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Short-, Medium-, and Long-Term Growth Impacts of Catastrophic and Non-catastrophic Natural Disasters

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Abstract
Using disaster data from 1960, this paper examines the effects of natural disasters on economic growth. The analysis considers disaster effects by combining the following four dimensions: 1) short-, medium-, and long-term impacts, 2) disaster severity, categorized as catastrophic (CAT) or non-catastrophic (NCAT), 3) disaster type: hydro-meteorological, geophysical, and other specific disaster types, and 4) four income groups. The results show that the impacts of a disaster event on economic growth vary depending on the time frame, severity, disaster type, and income level. Overall, CAT disasters have negative impacts regardless of the time frame, while NCAT disasters may have positive impacts depending on the disaster type. The results also indicate that economic growth in lower-middle-income countries is most sensitive to natural disasters, but developed countries also experience negative impacts from CAT disasters.

Keywords Natural disaster · Catastrophic disaster · Hydro-meteorological disaster · Geophysical disaster · Economic growth · Income level

JEL Classification O1 · Q54

Introduction

Understanding the economic impacts of natural disasters plays an important role in the effective mitigation of disaster damage, which is one of the key challenges facing nations that are aiming to achieve sustainable growth (UNISDR 2015). While substantial attention is given to the immediate losses incurred by natural disasters, previous studies suggest that the economic impacts of natural disasters are not necessarily uniformly negative.

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Traditional neoclassical growth models predict that the destruction of capital leads to a temporary decline in a country's economy, and then, the affected economy returns to a balanced growth path over time (Akao and Managi 2007). On the other hand, endogenous growth models suggest that the impacts of natural disasters depend on their relative effects on capital and labor ratios; a disaster event can cause losses of physical and human capital, but it can also increase physical capital per unit of labor (Cavallo et al. 2013). Chhibber and Laajaj (2008) suggested there are short-term negative impacts and a possible disappearance of negative impacts over the long term. The authors provided the following possible scenarios of long-term impacts from a disaster on economic growth that include growth components: (i) no impact on the long-term growth path[1]; (ii) a negative impact through a permanent reduction in capital stock, and (iii) a positive impact by enhancing technological changes during the recovery phase. Overall, the impact of natural disasters on economic growth is "ultimately an empirical one" (Cavallo et al. 2013).

Albala-Bertrand (1993) was one of the first empirical studies that examined the relationship between natural disasters and economic growth, and the study concluded that while economic growth declines immediately after a disaster, there are no significant permanent effects on outputs. This conclusion was consistent with predictions of traditional neoclassical growth models. However, this finding has been criticized because empirical results are sensitive to disaster type and the severity of the disaster as well as the specification of the model and the country sample used in the empirical estimation (Klomp and Valckx 2014).

Following Albala-Bertrand (1993), numerous studies have examined the impacts of natural disasters on economic growth considering various combinations of factors such as time frames, the definition of severity, disaster types and country samples (e.g., Cavallo et al. 2013; Felbermayr and Gröschl 2014; Fomby et al. 2013; Heger et al. 2008; Klomp 2016; Loayza et al. 2012; McDermott et al. 2014; Noy 2009; Raddatz 2009; Skidmore and Toya 2002).[2]

There seems to be some consensus among previous empirical studies that the aggregate economic effects of a disaster appear to be negative in the short term; where short term is commonly defined as the one to five year post-disaster period (Heger et al. 2008; Cavallo et al. 2013; Kousky 2014). Some studies found negative effects of specific disaster types such as droughts, hurricanes and storms on economic growth (Strobl 2012; Fomby et al. 2013; Hsiang and Jina 2014). On the other hand, few studies have found positive growth impacts of disasters for specific disaster occurrences. For instance, Noy (2009) found that disasters reduce output growth by 9% in developing countries but have a very small positive growth impact in developed countries. Additionally, Fomby et al. (2013) and Cunado and Ferreira (2014) found that floods tend to have a positive economic impact.

Studies on the long-term effects of natural disasters are relatively limited in comparison to studies on the immediate impacts and tend to lack a theoretical framework for the mechanisms and channels of disaster impacts over the long-term (Cavallo and Noy 2011). Empirical studies on the relatively long-term impacts of disasters frequently define long term as 5–10 years after

[1] There is a case of increased investment, beyond the initial balanced growth path before the disaster occurred, in the intermediate term after a disaster. However, in the long run, the GDP per capita may return to its initial balanced growth path for the following reasons: the depreciation of capital is larger than the replacement investments (Albala-Bertrand 1993) and the temporary inflow of foreign aid/assistance stops at a certain point in time (Klomp and Valckx 2014).

[2] See Cavallo and Noy 2011; Klomp and Valckx 2014; Kousky 2014; Lazzaroni and van Bergeijk 2014 for a comprehensive literature review.

the occurrence of a disaster. Overall, there is little consensus in terms of the direction of long-term economic impacts of natural disasters. McDermott et al. (2014) used a 10-year lag model and found persistent negative effects on economic growth in countries with low levels of financial sector development. Similarly, Hsiang and Jina (2014) found robust negative impacts of storm events up to 20 years after the occurrence of the disaster, and the direction of the impact does not depend on a country's income level. Coffman and Noy (2011) showed that the economy of the Hawaiian island of Kauai has yet to recover even 18 years after Hurricane Iniki. On the other hand, Loayza et al. (2012) and Cavallo et al. (2013) did not find robust negative economic impacts of natural disasters. Cavallo et al. (2013) observed the negative effects of extremely large-scale severe disasters on GDP growth both in the short and long term but claimed that the results may reflect the negative impact of radical political revolutions, which occurred concurrently with the disasters. In addition, Loayza et al. (2012) even found some positive growth impacts from relatively less severe disaster events in some sectors.

Building on previous empirical studies on the relationship between natural disasters and economic growth, this study provides an inclusive analysis that dissects disaster impacts from various dimensions and combines factors such as post-disaster times frames, severity, disaster types, and economic development of a country. Most previous papers studied growth impacts up to 10 years after a disaster occurred; we extend the analysis by analyzing the long-term impacts at 30 years and analyze short-, medium-, and long-term growth impacts of natural disasters. In terms of severity, we follow the decision rule used by Cavallo et al. (2013) to analyze the variation in the growth impacts between a catastrophic (CAT) and non-catastrophic (NCAT) disaster. Moreover, we consider the various disaster types, including metrological and geological disasters as well as more specific disaster types such as extreme temperatures, floods, storms, earthquakes, and droughts. Finally, we divide the country sample according to income groups based on the World Bank income groupings and analyze the variation in the growth impacts of natural disasters.

The remainder of this paper is organized as follows: Section 2 provides a description of the data and variables. Section 3 describes the empirical framework. Section 4 presents the estimation results and provides a discussion. Section 5 provides the conclusions.

Data and Variables

We use data on natural disasters from the Emergency Events Database (EM-DAT) constructed by the Centre for Research on the Epidemiology of Disasters (CRED), which is the most frequently used public database in the disaster studies (Guha-Sapir et al. n.d.; www.emdat.be). The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. The EM-DAT includes all major natural disaster events in the world during 1900–2016. The CRED includes a disaster event if the event fulfills at least one of the following criteria: 1) 10 or more people reported killed in an event, 2) 100 or more people reported to be affected, 3) a state of emergency was declared, and/ or 4) a call for international assistance occurred.

The EM-DAT includes the death tolls, the number of people affected, and the economic damages for each disaster event. This study uses data on disaster events during 1960 and 2010 to construct country-year observations from 1990 to 2010 given that we use the maximum of a 30-year lag. Of the available disaster measures, we use death tolls and provide subsample analyses for different disaster types (i.e., extreme temperatures, floods, storms, droughts, wildfires, landslides, earthquakes, and volcanic eruptions). We also use socioeconomic variables in the regression analysis; GDP per capita, population growth, investment, government spending, trade openness, and inflation rates are obtained from the Penn World Tables 7.1 (see Heston et al. 2012; Managi et al. 2009; Tsurumi and Managi 2014; Abe et al. 2017; Onuma et al. 2017). The inflation rate is taken from the World Bank's the World Development Indicators. Overall, our analysis uses 3232 country-year observations, covering 173 countries. In the subsample analyses by the level of economic development, we use income group classifications (low-, lower-middle-, upper-middle-, and high-income) of the World Bank based on gross national income (GNI) per capita.[3]

Disaster Measures

To capture disaster impacts on economic growth, previous studies have used various disaster measures,[4] such as dummy variables of disaster occurrence (e.g., McDermott et al. 2014), disaster frequency (e.g., Fomby et al. 2013; Loayza et al. 2012; Skidmore and Toya 2002), intensity of a disaster (e.g., Felbermayr and Gröschl 2014; Hsiang and Jina 2014),[5] and the share of population affected/killed by a disaster (e.g., Noy 2009; Cavallo et al. 2013). Some studies considered injured as affected, in addition to fatalities (Fomby et al. 2013; Loayza et al. 2012; McDermott et al. 2014; Klomp 2016).[6] Cavallo et al. (2013) used the share of the death toll in the total population to define a large disaster and coded an event as severe if the share of fatalities was above the 99th, 90th, and 75th percentiles among the samples.

Skidmore and Toya (2013) noted that the estimated impacts of economic damages and the numbers affected are sometimes unavailable in the EM-DAT. Similarly, Kousky (2014) stated that estimates of the full range of the economic costs of disaster events are limited by the lack of complete and systematic data worldwide, or even within a country. Hence, our analysis follows the decision rule of severity in Cavallo et al. (2013), which is based on death tolls and excludes the number affected or economic damage.

We use the average number of disaster events (E) during [t, t-s] the short term (*Short*), [t-s-1, t-m] the medium term (*Mid*), and [t-11 to t-l] the long term (*Long*)[7] and can be written as

$$Short_{i,t}^{k} = \frac{1}{s}\sum_{j=t}^{t-s} E_{i,j}^{k}, \qquad Mid_{i,t}^{k} = \frac{1}{m}\sum_{j=t-s-1}^{t-m} E_{i,j}^{k}, \qquad Long_{i,t}^{k} = \frac{1}{l}\sum_{j=t-m-1}^{t-l} E_{i,j}^{k} \tag{1}$$

[3] See Appendix Table 6 for specific income group thresholds in the analytical period from 1990 to 2010.

[4] Some studies use NatCatSERVICE, which is a private database provided by the insurance firm Munich Re, and adopt an alternative decision rule known as "an adaptation of Munich Re's great natural catastrophe category" (e.g., Felbermayr and Gröschl 2014; Gassebner et al. 2010; Klomp 2016). These studies define a catastrophic disaster if a disaster event satisfies any of the following criteria: (i) number of killed is no fewer than 1000, (ii) number of injured is no fewer than 1000, (iii) number of affected is no fewer than 100,000, and (iv) the amount of the damages is larger than $1 billion.

[5] Recent papers used original data on hazard strength and hazard intensity (See Hsiang and Jina 2014; Felbermayr and Gröschl 2014; Newmayer et al., 2014).

[6] Fomby et al. (2013), Loayza et al. (2012), and Klomp (2016) constructed a disaster variable, which divides the sum of fatalities and 30% of the total number of people affected by the total population; the number of affected is counted by the definition of the IMF (2003).

[7] We consider the lagged year as more than 10 years and as the long-term effect, which is longer than lagged years used in previous studies (Cavallo et al. 2013; Cunado and Ferreira 2014; Klomp et al., 2016; McDermott et al. 2014).

where $s = 5$, $m = 10$, and $l = 30$. k represents the category of severity: CAT as a severe disaster or $NCAT$ as a non-severe disaster. Based on Cavallo et al. (2013), we classify the disaster events into CAT and $NCAT$ events using the following definition:

$$k = CAT, if \frac{death_{i,j}}{population_{i,j}} \geq Nth\ cutoff\ values, \\ = NCAT, otherwise. \tag{2}$$

We consider a disaster event as a CAT event if the death tolls per population are ranked in the top one percent ($N = 99$) of our sample. The cut-off value in our data is 0.0183 for the 99th percentile, and there are 98 CAT events from 1960 to 2010.[8] Fig. 1 provides the map of countries that have experienced CAT disasters during the period of analysis. Unsurprisingly, the marked countries are mostly developing countries and/or located in relatively high-risk areas such as a plate boundary zone that is more likely to experience earthquakes or a climate zone with higher risk of extreme weather events. While the share of developing countries is high in the sample that experiences CAT disasters, there are various developed countries with CAT events. Notably, European countries such as France, Italy, Netherlands, and Spain are included due to the effects of the heatwave in Europe during the summer of 2003, which caused more than 72 thousand deaths. Table 1 provides descriptive statistics of the disaster measures. The average likelihood of a CAT event occurrence is 0.008 per year, and NCAT events are 133 times more likely to occur compared to a CAT event.

Empirical Model

We examine whether the impacts of disasters on economic growth vary depending on time frame (short-, medium-, and long-term), severity (CAT or NCAT) for different disaster categories and types, and the level of economic development, using the following panel regressions model:

$$\Delta \ln y_{i,t} = (\rho - 1)\ln y_{i,t-1} + \beta_{1,k}\boldsymbol{Short}_{i,t}^{k} + \beta_{2,k}\boldsymbol{Mid}_{i,t}^{k} + \beta_{3,k}\boldsymbol{Long}_{i,t}^{k} + \gamma'\boldsymbol{X_{i,t}} + \eta_i + \mu_t + \varepsilon_{i,t} \tag{3}$$

$\Delta \ln y_{i,\,t}$ is the annual growth rate of GDP per capita of country i in year t. $\boldsymbol{Short}_{i,t}^{k}$, $\boldsymbol{Mid}_{i,t}^{k}$, and $\boldsymbol{Long}_{i,t}^{k}$ are the vectors of disaster related measures. We control the lagged income term, $\ln y_{i,\,t-1}$, to capture the implication of the convergence hypothesis that per capita incomes of poorer economies tend to grow faster than those of richer economies (Barro and Salai-i-Martin 1992; Mankiw et al. 1992). We also control for the lagged socioeconomic variables to control for structural characteristics of countries such as population growth and the size of government denoted as $\boldsymbol{X}_{i,\,t-1}$. The parameter η_i is a country-specific factor to control for unobserved time-invariant country characteristics such as geographical factors. μ_t is the year fixed effects to control for global shocks such as technological progress and economic trends that affect the world business cycle. $\varepsilon_{i,\,t}$ is the error term.

We use a fixed-effect model in the analysis to address potential dynamic panel bias by including the lagged dependent variable as a control variable (Nickell 1981). Arellano and

[8] If interested in the results of other thresholds (95th, 90th, 75th) and the IMF (2003) decision rule, they are available upon request.

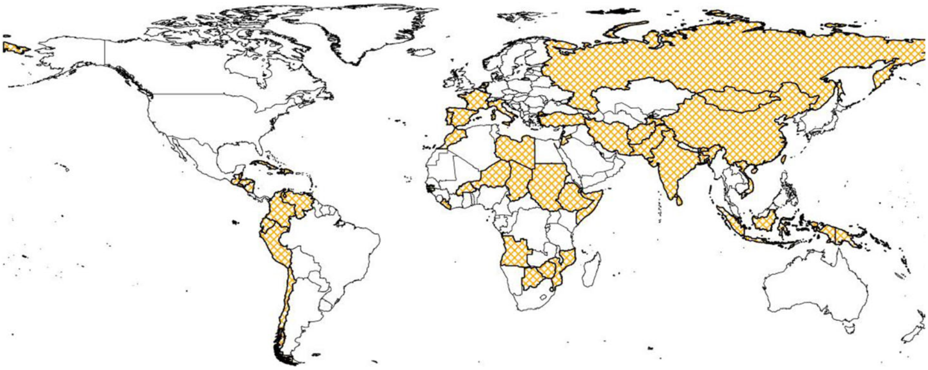

Fig. 1 World Map of Countries with Catastrophic Disasters (99th percentile)

Bover (1995) and Blundell and Bond (1998) used the dynamic panel estimators and the difference and system generalized method of moments (GMM) to address the issue of this bias. However, Roodman (2009) noted that in data with longer time series, "dynamic panel bias becomes insignificant, and a more straightforward fixed effects estimator works." Given that our dataset includes relatively long panel data that cover over a 20-year period, we use the fixed-effect model in the analysis.

We address the potential endogeneity between disasters and economic development, partially by using country fixed effect. The specification of our empirical model places the emphasis on effect identification of the within-country variation over time, which reduces possible selection bias from over-represented poorer countries, which tend to have a greater share of death tolls than do developed countries (McDermott et al. 2014).

Table 1 Descriptive Statistics

Variable	Obs (n)	Mean	Std. Dev.	Min	Max
Dependent variable					
Growth rate	3232	0.022	0.060	−0.709	0.767
Independent variable					
CAT (Severe disaster)					
aggregate (t - t-30)	3232	0.008	0.021	0	0.226
Short-run (t - t-5)	3232	0.008	0.038	0	0.333
Medium-run (t-6 - t-10)	3232	0.008	0.040	0	0.400
Long-run (t-11 - t-30)	3232	0.008	0.025	0	0.350
NCAT (Non-severe disaster)					
aggregate (t - t-30)	3232	1.061	2.033	0	20.548
Short-run (t - t-5)	3232	1.750	3.248	0	29.167
Medium-run (t-6 - t-10)	3232	1.413	2.828	0	29.200
Long-run (t-11 - t-30)	3232	0.766	1.578	0	19.100
Controls					
GDP per capita	3232	11,240	13,191	180	118,836
Population growth	3232	0.015	0.021	−0.818	0.399
Share of investment	3232	0.229	0.100	0.007	0.830
Share of government spending	3232	0.110	0.073	0.009	0.672
Trade	3232	0.824	0.495	0.075	4.330
Inflation rate	3232	1.386	4.843	0.819	238.731

Results and Discussion

Results of all the Disasters

Table 2 presents the estimation results with the aggregated data from all the disasters. The results in the first two columns do not consider severity, while the last two columns incorporate severity aspects. The same set of explanatory variables is included as control variables across all models. Column (1) shows the results of the aggregate data, which evaluate the impacts of disasters without differentiating the disaster types, severity and timespans (short, medium, and long term). This estimation model simply considers the effect of a disaster that has happened within a 30-year period, and a disaster has a statistically significant positive effect.

Column (2) shows the results by time periods and demonstrates that a disaster seems to have positive impacts in the short term [t, t-5] and medium term [t-6, t-10]. The coefficients of the disasters in column (2) indicate that positive impacts in the medium term are larger than those in the short term, but long-term impacts are not statistically significant. This difference may be partly from the economic boost due to initial public investment and international disaster relief during the recovery process (Strömberg 2007), which may continue to affect recovery in the medium term. Additionally, no significant impact of the disaster measure of [t-11, t-30] on the growth rate seems support the theoretical implication that over the long term, society recovers and returns to the stable path of economic growth. However, as further examinations indicate, this result should not be considered a generalized result for all disaster events because the signs and statistical significance of disaster impacts depend on the severity of a disaster and the disaster type.

When we add severity dimension to the analysis, we do not find consistent positive impacts of disasters on economic growth as in columns (1) and (2). Column (3) provides the impacts of severe disasters (CAT) and non-severe disasters (NCAT). CAT disasters have large negative coefficients, and NCAT disasters have smaller positive coefficients, which are about one-tenth of the absolute magnitude of a CAT impact. Since CAT refers the top one percent severe disasters, negative impacts and larger coefficients are relatively unsurprising. However, the average number of disaster events in past 30 years is 0.008 for CAT disasters and 1.061 for NCAT disasters (see Table 1). Thus, most countries are less likely to suffer from a CAT disaster than an NCAT disaster. Therefore, the aggregate impacts of CAT and NCAT can be positive, as shown in columns (1) and (2). While positive average aggregate impacts of disasters seem reasonable after summing the results, it is misleading to conclude that there are positive impacts on economic growth.

Column (4) shows the impacts of a disaster by both severity and time frames. In terms of an NCAT disaster, the results are similar to the results in column (2); on average, disasters have positive effects on growth rates. A disaster that occurs over a medium term [t-6, t-10] has larger impacts in than does a disaster that occurs over a short term [t, t-5]. We found no statistically significant impact of a disaster that occurs over a long-term period [t-11, t-30]. Hence, an NCAT disaster does not seem to have long-term impacts, but this trend does not hold for CAT disasters. The results of short-, medium- and long-term impacts of CAT disasters indicate negative impacts for all time frames. These results are consistent with the average negative impacts found in column (3).

Additionally, negative impacts for a severe disaster in the short term [t, t-5] are consistent with the results of Klomp (2016) regarding the negative impacts of extreme disasters defined as “one percent largest natural disasters based on their damage created or number of people

Table 2 Estimation Results for All Disasters

Decision Rules of Severity	not separated	not separated	99%	99%
	(1)	(2)	(3)	(4)
All Disasters				
Mean Effects (t - t-30)	0.043***			
	(0.012)			
Short-run (t - t-5)		0.009*		
		(0.005)		
Medium-run (t-6 - t-10)		0.018***		
		(0.004)		
Long-run (t-11 - t-30)		0.005		
		(0.009)		
CAT				
Mean Effects (t - t-30)			−0.350***	
			(0.097)	
Short-run (t - t-5)				−0.093***
				(0.027)
Medium-run (t-6 - t-10)				−0.082***
				(0.029)
Long-run (t-11 - t-30)				−0.173**
				(0.077)
NCAT				
Mean Effects (t - t-30)			0.041***	
			(0.012)	
Short-run (t - t-5)				0.010**
				(0.005)
Medium-run (t-6 - t-10)				0.016***
				(0.004)
Long-run (t-11 - t-30)				0.008
				(0.010)
Controls				
Initial GDP per capita	−0.086***	−0.086***	−0.087***	−0.086***
	(0.017)	(0.017)	(0.017)	(0.017)
Population Growth	−0.075	−0.076	−0.072	−0.071
	(0.129)	(0.130)	(0.130)	(0.130)
Investment	0.095***	0.093***	0.096***	0.093***
	(0.031)	(0.031)	(0.031)	(0.031)
Size of Government	−0.166**	−0.162**	−0.169**	−0.161**
	(0.069)	(0.069)	(0.069)	(0.070)
Trade Openness	0.039***	0.040***	0.040***	0.041***
	(0.009)	(0.009)	(0.009)	(0.009)
Inflation Rate	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.693***	0.690***	0.704***	0.694***
	(0.140)	(0.144)	(0.140)	(0.144)
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	3232	3232	3232	3232
Number of Countries	173	173	173	173
Adjusted R-squared	0.198	0.199	0.201	0.201

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Robust standard errors are reported in parentheses

affected". McDermott et al. (2014) also found a reduction in annual growth over the medium term (over a five-year period), in which a disaster was defined "as = 1 if the total number of people affected by disasters over the five-year period exceeds 2.5% of the country's population". Klomp (2016) and McDermott et al. (2014) did not assess the impacts of a disaster beyond 10 years of its occurrence. Hence, our results add to those of previous studies by determining that the negative impacts of extremely severe disasters affect economic growth longer than for a decade.

The magnitudes of CAT impacts do not vary greatly, and when a CAT disaster occurred in the short term [t, t-5] or the medium term [t-6, t-10], on average, it had −0.09% and − 0.08% growth rate at year t, respectively.[9] However, if a CAT disaster occurred in between [t-11, t-30], then it had a relatively larger negative impact of −0.17% on the growth rate. These results indicate that a series of disaster responses such as governmental and international assistance may have positive effects on economic growth (Strömberg 2007), and these assistance effects partially offset the negative impacts of a disaster. Nevertheless, the offset effect may be limited to approximately 10 years. Such a positive effect over a limited period time may be explained by the temporary inflow of foreign aid/assistance that is reduced gradually and eventually terminated (Klomp and Valckx 2014).

The results, in terms of signs and magnitude, of most control variables are consistent with those of Felbermayr and Gröschl (2014), using the same estimation strategy. The initial GDP per capita is negative and statistically significant. This negative coefficient supports the convergence hypothesis. Investment and trade openness are positive and statistically significant, whereas population growth and inflation rates are not positive and statistically significant in our results.

Results by Disaster Categories and Types

Table 3 provides the results in terms of hydro-meteorological and geophysical disasters. In both disaster categories, NCAT disasters have positive effects on economic growth in the short term and medium term. On the other hand, the impacts of CAT disasters vary depending on the categories; severe hydro-meteorological disasters have negative impacts for all time frames, while we observe negative effects of geophysical disasters only in the medium term. The similarity between the results of hydro-meteorological disasters and the results of the aggregated sample in Table 2 is partly explained by the fact that hydro-meteorological disasters occur relatively more frequently than geophysical disasters. The positive effects of an NCAT hydro-meteorological disaster is consistent with the result of Skidmore and Toya (2002), which found a positive relationship between the frequency of NCAT disasters and growth in the case of climate-related disasters. Additionally, the result for CAT geophysical disasters is consistent with the negative relationship between geological disasters and economic growth found in Skidmore and Toya (2002).

Table 4 shows that the disaster impacts vary depending on the disaster types. Models 1 and 2 examine the impacts of short-, medium- and long-term impacts of CAT and NCAT separately. The impacts of extreme temperature events, particularly heat waves, are similar to the results of all disasters in Table 2 as well as the results of hydro-meteorological disasters in Table 3. CAT disasters have negative impacts on economic growth in the short and medium term. On the other hand, NCAT disasters have positive short- and medium-term impacts.

[9] With different definitions of a short-term period, particularly the shorter term (e.g. [t, t-1], [t, t-3]), the negative coefficients of disaster variables are smaller. Moreover, the negative coefficients of the medium-term period are larger.

Table 3 Estimation Results for Hydro-meteorological and Geophysical Disasters

Decision Rules of Severity	not separated	not separated	99%	99%
	(1)	(2)	(3)	(4)
Hydro-meteorological Disasters				
Mean Effects (t - t-30)	0.036*** (0.012)			
Short-run (t - t-5)		0.008* (0.005)		
Medium-run (t-6 - t-10)		0.016*** (0.004)		
Long-run (t-11 - t-30)		0.010 (0.011)		
CAT				
Mean Effects (t - t-30)			−0.390*** (0.106)	
Short-run (t - t-5)				−0.103*** (0.035)
Medium-run (t-6 - t-10)				−0.067* (0.038)
Long-run (t-11 - t-30)				−0.207** (0.084)
NCAT				
Mean Effects (t - t-30)			0.035*** (0.012)	
Short-run (t - t-5)				0.008* (0.005)
Medium-run (t-6 - t-10)				0.013*** (0.004)
Long-run (t-11 - t-30)				0.012 (0.011)
Geophysical Disasters				
Mean Effects (t - t-30)	0.022 (0.024)			
Short-run (t - t-5)		0.019** (0.008)		
Medium-run (t-6 - t-10)		0.021*** (0.008)		
Long-run (t-11 - t-30)		−0.019 (0.020)		
CAT				
Mean Effects (t - t-30)			−0.243 (0.217)	
Short-run (t - t-5)				−0.075 (0.046)
Medium-run (t-6 - t-10)				−0.107** (0.049)
Long-run (t-11 - t-30)				−0.102 (0.176)
NCAT				
Mean Effects (t - t-30)			0.017 (0.024)	
Short-run (t - t-5)				0.016** (0.008)
Medium-run (t-6 - t-10)				0.015** (0.008)
Long-run (t-11 - t-30)				−0.014 (0.021)
Observations	3232	3232	3232	3232

Table 3 (continued)

Decision Rules of Severity	not separated	not separated	99%	99%
Number of Countries	173	173	173	173
Adjusted R-squared	0.198	0.199	0.200	0.200

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Robust standard errors are reported in parentheses. Controls, country and year fixed effects are included but not reported

We find contrasting effects in the analyses of other disaster types, including floods, storms, earthquakes, and droughts. For floods, NCAT events have positive impacts in medium and long term, which is consistent with previous studies on the impacts of floods on economic growth (Cunado and Ferreira 2014; Fomby et al. 2013).

Storms have negative economic impacts for both CAT and NCAT events according to Model 1. In Model 2, however, we find impacts only for NCAT events. Although an average number of CAT storms in the past 30 years negatively affected economic growth, we find no statistically significant impact of CAT storms when we examine separate time frames. On the other hand, a storm is only considered a disaster type when NCAT events have statistically significant negative impacts on economic growth, and this result is consistent with the findings of Hsiang and Jina (2014) that showed short- and long-term negative impacts of storms through a 20-year period.

Table 4 Estimation Results for Each Disaster Type

	Extreme Temperature	Flood	Storm	Earthquake	Drought
Model 1					
CAT					
Mean Effects (t - t-30)	−1.353***	0.162	−0.384**	−0.587*	−0.486
	(0.245)	(0.595)	(0.193)	(0.304)	(0.820)
NCAT					
Mean Effects (t - t-30)	0.113***	0.0521***	−0.115***	0.0265	0.199***
	(0.0415)	(0.0184)	(0.0213)	(0.0332)	(0.0633)
Observations	3232				
Adjusted R-squared	0.205				
Model 2					
CAT					
Short-run (t - t-5)	−0.206***	0.022	−0.056	−0.105**	omitted
	(0.045)	(0.158)	(0.065)	(0.046)	
Medium-run (t-6 - t-10)	−0.285***	0.177	0.016	−0.121**	−0.138
	(0.049)	(0.125)	(0.067)	(0.052)	(0.121)
Long-run (t-11 - t-30)	omitted	−0.282	−0.141	0.027	−0.366
		(0.326)	(0.114)	(0.194)	(0.278)
NCAT					
Short-run (t - t-5)	0.0200**	0.008	−0.021***	0.016*	0.009
	(0.008)	(0.005)	(0.006)	(0.009)	(0.013)
Medium-run (t-6 - t-10)	0.0175*	0.012**	−0.013**	0.018**	0.037***
	(0.010)	(0.005)	(0.006)	(0.008)	(0.012)
Long-run (t-11 - t-30)	0.001	0.030*	−0.062***	−0.001	0.128***
	(0.034)	(0.016)	(0.013)	(0.025)	(0.046)
Observations	3232				
Adjusted R-squared	0.206				

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Robust standard errors are reported in parentheses. Controls, country and year fixed effects are included but not reported. Landslides, wildfires and volcanic eruptions are also included but not reported in this Table, due to zero or very small observations

In the case of earthquakes, our results show that the CAT earthquakes have short- and medium-term negative impacts on economic growth but no long-term impacts. On the other hand, we find that NCAT earthquakes have a positive impact on economic growth in the short and medium terms, and the initial recovery process with relief funds that follow an earthquake to rebuild residential housing, public infrastructure, and industrial plants may explain the positive impact (Fomby et al. 2013).

We find negative impacts of storms and earthquakes, the negative impacts of earthquakes increase through a medium time frame, and the impacts of storms remain for an extensive period and have larger impacts over the long term. These differences between the effects of different disaster categories may be explained by the difference in the likelihood of storm and earthquake occurrences. Severe earthquakes tend not to strike the same area at least over several decades, while storms including high-intensity events are more likely to occur frequently over a short time frame in the same area. Hence, a country affected by a severe earthquake could return to its previous balanced growth path or an improved state over a shorter period than could countries affected by storms. For storms, there is a slight chance that recovery efforts as well as investments for damage mitigation will be negatively affected by a similar type of disaster within short time frame. Therefore, recovery and adaptation efforts may be disrupted, and countries affected by storms experience negative growth over the long term. Furthermore, the long-term negative impacts of storms are greater than are short- and medium-term impacts because, as previously mentioned, support from public emergency investments and international financial aid might end after a certain period (Strömberg 2007).

The results demonstrate the medium- and long-term positive growth effects of NCAT droughts. These results differ from the negative impacts found in previous studies (Loayza et al. 2012; Fomby et al. 2013). This opposite disaster effect may be partially explained by the fact that these previous studies analyzed the impacts of drought in the short term, while our study covers a much longer period. This positive impact is consistent with findings that the farmers in drought-prone areas are more likely to adopt adaptation strategies such as supplementary irrigation and crop switching that are known to increase agricultural productivity (Alauddin and Sarker 2014; Kurukulasuriya and Mendelsohn 2008).

Varying Disaster Effects by Economic Development

Table 5 presents results of the impacts of hydro-meteorological and geophysical disasters by four income groups. Given the rarity of CAT disasters, high-income countries do not experience long-term impacts from hydro-metrological disasters and geophysical disasters for all time frames.

There are several results worth noting. In low-income countries, we do not find any statistically significant disaster impacts on economic growth except for geophysical CAT disasters in the short term. In contrast, all the CAT and NCAT disasters of both disaster categories have statistically significant impacts in lower-middle-income countries; the results show the positive impacts of hydro-metrological NCAT disasters and the negative impacts of other disasters. According to the results in Table 3, geophysical CAT and NCAT disasters have no statistical significance without the distinction of the time frames. However, the results of the subsample analysis by income group indicate that depending on the income group, geophysical disasters have statistically significant impacts on economic growth. In upper-middle-income countries, hydro-metrological CAT disasters have negative impacts similar to those in lower-middle-income countries.

Table 5 Estimation Results by Income Level

Income Levels	Low		Lower Middle		Upper Middle		High	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hydro-meteorological Disasters								
CAT								
Mean Effects (t - t-30)	−0.050 (0.137)		−0.755** (0.301)		−1.015** (0.413)		−0.707*** (0.164)	
Short-run (t - t-5)		−0.075 (0.072)		0.032 (0.115)		−0.202** (0.100)		−0.164*** (0.036)
Medium-run (t-6 - t-10)		−0.099 (0.067)		0.003 (0.085)		−0.121 (0.115)		−0.129*** (0.048)
Long-run (t-11 - t-30)		−0.046 (0.111)		−0.553** (0.220)		−0.750** (0.335)		omitted
NCAT								
Mean Effects (t - t-30)	0.018 (0.030)		0.080** (0.037)		0.022 (0.033)		−0.033 (0.022)	
Short-run (t - t-5)		0.011 (0.010)		0.017 (0.012)		−0.015 (0.015)		−0.012 (0.008)
Medium-run (t-6 - t-10)		−0.005 (0.012)		0.020** (0.010)		0.031** (0.013)		0.003 (0.007)
Long-run (t-11 - t-30)		−0.004 (0.036)		0.04 (0.035)		−0.023 (0.035)		−0.012 (0.015)
Geophysical Disasters								
CAT								
Mean Effects (t - t-30)	0.358 (0.417)		−0.435** (0.202)		2.163* (1.186)		omitted	
Short-run (t - t-5)		0.145 (0.090)		−0.119** (0.053)		0.233 (0.189)		omitted
Medium-run (t-6 - t-10)		0.003 (0.118)		−0.072 (0.048)		0.187 (0.190)		omitted
Long-run (t-11 - t-30)		0.412 (0.373)		−0.237 (0.159)		1.900** (0.907)		omitted
NCAT								
Mean Effects (t - t-30)	0.057 (0.093)		−0.092** (0.046)		−0.076 (0.082)		−0.074 (0.052)	
Short-run (t - t-5)		0.068** (0.030)		−0.018 (0.013)		−0.014 (0.019)		−0.001 (0.015)
Medium-run (t-6 - t-10)		0.017 (0.024)		−0.013 (0.013)		−0.013 (0.022)		0.001 (0.014)
Long-run (t-11 - t-30)		−0.049 (0.061)		−0.056 (0.043)		−0.008 (0.083)		−0.053* (0.031)
Observations	915	915	956	956	589	589	761	761
Number of Countries	65	65	89	89	68	68	50	50
Adjusted R-squared	0.205	0.206	0.339	0.335	0.327	0.333	0.20	0.287

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Robust standard errors are reported in parentheses. Controls, country and year fixed effects are included but not reported

However, in this income category, geophysical CAT disasters have positive impacts on economic growth. The contrasting impacts of geophysical CAT disasters in upper-middle- and lower-middle-income groups may explain the lack of statistical significance for the coefficient of the geophysical CAT disaster when the sample is not distinguished by income group (See column (3) in Table 3). Lastly, in high-income countries, similar to the results for lower-middle and upper-middle-income groups, we find negative impacts of hydro-metrological CAT disasters.

Overall, we consistently find negative impacts from hydro-metrological disasters across the income groups. Additionally, the results indicate that natural disasters have the most significant and robust impacts in lower-middle-income countries. Furthermore, the positive impacts of hydro-metrological NCAT disasters observed in the aggregate analysis shown in the column (3) of Table 3 reflect the impacts in lower-middle-income groups and do not apply to the other income categories. Our findings are relevant to the 17th goal of the Sustainable Development Goals (SDGs), which is an urgent call to action for all countries - developed and developing – to join a global partnership to address issues such as climate change (see Kanie et al. 2014; Kanie and Managi 2014; Dasgupta et al. 2015). This goal is related to natural disasters around the world.

Conclusion

This study provides extensive empirical analyses on the impacts of natural disasters on economic growth by considering variations in the time frame, disaster severity, disaster type, and level of economic development in a country. When we analyze natural disasters only in terms of time frames, we find positive impacts from the disasters in the short and medium term but not in the long term. Severity also plays a significant role in determining disaster impacts. CAT disasters tend to have negative impacts, while we find some statistically significant positive impacts of NCAT disasters depending on disaster type and income level of the country. The findings of greater long-term impacts from severe disasters than of short- and medium-term impacts imply potential imperfect recovery from large-scale disasters after governmental and international assistance ends (Strömberg 2007).

The results also indicate that the impacts of natural disasters on economic growth depend on disaster type. Even within the commonly used categories and specific types of natural disasters, some disaster categories or specific types of disasters have positive impacts when the severity of disaster is NCAT, with the exception of storms, which have negative impacts on economic growth regardless of severity.

Overall, we find robust long-term negative impacts of CAT disasters on economic growth. Specifically, negative impacts are widely observed for meteorological disasters such as storms and extreme temperature events, which are growing in their intensity and frequency due to climate change. The results of the subsample analyses by income group indicate that disaster impacts differ significantly by the level of economic development; economic growth in lower-middle-income countries is most sensitive to natural disasters, but developed countries also experience negative impacts from CAT disasters.

Finally, as Cavallo et al. (2013) noted, “It is important to notice that many of the events that are recorded in the data set do not correspond to the catastrophic notion of natural disaster that one has in mind when thinking about the potential effect of natural disasters on the macroeconomy.” This problem in database construction might be one reason for the difficulty of finding robust long-term effects of disasters on economic growth. Continuous efforts in the data collection, analysis and examination of the mechanisms by which natural disasters affect economies and development would provide further insights to improve mitigation and adaptation policies as well as recovery efforts.

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Appendix 1

Table 6 Income Group Thresholds

Classifications	1990	1991	1992	1993	1994	1995	1996
Low-income	<= 610	<= 635	<= 675	<= 695	<= 725	<= 765	<= 785
Lower-middle-income	611–2465	636–2555	676–2695	696–2785	726–2895	766–3035	786–3115
Upper-middle-income	2466-7620	2556-7910	2696-8355	2786-8625	2896-8955	3036-9385	3116-9645
High-income	> 7620	> 7910	> 8355	> 8625	> 8955	> 9385	> 9645
	1997	1998	1999	2000	2001	2002	2003
Low-income	<= 785	<= 760	<= 755	<= 755	<= 745	<= 735	<= 765
Lower-middle-income	786–3125	761–3030	756–2995	756–2995	746–2975	736–2935	766–3035
Upper-middle-income	3126- 9655	3031-9360	2996-9265	2996-9265	2976-9205	2936-9075	3036-9385
High-income	> 9655	> 9360	> 9265	> 9265	> 9205	> 9075	> 9385
	2004	2005	2006	2007	2008	2009	2010
Low-income	<= 825	<= 875	<= 905	<= 935	<= 975	<= 995	<= 1005
Lower-middle-income	826–3255	876–3465	906–3595	936–3705	976–3855	996–3945	1006-3975
Upper-middle-income	3256-10,065	3466-10,725	3596-11,115	3706-11,455	3856-11,905	3946-12,195	3976-12,275
High-income	> 10,065	> 10,725	> 11,115	> 11,455	> 11,905	> 12,195	> 12,275

Source: World Development Indicators

Appendix 2

Table 7 List of Countries in the Samples

Afghanistan*	Dominican Rep*	Lesotho	Saudi Arabia
Albania	Ecuador*	Liberia*	Senegal
Algeria	Egypt	Libyan Arab Jamah*	Serbia
Angola*	El Salvador*	Lithuania	Seychelles
Antigua and Barbuda	Equatorial Guinea	Luxembourg*	Sierra Leone
Armenia	Estonia	Macau	Singapore
Australia	Ethiopia*	Macedonia FRY	Slovakia
Austria	Fiji	Madagascar	Slovenia
Azerbaijan	Finland	Malawi	Solomon Is*
Bahamas	France*	Malaysia	South Africa
Bahrain*	Gabon	Maldives*	Spain*
Bangladesh*	Gambia*	Mali	Sri Lanka*
Barbados*	Georgia	Malta	St Kitts and Nevis
Belarus	Germany	Mauritania	St Lucia*
Belgium	Ghana	Mauritius	St Vincent and The Grenadines*
Belize	Greece	Mexico	Sudan*
Benin	Grenada*	Moldova Rep	Suriname
Bhutan*	Guatemala*	Mongolia*	Swaziland*
Bolivia	Guinea	Montenegro	Sweden
Bosnia-Hercegovina	Guinea Bissau*	Morocco*	Switzerland
Botswana*	Guyana	Mozambique*	Syrian Arab Rep
Brazil	Haiti*	Namibia	Tajikistan*
Brunei Darussalam	Honduras*	Nepal	Tanzania Uni Rep
Bulgaria	Hong Kong (China)	Netherlands*	Thailand
Burkina Faso*	Hungary	New Zealand	Togo
Burundi	Iceland	Nicaragua*	Tonga
Cambodia	India*	Niger*	Trinidad and Tobago
Cameroon	Indonesia*	Nigeria	Tunisia
Canada	Iran Islam Rep*	Norway	Turkey*
Cape Verde Is	Iraq	Oman	Uganda
Central African Rep	Ireland	Pakistan*	Ukraine
Chad*	Israel	Panama	United Arab Emirates
China P Rep*	Italy*	Papua New Guinea*	United Kingdom
Colombia*	Jamaica	Paraguay	United States
Comoros*	Japan	Peru*	Uruguay
Congo	Jordan*	Philippines	Vanuatu*
Costa Rica	Kazakhstan	Poland	Venezuela*
Cote d'Ivoire	Kenya	Portugal*	Viet Nam*
Croatia	Korea Rep	Qatar	Yemen
Cyprus	Kuwait	Romania	Zaire/Congo Dem Rep
Czech Rep	Kyrgyzstan	Russia*	Zambia
Denmark	Lao P Dem Rep	Rwanda	
Djibouti*	Latvia	Samoa*	
Dominica*	Lebanon*	Sao Tome et Principe*	

*denotes countries that have experienced a top one-percent catastrophic disaster in the world disaster distribution

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