3	5.0
South-East Asia & Pacific	86.3	29.6	2.1	52.8	15.5
Latin America and the Caribbean	3.7	37.7	13.0	29.4	19.9
North America	1.5	1.2	0.1	10.9	87.8
World	**100**	**33.2**	**2.6**	**48.3**	**16.0**

Source: Authors' calculations based on EM-DAT and World Development Indicators.

As in the case of affected, the types of natural hazards have differential effects on the disaster's mortality. Table 3 shows the percentage of people killed by each type of event and region. Climatological events are the most lethal in Middle East and Africa, where they account for over 80 percent of fatalities. In other regions, however, climatological events account for a small share of fatalities, and overall they account for about 20 percent of total fatalities. Instead, geophysical events–especially in the Latin America and the Caribbean—and meteorological events–especially in Europe and Central Asia, and in North America—account for the largest shares of fatalities (they respectively account for 40 percent and 29 percent of total fatalities). Hydrological events (floods and landslides) are the least lethal across regions, despite being among the most frequent in the EM-DAT database and despite affecting the most people globally.

In brief, the following stylized facts emerge from the statistical properties concerning frequency of occurrence, duration, number of people affected and mortality by each type of episode:

1. *Hydrological* events, including floods and landslides, are the most frequent, affecting large segments of the global population, but they are less lethal than other types.
2. *Geophysical* events, including earthquakes and tsunamis, are the least frequent, affecting small segments of the global population, but they are the most lethal.
3. *Meteorological* events, including storms and extreme temperatures, fall in between hydrological and geophysical events in all three dimensions: frequency, number of people affected, and fatalities.
4. *Climatological* events, which are mainly droughts, are different in all three dimensions. They are less frequent and significantly less lethal than the other types of events (except in the Middle East and Africa, a region where droughts affect large portions of the population). Finally, they last significantly longer than any of the other type of events.
5. Hydrological, geophysical, and meteorological events are similar in terms of their shock-like characteristics. Climatological events, on the other hand, are slow-moving processes.

Table 3. Distribution of Persons Killed by Type of Event and Region, 1970-2019

	Killed	Climatological	Geophysical	Hydrological	Meteorological
	(% of total)	(% within region)			
Europe & Central Asia	6.7	0.3	29.0	4.4	66.2
Middle East & Africa	25.1	81.2	13.8	4.1	0.9
South-East Asia & Pacific	53.4	0.4	43.5	13.6	42.6
Latin America and the Caribbean	14.2	0.1	76.1	14.0	9.8
North America	0.5	1.8	1.9	12.9	83.4
World	**100**	**20.6**	**39.5**	**10.6**	**29.2**

Source: Authors' calculations based on EM-DAT and World Development Indicators.

Evaluating the economic impacts of natural disasters requires a taxonomy of the different types of events. It also requires defining the adequate level of aggregation of the data. As in the literature of macroeconomic impacts of shocks, most of the empirical studies focusing on the effects of natural disasters on economic growth are assessed at the country/year level. In the case of natural disasters, however, there are usually more than one event per country each year. Therefore, in order to assess the macroeconomic impacts of natural disasters, the sample of events must be collapsed. Table 4 shows the results of collapsing the individual events in Table 1 to the country/year level.

There are a total of 3,682 country/year observations with disasters in the database. This implies that events classified as natural disasters are prevalent: they represent about 45 percent of the total country/year observations (out of a total of a maximum of 8,120 observations = 203 countries times 40 years). When the sample is restricted to episodes with information on fatalities, the total number of observations falls to 1,616 (20 percent of the total). Moreover, when the sample is further restricted to high-mortality events, which in this case are defined as country / year observation where the mortality is above the mean mortality in the collapsed sample (62.9 people per million inhabitants, see Table A1), then the total number of observations with disasters falls to 89 (which is about 1 percent of the total). Therefore, while natural disasters are quite common, high-mortality events—which are conceivably the ones with the highest potential of generating macroeconomic effects—are much rarer. This is so because the distribution of events once the data are collapsed is also skewed to the right, with the mean mortality falling in between the 90th and the 99th percentile of the distribution.

Another characteristic of the collapsed sample is the emergence of the "combined" category in Table 4. This category corresponds to the country/year observations that contain more than one type of event occurring in that country within the year. Combined events account for 40 percent of the observations in the unrestricted sample, and about 30 percent when the sample is restricted to events with fatalities. Since most individual events are either hydrological, meteorological, and geophysical, then most combined events after the data are collapsed represent a mixture of the three types. Moreover, the average duration and mortality of combined events are more like those of the hydrological, meteorological, and geophysical, rather than those of climatological events, which are less frequent.

Table 4. Distribution of Disaster Type: Country-Year Level, 1970-2019

Disaster Type	All disasters			Disasters with number of deaths				Large disasters[1]			
	Occurrence		Duration	Occurrence		Duration	Mortality	Occurrence		Duration	Mortality
	Observations	(%)	in days[2]	Observations	(%)	in days	Rate	Observations	(%)	in days	Rate
Climatological											
Wildfire	45	1	5	15	1	4	1	0	0		
Drought	218	5.9	311.5	14	0.9	677.9	1312.4	5	5.6	876	3658.9
Geological											
Volcanic Activity	37	1	6.2	9	0.6	0.1	500	3	3.4	0.3	1488.7
Mass Movement (Dry)	10	0	< 1	10	1	< 1	8	0	0		
Earthquake	160	4	<1	107	7	<1	195	19	21	<1	1065
Hydrological											
Landslide	68	2	0	59	4	0	27	2	2	<1	550
Flood	977	27	9	555	34	10	6	9	10	4	129
Meteorological											
Extreme Temperature	82	2	7	64	4	6	17	3	3	20	205
Storm	579	16	2	318	20	2	47	24	27	2. 1	540
Combined	1,506	41	5	465	29		79	24	27	12	1,417
Total	**3,682**	**100**	**29**	**1,616**	**100**	**13**	**63**	**89**	**100**	**54**	**1,043**

Source: Authors' calculations based on EM-DAT and World Development Indicators.
Notes:
[1] We define a large disaster as a disaster with a mortality rate over the mean across all disasters (after aggregation).
[2] Duration is the average duration in days of each type of disaster.

In the next section, we draw from the sample of country/year observations with natural disasters to assess impacts on economic growth.

4. Empirical Evidence on the Impacts of Natural Disasters on GDP Growth

4.1 Which Natural Disasters?

Natural disasters produce direct and indirect damages on impact. Direct damages are mortality and morbidity, the destruction of physical assets, and damages to raw materials and extractable natural resources because of the natural phenomenon. Indirect damages refer to other economic outcomes following the disaster such as possible impacts on economic growth, on poverty, and on income inequality.

This paper focuses on the impacts on economic growth, which can be quantified by examining the performance of the economy following natural disasters as measured by changes in real GDP per capita.

We focus on the four types of natural disasters considered in the previous section: geophysical; meteorological; hydrological and climatological. Starting from the 1,616 country/year observations with data on fatalities, we rank the severity by the associated mortality rate. The summary statistics are reported in Table A1. The average mortality rate is 62.9 people per million but exceeded 22,000 people per million in the 2010 Haiti episode.

Table A2 in the Appendix lists the 200 top disasters according to the mortality raking in descending order. At the top of the list is Haiti 2010, which is a combined episode because, in addition to the earthquake, there were 3 floods and 2 storms that beset Haiti that year. The combined mortality of the 6 events was 22,723 per million people, the most catastrophic of which was the earthquake.

Table A2 presents the rank order of the episodes for three distinct groups:

- Group 1: All four types of disasters.
- Group 2: All disasters *excluding* climatological. As explained before, climatological events are different from the rest in terms of frequency, number of people affected, people killed and especially, in terms of duration.
- Group 3: Only earthquakes, floods, and storms. These are the most common types of events in the sample; the ones with the most complete information in

the dataset, and the types that were considered in the Borensztein et al. (2017) study.

From the three lists in Table A2, we will draw on the country/year observations to perform a comparative event study on various subsamples. We consider the top 20, top 30 and top 50 disasters with highest mortality in the different groups, and we apply a common event study methodology across groups. We then perform a battery of robustness checks. The next subsection provides further details on the methodology.

4.2 Empirical Strategy

Having determined the pool of episodes, the next step is to trace the evolution of real GDP per capita growth for the impacted economies over a specified time horizon. In the baseline, we work with 6 years before and after the onset, but we subsequently adjust the time horizon to three years as a robustness check. In terms of pooling across episodes with different dates of real GDP per capita, we follow the methodology implemented in Cerra and Saxena (2008), which consists of calculating indices depicting the average behavior of the level of real GDP per capita for the selected episodes.[16]

The base year T is defined as the year of the episode (i.e., in Haiti 2010, T is 2010). To construct a timeline comprising several episodes across countries and time, we align T's across all episodes in a given group and trace the average growth rate, and the average level of the real GDP per capita, respectively, in the 13-year window centered on T for each country/episode. To avoid problems in the comparison of real GDP per capita levels between countries and periods, we normalize the real GDP per capita level series of each country to 100 in the year T, and then we rescale each series accordingly for years *T-6, …, T-1* and *T+1, …, T+6*. Next, we take the simple averages of the series (i.e., the real GDP per capita growth and the rescaled GDP per capita level) within a group, according to the following formula:

$$\bar{y}_s = \frac{1}{n_s}\sum_{i=1}^{n} y_{i,s}\,; \qquad s = T-6, \dots, T, \dots, T+6,$$

[16] The source of real GDP per capita measures is the World Bank's World Development Indicators (WDI). We use the series: GDP per capita (constant 2010 US$) (NY.GDP.PCAP.KD); GDP per capita growth (annual %) (NY.GDP.PCAP.KD.ZG); and GDP per capita, PPP (constant 2017 international $) (NY.GDP.PCAP.PP.KD). The data cover most countries in the world for the period 1960-2019.

where n_s is the number of countries/episodes in a period s, and s represents the time index around T. Note that, by construction, the result for the real GDP per capita is a *synthetic* average GDP per capita index for a group of country/episodes that is equal to 100 in period T, and for the rest of the years, is the simple average across indices computed.

When presenting the results, we focus on the average values. We distinguish between the short-run effects, defined as the average effect of the shock at the year of the disaster, and the medium-term effects, defined as the difference in the pre- and post-disaster averages. Under the assumption that the distribution of the real GDP per capita growth would have evolved smoothly around T absent the disaster, those differences are estimates of the effect of natural disasters on economic growth. We implement a similar procedure for the synthetic GDP per capita index, including pre- and post-disaster trends of the *synthetic* index, and test if there are significant differences before and after T.[17] In this case, the size of the fall in output is calculated as the difference between the counterfactual and the actual real GDP per capita in T.

We make several refinements to the methodology to get unbiased estimates. First, if for a given country/episode there is no real GDP per capita data for year T, then that country/episode is excluded. Also, there are some episodes in which T is either before 1975, or after 2014 such that for those episodes there is not going to be a complete 13-year window around T in the period 1970-2019. In the case of the country/episodes that occur before 1975, the issue is solved by including real GDP per capita data from the 1960s. For episodes that occur after 2014, we leave them in the study and use a shorter window for the analysis. However, we check whether the inclusion of those country/episodes biases the results in the robustness tests. We also leave in the sample episodes for which there are no real GDP per capita data for the full 13-year window around T and episodes where there is more than one event in the same country within a 13-year window of another event, and then exclude them to check robustness.

[17] More specifically, we run the regressions

$$g_{i,s} = \alpha_0 + \alpha_1 \times disaster_T + \alpha_2 \times after_T + u_{i,s},$$

for real GDP per capita growth ($g_{i,s}$), and

$$y_{i,s} = \beta_0 + \beta_1 \times s + \beta_2 \times disaster_T + \beta_3 \times after_T + \beta_4 \times s \times after_T + v_{i,s},$$

for the normalized real GDP per capita ($y_{i,s}$). In both equations, s denotes a time index over the 13-year window centered on T; $disaster_T$ is an indicator variable that is equal to one for the period the disaster occurred ($s = T$); $after_T$ is an indicator variable that is equal to one for all the periods after the disaster ($s > T$). The parameters α_1 and β_2 capture the effect of natural disasters on economic growth in the short term, while α_2 and β_4 capture the medium-term effects.

The second consideration is about possible outliers that may distort the calculations. There may be some anomalous behavior of real GDP per capita, or GDP per capita growth for some countries/episodes. To identify possible outliers that may distort the averages, we calculate the studentized residual for the GDP per capita, and the GDP per capita growth, respectively for all country episodes with high mortality. For this process, we analyze the sample of the 100 highest mortality disasters from Table A.2 and take the residual variation for the regression:

$$z_{i,s} = \beta_s + e_{i,s}; \quad s = T-6, \dots, T-1, T+1, \dots, T+6,$$

where $z_{i,s}$ is the real GDP per capita growth, or GDP per capita index, for country i in period s, for each one of the country/episodes in the list of 100 highest mortality disasters. We run a separate regression for every period s and compute the studentized residuals as $\hat{e}_{i,s} = \frac{y_{i,s}-\hat{\beta}_s}{\hat{\sigma}_{e,s}}$, where $\hat{\sigma}_{e,s}$ is an estimate the standard deviation of $e_{i,s}$ (estimated from a separate regression in which we exclude the country/episode i from the regression). Thus, for every country/episode included in the analysis, there are 12 studentized residuals (one for each s). We drop countries/episodes for which studentized residuals are larger than 2.5 in 15 percent or more of periods. The countries/years excluded using this procedure are Iran 1972, 1978, and 1981; Kiribati 1972; Northern Mariana Islands 2004; Tajikistan 1989, and 1992; Georgia 1991, El Salvador 1986; and Oman 1977.

4.3 Results

There are two outcome variables: i) real GDP per capita growth and ii) real GDP per capita level, taken from the World Development Indicators.[18] There are three groups from which we draw episodes: group 1 (all episodes), group 2 (all episodes excluding climatological), group 3 (only earthquakes, floods, and storms). For each of the groups we focus on the top 20, 30 and 50 natural disasters with the highest mortality.

Figure 4 show the results for the 20 largest events in group 3, which is the smallest and most homogenous group. In the figures, T is the is the year when the disaster occurred. Each dot is the simple (unweighted) average across the 20 episodes, for each of the six years before and the six years after T. Pre- and post-crisis trend lines are included in all figures. In the left panel of

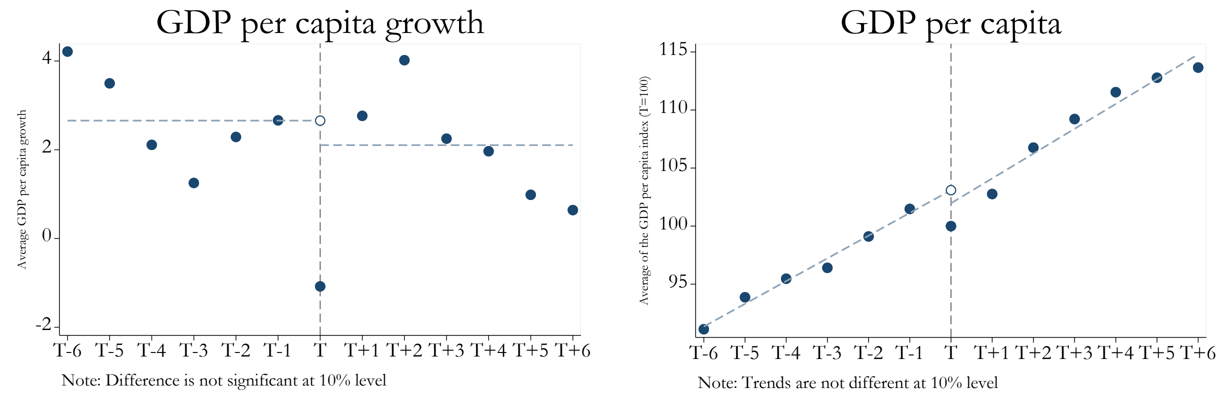
[18] We also estimate the models presented below using the real GDP per capita adjusted by purchasing power parity (PPP). Our results are robust to changing the measure of GDP per capita (See Table 6).

Figure 4, the estimated short-run effect on GDP growth is the difference between the pre-disaster average (plotted as an empty dot on the vertical line at T) and the actual average growth rate on T (solid dot on the vertical line at T). In right panel of Figure 4, the estimated short-run output loss at T is measured as the difference between the counterfactual GDP per capita (plotted as an empty dot on the vertical line at T) and actual GDP per capita (solid dot on the vertical line at T).

We find that during the year of the disaster, real GDP per capita growth declines by 3.7 percentage points (p.p.) on average, vis-à-vis the average pre-disaster growth for the 20 largest disasters (bottom panel of Table 5). This number becomes 3.1 and 2.1 p.p. in the cases of the top 30 and 50 disasters. The estimated average effect at T is statistically different from zero. In addition, the pre- and post-disaster average growth rates are not statistically different, which suggests that the occurrence of the natural disaster does not affect real GDP per capita growth in the medium term. Overall, our results imply that the affected economies suffer a loss that is not subsequently offset by above-average growth.

For the normalized GDP level, we find that during the year of the disaster, the average output loss is 3.1 percent. for the 20 largest disasters (Table 5). As more episodes with lower mortality are included, the average output loss is lower: for the top 30 and 50 in that group, the average output loss is 2.7 percent and 1.6 percent, respectively. The estimated short-term effect is significant for all samples and groups. The before and after trends are not statistically different at the 10 percent level, which suggests that after the natural disasters, real GDP per capita level remains on the same trend as before the disaster. Therefore, the level of real GDP per capita after T remains permanently below the counterfactual level that would have been achieved if the disaster had not materialized. Similarly, the results for the model in levels indicate an output loss; however, they are not precise enough at the 10 percent level to conclude that they are different from zero.

Figure 4. Real GDP Per Capita Growth and Level around a Natural Disaster: 20 Largest Disasters



Source: Authors' calculations based on EM-DAT and World Development Indicators.
Note: The figure shows the averages of the real GDP per capita annual growth rates (panel A) and the level of real GDP per capita (panel B) across the 20 largest natural disasters (based on mortality rate) listed in Table A.2, group 3, in a 13-year window centered on the event. The pre- and post- event trends are also included in both panels. In panel A, the level of output per capita for every event is normalized to 100 in the year of the event (T) before taking averages across countries. In panels A and B, the post-disaster trends are not statistically different from the pre-disaster trends, suggesting that output losses are not recovered.

The results are consistent across the different groups of disasters. In the case of all disasters (group 1, top panel of Table 5), which includes climatological events (which are much more persistent than the other types of disasters), short-run growth losses are smaller but statistically significant: 2.9 p.p., 2.6 p.p. and 2.3 p.p. for the top 20, 30 and 50 disasters, respectively. As in the case of group 3's estimates, the pre- and post-disaster average growth rates are not statistically different at the 10 percent level. Regarding real GDP levels, the average estimated declines at T are 2.9 percent, 2.3 percent and 1.8 percent while consistently negative, are not statistically different from zero. Finally, in the case of group 2, average effects on growth rates are very close to those of group 3: 3.8 p.p., 2.6 percent and 2.2 percent for the top 20, 30 and 50 disasters, respectively.

Table 5. Baseline Results: Effects of Natural Disasters on Growth

	Top 20		Top 30		Top 50	
	Real GDP per capita growth	Real GDP per capita	Real GDP per capita growth	Real GDP per capita	Real GDP per capita growth	Real GDP per capita
Group 1 (All disasters)						
Effect of the disaster at time T	-2.89	-2.90	-2.62	-2.32	-2.25	-1.81
	(0.46)	(2.04)	(0.35)	(1.51)	(0.25)	(1.16)
Medium-term effect	-0.08	0.96	-0.29	0.65	-0.53	0.26
	(0.63)	(0.99)	(0.51)	(0.74)	(0.36)	(0.56)
Group 2 (All disasters excluding climatological)						
Effect of the disaster at time T	-3.79	-3.55	-2.58	-2.00	-2.15	-1.61
	(0.39)	(1.79)	(0.29)	(1.3)	(0.23)	(1.06)
Medium-term effect	-0.70	-0.08	-0.68	0.00	-0.60	-0.03
	(0.55)	(0.85)	(0.44)	(0.63)	(0.33)	(0.49)
Group 3 (Earthquakes, Floods, and Storms)						
Effect of the disaster at time T	-3.74	-3.10	-3.14	-2.67	-2.08	-1.59
	(0.41)	(1.84)	(0.32)	(1.57)	(0.24)	(1.08)
Medium-term effect	-0.55	0.18	-0.38	0.20	-0.30	0.39
	(0.61)	(0.89)	(0.46)	(0.7)	(0.34)	(0.52)

Source: Authors' calculations based on EM-DAT and World Development Indicators.

Note: The table shows the results for Top 20, 30 and 50 highest mortality rate episodes listed in Table A.2; for groups 1 (all episodes), 2 (all episodes except climatological), and 3 (only earthquakes, floods, and storms) respectively. Within each subset, results are shown for Real GDP per capita growth (left column) and Real GDP per capital level (right column). The short-run effects are the average estimated effect of the shock at the year of the disaster T in percentage points for growth, and in % for levels (standard errors in parenthesis below the point estimate). The medium-term effects are defined as the difference in the pre- and post-disaster averages that are calculated based on the regressions

$$g_{i,s} = \alpha_0 + \alpha_1 \times disaster_T + \alpha_2 \times after_T + u_{i,s},$$

for real GDP per capita growth ($g_{i,s}$), and

$$y_{i,s} = \beta_0 + \beta_1 \times s + \beta_2 \times disaster_T + \beta_3 \times after_T + \beta_4 \times s \times after_T + v_{i,s},$$

for the normalized real GDP per capita ($y_{i,s}$), respectively. In both equations, s denotes a time index over the 13-year window centered on T; $disaster_T$ is an indicator variable that is equal to one for the period the disaster occurred ($s = T$); $after_T$ is an indicator variable that is equal to one for all the periods after the disaster ($s > T$). The parameters α_1 and β_2 capture the effect of natural disasters on economic growth in the short-term, while α_2 and β_4 capture the medium-term effects. Standard errors are reported in parenthesis below the point estimates.

4.4 Sensitivity Analysis

The results suggest that, for catastrophic events, the short-run effect of natural disasters on economic growth is negative, showing an output loss at time T, and that this loss is permanent. The effects are stronger for the largest disasters, as they tend to diminish when we include less deadly events. We perform a battery of robustness checks to the main results. The results for the largest 20 earthquakes, floods, and storms (group 3) are presented in Table 6 and in Tables A3 and A4 of the Appendix for the largest 30 and 50 events.[19]

The first set of results is related to the treatment of overlapping episodes within the 13-year window of the event study. There are cases when there is more than one episode in a country over a window such that one of the T's or both fall within the event window of the other. This overlap can bias the estimates of the average treatment effects and the calculations about trends. To check whether the results are significantly affected by overlaps we perform three sensitivity analyses:

1. If there are two or more episodes that overlap, we keep the one with the highest mortality and drop the others from the estimation sample
2. We drop all overlapping episodes from the estimation.
3. We drop all countries with overlapping episodes, even if some of the episodes do not overlap with others.

In all cases, when we drop an episode from the estimated sample, we replace it with the next one in the corresponding list, such that we always have 20, 30 and 50 episodes in all estimations. Our results are robust to the exclusion of countries with overlapped events. Using the sample of the top 20 largest episodes, the estimated contemporaneous effect on growth caused by the disaster changes from 3.74 p.p. to 4.3 p.p., and there are no significant differences between the average growth levels before and after the disaster. In line with this result, when we evaluate the effects on output levels, the contemporaneous effect is negative changes from 3.1 percent to 3.6 percent. Moreover, we do not find evidence that suggest that the time trend in GDP levels changes after the disaster.[20]

[19] Results for groups 1 (all disasters) and 2 (all disasters except climatological) are available upon request.
[20] Despite a reduction in their magnitude, the same patterns hold for the samples of the top 30 and top 50 disasters (see Tables A.3 and A.4)

Another concern in this analysis is that the estimated effects of the disasters are influenced by the window used in the event study. Similar to the literature related to Regression Discontinuity Designs, including more periods in the window yields more precise estimates; however, if the effects are local around the period in which the disaster occurred, the estimates will be biased using wider windows. To test the robustness of the estimated effects to changes in the selected event window, we change the event window from 13 years to 7 years: 3 years before and after T. Using this narrower event window, the contemporaneous effect of the disaster on growth changes slightly, from -3.74 p.p. to -3.16 p.p. for the top 20 episodes, and the differences in average growth rates before and after the disaster remains not significant. Although estimated with lower precision, the contemporaneous effect on the GDP level is negative, and there is no evidence suggesting a change in trend after the occurrence of the disaster.

We also test the sensitivity of the results to the unbalanced nature of the panel. For the baseline estimations, the only requirement to include a country/episode in the estimation sample is that there are data on real GDP per capita (and growth) on T. Some countries, however, may have data only on T but not on other years within the window, and that may bias the results. For instance, small countries with poor data quality could influence the results by reporting stronger effects on economic growth after the disaster. Therefore, we drop from the sample all country/episodes without complete data over the estimation window and re-estimate. Restricting the sample to countries with complete data within the event window reduces the size of contemporaneous effect of disasters on growth (from -3.74 p.p. to -2.71 p.p. for the top 20 results), and this effect is estimated with more precision.

We also consider the role of aggregation of events in the results and check the robustness of the results to the aggregation procedure. The raw data from EM-DAT is at the event level, and there may be more than one event per country/year. In order to convert the data to the country/year dimension we collapsed the data for individual events. However, when collapsing, a decision must be made regarding the treatment of missing values of individual events. If for example, there are 4 single events in one country on a given year, and all of them except one have data on fatalities, should the missing value be treated as zero (and therefore keep the country/year observation), or should the entire country/year observation be set to missing? For the baseline regressions, we opted for the latter. In a robustness check, we implement the former. Treating events with no information as zeroes and including the aggregate country/episodes in the estimation reduces the magnitude of the estimated effect of natural disasters on growth (from -3.74 percent to -1.73 percent for the top 20 results). This result is explained by the fact that some events in large countries were not considered in the list of top 20 events. Nonetheless, even though the magnitude of the effects falls, the contemporaneous effects of the natural disaster on growth continue to be significant, and we found no evidence of differences in the average growth rate before and after the disaster's occurrence.

Table 6 shows two other robustness checks to test the sensitivity of the results to the timing of the disaster, and to removing small countries (countries with less than one million inhabitants) from the sample. The aggregate effects of events taking place at the beginning of the year could be different from those happening by the end of the year; in the latter case, macro effects may not appear in the year's data (see, for example, Noy, 2009). To account for the timing of the occurrence of the disaster, we allocate any event happening during the last quarter of a year to the next year and recompute the exercises. Second, we exclude countries with less than one million inhabitants because small countries may be overrepresented in the top of the list of mortality rate due to population size. In both cases, the contemporaneous effects of the disaster on GDP growth remain negative and statistically significant, but they are smaller in magnitude: between -1.95 percent and -2.78 percent.

Finally, Table 6 includes two additional sensitivity analyses: on alternative measures for the GDP per capita and GDP per capita growth, and on the way in which we select disasters for the estimating sample. First, rather than using the real GDP per capita based on constant US Dollars, we use the real GDP per capita adjusted by PPP, taken from the World Development Indicators. Results are that despite a small reduction of the magnitude of the effect of the disaster on economic growth (it changes from -3.74 percent to -3.13 percent), the sign and significance remain unchanged compared to the baseline. Second, rather than using the 20 largest events, we select the events with a mortality rate of one standard deviation above the average mortality in the sample, as in Borensztein et al. (2017). Applying the alternative criterion over the whole sample, we end up with only the top 9 events reported in the Table A.2 in the estimating sample. Despite changes in the magnitude, the sign and significance of the coefficient estimates associated with GDP per capita growth and GDP per capita remain unchanged compared to the baseline.

Table 6. Robustness Checks: Effects of Natural Disasters on Growth, 20 Largest Events

Dependent Variable	Real GDP per capita growth: Effect of the disaster at time T	Real GDP per capita growth: Medium-term effect	Real GDP per capita: Effect of the disaster at time T	Real GDP per capita: Medium-term effect
Main Results	-3.74	-0.55	-3.10	0.18
	(0.41)	(0.61)	(1.84)	(0.89)
No overlapping	-3.80	-0.65	-3.20	0.08
(keep worst)	(0.42)	(0.63)	(1.92)	(0.93)
No overlapping	-4.29	-3.51	-4.19	-3.55
(excl. both)	(0.52)	(2.37)	(0.55)	(2.53)
No overlapping	-0.65	0.36	-0.77	0.2
(excl. country)	(0.77)	(1.13)	(0.82)	(1.21)
3-year window	-3.16	0.93	-4.07	0.69
	(0.58)	(0.93)	(2.55)	(1.84)
All values of GDP	-2.71	-1.04	-2.02	-0.24
	(0.37)	(0.58)	(1.45)	(0.78)
Missing as zeroes	-1.73	0.60	-1.03	0.63
	(0.41)	(0.59)	(1.76)	(0.87)
Next year	-2.78	-0.10	-2.57	0.50
	(0.45)	(0.68)	(1.91)	(0.97)
Excluding small	-1.95	-0.4	-1.6	0.4
countries	(0.39)	(0.5)	(1.91)	(0.82)
GDP per capita	-3.13	-0.40	-3.14	-0.20
(PPP)	(0.44)	(0.60)	(1.80)	(0.81)
One standard deviation above	-2.64	-0.70	-2.07	0.22
the mean	(0.54)	(0.77)	(2.38)	(1.27)

Source: Authors' calculations based on EM-DAT and World Development Indicators.
Note: The table shows the results for Top 20 highest mortality rate episodes listed in Table A.2 for group 3 (only earthquakes, floods, and storms) respectively. Each row corresponds to a particular robustness check. Within each subset, results are shown for Real GDP per capita growth (two left columns) and Real GDP per capital level (two right columns). The short-run effects are the average estimated effect of the shock at the year of the disaster T in percentage points for growth, and in % for levels (standard errors in parenthesis below the point estimate). The medium-term effects are defined as the difference in the pre- and post-disaster averages that are calculated based on the regressions

$$g_{i,s} = \alpha_0 + \alpha_1 \times disaster_T + \alpha_2 \times after_T + u_{i,s},$$

for real GDP per capita growth ($g_{i,s}$), and

$$y_{i,s} = \beta_0 + \beta_1 \times s + \beta_2 \times disaster_T + \beta_3 \times after_T + \beta_4 \times s \times after_T + v_{i,s},$$

for the normalized real GDP per capita ($y_{i,s}$), respectively. In both equations, s denotes a time index over the 13-year window centered on T; $disaster_T$ is an indicator variable that is equal to one for the period the disaster occurred ($s = T$); $after_T$ is an indicator variable that is equal to one for all the periods after the disaster ($s > T$). The parameters α_1 and β_2 capture the effect of natural disasters on economic growth in the short term, while α_2 and β_4 capture the medium-term effects. Standard errors are reported in parenthesis below the point estimates.

Taken altogether, the results suggest that large natural disasters have a negative effect on economic growth in the short term (at the year of the disaster), and this effect disappears in the medium term. The estimated contemporaneous effect ranges between -1.7 and -4.3 percentage points of GDP growth, depending on the sample. Moreover, the average growth rate after the disaster is not different than the average growth rate before the disaster. The estimated effects tend to be stronger when we focus on smaller countries. The results suggest that even when the effect of the disaster is short-lived (lasting for about one year) and the economy returns to its growth path pre-disaster, the post-disaster growth rate is not higher than before, and therefore GDP per capita losses that materialize during the disaster are never fully recovered.

4.5 Alternative Set of Episodes

The choice of the mortality rate to rank the severity of natural disasters has the implication that the resulting list of country/years included in the comparative case studies comprises preeminently developing countries (see Table A.2). As a result, the estimated effect of natural disasters on economic growth is an average effect for a treatment group of mainly developing countries. In this subsection, we use different criteria to group events to compare the results.

A first alternative criterion consists of using the information on the physical intensity of the natural disasters rather than mortality to rank events by severity. A second alternative criterion is to use the information on monetary damages, both in real US dollars (total damages) and share of GDP (total damages/GDP) to rank events. Tables A.5-6 in the Appendix provide the list of the Top 20 country/years under the alternative criteria. In the case of ranking according to physical intensity, the exercise is done for earthquakes (Richter scale, using data from United States Geological Survey, USGS). In the case of the ranking according to damages, data on total damages come from EM-DAT.

Table 7. Results with Alternative Samples

Dependent Variable	Real GDP per capita growth		Real GDP per capita	
	Effect of the disaster at time T	Medium-term effect	Effect of the disaster at time T	Medium-term effect
Main Results	-3.74	-0.55	-3.1	0.18
	(0.41)	(0.61)	(1.84)	(0.89)
Top earthquakes	-0.56	0.08	-0.41	0.87
(Richter scale)	(0.28)	(0.41)	(1.32)	(0.7)
Top earthquakes	-0.3	0.38	0.26	0.54
(mortality rate)	(0.43)	(0.57)	(1.39)	(0.63)
Top damages	-0.35	-0.29	0.17	0.09
	(0.23)	(0.31)	(0.69)	(0.37)
Top $Damages/$	-1.08	0.02	0.58	0.5
$GDP_{(t-1)}$	(0.38)	(0.47)	(1.32)	(0.59)
Advanced	-0.29	-0.45	-0.60	-0.71
countries	(0.35)	(0.48)	(1.41)	(0.90)

Source: Authors' calculations based on EM-DAT and World Development Indicators, Richter Scale records from USGS, and wind speed data from EM-DAT.
Note: The table shows the results for Top 20 highest mortality rate episodes listed in Tables A.5-6 respectively. Each row corresponds to a particular group. Within each subset, results are shown for Real GDP per capita growth (two left columns) and Real GDP per capital level (two right columns). The short-run effects are the average estimated effect of the shock at the year of the disaster T in percentage points for growth, and in % for levels (standard errors in parenthesis below the point estimate). The medium-term effects are defined as the difference in the pre- and post-disaster averages that are calculated based on the regressions

$$g_{i,s} = \alpha_0 + \alpha_1 \times disaster_T + \alpha_2 \times after_T + u_{i,s},$$

for real GDP per capita growth ($g_{i,s}$), and

$$y_{i,s} = \beta_0 + \beta_1 \times s + \beta_2 \times disaster_T + \beta_3 \times after_T + \beta_4 \times s \times after_T + v_{i,s},$$

for the normalized real GDP per capita ($y_{i,s}$), respectively. In both equations, s denotes a time index over the 13-year window centered on T; $disaster_T$ is an indicator variable that is equal to one for the period the disaster occurred ($s = T$); $after_T$ is an indicator variable that is equal to one for all the periods after the disaster ($s > T$). The parameters α_1 and β_2 capture the effect of natural disasters on economic growth in the short term, while α_2 and β_4 capture the medium-term effects. Standard errors are reported in parenthesis below the point estimates.

Table 7 includes the baseline results in row 1 for comparison. Rows 2 – 3 show the results for earthquakes: in row 2 it is shown that the top 20 earthquakes in terms of physical intensity do not have significant short- or medium-term effects on growth or on GDP levels. Row 3 shows that the same is true for the largest earthquakes based on mortality. The list of top earthquakes in Table A.5. shows a preeminence of large countries in the sample (i.e., India, Indonesia, Japan), especially when episodes are ranked by the Richter scale rather than mortality. The lack of macroeconomic impacts suggests that either the impacts of earthquakes are localized within large countries, or that large and/or advanced economies have better ways of mitigating the impacts.

Rows 4 and 5 show the results when the episodes are ranked based on total damages (row 4) and total damages over pre-disaster GDP (row 5). In the case of total damages, the list of country/years is comprised of rich and large countries (see Table A.6). We find those countries do not suffer significant short- or medium-term effects on growth in the aftermath of large disasters. In the case of total damages/GDP, instead, where the sample includes smaller/poorer countries, we find that large disasters impose negative effects on real GDP per capita growth in the short run (about one-third of the baseline results) but no medium-run effects and no effects on GDP levels.

Finally, row 6 shows the results of the event study approach on the top 20 catastrophic events for advanced economies based on the mortality criterion.[21] The list of the 20 largest disasters with their associated mortality rate is shown in Table A.7. Those events exhibit a lower mortality rate compared with those in the baseline estimating sample, ranging from 155 deaths per 100,000 inhabitants (the Japan 2011 earthquake) to 4.9 deaths por 100,000 inhabitants (two earthquakes in Greece in 1995). In contrast to the baseline results, the estimated negative effect of the disasters on economic growth in the short and in the long run are not statistically different from zero.

The bottom line is that sample selection affects the estimates of catastrophic natural disasters on growth. The heterogeneity of results found in the literature is therefore not surprising, as different methods and samples are used to approximate the impacts of natural disasters on economic growth. The estimated negative impacts of natural disasters on economic growth that we identify in this paper accrue to the treated countries only, which in this case, given the way in which the natural disasters were ranked, comprises mainly small and developing countries.

5. Policy Implications and Conclusions

The results show that catastrophic natural disasters—based on the associated mortality—have negative impacts on economic growth in the short run that are not fully recovered. The negative impacts are larger for small and poorer countries, suggesting that the incidence of natural disasters is mostly an economic development issue. At the microeconomic level as well, the negative impacts disproportionally affect more poor households who tend to work in the agricultural sector, spend a greater share of their income on necessities, and have less access to savings and credit to smooth the negative economic impacts of temperature shocks (Hallegatte et al., 2016; Hallegatte and Rozenberg, 2017; IMF, 2016).

[21] Advanced economies are classified based on the IMF's World Economic Outlook country classification.

What can countries do to reduce the negative impacts of catastrophic natural disasters? One option is to seek to reduce the frequency of occurrence through mitigation. This in turn requires global coordination. As shown in preceding sections, the frequency of occurrence of natural disasters is on the rise, and at least part of that may be due to climate change. Rising temperatures and sea levels will likely increase the severity of hydrometeorological natural disasters, especially storms, floods, and droughts. To avoid catastrophic effects, countries around the world must reduce their carbon emissions as part of a coordinated strategy to mitigate climate change globally.[22]

A second line of action involves curtailing losses caused by climate change—i.e., adaptation. Governments need policies to help reduce the direct economic impact of rising temperatures. For natural disasters, adaptation requires "shrinking the target" with policy interventions that can lessen the effect of disaster impacts. Such policies include land use planning, strengthening building codes, and other engineering interventions to increase resilience.

A wide range of specific measures are available. For example, seawalls and early warning systems can be improved. Likewise, zoning can be improved so that urban sprawl and agricultural projects do not replace the mangrove swamps that hold back storm surge, the wetlands that absorb excess water, and the forests that bind the soil and stop rains from turning into landslides on mountains slopes. Other key defenses include implementing and enforcing building codes that make structures more resistant to earthquakes, as well as improving sewage and drainage. Some adaptation measures are costly and, therefore, governments must carefully evaluate the likely ex post impacts, and the probability of disasters occurring.

Political, economic, and institutional factors are very important for the economics of natural disasters. For example, fiscal stimulus is an economic policy instrument that, in principle, all countries have at their disposal to weather a crisis, regardless of its origin. Unfortunately, however, many countries often lack the fiscal space necessary in this type of situation.

In the aftermath of natural disasters, governments must deal with the costs of humanitarian assistance and the eventual reconstruction of assets destroyed—and doing so can be costly. One source of financing that is usually available in the aftermath of disasters is foreign aid. Median aid flows to countries the year a natural disaster occurs increase by 18 percent compared to the previous two years (Becerra, Cavallo, and Noy, 2014). However, that is equivalent to only 0.25 percent of GDP, and, on average, to less than 3 percent of total estimated damages caused by those

[22] See International Panel on Climate Change Report (2018), available at https://www.ipcc.ch/2019/.

disasters. Moreover, some of that assistance is not new aid; it is simply reallocated by donors from other sectors (i.e., aid earmarked to build up infrastructure is reallocated to humanitarian assistance). In addition, the aid pledged by donors when the crisis is at its peak is usually higher than the amount of foreign aid that is effectively disbursed, especially if donors perceive that the aid may not spent according to their priorities.[23]

If foreign aid is not large enough to help developing countries deal with the costs imposed by natural disasters, what else can countries do? Some alternative financing tools available to developing countries include reserve funds (which imply saving ex ante to build up a reserve), contingency credit lines from international organizations, regional risk pools, or insurance and re-insurance contracts.[24] These mechanisms require political will to pay up-front costs to reduce the fiscal impacts of disasters ex post.

A deeper market for catastrophe insurance could play a valuable role by helping countries raise money on capital markets and buffer the worst of a calamity. One of the most promising forms of disaster insurance is what is known as a catastrophe (or cat) bond: a tradable financial instrument that spreads risk across global capital markets. These bonds are usually issued by governments or reinsurance companies—the insurers of the insurers—and backed by U.S. Treasury bills. Although they typically only cover a fraction of the damages, they can provide financial relief very swiftly in the case of severe events, as the financial terms are based on the characteristics of the event rather than on an estimate of the losses; in this way they resemble parametric insurance. Thus, the financial benefits tend to be less contentious, and governments can provide relief quickly.

This type of insurance provides an additional, perhaps less understood, benefit. Countries at high risk of a natural disaster are also more in danger of defaulting on their debt if a catastrophe strikes.[25] Consequently, they have less credibility in capital markets and must sell their debt at higher yields. By reducing the risk of default and lowering financing costs, cat bonds allow countries to borrow more. Estimates from Borensztein, Cavallo, and Jeanne (2017) suggest governments could increase their external borrowing from around 30 percent to more than 60

[23] An example is aid pledged after the 2010 earthquake in Haiti; only 62 percent was ultimately disbursed (see Becerra, Cavallo, and Noy, 2015).
[24] See Hallegate et al. (2017) for a broader discussion of each of the options.
[25] See Borensztein, Cavallo, and Valenzuela (2009).

percent of GDP on average, providing welfare gains equivalent to several percentage points of overall consumption.

Developing countries face three types of obstacles implementing ex ante financing mechanisms that would increase the capacity to respond and mitigate the impacts of natural disasters. The first is paucity of markets; insurance markets remain undeveloped, especially in developing countries. A second obstacle is political resistance: politicians may balk at supporting expenditures to protect against risks that may not materialize and that, if they materialize, could result in benefits capitalized on by other politicians. A final obstacle is an inadequate institutional framework, as risk assessment analysis is lacking and the legal framework to enforce contracts is weak in many countries.

Against that background, international organizations and donor countries can play a catalytic role. They can subsidize research and the studies forecasting the probability of disasters that are required to support local insurance markets or share the results of public research on risk assessment with the private sector to support insurance markets. International organizations and donor countries can also create markets themselves. They can additionally help countries reduce any internal political resistance to the purchase of insurance policies by making concessional loans or post-disaster aid contingent on government investment in preparedness measures, including insurance mechanisms.

The bottom line is that dealing with negative consequences of catastrophic natural disasters requires a combination of mitigation, especially at the global level, and adaptation measures at the local level. But in the end, the countries that best recover from natural disasters are those best able to help themselves, and therefore boosting preparedness through adequate financing mechanisms mut be part of the mix. With climate change threatening everything from rising seas and hurricanes to searing temperatures and drought, this is the moment to prepare for what appears to be the inevitability of much more extreme weather events as the century unfolds.

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Appendix

Table A1. Summary Statistics

General Statistics

Sample	1970-2019
Number of countries	203
Number of disasters[1]	12,377
Number of disasters with deaths info[1]	8,500

Mortality Rate (Disaster Level)

Mean	17.4
Median	0.3
Standard Deviation	339.1
Maximum	22,715.8
Minimum	0.000718
95th percentile	12.8
99th percentile	131.6

Mortality Rate (Country / year Level)

Mean	62.9
Median	2.1
Standard Deviation	691.5
Maximum	22,723
Minimum	0.009
95th percentile	73.2
99th percentile	971.5

[1]Before yearly aggregation.

Source: Authors' calculations based on EM-DAT and World Development Indicators.

Table A2. Top 200 Episodes at the Country/Year Level Based on Mortality Rate (1970-2019)

Country	Year	All disasters that year	Most Catastrophic	Mortality Rate	1	2	3
Haiti	2010	Earthquake (1), Flood (3), Storm (2)	Earthquake	22723.0	1	1	1
Ethiopia	1983	Drought (1)	Drought	8109.1	2		
Armenia	1988	Earthquake (1)	Earthquake	7242.3	3	2	2
Somalia	1974	Drought (1)	Drought	5409.1	4		
Peru	1970	Earthquake (3), Flood (1)	Earthquake	5104.9	5	3	3
Nicaragua	1972	Earthquake (1)	Earthquake	4030.1	6	4	4
Guatemala	1976	Earthquake (1)	Earthquake	3751.3	7	5	5
Montserrat	1997	Volcanic activity (1)	Volcanic Activity	3549.6	8	6	
Ethiopia	1973	Drought (1)	Drought	3317.8	9		
Myanmar	2008	Storm (1)	Storm	2788.4	10	7	6
Honduras	1974	Storm (1)	Storm	2694.5	11	8	7
Honduras	1998	Storm (1)	Storm	2414.9	12	9	8
Sri Lanka	2004	Earthquake (1), Flood (1)	Earthquake	1841.7	13	10	9
Solomon Islands	1975	Earthquake (1)	Earthquake	1073.6	14	11	10
Tuvalu	1972	Storm (1)	Storm	1040.6	15	12	11
Montserrat	1989	Storm (1)	Storm	1034.0	16	13	12
Honduras	1973	Landslide (1)	Landslide	971.5	17	14	
Samoa	2009	Earthquake (1)	Earthquake	807.6	18	15	13
Eswatini	1983	Drought (1)	Drought	793.9	19		
Colombia	1985	Volcanic activity (1)	Volcanic Activity	743.2	20	16	
Iran (Islamic Republic of)	1978	Earthquake (2)	Earthquake	719.6	21	17	14
Chad	1981	Drought (1)	Drought	664.5	22		
Haiti	2004	Flood (1), Storm (2)	Storm	609.2	23	18	15
American Samoa	2009	Earthquake (1)	Earthquake	591.4	24	19	16
Dominica	1979	Storm (1)	Storm	538.5	25	20	17

Pakistan	2005	Earthquake (1), Extreme temperature (1), Flood (5), Landslide (1), Storm (1)	Earthquake	473.4	26	21	18
Papua New Guinea	1998	Earthquake (1)	Earthquake	400.6	27	22	19
Luxembourg	2003	Extreme temperature (1)	Extreme Temperature	381.0	28	23	
Grenada	2004	Storm (1)	Storm	375.0	29	24	20
Solomon Islands	1986	Storm (1)	Storm	373.0	30	25	21
Spain	2003	Extreme temperature (1), Wildfire (1)	Extreme Temperature	364.3	31	26	
Vanuatu	1987	Storm (1)	Storm	360.9	32	27	22
Bhutan	2000	Flood (1)	Flood	346.1	33	28	23
Maldives	2004	Earthquake (1)	Earthquake	337.0	34	29	24
France	2003	Extreme temperature (1), Flood (2), Storm (2), Wildfire (1)	Extreme Temperature	315.7	35	30	
Tajikistan	1992	Flood (1), Landslide (1), Mass movement (dry) (1)	Flood	296.4	36	31	27
Solomon Islands	1977	Earthquake (2)	Earthquake	259.2	37	32	25
Dominican Republic	1979	Flood (1), Storm (1)	Storm	258.5	38	33	26
Vanuatu	1999	Earthquake (1), Storm (1)	Storm	247.2	39	34	28
Yemen	1982	Earthquake (1), Flood (1)	Earthquake	241.6	40	35	29
Djibouti	1994	Flood (1)	Flood	234.4	41	36	30
El Salvador	1986	Earthquake (1)	Earthquake	222.8	42	37	31
Puerto Rico	1985	Flood (1), Landslide (1)	Flood	179.4	43	39	37
Iran (Islamic Republic of)	1972	Earthquake (1), Storm (1)	Earthquake	174.8	44	40	32
Cameroon	1986	Volcanic activity (1)	Volcanic Activity	173.4	45	41	
Bangladesh	1985	Flood (2), Storm (3)	Storm	171.4	46	42	33

Japan	2011	Earthquake (2), Extreme temperature (1), Flood (1), Storm (3)	Earthquake	156.0	47	43	34
Haiti	1994	Storm (1)	Storm	150.4	48	44	36
Slovenia	2003	Extreme temperature (1)	Extreme Temperature	144.9	49	45	
Algeria	1980	Earthquake (1)	Earthquake	141.2	50	46	38
Thailand	2004	Earthquake (1), Flood (3), Landslide (1), Storm (2)	Earthquake	129.7	51	47	39
Iceland	1995	Landslide (2)	Landslide	127.8	52	48	
Mexico	1985	Earthquake (1)	Earthquake	127.8	53	49	40
Saint Kitts and Nevis	1998	Storm (1)	Storm	116.7	54	50	41
Oman	1977	Storm (2)	Storm	115.4	55	51	42
Afghanistan	1991	Earthquake (2), Extreme temperature (1), Flood (3)	Flood	115.0	56	52	45
Germany	2003	Extreme temperature (1), Storm (2)	Extreme Temperature	113.6	57	53	
St. Vincent and the Grenadines	2013	Flood (1)	Flood	110.7	58	55	44
Solomon Islands	2007	Earthquake (1)	Earthquake	108.1	59	56	46
Taiwan	1999	Earthquake (2)	Earthquake	103.7	60	58	47
American Samoa	2003	Flood (1)	Flood	101.6	61	59	48
Comoros	1983	Storm (1)	Storm	100.9	62	60	49
Turkey	1976	Earthquake (3), Landslide (2)	Earthquake	99.6	63	61	51
Cabo Verde	1984	Storm (1)	Storm	96.6	64	62	52
Guam	1976	Storm (1)	Storm	96.4	65	63	53
Belgium	2006	Extreme temperature (1)	Extreme Temperature	89.7	66	64	
Iran (Islamic Republic of)	1981	Earthquake (2), Flood (1), Storm (1)	Earthquake	89.5	67	65	54
Guatemala	1982	Flood (1)	Flood	87.7	68	66	55

Tonga	2009	Earthquake (1)	Earthquake	87.1	69	67	56
Fiji	1979	Storm (1)	Storm	87.0	70	68	57
Italy	1980	Earthquake (1)	Earthquake	83.3	71	69	58
Samoa	1991	Storm (1)	Storm	79.9	72	72	61
Philippines	2013	Earthquake (1), Flood (5), Storm (8)	Storm	79.7	73	73	62
Honduras	1993	Flood (2)	Flood	78.7	74	74	63
Saint Lucia	1980	Storm (1)	Storm	77.5	75	75	64
Romania	1977	Earthquake (1)	Earthquake	76.1	76	76	65
Tonga	1982	Storm (2)	Storm	74.9	77	77	66
Pakistan	1974	Earthquake (1)	Earthquake	74.5	78	78	67
Algeria	2003	Earthquake (2), Extreme temperature (1), Flood (3), Storm (1)	Earthquake	74.4	79	79	70
Haiti	2008	Storm (4)	Storm	73.5	80	80	68
Bhutan	1994	Flood (1), Storm (1)	Flood	73.2	81	81	69
Vanuatu	1985	Storm (1)	Storm	70.8	82	82	71
Djibouti	1981	Flood (1)	Flood	69.6	83	83	72
Djibouti	2004	Flood (1)	Flood	67.1	84	84	73
Comoros	1987	Storm (1)	Storm	65.6	85	85	74
Seychelles	1997	Flood (1)	Flood	65.4	86	86	75
Samoa	2012	Storm (1)	Storm	64.0	87	87	76
Bermuda	2003	Storm (1)	Storm	63.6	88	88	77
Peru	1971	Flood (1), Landslide (1)	Landslide	63.2	89	89	
Turkey	1975	Earthquake (1)	Earthquake	62.2	90	90	78
Netherlands	2006	Extreme temperature (1)	Extreme Temperature	61.3	91	91	
Netherlands	2003	Extreme temperature (1)	Extreme Temperature	59.8	92	92	
Belize	2000	Storm (1)	Storm	58.6	93	93	79
Cyprus	1998	Extreme temperature (1)	Extreme Temperature	58.3	94	94	

Georgia	1991	Earthquake (2)	Earthquake	57.9	95	95	80
Kiribati	1972	Storm (1)	Storm	57.7	96	96	81
Micronesia, Fed. Sts.	1987	Storm (1)	Storm	56.9	97	97	82
Iceland	1974	Landslide (1)	Landslide	56.5	98	98	
Mozambique	1971	Flood (1)	Flood	55.4	99	99	83
French Polynesia	1987	Landslide (1)	Landslide	55.0	100	100	
Tajikistan	1989	Earthquake (1)	Earthquake	54.8	101	101	84
Guinea	1983	Earthquake (1)	Earthquake	54.2	102	102	85
Northern Mariana Islands	2004	Storm (1)	Storm	51.8	103	103	87
Nepal	1988	Earthquake (1), Flood (1), Landslide (1), Storm (1)	Earthquake	51.7	104	104	96
Namibia	2011	Flood (1)	Flood	51.0	105	105	88
Samoa	2005	Storm (1)	Storm	50.4	106	107	90
Malawi	1991	Flood (1)	Flood	50.2	107	108	91
Nepal	1981	Flood (2)	Flood	49.9	108	109	92
Hungary	2007	Extreme temperature (1)	Extreme Temperature	49.6	109	110	
Samoa	1990	Storm (1)	Storm	49.4	110	111	93
Mozambique	2000	Flood (1), Storm (4)	Flood	48.2	111	112	94
Afghanistan	1992	Earthquake (1), Flood (2)	Flood	46.2	112	113	95
Fiji	1985	Storm (3)	Storm	45.7	113	114	97
Guyana	2005	Flood (1)	Flood	45.6	114	115	98
Portugal	2005	Extreme temperature (1), Wildfire (1)	Extreme Temperature	45.5	115	118	
Namibia	2009	Flood (1)	Flood	45.0	116	116	99
Malawi	2002	Drought (1), Flood (2)	Drought	44.5	117		
Papua New Guinea	1991	Landslide (1)	Landslide	43.3	118	119	
Albania	1985	Extreme temperature (1), Landslide (1)	Extreme Temperature	43.0	119	120	

French Polynesia	1983	Storm (2)	Storm	43.0	120	121	101
Ecuador	1993	Landslide (3)	Landslide	42.9	121	123	
Dominican Republic	1998	Storm (1)	Storm	42.9	122	124	103
Gambia	1999	Flood (1)	Flood	42.8	123	125	104
Austria	2003	Extreme temperature (1)	Extreme Temperature	42.7	124	126	
Nicaragua	1992	Earthquake (1), Volcanic activity (1)	Earthquake	42.2	125	127	105
New Zealand	2011	Earthquake (2)	Earthquake	41.8	126	128	106
Solomon Islands	2009	Flood (1)	Flood	41.7	127	129	107
Czech Republic	2003	Extreme temperature (1)	Extreme Temperature	41.0	128	130	
Belize	1998	Storm (1)	Storm	40.6	129	131	108
Bangladesh	2007	Extreme temperature (1), Flood (2), Storm (2)	Storm	40.0	130	132	110
Bahamas	2004	Storm (3)	Storm	38.3	131	134	111
Afghanistan	1982	Earthquake (1)	Earthquake	38.0	132	135	112
Ecuador	1982	Flood (1)	Flood	37.4	133	136	113
Nepal	1996	Flood (2), Storm (1)	Flood	37.4	134	137	114
St. Vincent and the Grenadines	2002	Storm (1)	Storm	37.1	135	138	115
Bangladesh	1988	Earthquake (1), Flood (2), Storm (4)	Flood	36.6	136	139	116
Belize	1978	Storm (1)	Storm	36.5	137	140	117
Seychelles	2004	Earthquake (1)	Earthquake	36.2	138	141	118
Papua New Guinea	1971	Landslide (1)	Landslide	35.9	139	142	
Nicaragua	2007	Flood (1), Storm (1)	Storm	35.9	140	143	119
Kyrgyzstan	1994	Landslide (2)	Landslide	35.9	141	144	
Peru	1973	Landslide (1)	Landslide	35.2	142	145	
Tonga	1973	Storm (1)	Storm	34.8	143	146	121
Bhutan	2009	Earthquake (1), Storm (1)	Storm	34.2	144	147	122

Saint Lucia	2013	Flood (1)	Flood	34.0	145	148	123
Rwanda	1989	Drought (1)	Drought	33.4	146		
Colombia	1999	Earthquake (1), Flood (3), Landslide (2), Storm (1)	Earthquake	33.3	147	150	128
Nicaragua	1988	Storm (1)	Storm	33.3	148	151	125
Iran (Islamic Republic of)	1977	Earthquake (5)	Earthquake	33.0	149	153	126
Antigua and Barbuda	1989	Storm (1)	Storm	32.4	150	154	127
Fiji	1997	Storm (1)	Storm	31.9	151	155	129
Nepal	1970	Flood (1), Landslide (1)	Flood	31.3	152	156	133
Antigua and Barbuda	1995	Storm (1)	Storm	29.8	153	157	130
Morocco	1995	Flood (3)	Flood	29.8	154	158	131
Algeria	2001	Flood (1)	Flood	29.7	155	159	132
Philippines	1972	Flood (1), Storm (3)	Flood	29.5	156	160	134
Oman	2007	Storm (1)	Storm	29.4	157	161	135
Turkey	1983	Earthquake (1)	Earthquake	29.2	158	162	136
Cambodia	2000	Flood (1)	Flood	29.2	159	163	137
Hungary	1970	Flood (1)	Flood	29.1	160	164	138
Mozambique	1977	Flood (1), Storm (1)	Flood	29.0	161	166	140
Fiji	1980	Storm (1)	Storm	29.0	162	167	141
Georgia	1987	Flood (1), Landslide (1)	Flood	28.9	163	168	163
Mongolia	1996	Flood (1), Wildfire (1)	Flood	28.7	164	229	193
Dominica	2007	Storm (1)	Storm	28.3	165	169	142
Fiji	1993	Storm (1)	Storm	28.2	166	170	143
Fiji	1986	Flood (1), Storm (1)	Flood	28.1	167	171	144
Antigua and Barbuda	1998	Storm (1)	Storm	27.9	168	173	146
Saint Lucia	1994	Storm (1)	Storm	27.9	169	174	147
St. Vincent and the Grenadines	1992	Flood (1)	Flood	27.8	170	175	148

Virgin Islands (U.S.)	1999	Storm (1)	Storm	27.6	171	176	149
Taiwan	2009	Storm (1)	Storm	27.4	172	177	150
Antigua and Barbuda	1999	Storm (2)	Storm	27.3	173	178	151
Colombia	1979	Earthquake (2), Flood (1)	Earthquake	27.2	174	179	152
Peru	1974	Earthquake (2), Landslide (1)	Landslide	27.2	175	180	
Dominica	1984	Storm (1)	Storm	26.9	176	181	153
Turkey	1971	Earthquake (2)	Earthquake	26.8	177	182	154
Belize	2008	Flood (1), Storm (1)	Storm	26.8	178	183	155
Papua New Guinea	2007	Storm (1)	Storm	25.9	179	184	156
Vanuatu	1993	Storm (1)	Storm	25.8	180	185	157
New Caledonia	1972	Storm (1)	Storm	25.0	181	186	158
Saint Kitts and Nevis	1989	Storm (1)	Storm	24.6	182	187	159
Bangladesh	1987	Flood (2), Storm (1)	Flood	24.6	183	188	160
China	1975	Earthquake (1), Flood (1)	Flood	24.4	184	189	161
Peru	2007	Earthquake (1), Extreme temperature (1), Flood (1)	Earthquake	24.1	185	190	175
Liberia	1982	Mass movement (dry) (1)	Mass movement	24.0	186	191	
Haiti	1998	Storm (1)	Storm	23.7	187	192	162
Slovakia	2010	Extreme temperature (1), Flood (2)	Extreme Temperature	23.4	188	193	
Haiti	1986	Flood (2)	Flood	23.4	189	194	164
India	1977	Flood (2), Storm (2)	Storm	23.2	190	195	165
Yemen	1996	Flood (2)	Flood	23.1	191	196	166
Jamaica	1986	Flood (1)	Flood	23.1	192	197	167
Philippines	2004	Flood (3), Landslide (1), Storm (8)	Storm	23.1	193	198	168
Madagascar	2004	Storm (2)	Storm	22.9	194	199	169

Republic of Korea	1972	Flood (2)	Flood	22.7	195	200	170
China	1974	Earthquake (1)	Earthquake	22.7	196	201	171
Oman	1981	Storm (1)	Storm	22.5	197	203	173
Puerto Rico	1970	Flood (1)	Flood	22.4	198	204	174
Afghanistan	1995	Flood (2), Landslide (1)	Landslide	22.3	199	205	
France	2006	Extreme temperature (1), Storm (2)	Extreme Temperature	22.0	200	206	
Colombia	1987	Flood (1), Landslide (2)	Landslide	22.0	201	207	
Nepal	2002	Extreme temperature (1), Landslide (1)	Landslide	21.9	202	208	
Nicaragua	1982	Storm (1)	Storm	21.1	203	209	176
Morocco	2004	Earthquake (1)	Earthquake	21.1	204	210	177
Tunisia	1973	Flood (2)	Flood	21.0	205	211	178
Namibia	2008	Flood (1)	Flood	20.9	206	213	180
Jamaica	1979	Flood (2)	Flood	20.9	207	214	182
Fiji	2003	Storm (1)	Storm	20.9	208	215	183
Georgia	1989	Landslide (2)	Landslide	20.5	209	216	
St. Vincent and the Grenadines	1979	Volcanic activity (1)	Volcanic Activity	20.3	210	217	
Peru	2009	Extreme temperature (1), Flood (1), Landslide (4)	Extreme Temperature	20.2	211	218	
Mongolia	2008	Storm (1)	Storm	20.0	212	219	184
Senegal	1999	Storm (2)	Storm	20.0	213	220	185
Fiji	2012	Flood (2), Storm (1)	Flood	19.7	214	221	186
Bolivia (Plurinational State of)	1998	Earthquake (1), Landslide (1)	Earthquake	19.5	215	223	263
Sri Lanka	1989	Flood (1)	Flood	19.3	216	224	188
Dominican Republic	2007	Flood (2), Storm (3)	Storm	19.0	217	225	189
Djibouti	1989	Flood (1)	Flood	18.9	218	226	190
Madagascar	1988	Drought (1)	Drought	18.8	219		

Latvia	2006	Extreme temperature (1)	Extreme Temperature	17.9	220	227	
Tunisia	1982	Flood (1)	Flood	17.9	221	228	192
Somalia	1994	Flood (1), Storm (1)	Flood	17.8	222	230	194
Papua New Guinea	1988	Mass movement (dry) (1)	Mass movement	17.7	223	231	
Honduras	2010	Flood (2), Storm (2)	Flood	17.7	224	232	195
Iran (Islamic Republic of)	1987	Earthquake (1), Flood (6)	Flood	17.6	225	233	196
Haiti	2007	Flood (4), Storm (3)	Storm	17.4	226	234	198
Colombia	1974	Earthquake (1), Landslide (2)	Landslide	17.4	227	235	
Peru	2010	Extreme temperature (1), Flood (1), Landslide (1)	Extreme Temperature	17.3	228	236	
Cambodia	2011	Flood (1)	Flood	17.3	229	237	199
Italy	1976	Earthquake (3)	Earthquake	17.0	230	238	200

Source: Authors' calculations based on EM-DAT and World Development Indicators.

Table A3. Robustness Checks: Effects of Natural Disasters on Growth, 30 Largest Events

Dependent Variable	Real GDP per capita growth: Effect of the disaster at time T	Real GDP per capita growth: Medium-term effect	Real GDP per capita: Effect of the disaster at time T	Real GDP per capita: Medium-term effect
Main Results	-3.14	-0.38	-2.67	0.20
	(0.32)	(0.46)	(1.57)	(0.7)
No overlapping (keep worst)	-3.16	-0.43	-2.72	0.14
	(0.33)	(0.47)	(1.62)	(0.72)
No overlapping (excl. both)	-3.34	-0.39	-2.82	0.32
	(0.37)	(0.53)	(1.85)	(0.82)
No overlapping (excl. country)	-3.24	-0.45	-2.81	0.23
	(0.39)	(0.55)	(1.92)	(0.85)
3-year window	-2.59	0.92	-3.05	0.84
	(0.46)	(0.7)	(2.12)	(1.52)
All values of GDP	-2.24	-0.53	-1.68	0.11
	(0.31)	(0.44)	(1.39)	(0.63)
Missing as zeroes	-1.65	0.38	-0.86	0.83
	(0.36)	(0.52)	(1.44)	(0.69)
Next year	-2.81	0.13	-2.77	0.44
	(0.34)	(0.52)	(1.45)	(0.73)
Excluding small countries	-1.32	-0.56	-0.97	0.14
	(0.29)	(0.37)	(1.38)	(0.61)
GDP per capita (PPP)	-1.86	-0.45	-1.68	-0.13
	(0.34)	(0.46)	(1.34)	(0.61)
One standard deviation above the mean	-2.64	-0.7	-2.07	0.22
	(0.54)	(0.77)	(2.38)	(1.27)

Source: Authors' calculations based on EM-DAT and World Development Indicators.

Note: The table shows the results for Top 30 highest mortality rate episodes listed in Table A.2 for group 3 (only earthquakes, floods, and storms) respectively. Each row corresponds to a particular robustness check. Within each subset, results are shown for Real GDP per capita growth (two left columns) and Real GDP per capital level (two right columns). The short-run effects are the average estimated effect of the shock at the year of the disaster T in percentage points for growth, and in % for levels (standard errors in parenthesis below the point estimate). The medium-term effects are defined as the difference in the pre- and post-disaster averages that are calculated based on the regressions

$$g_{i,s} = \alpha_0 + \alpha_1 \times disaster_T + \alpha_2 \times after_T + u_{i,s},$$

for real GDP per capita growth ($g_{i,s}$), and

$$y_{i,s} = \beta_0 + \beta_1 \times s + \beta_2 \times disaster_T + \beta_3 \times after_T + \beta_4 \times s \times after_T + v_{i,s},$$

for the normalized real GDP per capita ($y_{i,s}$), respectively. In both equations, s denotes a time index over the 13-year window centered on T; $disaster_T$ is an indicator variable that is equal to one for the period the disaster occurred ($s = T$); $after_T$ is an indicator variable that is equal to one for all the periods after the disaster ($s > T$). The parameters α_1 and β_2 capture the effect of natural disasters on economic growth in the short term, while α_2 and β_4 capture the medium-term effects. Standard errors are reported in parenthesis below the point estimates.

Table A4. Robustness Checks: Effects of Natural Disasters on Growth, 50 Largest Events

Dependent Variable	Real GDP per capita growth: Effect of the disaster at time T	Real GDP per capita growth: Medium-term effect	Real GDP per capita: Effect of the disaster at time T	Real GDP per capita: Medium-term effect
Main Results	-2.08	-0.30	-1.59	0.39
	(0.24)	(0.34)	(1.08)	(0.52)
No overlapping	-2.12	-0.21	-1.65	0.46
(keep worst)	(0.26)	(0.37)	(1.17)	(0.56)
No overlapping	-2.13	-0.17	-1.61	0.59
(excl. both)	(0.28)	(0.4)	(1.27)	(0.6)
No overlapping	-2.04	-0.20	-1.58	0.55
(excl. country)	(0.29)	(0.4)	(1.3)	(0.62)
3-year window	-1.77	0.29	-1.93	0.46
	(0.33)	(0.5)	(1.44)	(1.06)
All values of GDP	-1.31	-0.56	-1.07	0.03
	(0.22)	(0.32)	(0.97)	(0.47)
Missing as zeroes	-1.52	0.19	-0.79	0.63
	(0.26)	(0.36)	(1.1)	(0.5)
Next year	-2.08	-0.05	-1.94	0.36
	(0.26)	(0.38)	(1.04)	(0.54)
Excluding small	-1.54	-0.25	-1.21	0.29
countries	(0.22)	(0.29)	(1.32)	(0.51)
GDP per capita	-2.05	-0.11	-2.01	0.06
(PPP)	(0.24)	(0.33)	(1.25)	(0.48)
One standard deviation above	-2.64	-0.7	-2.07	0.22
the mean	(0.54)	(0.77)	(2.38)	(1.27)

Source: Authors' calculations based on EM-DAT and World Development Indicators.

Note: The table shows the results for Top 50 highest mortality rate episodes listed in Table A.2 for group 3 (only earthquakes, floods, and storms) respectively. Each row corresponds to a particular robustness check. Within each subset, results are shown for Real GDP per capita growth (two left columns) and Real GDP per capital level (two right columns). The short-run effects are the average estimated effect of the shock at the year of the disaster T in percentage points for growth, and in % for levels (standard errors in parenthesis below the point estimate). The medium-term effects are defined as the difference in the pre- and post-disaster averages that are calculated based on the regressions

$$g_{i,s} = \alpha_0 + \alpha_1 \times disaster_T + \alpha_2 \times after_T + u_{i,s},$$

for real GDP per capita growth ($g_{i,s}$), and

$$y_{i,s} = \beta_0 + \beta_1 \times s + \beta_2 \times disaster_T + \beta_3 \times after_T + \beta_4 \times s \times after_T + v_{i,s},$$

for the normalized real GDP per capita ($y_{i,s}$), respectively. In both equations, s denotes a time index over the 13-year window centered on T; $disaster_T$ is an indicator variable that is equal to one for the period the disaster occurred ($s = T$); $after_T$ is an indicator variable that is equal to one for all the periods after the disaster ($s > T$). The parameters α_1 and β_2 capture the effect of natural disasters on economic growth in the short term, while α_2 and β_4 capture the medium-term effects. Standard errors are reported in parenthesis below the point estimates.

Table A5. Top 20 Earthquakes at the Country/Year Level
Based on Physical Intensity and Mortality (1970-2019)

Ranking	Original top 20		Richter Scale			Mortality rate		
	Year	Country	Year	Country	Richter	Year	Country	Mortality Rate
1	2010	Haiti	2004	India	9.1	2010	Haiti	22715.8
2	1970	Peru	2011	Japan	9.1	1970	Peru	5104.7
3	1972	Nicaragua	2005	Indonesia	8.6	1972	Nicaragua	4030.1
4	1976	Guatemala	2001	Peru	8.4	1976	Guatemala	3751.3
5	2008	Myanmar	2007	Indonesia	8.4	2004	Sri Lanka	1841.4
6	1974	Honduras	1977	Indonesia	8.3	2009	Samoa	807.6
7	1998	Honduras	1994	Bolivia	8.2	2004	Indonesia	752.7
8	2004	Sri Lanka	2012	Indonesia	8.2	1990	Iran (Islamic Republic of)	730.0
9	2009	Samoa	2017	Mexico	8.2	2009	American Samoa	591.4
10	2004	Haiti	2003	Japan	8.2	1987	Ecuador	538.3
11	2009	American Samoa	2007	Solomon Islands	8	2005	Pakistan	468.1
12	1979	Dominica	2009	Samoa	8	1998	Papua New Guinea	400.6
13	2005	Pakistan	1996	Indonesia	8	2004	Maldives	337.0
14	1998	Papua New Guinea	1970	Colombia	8	1986	El Salvador	222.8
15	2004	Grenada	1976	New Zealand	8	2001	El Salvador	196.8
16	1986	Solomon Islands	1985	Mexico	8	2011	Japan	155.0
17	1987	Vanuatu	1995	Mexico	8	1976	Philippines	145.3
18	2000	Bhutan	2000	Papua New Guinea	8	1980	Algeria	141.2
19	2004	Maldives	2007	Peru	8	2004	Thailand	129.3
20	1979	Dominican Republic	2013	Solomon Islands	8	1985	Mexico	127.8

Note: Richter Scale records from USGS.

Table A6. Top 20 Episodes at the Country/Year Level Based on Damages (1970 -2019)

Ranking	Original top 20		Damage			Damage / GDP		
	Year	Country	Year	Country	Damage (Billions 2019 USD)	Year	Country	Damage as a percentage of GDP
1	2010	Haiti	2011	Japan	210	2004	Grenada	137.9
2	1970	Peru	2005	United States of America (the)	125	1998	Saint Kitts and Nevis	63.3
3	1972	Nicaragua	1995	Japan	100	2010	Haiti	43.5
4	1976	Guatemala	2012	United States of America (the)	95	1995	Antigua and Barbuda	37.4
5	2008	Myanmar	2011	Thailand	40	1996	Mongolia	26.5
6	1974	Honduras	1994	United States of America (the)	30	1995	Dominica	25.6
7	1998	Honduras	2010	Chile	30	2000	Belize	19.7
8	2004	Sri Lanka	2008	United States of America (the)	28	1998	Honduras	17.8
9	2009	Samoa	2004	Japan	28	2001	Belize	15.5
10	2004	Haiti	1992	United States of America (the)	26.5	2001	El Salvador	11.0
11	2009	American Samoa	1980	Italy	20	1989	Antigua and Barbuda	10.7
12	1979	Dominica	1999	Turkey	20	1998	Antigua and Barbuda	10.5
13	2005	Pakistan	2004	United States of America (the)	18	1989	Saint Kitts and Nevis	10.2
14	1998	Papua New Guinea	2005	United States of America (the)	16	1996	Yemen	10.1

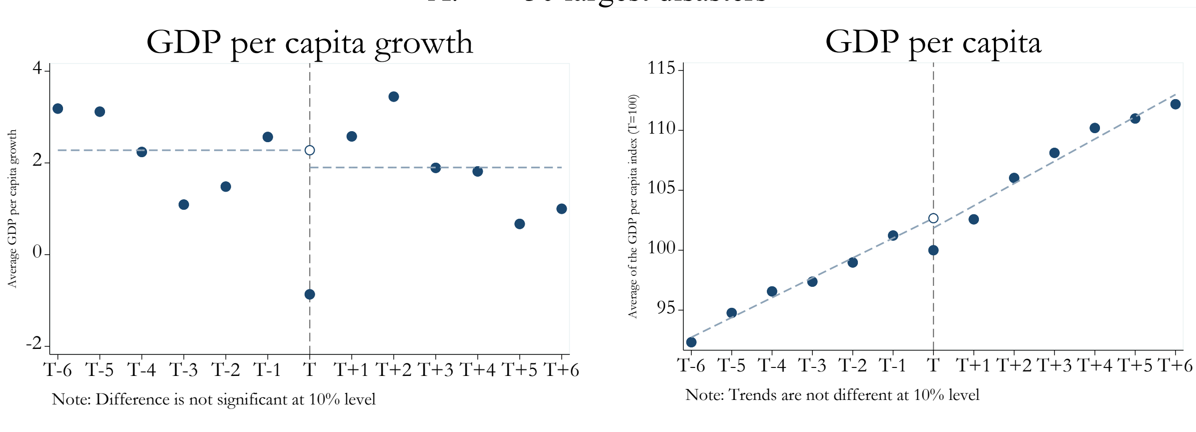
15	2004	Grenada	2004	United States of America (the)	16	2010	Chile	10.1
16	1986	Solomon Islands	2012	Italy	15.8	2011	New Zealand	9.8
17	1987	Vanuatu	2011	New Zealand	15	2005	Guyana	9.3
18	2000	Bhutan	2005	United States of America (the)	14.3	2013	Saint Vincent and the Grenadines	9.2
19	2004	Maldives	2011	United States of America (the)	14	1988	Jamaica	9.0
20	1979	Dominican Republic	2013	Germany	12.9	1980	Saint Lucia	8.7

Table A7. Top 20 Episodes at the Country/Year Level Based on Mortality, Advanced Economies (1970 -2019)

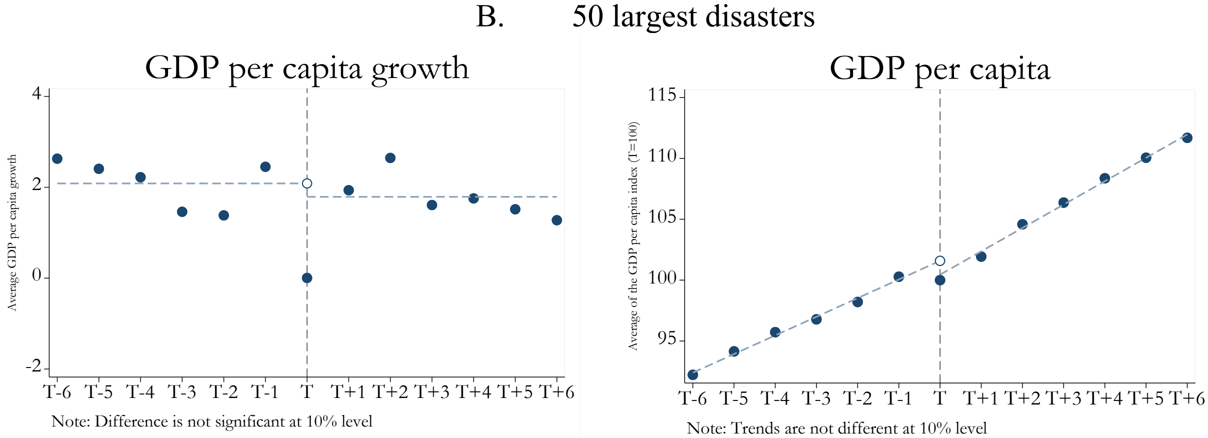
Ranking	Country	Year	Mortality rate
1	Japan	2011	155.7
2	Italy	1980	83.3
3	New Zealand	2011	41.8
4	China, Hong Kong SAR	1971	29.0
5	Republic of Korea	1972	22.7
6	Italy	1976	17.0
7	Republic of Korea	1987	16.2
8	Spain	1973	15.0
9	Greece	1999	13.3
10	China, Hong Kong SAR	1997	12.6
11	Republic of Korea	1998	10.9
12	Slovakia	1998	10.0
13	Republic of Korea	1977	8.8
14	Portugal	1980	7.1
15	Australia	1974	6.7
16	Italy	1985	5.8
17	Japan	1982	5.7
18	Italy	2009	5.7
19	Greece	1978	5.4
20	Greece	1995	4.9

Figure A1. Real GDP Per Capita Growth and Level around a Natural Disaster

A. 30 largest disasters



B. 50 largest disasters



Note: The figure shows the averages of the real GDP per capita annual growth rates (left panels) and the level of real GDP per capita (rights panels) across the 30 (panel A) and 50 largest (panel B) natural disasters (based on mortality rate) listed in Table A.2, group 3, in a 13-year window centered on the event. The pre- and post-event trends are also included in both panels. In panel A, the level of output per capita for every event is normalized to 100 in the year of the event (T) before taking averages across countries. In panels A and B, the post disaster trends are not statistically different from the pre-disaster trends, suggesting that output losses are not recovered.