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Economic growth, natural disasters and climate change: New empirical estimates

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ABSTRACT

This paper analyzes the association between climate change variables and the incidence of intense hydro meteorological disasters within a framework that include global and local climate variables as well as socio-economic factors that aggravate disasters. We have shown that atmospheric carbon dioxide accumulation significantly increases hydro meteorological disasters and that the losses of human capital caused by such disasters induce significant negative effects on the rate of economic growth. A distinctive feature of this research is that the statistical-econometric analysis used considers all reported significant climate-related disasters during the period 1970-2013 in 184 countries, instead of focusing merely on selected disasters, periods or countries as most previous research has done.

Keywords: Hydro meteorological disasters, economic growth, carbon dioxide accumulation.

JEL classification: O47, Q51, Q54, C22

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1. Introduction

Intense climate-related disasters, comprising hydro meteorological events (floods and storms) and climatological ones (droughts and heat waves), have been rising in recent decades worldwide. This paper examines the link between climate change and the increase of hydro meteorological incidents and their impact on economic growth.

Most previous studies on the climate-disaster link have simulated the likelihood of disasters in particular geographic areas using climate change models (Easterling et al 2000; Pall et al. 2011; Schreider, Smith and Jakeman 2000; Cornwall 2016). Others have analyzed particular disasters in specific regions (Stott et al. 2004; Hoerling et al. 2012). While analyzing particular disasters may have the advantage of gaining greater depth on understanding them the results using this approach are likely to be affected by selection biases (Heckman et al. 1998) as it is difficult to ascertain their general validity. Similarly, most studies on the effects of climate-related disasters on economic growth have focused on particular events or on subsets of disasters in particular regions and times which obviously raises the question of whether these studies are also affected by selection biases (Albala-Bertrand, 1993; Otero & Marti, 2005).

In contrast, the present statistical-econometric analysis considers all reported intense climate-related disasters worldwide during the period 1970-2013 in 184 countries. Having established correlations between climate change indicators and hydro meteorological disasters, the paper applies co-integration tests to see if the correlations represent meaningful or non-spurious correlations concluding that a meaningful association between the number of such disasters and the accumulation of carbon dioxide in the atmosphere does exist. Subsequently we examine how climate-related disasters and hence how atmospheric carbon accumulation have affected the potential for economic growth using a panel country data for the full sample of disasters available for most countries in the world.

Two previous studies have also used multi-country statistical analyses. Thomas et al. (2014) used a sample of 25 Asian countries, but only traced country-specific climatic conditions rather than global climatic trends. Moreover, while the authors found a significant statistical relationship between disasters and local climatic conditions, they did not check for potential biases in their results from the omission of certain variables affecting the likelihood of disasters and local climatic conditions.

López et.al (2016) relied on cross-country, time-series statistical analyses to connect disasters and climate change using annual panel data for 153 countries. This study showed a positive impact of global climate change indicators and local ones on hydro meteorological disasters. It also probed if this connection was meaningful using co-integration analysis. However, since the sample covered only 43 time observations, the time series analysis underlying co-integration was likely weak. Also, this study does not consider the economic impact of disasters. Neither of these two studies considers the effects of disasters on economic growth.

The present study is a more solid basis for the conclusions than the above papers in two ways. First, it uses the broadest sample available of 184 countries across five continents for 43 years. Second, it uses quarterly data instead of annual data, lengthening the longitudinal component of the series to nearly 180 observations and making the co-integration analysis more robust. Most authors recognize that using appropriate methods, a time series analysis with more than 100 time observations is adequate.

More broadly, this paper integrates three major factors affecting natural disasters. One is global climatic factors, viz., atmospheric Co2 accumulation and global temperature, a second is local climatic variables, viz., local precipitation and temperature, and the third is socio-economic variables, viz., per capita GDP, population density. The use of socio-economic variables is designed to capture vulnerability and exposure of populations to disasters. The fact that we focus on intense disasters—defined as disasters that have caused a certain minimum number of deaths and/or people affected—justifies considering vulnerability and exposure that help turn hazards into disasters. Also, we postulate that global climatic changes are likely to affect intense climate-related disasters in addition to the local weather events. Global climatic factors may increase the vulnerability of countries to local weather events. For example, as atmospheric carbon dioxide accumulates sea levels tend to increase making coastal areas much more affected by storms.

Finally, the present study differs from previous ones in providing estimates of the impact of intense hydro meteorological disasters on economic growth using all available data worldwide instead of focusing only on particular events or regions. It shows that losses of human capital, but not the material losses, caused by disasters are the most important factor explaining the estimated negative impact of disasters on economic growth.

2. Data and econometric methods

We use quarterly data on disasters for a sample covering most countries in the world. The list of countries is shown on Table A1 in Appendix. The model considers count data of disasters by country i and quarter t for 1970–2013 from EM-DAT (Guha-Sapir et al 2015). We focus on intense disasters, i.e, disasters that cause at least 100 deaths and/or directly affect at least 1,000 people.

We use two alternative approaches to estimate the impact of global climate change on disasters:

In ***approach I***, using the number of natural disasters per country and quarter as the dependent variable, we estimate the effect of global climate indicators as a separate variable directly in the regression analysis, controlling for country-specific effects. The global indicators used are the global average temperature and the atmospheric carbon dioxide (CO_2) accumulation. A hypothesis is that global climate variables exert an independent effect on disasters over and above local country conditions. A problem with using Approach I is that the global temperature and the atmospheric CO_2 level may correlate with omitted variables affecting natural disasters, thus biasing the estimates.

In ***approach II***, we estimate two-way fixed effects. In a first stage we control for both country-specific fixed effects and common-to-all-country global effects which vary over time (represented by the coefficients of the time dummy variables). In a second stage, we perform a co-integration analysis between global temperature and atmospheric CO_2 accumulation and the estimated global time effects obtained from the first stage to test whether these changing global time effects are meaningfully associated with hydro meteorological disasters.

The dependent variable is the number of intense natural disasters, consisting of non-negative count values. So count regression models such as the Poisson (P) or Negative Binomial (NB) need to be used. We use the NB model (equation 1 below), which unlike the P model, allows for over dispersion between the mean and the variance of the distribution (Johnson et al 1992, Lambert 1992). We estimate equation (1) below using quarterly data for 184 countries during 1970-2013, a total of 25,876 observations. (Table A2 in the appendix shows the descriptive statistics of the data used). In equation (1) the dependent variable is the annual frequency of intense hydro meteorological disasters, (H_{it}). The independent variables are: W_{it}, the average local precipitation deviation in the country' measured as departures from the average for its 30-year base 1961–1990 (Schneider et al 2015) and Z_{it}, the average local temperature deviation in the country, V_{it}, per capita gross domestic product as a proxy for vulnerability to disasters; U_{it}, population per country as an indicator of exposure to disasters; G_t, global effects varying at each point of time.[1] We estimate the parameters $\alpha_0, \alpha_1, \alpha_2, \alpha_3$, α_4 and α_5 of the following regression equation .

$$E[H_{it} | U_{it}, V_{it}, W_{it}, Z_{i,t}, G_t, \nu_{it}] = \exp(\alpha_0 + \alpha_1 U_{it} + \alpha_2 V_{it} + \alpha_3 W_{it} + \alpha_4 Z_{it} + \alpha_5 G_t)\exp(\nu_{it}) \qquad (1)$$

Where ν_{it} is the stochastic error term. The count of intense disasters—the dependent variable—is characterized by excess zeros. In particular, a high proportion of the quarterly country observations for hydro meteorological disasters have zero counts. Failing to account for the prevalence of zeros in the dependent variable would likely result in inconsistent estimators. For this reason, we use the Zero-inflated (ZI) count model (Johnson et al 1992, Lambert 1992). The ZI model allows elucidating whether the zero-observed dependent variable may either mean a zero probability of having a disaster or a positive probability but no disaster because of random factors (Vuong 1989). (See Appendix, method 1)

[1] Considering only intense disasters (those that cause at least 100 deaths and/or affect at least 1,000 people) implies that vulnerability and exposure variables need to be considered as explanatory variables.

Thus we estimate the determinants of hydro meteorological disasters using a Zero-Inflated Negative Binomial (NBZI) regression model. Vuong tests revealed significant positive test statistics favoring the zero-inflated models over the NB count regression models.

Co-integration

Two problems that affect common regression analysis particularly concern us: (a) The series may change together over time on a similar upward trend basis which, as is well-known, implies that any regression analysis between them would yield a positive and significant coefficient without necessarily meaning that they are in fact related (Granger and Newbold, 1974). This is the case when the series are not co-variance stationary. That is, when the series do not have finite means and auto covariance change over time; (b) the relationship between the series may be affected by other variables (often impossible to observe) that are not controlled for in the regression analysis. This is the so-called omitted variable biases.

Co-integration allows us to deal with these two problems by permitting us to test whether particular transformations of the series do yield co-variance stationary processes and hence can be used to obtain meaningful econometric estimates of the key parameters, and whether or not the existence of omitted variables is still consistent with obtaining non-spurious correlations over the long run.

To implement the analysis of co integration we proceed as follows. The estimated coefficients of the quarterly time dummies obtained from the two-way fixed effects model (first stage of the Approach II) are subjected to a co-integration analysis (Engle & Granger 1991) with the quarterly data on atmospheric CO_2. We can think of co-integration as describing a particular kind of *long-run equilibrium* relationship. In particular, we seek to understand whether the estimated coefficients of the time dummies and the global climate variable are positively correlated in a non-spurious way. We use co-integration analysis not as a tool to determine causality but merely as an instrument to confirm the existence of a *meaningful or non-spurious correlation* between the carbon accumulation in the atmosphere and hydro meteorological disasters. We thus first regress the coefficients of the time dummies (y_t) on the series of atmospheric CO_2 (x_t),

$$y_t = \beta_0 + \beta_1 \cdot x_t + \mu_t \tag{2}$$

Where β_0 is a fixed coefficient, $\hat{\beta}_1$ is the predicted value of the co-integrating coefficient obtained from the ordinary least squares (OLS) estimation and μ_t is the predicted error series. The OLS estimation of equation (2) gives us an unbiased estimation of $\hat{\beta}_1$. However, its standard error estimate is inconsistent and is not normally distributed. Hence, the usual inferential procedures do not apply.

With respect to the significance of β_1—the co-integrating coefficient—it has been shown that both the dependent and independent variables co-integrate if and only if there is an error correction model (ECM) for either y_t and x_t or both (Engle & Granger 1991; Johansen 1988-1995). ECM involves a particular transformation of equation (2) to allow for a consistent estimation of the co-integrating coefficient (see Appendix, Methods 2, for derivation of the ECM).

The ECM requires the specification of a time process for the stochastic error, μ_t. If μ_t is a stationary of mean zero variable, there exist a stationary autoregressive moving average (ARMA) model for μ_t. We assume an autoregressive model AR(2) for μ_t as follows,

$$\mu_t = \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \varepsilon_t \quad (3)$$

In appendix, Methods 2, we show that (2) and (3) imply an autoregressive distributed lag model, ARDL

$$y_t = \delta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \varphi_0 x_t + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \varepsilon_t \quad (4)$$

It can be transformed into the following ECM model (Appendix, Method 2),

$$\Delta y_t = \delta + \lambda_1 \Delta y_{t-1} + k_0 \Delta x_t + k_1 \Delta x_{t-1} + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \varepsilon_t \quad (5)$$

Where δ k_0, k_1, λ_1, γ_1 and γ_2 are parameters. From (5) the estimator of the co-integrating coefficient is given by the long-run solution:

$$\hat{\beta}_1 = -\frac{\widehat{\gamma}_2}{\widehat{\gamma}_1} \quad (6)$$

Thus, using the estimated coefficients $\hat{\gamma}_1$, and $\hat{\gamma}_2$ and their respective standard errors we can obtain a consistent measure for $\hat{\beta}_1^*$ and its correct standard error to analyze its significance.[2]

With respect to the problem of omitted variables, it has been shown that if the tests of co-integration are passed it means that regardless of the possible existence of omitted variables the estimated co-integrating coefficient from (6) is unbiased and consistent (Pashourtidou 2003). While the adjustment coefficients (short run estimates) may be biased our focus is on the long run correlation between the variables of interest. In fact,

[2] Another test used to verify co integration is maximum likelihood method developed by Johansen (Johansen 1988-1995) of vector error correction modeling (VECM) (See Appendix, Method 3, for details).

what we seek to discover is precisely how a continuous accumulation of CO_2 in the atmosphere (a long run effect) may be associated with the increase of natural disasters over the long run.

3. Estimating impacts of climate indicators on country disasters

The first column in Table 1 shows the estimates using one way fixed effects (Approach I), using CO_2 accumulation as an indicator of global climate effect. The second column shows the estimates of the two-way fixed effects (first stage of Approach II) using quarterly time dummies in addition to country effects. Voung test rejects the hypothesis that NBZI estimators are equal to the NB estimators at 1% level of significance. Therefore, there is evidence that the ZINB model is needed to avoid inconsistent estimators.

Precipitation deviation, the key feature of floods and storms, has a positive and significant association with the incidence of local hydro meteorological disasters. Local temperature deviation is negative and significant. Atmospheric CO_2 concentration lagged by 1 year shows a positive and highly significant relation showing an additional impact on hydro meteorological disasters. Thus, the global effects associated with the atmospheric accumulation of carbon dioxide appears to exert an independent effect over and above local climatic events. This makes sense as global climatic factors may increase the vulnerability of countries to local weather events. For example, as atmospheric carbon dioxide accumulates sea levels tend to increase making coastal areas much more affected by storms.

Table 1. Determinants of intense hydro meteorological disasters

	(1) NBZI (One way fixed effects)	(2) NBZI (Two way fixed effects)
Ln Population Density	0.151***	0.112***
	[0.0361]	[0.033]
Ln GDP pc	0.148**	0.183***
	[0.0751]	[0.070]
Squared Ln GDP pc	-0.00678**	-0.0085***
	[0.00314]	[0.0029]
Precipitation Deviation	0.000497	0.0050***
	[0.000587]	[0.00116]
Temperature Deviation	-0.682***	-0.4941***
	[0.0817]	[0.0798]
Population (million)	0.00155***	0.0015***
	[0.0000953]	[0.00008]
Co_2 atmospheric Level (1 Year lag)	0.0175***	
	[0.00109]	
Time dummy variables		Table A3 in Appendix
Observations	25,876	25,876
Akaike Information Criterion (AIC)	17833.27	17603.71
Bayesian Information Criterion (BIC)	18135.23	19325.7
LR Test	56.85***	77.26***
Vuong Test	15.69***	14.98***

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are in brackets.
Column 2 includes time dummy coefficients which are shown Table A3 in appendix
Source: Authors' calculations.

It is possible that global climate variables used in Approach I (first two columns in Table 1) are correlated with other global variables unrelated to climate change impacting the likelihood of disasters in the same direction. This would then imply that the coefficients of global temperature and the CO_2 variables may be inconsistent. That is why we use Approach II which in its second stage uses co-integration to test for specific effects of the global climate variables.

The second column of Table 1 reports the first stage of the Approach II. The common-to-all countries time effect represented by the coefficients of the quarterly time dummy variables captures any global effects. The time dummy coefficients (not reported in Table 1 but available in Table A3 of the Appendix) are highly significant and become larger over the time period. In the second stage we implement co-integration analysis between the estimated time dummy coefficients and the average global temperature and atmospheric CO_2.

The first column of Table 2 provides the OLS estimates of regressing the coefficients of the time dummy variables with CO_2 atmospheric concentration. The coefficients are not distributed asymptotically normal due to the lack of stationarity of the series, so that the usual t-statics do not apply. But we can use the estimated coefficients to test if the predicted errors are stationary. Even if all individual series are non-stationary, the linear combination of non-stationary series could be stationary.

Table 2 shows the results of the tests for stationarity or co-integration using the series of predicted errors. Since the time series is quite short, we use an unrestricted autoregressive distributed lag (ARDL) model which has shown to be appropriate for time series between 100 and 500 observations (Box and Tiao, 1975 and Simonton, 1977)). Both Dickey-Fuller (DF) and Dickey-Fuller generalized least squares (DF-GLS) test whether a unit root is present in the series of the predicted errors. Tabulated critical values at 1% and 5% are more exigent than usual Test T (MacKinnon 1994-2010, Elliott et al 1996).The DF and DF-GLS statistics allow rejection of the null hypothesis that the series have a unit root. The time dummy coefficients and the global variables are integrated of order one—that is, the predicted error is stationary—suggesting that the series co-integrate.

In addition to the tests reported in the first column of Table 2, we also implemented a more powerful co-integration test developed by Johansen (Johansen 1995) presented in Appendix, Table A4. This test estimates a vector error correction models (VECM) between hydro meteorological disasters and the CO2 concentrations in the atmosphere. Johansen test also shows clear evidence of co-integration between the series.

All the above-mentioned tests conclude that the two series do co-integrate. However, these tests are not in general considered to have sufficient power when the sample size for each series is relatively small. When samples are small the literature recommends the use of autoregressive distributed lags (ARDL) to obtain a more reliable test for co-integration (Pesaran et al. 2001). Thus we corroborate the existence of stationarity and co-integration using an ECM as shown in equation (5) implemented using an ARDL. The second column in Table 2 shows the estimates of the ECM using an ARDL for the series. The coefficient of $CO_{2(t-1)}$ $(\hat{\gamma}_2)$ is positive and significant, and the error correction coefficient, associated with the time dummy coefficients $_{(t-1)}$ $(\hat{\gamma}_1)$, is negative and significant. Statistical significance of these two coefficients implies that there may exist a non-spurious correlation between the series. Moreover, the adjustment process is stable due to the fact that $|\hat{\gamma}_1| < 1$.

The estimates of the γ_1 and γ_2 coefficients allow us to obtain a measure of the key coefficient $\hat{\beta}_1^*$ by using equation (6). Most importantly, this estimate of $\hat{\beta}_1^*$ is unbiased and distributes according to a normal distribution; this allows us to obtain consistent statistical inference. From the standard errors and co variances of γ_1 and γ_2 coefficients we derive the standard error of $\hat{\beta}_1^*$ using the Delta method (Oehlert 1992). Table A5 in appendix shows the estimated value of $\hat{\beta}_1^* = 0.0180$ with its standard error thus estimated equal to 0.0042. That is, the co-integrating coefficient is in fact positive and statistically significant at a 1% level of significance.

Table 2. Co-integration estimates of Disasters-CO_2 Series

	Hydro meteorological	
	Level (Equation 2)	**First Diff. (D.1) (ECM) (Equation 5)**
$CO_{2(t)}$	0.0184	
	[0.0021]	
D.1 Time Dummy Coefficients $_{(t-1)}$ $(\hat{\lambda}_1)$		-0.232***
		[0.0789]
D.1 $CO_{2\ (t-1)}$ $(\hat{\kappa}_0)$		-0.0654***
		[0.0109]
D.2 $CO_{2\ (t-1)}$ $(\hat{\kappa}_1)$		0.0464***
		[0.0114]
Time Dummy Coefficients $_{(t-1)}$ $(\hat{\gamma}_1)$		-0.348***
		[0.0852]
$CO_{2\ (t-1)}$ $(\hat{\gamma}_2)$		0.00628***
		[0.00216]
Constant	-5.424***	-1.827**
	[0.746]	[0.703]
Observations	175	173
Akaike Information Criterion (AIC)	242.8	151.3
Bayesian Information Criterion (BIC)	249.1	170.2
Tests for Stationarity		
Dickey-Fuller (DF)	-2.662*	
Dickey-Fuller Generalized Least Squares (DF-GLS)	-2.071**	

Notes: * = significant at 10%, *** = significant at 1%. Standard errors in brackets.
Source: Authors' calculations.

Table A5 in appendix shows the short and long run estimates of $\widehat{\beta}_1$ for hydro meteorological disasters. The long run coefficient is statistically significant at 1% and is quite similar to the short run coefficient. Using the $\widehat{\beta}_1$ reported in Table A5 in appendix we calculate the elasticity of time dummy coefficients with respect to the CO_2 level (Table A6 in appendix).

Next we calculate the simulated variation in disasters due to current observed rates of increase of CO_2 concentration level using the period 2010-2013 as baseline (Table A7). Thus, if the atmospheric CO_2 levels continue increasing at the same rate as in the period 2010-13, the number of intense hydro meteorological disasters per quarter per country would increase by 0.035 events, that is, the number of disasters would double in 7 years.

Causality

Co-integration may show the existence of meaningful correlations but not necessarily of causality. If a meaningful correlation between the series exists then our approach to ascertaining causality relies on the observation that *if two variables exhibit a non-spurious correlation there must be at least one direction of causality between them (Asteriou et al. 2011; Granger 1988)*. The next step, therefore, is to establish whether prior reasoning and scientific knowledge may allow us to discard one of the directions of causality. If so, we can conclude without further statistical test which is the causal relation associated with the existence of a non-spurious correlation between the two series. This is the approach that we use here. This observation leads us to the following conclusion: It is highly implausible that hydro meteorological disasters *cause* the accumulation of carbon in the atmosphere (of course in the case of other disasters such as volcanic eruptions this may not be true).

Hence, it must be the case that the causal direction is from atmospheric carbon accumulation to hydro meteorological disasters.

4. Disasters and economic growth

Finding an effect of disasters on economic growth has been difficult. World Bank (2010) did a literature review of natural disasters and their growth effects but did not find a consistent conclusion. The main reason is the potential effect of omitted variables that may affect both GDP growth and natural disasters. No matter how many control variables are used, one is never sure that there might not be other relevant unobserved omitted variables.

Several studies do find a negative effect on GDP growth (Otero & Marti (2005), Benson (1997), Benson & Clay (1998), Murlidharan & Sha (2001), Hochrainer (2006), Cuaresma et al (2008)). They show that the impact depends on the size of the disasters, the size of the economy and the economic conditions. However, Albala-Bertrand (1993) found no significant long-term effect in developed countries, and in developing countries they report a negative effect that tends to disappear after 2 years while Caselli and Malhotra (2004) argue that disasters do not reduce GDP growth.

Loayza, et al (2009) estimate the medium-term effects on economic growth of different natural hazards using a model with three main sectors (agriculture, industry and services) and the whole economy. Their main conclusion is that economic growth is generally lower after a disaster; however, the effect depends on the type of natural hazard and it is not always statistically significant. Fomby, et al (2009) found that moderate and severe disasters affect growth more in poor countries than in rich countries.

There are differential impacts of disasters on various assets. Disasters affect human capital mainly through their effects on deaths and injuries of people, and non-human capital including losses of infrastructure, animals and productive capital. We hypothesize that these two types of assets affected by disasters entail fundamentally different effects on economic growth. While the losses of human capital hurt economic growth in a fundamental way, the losses of non-human capital can be recovered quite rapidly.

The process of rebuilding physical capital often entails greater demand for domestic industries. If there is excess industrial capacity, this increased demand may allow for a greater use of the production capacity.[3] Thus, paradoxically rebuilding physical capital losses may induce greater industrial production and a faster rate of economic growth. Regressing growth on disasters without separating their effects on these two types of assets would likely give weak and ambiguous correlations. However, if we focus on the human capital consequences, we are likely to obtain stronger linkages. Below we show this by first using the standard approach of estimating the effects of disasters without separating the effects finding no statistically significant effects of disasters on growth, but focusing on the human losses caused by disasters gives negative and statistically significant effects.

[3] In most cases natural disasters affect only part of the country´s territory, rarely the whole of it. This means that in most cases the industries located in unaffected areas may expand production quite rapidly to satisfy the demands for material goods from the affected areas. Moreover, if the marginal costs of production do not increase too rapidly with production levels (as may be expected when there is unused capacity) one may expect that the increased supply of goods will attain with little price increases.

An additional contribution to the literature of our analysis is the use of a new model that controls for both fixed country and unobserved time-varying country-specific effects (TVCE) as developed and first applied by López and Palacios (2014). The idea is that many potentially omitted factors affecting the impact of disasters may be captured by the TVCE. That is, while previous studies do control for country fixed effects and common-to-all countries time effects, they fail to control for time-varying country-specific effects. We hope that the use of TVCE considerable mitigates the potential biases due to omitted variables that may affect each country over time in a changing manner.

We estimate a model where growth of GDP per capita is the dependent variable and our main variable is an approximation of disaster's impact. We control for lags of GDP Growth as well as for fixed effect per country and time-varying country effects. The TVCE method is a parsimonious approach directed to control for country-specific variables that are either unobserved or difficult to measure which may change over time and are specific to each country. The TVCE approach is a generalization of both the standard fixed effects model (FCE) and the country-specific time trends approach.

Taking into consideration the length of our data base we control for 5 year country-specific variable effects. In other words, we have a different dummy variable for each country for every 5 year period. Equation (7) shows the estimating equation. In this case $\alpha_{i,j}$ represents how previous per capita GDP growth affects the current level while β_{i,t^*} is the parameter which estimates the time variable country-specific effect (TVCE). $\theta_{i,t-j}$ is our parameter of interest relating disasters to per capita GDP growth. Moreover, ε_i is the fixed country effect and $\mu_{i,t}$ is the error of the estimation.

$$Gdp\ Growth_{i,t} = \sum_{j=1}^{n} \alpha_{i,j} \cdot Gdp\ Growth_{i,t-j} + \sum_{j=0}^{m} \theta_{i,t-j} \cdot Disaster_{i,t-j} + \sum_{t^*=\{t:t+5\}}^{T-5} \beta_{i,t^*} \cdot v_{i,t^*} + \varepsilon_i + \mu_{i,t} \quad (7)$$

We use two different definitions of the variable "Disaster". Firstly, we use directly the proportion of the total country population that died due to hydro meteorological disasters. This variable is named "proportion of deaths". Secondly, we generate a dummy variable for the disasters which killed more than 100 people o affected at least 1,000 people. We called this variable hydro meteorological disaster.

5. Measuring the economic effects of disasters

We estimate the model using annual data (as no quarterly data for GDP is available). This sample contains the same countries that we used to determine the variables which affect intense hydro meteorological disasters (Table A1 in appendix). Table A9 in Appendix shows the main statistics for the 184 countries included in the analysis.

Table A10 in the appendix shows the TVCE estimates of the effects of the number of intense hydro-meteorological on per capita GDP growth without distinguishing human capital versus physical capital losses. As can be seen in Table A10 there are no significant parameters. One interpretation is that the likely positive effects of disasters due to the rebuilding of physical capital losses on economic activity when excess productive capacity exists may be offset by the negative effects of the loss of human capital.

That is why here we focus exclusively on the human capital losses caused by disasters (Table 4). In particular we use the number of deaths induced by disasters as a proportion of the total population in the country, instead of merely number of disasters as the key explanatory variable. In sharp contrast with the results reported in Table A10, using the proportion of deaths over the total population caused by disasters, the effect of the first, second and third lags of this variable on per capita GDP growth are all negative and almost all of them are statistically significant. The net effect of the three lags is also negative and significant.

However, the relationship between economic growth and deaths may be affected by reverse causality as it is plausible to assume that economic growth reduces the rate of population death. To mitigate this problem we also control for the proportion of deaths (over the total population) not due to disasters finding a negative relationship as expected. The key issue is that even controlling for deaths not due to disasters the coefficient of the variable proportion of deaths caused by disasters is still negative and highly significant. Moreover, there is an extremely low correlation of deaths caused by disasters and deaths due to other factors (correlation coefficient, 0.002), which reinforces our hypotheses that causality goes from proportion of disaster-induced deaths to economic growth and not the other way around. In addition, the regression reported in table 4 also controls for country per capita income to reflect the fact that per capita income and economic growth may be (negatively) correlated.

Table 4: Per capita GDP growth and proportion deaths due to disasters

	(1) TVCE	(2) TVCE	(3) TVCE
L. Per capita GDP growth	0.0639*** [0.0135]	0.0634*** [0.0135]	0.0632*** [0.0135]
L2. Per capita GDP growth	-0.0000917 [0.0129]	0.000219 [0.0129]	0.000202 [0.0129]
L. Ln GDP pc	-28.03*** [1.023]	-28.07*** [1.023]	-28.06*** [1.023]
L. Proportion of deaths due to disaster	-0.195 [0.135]	-0.226* [0.136]	-0.248* [0.136]
L2. Proportion of deaths due to disaster		-0.238* [0.131]	-0.273** [0.132]
L3. Proportion of deaths due to disaster			-0.189** [0.0932]
L. Proportion of deaths unrelated to disaster	-0.0651*** [0.0170]	-0.0686*** [0.0171]	-0.0681*** [0.0171]
Net effect of disaster-induced deaths	-0.195 [0.135]	-0.464*** [0.200]	-0.709*** [0.233]
Observations	6669	6669	6668
AIC	41164.53	41162.36	41154.34
BIC	49378.44	49383.07	49381.67

Notes: * = significant at 10%, ** = significant at 5%, *** = significant at 1%. Standard errors in brackets. L: Lag operators.

In TVCE controls for 5 years variable country-specific effects.

Source: Authors' calculations.

An important implication of the results obtained is that the effect of deaths due to disasters on economic growth is much larger than the effects of normal mortality. This may reflect the fact that disaster-induced deaths are more traumatic especially because they often involve a greater proportion of younger people at their peak productive age. Also, the disaster-induced deaths tend to be more economically disruptive as they are often more unexpected than normal deaths.

Using the coefficient equal to -0.709 obtained when we use three lagged effects as reported in the last column of Table 4, we obtain that a 1% increase of disaster-induced deaths is likely to cause the growth rate of the representative country to decline by 0.0064% over the first three years after the disaster. Also, it appears that the negative effect of disasters' death on economic growth tends to persist over time for at least three years.

The final end of this analysis if to measure the impact of the accumulation of carbon dioxide in the atmosphere on economic growth. We proceed first using the elasticity of disasters with respect to CO_2 accumulation as reported earlier. Next, we estimate the impact of disasters on deaths as a proportion of the total country population and using this measure and the elasticity of disasters we can estimate the effect of CO_2 accumulation on the proportion of disaster-induced deaths. Finally, we combine this last effect with the elasticity of economic growth with respect to disaster-induced deaths to measure the net elasticity of growth with respect to the atmospheric CO_2 accumulation. That is, we use the following expression to estimate the net effect of CO_2 accumulation on economic growth,

$$\zeta_{Gdp\,Growth,Co_2} = \zeta_{Gdp\,Growth,\mathrm{Proportion\ of\ deaths}} \cdot \zeta_{\mathrm{Proportion\ of\ deaths},Disasters} \cdot \zeta_{Disasters,Co_2} \tag{8}$$

Where $\zeta_{Gdp\,Growth,Co_2}$, $\zeta_{Gdp\,Growth,\mathrm{Proportion\ of\ deaths}}$, $\zeta_{\mathrm{Proportion\ of\ deaths},Disasters}$ and $\zeta_{Disasters,Co_2}$ represent the elasticities of growth with respect to CO_2 accumulation, growth with respect to proportion of deaths, proportion of deaths with respect to number of disasters and number of disasters with respect to CO_2 accumulation, respectively.

We report details of this exercise in the appendix (Table A12). As shown there we find that a 1% increase in the level of CO_2 accumulated in the atmosphere causes a reduction of the rate of GDP growth for the average or representative country by 0.13%. This figure may seem small given that atmospheric CO_2 is increasing by only 0.5% per annum. However, we note that this effect applies to the *average of all countries* whether they are affected by a disaster or not. Moreover, if the rate of carbon accumulation in the atmosphere continues at the current rate one may expect that the average rate of economic growth for all countries may be reduced by 1.5% in 20 years due to the increased climate-related disasters.

6. Conclusion

This paper analyzed the association between climate change variables and the incidence of intense hydro meteorological disasters within a framework that included global and local climate variables as well as socio-economic factors that aggravate disasters. A key feature of the work is the focus on ascertaining the meaningfulness of the correlations between climate change indicators and disasters. The empirical analysis has shown that there are clear non-spurious connections between climate change indicators and the frequency of intense hydro meteorological disasters. Since a causal relationship going from disasters to carbon accumulation in the atmosphere is highly implausible, the finding of a meaningful positive correlation between atmospheric carbon accumulation and natural disasters must suggest a causal relationship going from CO2 accumulation in the atmosphere to the frequency of disasters.

Moreover, we have found that the quantitative effect of climate change indicators on the number of intense disasters is large. About one additional major annual disaster in the world can be attributed to the observed annual increases of carbon dioxide accumulations.

This implies that in a business-as-usual scenario where the global climatic indicators continue to deteriorate at recent rates, there would be a 4% annual increase in the number of intense hydro meteorological disasters worldwide attributed to climate change.

Finally, there is evidence of a negative impact of intense hydro meteorological disasters on per capita GDP growth. We found a negative and significant impact of the disaster-induced human capital losses on per capita GDP growth. We showed that a 1% increase of atmospheric carbon accumulation is associated with a 0.13% fall in the rate of growth of the representative country. Moreover, in a business-as-usual scenario where the global climatic indicators continue to deteriorate at recent rates, in 20 years the average rate of per capita economic growth would be reduced by 1.5% just as a consequence of the increased climate-related disasters. This estimate exclude other factors associated with atmospheric carbon accumulation which may impinge upon economic growth.

REFERENCES

Albala-Bertrand, J.M. 1993. The Political Economy of Large Natural Disasters. Oxford, U.K.: Clarendon Press.

Benson, C. 1997a. «The Economic Impact of Natural Disasters in Fiji.» Working Paper 97, Overseas Development Institute, London.

Benson, C. y E. Clay. 1998. «The Impact of Drought on Sub-Saharan African Economies.» Technical Paper 401, World Bank, International Bank for Research and Development, Washington, DC.

Box, George EP, & George C. Tiao. 1975 . "Intervention analysis with applications to economic and environmental problems." Journal of the American Statistical association 70.349: 70-79.

Caselli, F. y P. Malhotra. 2004. «Natural Disasters and Growth: From Thought Experiment to Natural Experiment.» International Monetary Fund, Washington, DC.

Cornwall, W, 2016. Efforts to link climate change to severe weather gain ground. Science, 351(6279),124-1250.

Cuaresma, J. 2009. «Natural Disasters and Human Capital Accumula tion.» Policy Research Working Paper 4862, World Bank, Washington, DC. Background paper for the report.

Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R., & Mearns, L. O. 2000. Climate extremes observations, modeling, and impacts. Science, 289(5487), 2068-2074.

Engle, R. F., and C. W. Granger. 1991. *Long-run Economic Relationships: Readings in Cointegration.* Oxford University Press.

Fomby, T., Y. Ikeda y N. Loayza. 2009. «The Growth Aftermath of Natu - ral Disasters.» Policy Research Working Paper 5002, World Bank, Washington, DC. Background paper for the report

Granger, Clive WJ. 1988. Some recent development in a concept of causality. Journal of econometric,, vol. 39, no 1, p. 199-211.

Guha-Sapir, D., R. Below, and Ph. Hoyois. 2015. *EM-DAT: International Disasters Database.* Prod. Belgium Universite Catholique de Louvain - Brussels.

Heckman, J., Ichimura, H., Smith, J. and Todd, P., 1998. Characterizing selection bias using experimental data (No. w6699). National bureau of economic research.

Hochrainer, S. 2009. «Assessing Macro-economic Impacts of Natural Di - sasters: Are There Any?» Policy Research Working Paper 4968, World Bank, Washington, DC. Background paper for the report.

Hoerling, M, J. Eischeid, J. Perlwitz, X. Quan, T. Zhang, and P. Pegion. 2012. On the Increased Frequency of Mediterranean Drought. Journal of Climate. 25: 2146-61.

Johansen, S. 1995. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models.* New York: Oxford University Press.

Johansen, S. 1988. Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control.* 12. No. 2-3: 231-254.

Johnson, N., L. Kotz, and A. Kemp. 1992. *Univariate Discrete Distributions.* New York: Wiley.

Lambert, D. 1992. Zero-Inflated Poisson Regression, With an Application to Defects in Manufacturing. *Technometrics.* 34. No. 1 : 1-14.

Loayza, N., E. Olaberria, J. Rigolini y L. Christiansen. 2009. «Natural Di - sasters and Growth: Going Beyond the Averages.» Policy Research Wor - king Paper 4980, World Bank, Washington, DC. Background paper for the report.

López, R., Thomas, V., Troncoso, P. A. 2016. Climate Change and Natural Disasters. Serie Documentos de Trabajo No. 414, pp. 1 - 44.

López, R., & Palacios, A. 2014. Why has Europe become environmentally cleaner? Decomposing the roles of fiscal, trade and environmental policies.Environmental and Resource Economics, 58(1), 91-108.

MacKinnon, J.G., 1994. Approximate asymptotic distribution functions for unit-root and cointegration tests. Journal of Business & Economic Statistics,12(2), pp.167-176.

MacKinnon, J. G. 2010. *Critical Values for Cointegration Tests.* Queen's Economics Department Working Paper No. 1227, Ontario, Canada: Department of Economics, Queen's University, 2010.

Murlidharan, T.L. y H.C. Shah. 2001. «Catastrophes and Macro-Economic Risk Factors: An Empirical Study.» Paper presented at the International Institute for Applied Systems Analysis conference «Inte grated Disaster Risk Management: Reducing Socio-Economic Vulnera bility,» Laxen - burg, Austria, August 1-4.

Otero, R.C. y R.Z. Marti. 1995. «The Impacts of Natural Disasters on Developing Economies: Implications for the International Development and Disaster Community.» In Disaster Prevention for Sustainable Development: Economic and Policy Issues, ed. M. Munasinghe and C. Clarke. Yokohama, Japan: World Bank.

Pall, P., Aina, T., Stone, D. A., Stott, P. A., Nozawa, T., Hilberts, A. G., & Allen, M. R. 2011. Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. *Nature*, *470*(7334), 382-385.

Schreider, S.Y., D.I. Smith, and A.J. Jakeman. 2000. Climate Change Impacts on Urban Flooding. *Climatic Change.* 47. No. 1-2: 91-115.

Simonton, Dean K. *"Cross-sectional time-series experiments: Some suggested statistical analyses." Psychological Bulletin 84.3 (1977): 489.*

Stott, P.A., Allen, M., Christidis, N., Dole, R.M., Hoerling, M., Huntingford, C., Pall, P., Perlwitz, J. and Stone, D., 2012. Attribution of weather and climate-related events. In Climate Science for Serving Society (pp. 307-337). Springer Netherlands.

Thomas, V., J.R.G. Albert, and C. Hepburn. 2014. Contributors to the Frequency of Intense Climate Disasters in Asia-Pacific countries. *Climatic Change.* 126. No. 3-4: 381-398.

Vuong, Q. H. 1989. Likelihood Ratio Tests for Model Selection and Non-nested hypotheses. *Econometrica* 57. Issue 2: 307-333.

World Bank. 2010. «Natural hazards, unnatural disasters: the economics of effective prevention. » World Bank, Washington, DC.

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Appendix

Table A1. Countries considered in the Analysis, 1970–2013

1	Afghanistan	38	Congo, Rep.	75	Indonesia	112	Montenegro	149	South Sudan
2	Albania	39	Costa Rica	76	Iran, Islamic Rep.	113	Morocco	150	Spain
3	Algeria	40	Cote d'Ivoire	77	Iraq	114	Mozambique	151	Sri Lanka
4	Angola	41	Croatia	78	Ireland	115	Myanmar	152	St. Kitts and Nevis
5	Antigua and Barbuda	42	Cuba	79	Israel	116	Namibia	153	St. Lucia
6	Argentina	43	Cyprus	80	Italy	117	Nepal	154	St. Vincent and the Grenadines
7	Armenia	44	Czech Republic	81	Jamaica	118	Netherlands	155	Sudan
8	Australia	45	Denmark	82	Japan	119	New Caledonia	156	Suriname
9	Austria	46	Djibouti	83	Jordan	120	New Zealand	157	Swaziland
10	Azerbaijan	47	Dominica	84	Kazakhstan	121	Nicaragua	158	Sweden
11	Bahamas, The	48	Dominican Republic	85	Kenya	122	Niger	159	Switzerland
12	Bangladesh	49	Ecuador	86	Kiribati	123	Nigeria	160	Syrian Arab Republic
13	Barbados	50	Egypt, Arab Rep.	87	Korea, Rep.	124	Norway	161	Tajikistan
14	Belarus	51	El Salvador	88	Kuwait	125	Oman	162	Tanzania
15	Belgium	52	Eritrea	89	Kyrgyz Republic	126	Pakistan	163	Thailand
16	Belize	53	Estonia	90	Lao PDR	127	Palau	164	Timor-Leste
17	Benin	54	Ethiopia	91	Latvia	128	Panama	165	Togo
18	Bermuda	55	Fiji	92	Lebanon	129	Papua New Guinea	166	Tonga
19	Bhutan	56	Finland	93	Lesotho	130	Paraguay	167	Trinidad and Tobago
20	Bolivia	57	France	94	Liberia	131	Peru	168	Tunisia
21	Bosnia and Herzegovina	58	Gabon	95	Libya	132	Philippines	169	Turkey
22	Botswana	59	Gambia, The	96	Lithuania	133	Poland	170	Turkmenistan
23	Brazil	60	Georgia	97	Luxembourg	134	Portugal	171	Tuvalu
24	Bulgaria	61	Germany	98	Macao SAR, China	135	Puerto Rico	172	Uganda
25	Burkina Faso	62	Ghana	99	Macedonia, FYR	136	Romania	173	Ukraine
26	Cabo Verde	63	Greece	100	Madagascar	137	Russian Federation	174	United Kingdom
27	Cambodia	64	Grenada	101	Malawi	138	Samoa	175	United States
28	Cameroon	65	Guatemala	102	Malaysia	139	Saudi Arabia	176	Uruguay
29	Canada	66	Guinea	103	Maldives	140	Senegal	177	Uzbekistan
30	Cayman Islands	67	Guinea-Bissau	104	Mali	141	Serbia	178	Vanuatu
31	Central African Republic	68	Guyana	105	Marshall Islands	142	Seychelles	179	Venezuela, RB
32	Chad	69	Haiti	106	Mauritania	143	Sierra Leone	180	Vietnam
33	Chile	70	Honduras	107	Mauritius	144	Slovak Republic	181	Virgin Islands (U.S.)
34	China	71	Hong Kong SAR, China	108	Mexico	145	Slovenia	182	Yemen, Rep.
35	Colombia	72	Hungary	109	Micronesia, Fed. Sts.	146	Solomon Islands	183	Zambia
36	Comoros	73	Iceland	110	Moldova	147	Somalia	184	Zimbabwe
37	Congo, Dem. Rep.	74	India	111	Mongolia	148	South Africa		

Table A2. Descriptive Statistics of the data used, 1970–2013

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variable: *Frequency of intense hydro meteorological disasters*	25876	0.154	0.569	0	15
Ln (population density)	25876	3.808	1.477	0.103	9.980
Ln GDP per capita (constant 2005 US$)	25876	10.650	2.360	3.988	17.439
Square of Ln GDP per capita	25876	118.997	53.083	15.904	304.114
Average precipitation deviation	25876	39.045	37.327	0.073	646.941
Average temperatura deviation	25876	0.743	0.496	0.009	6.539
Population (million)	25876	34.588	124.261	0.010	1357.380
Co2 level	25876	360.4	20.526	324.090	398.897

Source: Authors' calculations.

Method 1. Derivation of the ZI estimator

For each country in i and year t, there are two possible data generation processes for $H_{i,t}$ —the selection of which is a result of a Bernoulli trial. The first process, which generates only zero counts, is chosen with probability ρ_i. The second process $g(H_{it} \mid R_{it})$ with probability $1-\rho_i$ generates positive counts from a NB distribution. Where R_{it} is a vector of explanatory variables (in our case $U_{it}, V_{it}, W_{it}, G_t$) In general, we have:

$$H_{it} \sim \begin{cases} 0 & \textit{with probability } \rho_i \\ g(H_{it} \mid R_{it}) & \textit{with probability } 1-\rho_i \end{cases} \qquad (A1)$$

Then the probability of $\{H_{it} = h_{it} \mid R_{it}\}$ where $h_{i,t}$ is a particular value of the variable $H_{i,t}$ can be expressed as (Johnson et al. 1992; Lambert 1992):

$$P(H_{it} = h_{it} \mid R_{it}, I_{it}) = \begin{cases} \rho(\lambda' I_{it}) + \{1-\rho(\lambda' I_{it})\} g(0 \mid R_{it}) & \textit{if } y_{it} = 0 \\ \{1-\rho(\lambda' I_{it})\} g(h_{it} \mid R_{it}) & \textit{if } y_{it} > 0 \end{cases} \qquad (A2)$$

The probability ρ_i depends on the characteristics (a subset of the explanatory variables) of country i and year t. Hence, ρ_{it} is written as a function of $\lambda' I_{it}$ where I_{it} is the vector of zero-inflated covariates and λ is the vector of zero-inflated coefficients to be estimated.

A Probit function (using the same explanatory variables as described in equation (1) in the paper) is specified as the zero-inflated link function—relating the product $\lambda' I_{it}$ (which is scalar) to the probability ρ_{it}. We thus estimate hydro meteorological disasters using a negative binomial zero-inflated (NBZI) regression model. Vuong tests revealed significant positive test statistics which favor the zero-inflated models over the standard NB count regression models. This means that the zero-inflated method is necessary given the preponderance of zeroes of the dependent variable.

This model allows elucidating whether the zero-observed dependent variable may either correspond to countries which in a particular year had a zero probability of having a disaster or countries that had a positive probability of a disaster but that, due to random conditions in that year, experienced no disaster and consequently also had a zero dependent variable (Vuong 1989).

Method 2. Co-integration

First we have this model with the time dummies (y_t) and the series of atmospheric CO_2 (x_t). This can be expressed as:

$$y_t = \beta_0 + \beta_1 \cdot x_t + \mu_t \qquad (2)$$

Where β_0 and β_1 are the parameters and μ_t is the stochastic error term.

Assume for simplicity that it is an autoregressive model AR(1) (We also tried with AR(2) but, the additional parameters were not significant):

$$\mu_t = \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \varepsilon_t \qquad (3)$$

In particular, we can estimate equation (3) using OLS, the unrestricted autoregressive distributed lag (ARDL) model, where the lag lengths are set to eliminate residual autocorrelation, an ARDL(2,2) model. From (2) and (3) we have

$$y_t - \beta_0 - \beta_1 \cdot x_t = \mu_t$$

And

$$y_{t-1} - \beta_0 - \beta_1 \cdot x_{t-1} = \mu_{t-1}$$
$$y_{t-2} - \beta_0 - \beta_1 \cdot x_{t-2} = \mu_{t-2}$$

Using all expressions and equation (3)

$$y_t - \beta_0 - \beta_1 \cdot x_t = \theta_1 \left(y_{t-1} - \beta_0 - \beta_1 \cdot x_{t-1}\right) + \theta_2 \left(y_{t-2} - \beta_0 - \beta_1 \cdot x_{t-2}\right) + \varepsilon_t \qquad (A3)$$

Rearranging terms

$$y_t = \delta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \varphi_0 x_t + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \varepsilon_t \qquad (4)$$

Where $\delta = \left(\beta_0 - \theta_1\beta_1 - \theta_2\beta_1\right)$, $\varphi_0 = \beta_1$, $\varphi_1 = -\theta_1\beta_1$ and $\varphi_2 = -\theta_2\beta_1$. Equation (4) is an unrestricted autoregressive distributed lag model, ARDL (2,2).

To obtain the ECM form we used the next two equalities[4]:

$$y_t - \theta_1 y_{t-1} - \theta_2 y_{t-2} = \Delta y_t + \theta_2 y_{t-1} - (\theta_1 + \theta_2 - 1) y_{t-1}$$
$$\varphi_0 x_t + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} = \varphi_0 \Delta x_t - \varphi_2 \Delta x_{t-1} + (\varphi_0 + \varphi_1 + \varphi_2) x_{t-1}$$

Where $\Delta y_t \equiv y_t - y_{t-1}$, $\Delta x_t \equiv x_t - x_{t-1}$. Using both equalities in equation (4) and rearranging terms:

$$\Delta y_t = \delta - \theta_2 \Delta y_{t-1} + \varphi_0 \Delta x_t - \varphi_1 \Delta x_{t-1} + \left(\theta_1 + \theta_2 - 1\right) y_{t-1} + \left(\varphi_0 + \varphi_1 + \varphi_2\right) x_{t-1} + \varepsilon_t \qquad (A4)$$
$$\Delta y_t = \delta + \lambda_1 \Delta y_{t-1} + k_0 \Delta x_t + k_1 \Delta x_{t-1} + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \varepsilon_t \qquad (5)$$

[4] Developing right sides of both equalities directly reached the left sides.

Where $\lambda_1 = -\theta_2 \; k_0 = \varphi_0 \, , k_1 = -\varphi_1 \; \gamma_1 = \theta_1 + \theta_2 - 1, \gamma_2 = (\varphi_0 + \varphi_1 + \varphi_2)$. We estimate equation (5) using the OLS method. From (5) the estimator of the co-integrated coefficient is given by the long-run solution:

$$\hat{\beta}_1^{\,*} = -\frac{\hat{\gamma}_2}{\hat{\gamma}_1} \tag{6}$$

Method 3. Vector Error Correction Model (VECM) and Johansen Test

In a bivariate model with y_t and x_t variables, there exist a β_0, β_1 such that $y_t - \beta_0 - x_t\beta_1 = \mu_t$ is $I(0)$ even though x_t and y_t may be non-stationary series. This mean the two variables are co-integrated or have a stationary long run relationship even though individually they are non-stationary series.

A VAR model with l lags can be represented as shown in (A5)

$$z_t = \rho_1 z_{t-1} + \rho_2 z_{t-2} + ... + \rho_p z_{t-l} + \varphi\tau_t + \varepsilon_t \tag{A5}$$

Where $z_t = \begin{pmatrix} y_t \\ x_t \end{pmatrix}$ is an $2x1$ vector of $I(1)$ variables, τ_t is a vector of deterministic variable and ε_t is a $2x1$ vector of identically and normally distributed errors with mean zero and non-diagonal covariance matrix $\sum$. Given that the variables are co-integrated, equation (A5) can be represented by an equilibrium correction model shown in (A6) below.

$$\Delta z_t = \eta\omega' z_{t-l} + \sum_{i=1}^{l-1} \Gamma_i \Delta z_{t-1} + \delta \cdot t + \nu + \varepsilon_t \tag{A6}$$

Vectors η and ω are the key coefficients. ω is an $2xr$ matrix of co-integrating vectors that explains the long-run relationship of the variables. η is also an $2xr$ matrix that explains long –run disequilibrium of the variables. ν and t are the deterministic trend component. It is important to note that for co-integration to exist, matrices η and ω should have reduced rank r, where $r < 2$. The identification of the co-integrating vector uses maximum likelihood method developed by Johansen (Johansen 1988-1995).

Table A3. Estimated Coefficients of the Time Dummy Variables (Approach 2, Stage I)

Time	Coefficient	Time	Coefficient	Time	Coefficient	Time	Coefficient	Time	Coefficient
1970q1		**1979q1**	0.558	**1988q1**	0.509	**1997q1**	0.782	**2006q1**	1.842
1970q2	0.174	**1979q2**	1.000	**1988q2**	1.112	**1997q2**	1.139	**2006q2**	2.093
1970q3	1.168	**1979q3**	0.849	**1988q3**	1.815	**1997q3**	1.473	**2006q3**	2.280
1970q4	1.179	**1979q4**	1.021	**1988q4**	1.116	**1997q4**	1.062	**2006q4**	1.671
1971q1	0.233	**1980q1**	0.770	**1989q1**	-0.432	**1998q1**	1.523	**2007q1**	1.710
1971q2	0.588	**1980q2**	0.543	**1989q2**	1.218	**1998q2**	1.343	**2007q2**	1.595
1971q3	0.443	**1980q3**	1.360	**1989q3**	1.314	**1998q3**	1.927	**2007q3**	2.474
1971q4	-0.133	**1980q4**	0.393	**1989q4**	0.535	**1998q4**	1.551	**2007q4**	2.080
1972q1	-0.453	**1981q1**	0.728	**1990q1**	0.488	**1999q1**	1.334	**2008q1**	1.747
1972q2	0.788	**1981q2**	0.620	**1990q2**	1.306	**1999q2**	1.424	**2008q2**	1.314
1972q3	0.200	**1981q3**	1.202	**1990q3**	1.236	**1999q3**	2.169	**2008q3**	2.312
1972q4	-0.143	**1981q4**	1.418	**1990q4**	0.822	**1999q4**	1.819	**2008q4**	2.056
1973q1	0.411	**1982q1**	0.949	**1991q1**	0.758	**2000q1**	1.434	**2009q1**	1.716
1973q2	0.145	**1982q2**	1.017	**1991q2**	0.578	**2000q2**	1.776	**2009q2**	1.326
1973q3	0.010	**1982q3**	1.186	**1991q3**	1.633	**2000q3**	2.010	**2009q3**	2.121
1973q4	1.079	**1982q4**	1.018	**1991q4**	0.528	**2000q4**	1.654	**2009q4**	1.906
1974q1	0.932	**1983q1**	0.597	**1992q1**	1.080	**2001q1**	1.309	**2010q1**	1.770
1974q2	0.290	**1983q2**	0.890	**1992q2**	1.102	**2001q2**	1.917	**2010q2**	1.960
1974q3	0.997	**1983q3**	1.362	**1992q3**	1.410	**2001q3**	2.263	**2010q3**	2.118
1974q4	0.603	**1983q4**	1.145	**1992q4**	0.920	**2001q4**	1.627	**2010q4**	1.754
1975q1	0.204	**1984q1**	0.708	**1993q1**	1.756	**2002q1**	1.537	**2011q1**	0.757
1975q2	0.234	**1984q2**	1.027	**1993q2**	1.614	**2002q2**	1.731	**2011q2**	0.886
1975q3	-0.027	**1984q3**	0.972	**1993q3**	1.707	**2002q3**	2.178	**2011q3**	1.093
1975q4	-0.653	**1984q4**	1.149	**1993q4**	1.591	**2002q4**	1.604	**2011q4**	1.032
1976q1	-0.528	**1985q1**	1.236	**1994q1**	0.896	**2003q1**	1.690	**2012q1**	1.041
1976q2	0.262	**1985q2**	1.250	**1994q2**	1.374	**2003q2**	1.453	**2012q2**	1.021
1976q3	0.330	**1985q3**	1.041	**1994q3**	1.582	**2003q3**	1.829	**2012q3**	1.062
1976q4	0.802	**1985q4**	1.356	**1994q4**	1.361	**2003q4**	1.470	**2012q4**	0.897
1977q1	0.671	**1986q1**	0.740	**1995q1**	1.156	**2004q1**	1.609	**2013q1**	1.361
1977q2	0.740	**1986q2**	1.042	**1995q2**	1.664	**2004q2**	1.808	**2013q2**	0.788
1977q3	1.528	**1986q3**	1.339	**1995q3**	1.984	**2004q3**	1.983	**2013q3**	1.172
1977q4	0.576	**1986q4**	0.805	**1995q4**	1.763	**2004q4**	1.518	**2013q4**	0.755
1978q1	0.964	**1987q1**	0.952	**1996q1**	1.128	**2005q1**	1.847		
1978q2	0.945	**1987q2**	0.008	**1996q2**	1.069	**2005q2**	1.843		
1978q3	1.383	**1987q3**	1.328	**1996q3**	1.838	**2005q3**	2.380		
1978q4	1.104	**1987q4**	1.140	**1996q4**	1.413	**2005q4**	1.860		

Notes: * = significant at 10%, ** = significant at 5%, *** = significant at 1%. Standard errors in brackets.
Source: Authors' calculations.

Table A4. Johansen Test for Co-integration

Rank r	Johansen Test	Critical Value 1%
0	27,47***	16,31
1	5,7	6,51
2		

Notes: * = significant at 10%, ** = significant at 5%, *** = significant at 1%.
Source: Authors' calculations

Table A5. Co-integration: Disasters- Co_2 level

	Estimated coefficients of the time dummy variables	
	Short Run	**Long Run**
Co_2 Level	0.0184	0.0180***
	[0.0021]	[0.0042]

Notes: * = significant at 10%, ** = significant at 5%, *** = significant at 1%.
Standard errors in brackets.
Source: Authors' calculations.

Table A6. Time dummy coefficients and CO_2 level

	Co_2 Level
Marginal effect $(\hat{\beta})$	0.0180
Average sample value of Co_2 level (1970-2013)	360.4
Average value of time dummy coefficients (1970-2013)	1.16
Elasticity of time dummy coefficients with respect to Co_2 Level	5.6

Source: Authors' calculations.

Table A7. Co_2 concentration and hydro meteorological disasters: Simulated variation (2010-2013)

	Co_2 Level
Elasticity of disasters with respect to global variables	33.45
For Simulation:	
Co_2 Stock (in ppm)	395
Average disaster occurrence per annum	0.212
Average value of time dummy coefficients	1.216
Current annual increase: Co_2 Stock (in ppm)	2.0
Simulated variation in quarterly disasters due to current rate of increases in global variables	0.035

Source: Authors' calculations.

Table A8: Descriptive Statistics: 184 Countries with an intense Hydro-Meteorological Disaster

	Mean	Std Dev	Min	Max	Observations
Hydro Disaster Dummy	0.629	1.626	0	28	6754
Proportion of Deaths (One per each 10.000 People)	0.0327	0.521	0	26.52	6754
GDP Percapita Growth (%)	3.587	6.116	-64.04	106.2	6754

Source: Authors' calculations.

Table A9: Per capita GDP growth and number of hydro meteorological disasters

	(1) TVCE	(2) TVCE	(3) TVCE
L. Per capita GDP growth	0.0638***	0.0640***	0.0640***
	[0.0135]	[0.0135]	[0.0135]
L2. Per capita GDP growth	-0.000217	-0.000203	-0.000117
	[0.0129]	[0.0129]	[0.0129]
L.Ln GDP pc	-28.06***	-28.08***	-28.11***
	[1.023]	[1.023]	[1.024]
L. N° Hydro Disasters	-0.0847	-0.0830	-0.0755
	[0.0814]	[0.0814]	[0.0819]
L2. N° Hydro Disasters		0.0904	0.0918
		[0.0816]	[0.0816]
L3. N° Hydro Disasters			0.0691
			[0.0848]
L. Proportion of deaths unrelated to disaster	-0.0653***	-0.0647***	-0.0645***
	[0.0170]	[0.0170]	[0.0170]
Net effect	-0.0847	0.0073	0.085
	[0.0814]	[0.1163]	[0.1506]
Observations	6669	6669	6668
AIC	41164.53	41162.36	41154.34
BIC	49378.44	49383.07	49381.67

Notes: * = significant at 10%, ** = significant at 5%, *** = significant at 1%. Standard errors in brackets. L: lag operator
In TVCE estimation controls for 5 years variable effects.
Source: Authors' calculations.

Table A10: Estimating the proportion deaths due to disasters

	(1) TVCE	(2) TVCE	(3) TVCE
Ln GDP pc	-0.169	-0.172	-0.190
	[0.300]	[0.300]	[0.299]
Squared Ln GDP pc	0.00624	0.00643	0.00705
	[0.0144]	[0.0144]	[0.0144]
L. Proportion of deaths unrelated to disaster	-0.000343	-0.000376	-0.000363
	[0.00138]	[0.00138]	[0.00139]
N° Hydro Disasters	0.0311***	0.0310***	0.0296***
	[0.00823]	[0.00823]	[0.00821]
L.N° Hydro Disasters		-0.00716	-0.00701
		[0.00822]	[0.00817]
L2.N° Hydro Disasters			-0.000777
			[0.00848]
Net effect	0.0311***	0.0237**	0.0217
	[0.00823]	[0.0118]	[0.0151]
Observations	7094	7094	6981
AIC	11346.77	11347.82	11022.34
BIC	19930.52	19938.44	19599.73

Notes: * = significant at 10%, ** = significant at 5%, *** = significant at 1%. Standard errors in brackets.
In TVCE estimation controls for 5 years variable effects.
Source: Authors' calculations.

Table A11: Elasticity of per capita GDP growth with respect Co_2

	Representative Country	Countries with at least one disaster over the last decade
$\zeta_{Disasters, Co_2}$	33.45	33.45
$\zeta_{\Pr oportion\ of\ deaths, Disasters}$	0.6	0.6
$\zeta_{Gdp\,Growth, \Pr oportion\ of\ deaths}$	-0.0066	-0.0073
$\zeta_{Gdp\ Growth, Co_2}$	-0.13	-0.15