Carbon dioxide atmospheric concentration and hydrometeorological disasters

Andres Fortunato (✉ fortunato@hotmail.cl)

Universidad de Chile <https://orcid.org/0000-0003-1192-9029>

Helmut Herwartz

University of Göttingen Faculty of Business and Economics: Georg-August-Universität Göttingen
Wirtschaftswissenschaftliche Fakultät

Ramón E. López

Universidad de Chile Facultad de Economía y Negocios

Eugenio Figueroa

Universidad de Chile Facultad de Economía y Negocios

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Abstract

We study the long-run dynamic and predictive connection between atmospheric carbon dioxide (CO_2) concentration and the probability of hydrometeorological disasters. For a panel of 193 countries over the period 1970-2016 we estimate the probabilities of hydrometeorological disasters at country levels by means of Bayesian sampling techniques. We then separate the effects of climatological and socio-demographic factors (used as proxies for exposure and vulnerability) and other country-specific factors, from a global probability of disasters (GPOD). Finally, we subject these global probability time paths to a cointegration analysis with CO_2 concentration and run projections to year 2040 of the GPOD conditional on nine Shared Socioeconomic Pathways scenarios. We detect a stable long-term relation between CO_2 accumulation and the GPOD that allows to determine projections of the latter process conditional on the former. This way, we demonstrate that generally and readily available statistical data on CO_2 global atmospheric concentrations can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of occurrence of (global) hydrometeorological disasters.

KEYWORDS: Hydrometeorological Hazards, Carbon Dioxide, Disaster Forecast, Natural Disasters.

1. Introduction

The United Nations Intergovernmental Panel on Climate Change (IPCC) has concluded that warming of the planet climate system is unequivocal. The atmosphere and the oceans have warmed, the amounts of snow and ice have diminished and the sea level has risen (IPCC 2014, 2018). Human activities have caused approximately 1.0°C of global warming above pre-industrial levels, and between years 2030 and 2052 it is likely to reach 1.5°C if it continues to increase at the current rate. Moreover, projections from climate models show robust differences in regional climate characteristics between present-day temperatures, 1.5°C and 2°C global warming scenarios. These differences include increases in mean temperature in most land and ocean regions, hot extremes in most inhabited regions, heavy precipitation in several regions, and the probability of drought and precipitation deficits in some regions (IPCC 2018). In its most recent report the IPCC concludes that ocean and cryosphere changes are pervasive and observed from high mountains, to the polar regions, to coasts, and into the deep ocean. Most glaciers are shrinking, the Greenland and Antarctic ice sheets are losing mass, sea ice extent in the Arctic is decreasing, Northern Hemisphere snow cover is decreasing and permafrost temperatures are increasing (IPCC 2019).

Moreover, anthropogenic greenhouse gas emissions have increased since the pre-industrial era and are currently higher than ever. This has led to atmospheric concentrations of CO_2 , methane and nitrous oxide that are unprecedented in the last 800,000 years. As of April 2018, for the first time in history, the average concentrations of CO_2 in the atmosphere exceeded 410 parts per million (ppm), according to the Keeling Curve measurement series made at the Mauna Loa Observatory in Hawaii (USA National Oceanic Atmospheric Administration (NOAA)). July 2019 was the hottest month ever recorded, with a global average temperature of 0.95°C above the 20th century average (NOAA 2019c), and the highest daily average CO_2 concentration was recorded in 2021, February 5, reaching 419.45 ppm (Smith 2021). The rate of increase of atmospheric CO_2 accumulation thus appears to be accelerating (NOAA 2019a, 2019b).

It has been shown that the effects of anthropogenic climate change have intensified and become easier to distinguish from natural variability, and that temperatures are increasing and will continue to do so (IPCC 2018, SU 2019). Thus, it is very likely that heat waves will occur more often and last longer, and that extreme precipitation events will become more intense and frequent in many regions (IPCC 2014, Baker et al. 2018). This implies that the frequency of natural hazards will also increase, especially those related to flooding, severe weather and tropical cyclones. In the last two decades there were 3.9 billion people affected by climate disasters, quadrupling the figure of the 1980-1999 period (CRED 2020). According to Mora et al. (2018), by year 2100 the world population will be subject to at least one major disaster per year. They also highlight how human health, water, food, economy, infrastructure and security are affected by climate hazards. The overall costs caused by disasters will increase, not only in economic terms but also in human lives.

Natural disaster hazards are usually classified in four classes: Geophysical, climatological¹, meteorological² and hydrometeorological (floods, storm surges, hurricanes, cyclones, convective storms, droughts, dust storms, sandstorms)³. However, no other kind of disaster has caused more death and destruction than the hydrometeorological ones (NG 2011). During the past decade, water-related disasters have struck more frequently and more severely, hampering sustainable development by causing political, social, and economic upheaval in many countries (Seung-Soo 2018, NIDM 2019, FEMA 2019, Khan et al. 2019, AON 2019). In fact, hydrometeorological disasters account for 90% of all disasters in terms of people affected.

¹ A hazard caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability.

² A hazard caused by short-lived, micro- to mesoscale extreme weather and atmospheric conditions that last from minutes to days.

³ Although vector-borne diseases can be associated to some hydrometeorological disasters (see for example Chowell 2019, Nasci and Moore 1998, WHO 2006 and Khan et al. 2014), they are not considered as a disaster in a narrow sense.

77 According to the EM-DAT database, in 2018 floods affected 35.4 million people causing 2.859 deaths while
78 12.8 million people were affected by storms, which caused 1,593 deaths (UNISDR 2019).

79 To prepare and adapt to hydrometeorological disasters and reduce their high human and economic costs,
80 strategies for managing risks can be developed at any scale (IPCC 2012). However, as explained by Ramirez
81 (2011), Herrmann-Lunecke and Villagra (2020) and Loebach (2019), effective disaster risk management
82 involves amending land use practices, occupation habits, and economic activities that increase
83 vulnerabilities to disasters. This can be achieved by means of a set of instruments, such as modification
84 and reinforcement of infrastructure, relocations, establishment of no construction zones, land use
85 restrictions, livelihood improvement of high risk-groups, and the protection of natural buffers such as
86 forests, compacted dunes and wetlands. A better and more effective use of these instruments could be
87 facilitated by more accurate predictions on where hydrometeorological disasters have greater chances to
88 occur (IPCC 2012, Marvin et al. 2013, Sperling and Szekely 2005, Thomalla et al. 2006, Dore 2003, Cook et
89 al. 2020). Public spending on ex-ante risk reduction and warning projects may lead to reductions in
90 disaster's damages that are almost twice that of the spending on ex-post recovery programs
91 (Davlasheridze et al. 2017). This explains the large and growing literature attempting to provide better
92 predictions for different climate change induced disasters (Mora et al. 2018, Tan et al. 2019, Wei et al.
93 2017, 2019, Li and Wang 2018, Pei et al. 2016, Jayawardena 2015, Siverd et al. 2020).

94 The objective of the present work is to study the relationship between atmospheric *CO2* accumulation
95 and hydrometeorological disasters. Our critical assumptions are 1) that this relation manifests mainly
96 through three contributing factors, local climatic variance, local exposure/vulnerability conditions and a
97 global climatic pattern; and 2) that there is a long-term relation between the global climatic pattern and
98 *CO2* concentration in the atmosphere. We propose and assess a statistical tool using *CO2* concentrations
99 as a predictor for hydrometeorological disasters at the global level. In doing so we use panel country-level
100 data covering most countries in the world over the period 1970-2016. We provide a statistically valid

predictor of the probability of occurrence of climate change induced hydrometeorological disasters at country level, which can be instrumental to potentially affected countries to design and implement both appropriate and timely risk managing measures and adapting policies.

There are several studies predicting some characteristics and consequences of future hydrometeorological disasters. There is work relating disaster occurrence to temperature changes (Grinsted et al. 2013, Knutson et al. 2010, Hallegatte 2012, among others). Other studies have focused on specific geographical regions (Stott et al. 2004, Otto et al. 2012, Hoerling et al. 2012, Rahmstorf and Coumou 2011, Appendini et al. 2019, Smith et al. 2019, Siverd et al. 2019) or particular events (Min et al. 2011, Stott et al. 2012, Nuccitelli 2014, Kundzewicz et al. 2014, Arnell and Gosling 2016, Hirabayashi et al. 2013, Herring et al. 2014). Some have applied climate change models to selected episodes (Lee and Lee 2016, Diffenbaugh et al. 2015). Climate change models have also been used to analyze extreme events in particular settings (Easterling et al. 2000, Pall et al. 2000, Schreider et al. 2000).

Focusing on the relation between the climate phenomenon and human action, Anderson and Bausch (2006) find that a doubling of atmospheric *CO2* concentrations could triple Category 5 storms. The effects of greenhouse gas emissions on natural hazard incidence are also explored in Mora et al (2018), concluding that even under strong mitigating scenarios, there will still be significant human exposure to a multitude of climate hazards in future years, particularly in tropical coastal areas. The link between *CO2* stock and disaster occurrence has been further explored by López et al. (2020), who find a meaningful correlation between *CO2* accumulations and floods and storms incidence.

Most of these mentioned studies use climatological models based on physical relationships. Although recent technological developments have improved the scope of these models to link climate change to the incidence of disasters, understanding the emergence of hydrometeorological hazards still appears particularly intricate (Cornwall, 2016). A few recent works opt for a complementary econometric

approach, being some remarkable examples those of Pretis (2020) and López et al. (2020). We add to this body of work, with an approach similar to that in López et al. (2020), including climate as well as demographics and economic factors in one framework, updating to a more flexible methodology that allows us to capture further non linearities by which the link between *CO2* concentration and disaster's incidence may manifest.

In this paper, we provide in the first place a quantitative assessment of the long-term relationship between the observed increasing number of hydrometeorological disasters and the concentration of atmospheric *CO2*. A second contribution consists of a predictive tool for this type of disasters that operates at the global level and takes advantage of the aforementioned long-term relation. For these purposes we employ Bayesian simulation techniques to first obtain a global trend in the probabilities of hydrometeorological disaster occurrence, controlling for country-specific variables and flexible patterns of random effects. Then we analyze the relationship between the global disaster trends and *CO2* accumulation and use this information to project disaster incidences at the global level conditional on nine Shared Socioeconomic Pathways (SSP) scenarios, including the five high-priority scenarios for the Sixth Assessment report by the IPCC. We demonstrate that generally and readily available statistical data on *CO2* global atmospheric concentrations can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of occurrence of hydrometeorological disasters.

The remainder of this work is structured in the following way. Section 2 provides a general overview of the empirical strategy. Section 3 describes the data and its sources. Section 4 provides detailed explanations of the empirical approach and estimation results. In section 5, we test for atmospheric *CO2* concentration as a predictor of the global probability of disasters, and then realize projections of (global) disaster probabilities up to 2040. Section 6 concludes. Supplementary online Appendices provide robustness tests and some estimation results in more detail.

2. Empirical strategy

We focus on analyzing the potential of global atmospheric concentration of CO_2 as a meaningful explanatory and predictive factor for the global probability of disasters (GPOD). The key approach is to use the country panel data of disasters to separate country-specific factors from global common-to-all-countries effects. It is the latter effects that we expect to be related with the CO_2 concentration.

As our dependent variable is coded after human losses (see Section 3), some considerations are to be taken with regard to the country-specific factors to include in the model. Socioeconomic, institutional and demographic factors related to people's vulnerability and exposure to hazards have been highlighted in the works of Tyler and Moench (2012), Banholzer et al. (2014), Hauer et al. (2016), Hallegatte and Rozenberg (2017), Fang et al. (2019) and Mora et al. (2018), among others. Related to the capacity of people to protect themselves against hazards through socioeconomic and institutional factors, we employ GDP per capita to approximate population vulnerability. Similarly, we consider population density to approximate the exposure of people living in geographic locations prone to be affected by severe hazards. As in López et al. (2020), we also consider a set of climate related country-specific variables, that could influence the number and intensity of events beyond the global and long-term local climatic paths, namely annual precipitation and temperature deviations from their long-term averages. Finally, model flexibility is enhanced by random effects by country, region and time.

Our empirical strategy can be schematically resumed in the following steps:

1. We estimate the GPOD conditional on unbalanced panel of 193 countries and the period 1970-2016. To isolate a global (i.e. common-to-all-countries) trend in disaster probabilities as close (and flexible) as possible, we employ (i) a set of global as well as country-specific covariates (weather conditions, population density and per capita income), (ii) random time effects with flexible resolution (year and decade), and (iii) random effects for the spatial dimension (i.e. country and

isosubregion). We apply Bayesian MCMC techniques to a structured zero-inflated Poisson count data model, and use the posterior distributions for sampling model parameters.

2. Samples of the GPOD trends are drawn from the set of posterior parameters obtained in step 1. For this purpose, we use only common-to-all-countries time related information (e.g., time trends, time effects, annual changes in total carbon dioxide accumulation).
3. The GPOD samples obtained in step 2. are subjected to a cointegration analysis with the atmospheric $\log(CO_2)$. In this regard two remarks are worth making. First, beyond the detection of a viable relation between the GPOD and $\log(CO_2)$, it is important to investigate if the latter process can be regarded as weakly exogenous in this relation. Otherwise projections of the GPOD conditional on $\log(CO_2)$ scenarios could be subject to misspecification. Second, as a reflection of global trends in disaster probabilities our analysis takes suitably account of the causal channel from spatially differentiated climatic patterns to global trends in $\log(CO_2)$ or disaster occurrences. In its stylized form, however, our modelling strategy is agnostic with regard to an inverse linkage where $\log(CO_2)$ could show up as a potential determinant of local climatic conditions.⁴

3. The data

The dependent variable is the annual count of hydrometeorological disasters, i.e., floods and storms. The data on disasters comes from the EM-DAT (EM-DAT: The Emergency Events Database - Université Catholique de Louvain (UCL) - CRED, D. Guha-Sapir www.emdat.be, Brussels, Belgium). In addition to the

⁴ Changes in CO_2 seem to have two opposite effects on tropical precipitation. Its short-term response is increased by land surface temperature affecting circulation (Cao et al. 2012; Chadwick et al. 2014, Richardson et al. 2016), and reduced by the tropospheric radiative cooling system (Sugi and Yoshimura 2004, Bony et al. 2013). In midlatitudes the circulation changes are small, hence the troposphere cooling effect prevails. Precipitation patterns outside of the tropics are not well understood yet (Richardson et al. 2016).

EM-DAT coding for the disasters, we also use a more demanding criterion suggested in Thomas et al. (2013), Thomas et al. (2014) and López et al. (2020) for robustness analysis⁵.

Table 1 Summary statistics of the dataset

Variable	Statistic	Complete sample	1970	1980	Decade 1990	2000	2010
<i>General</i>							
Observations	Total number of	7516	1127	1402	1727	1930	1330
<i>Dependent Variable</i>							
	Total number of	4807	272	553	959	1860	1163
Hydrometeorological disasters	Mean per year/country	0.640	0.241	0.394	0.555	0.964	0.874
	Standard deviation	1.454	0.610	0.952	1.200	1.885	1.800
<i>Global</i>							
$\log(CO_2)$	Mean	5.896	5.802	5.846	5.888	5.937	5.982
	Standard deviation	0.061	0.011	0.013	0.013	0.015	0.012
$\Delta \log(CO_2)$ (annual %)	Mean	0.479	0.372	0.472	0.427	0.505	0.604
	Standard deviation	0.147	0.151	0.088	0.174	0.094	0.115
<i>Local socioeconomic-demographic</i>							
GDP per capita growth (annual %)	Mean per year/country	2.002	2.964	0.970	1.450	2.733	1.931
	Standard deviation	6.497	6.312	5.588	8.240	6.547	4.308
Population density growth (annual %)	Mean per year/country	1.723	2.162	2.097	1.643	1.482	1.408
	Standard deviation	1.590	1.326	1.619	1.565	1.740	1.399
<i>Local climate</i>							
Precipitation deviation (mm/month)	Mean per year/country	-21.141	-18.994	-28.801	-33.130	-12.407	-11.993
	Standard deviation	185.044	150.184	169.295	191.115	181.431	220.537
Temperature deviation (°C)	Mean per year/country	0.208	-0.043	0.105	0.216	0.278	0.416
	Standard deviation	0.450	0.382	0.356	0.393	0.458	0.517

Note: Data sources are EM-DATA and own calculations

Summary statistics of the dataset can be found in Table 1. An increasing incidence pattern can be observed for hydrometeorological disasters. In fact, over the last two decades there has been an average of almost one disaster per year and country. However, there are many countries which have experienced no disasters for several years.

The annual global CO_2 stock in logarithm ($\log(CO_2)$) is subjected to a cointegration analysis and used for projections of the GPOD in the second step, while its annual change is used as a global climatological

⁵ EM-DAT codes a natural event as disaster after fulfilling one of the following conditions: 10 or more people dead, 100 or more people affected, declaration of state of emergency or a call for international assistance was given (CRED 2009). The alternative criterion is 100 or more people dead, or 1000 or more people affected.

control variable in the first step estimation. CO₂ data was drawn from the NOAA\ESRL Global Monitoring Division (Dr. Pieter Tans, NOAA/ESRL (www.esrl.noaa.gov/gmd/ccgg/trends/) and Dr. Ralph Keeling, Scripps Institution of Oceanography (scrippsco2.ucsd.edu/)).

As mentioned in section 2, country-specific controls used in the first step of the analysis can be divided into two groups, i.e., 1) a set of demographic (population density growth) and economic (GDP per capita growth) variables used as proxies for population's exposure and vulnerability, drawn from the World Development Indicators published by the World Bank, and 2) a set of climatological controls, namely precipitation and temperature deviations from their 1961 to 1990 period averages. Annual precipitation and temperature means by country were obtained from monthly grid geographical data. We first obtained annual averages from monthly measures for each grid point in the original datasets. Then we built geographical quadrants for each country using information on maximum and minimum latitude and longitude boundaries⁶, to finally take the mean of all grid points within these quadrants. Precipitation data was drawn from the Global Precipitation Climatology Centre (GPCC) database⁷, and temperature data was obtained from the HadCRUT4 global temperature dataset⁸. Prior to model estimation, all explanatory variables have been standardized. Hence, the interpretation of marginal results should be made in terms of standard deviations.

⁶ Each boundary was expanded by half the distance between two grid data points, to assure that small countries (e.g. San Marino) had at least one point associated.

⁷Full Data Monthly Product Version 2018, 1°x1° grid resolution monthly land surface precipitation information (Schneider et al. 2018).

⁸ 5°x5° grid resolution (Morice et al. 2012).

4. The count data model for disaster probabilities

Our goal is to estimate an annual common-to-all-countries factor in disaster occurrence probabilities (i.e., the GPOD) conditional on country-specific climatological, demographic and socioeconomic characteristics. To do this we first estimate a flexible random effects panel model to extract subsequently the time related global information.

One issue we must deal with is the excess of zeros present in the dependent variable. As a suitable generalization of a standard Poisson count data model, we rely on a Zero-Inflated Poisson (ZIP) model. The ZIP model formalizes the occurrence of a structural zero with probability π . Moreover, disaster counts exhibit a Poisson distribution with parameter λ . The ZIP model adopted here is structural in the sense that both model parameters π and λ depend on covariate information. Let $y_{it}, i = 1, \dots, N_t, t = 1, \dots, T$, denote the number of disasters in country i and time t . Then, the probability of a number of disasters to occur is

$$P(y_{it}) = \pi_{it}I(y_{it} = 0) + (1 - \pi_{it})\frac{\lambda_{it}^{y_{it}}e^{-\lambda_{it}}}{y_{it}!}, \quad (1)$$

where $I()$ is an indicator function. The parameters λ and π accord with representations

$$\ln(\lambda_{it}) = c^{(\lambda)} + f_t'\gamma^{(\lambda)} + x_{it}'\beta^{(\lambda)} + \alpha_{1i}^{(\lambda)} + \alpha_{2t}^{(\lambda)} \quad (2)$$

$$\text{and } \pi_{it} = \frac{B_{it}}{1+B_{it}}, \text{ with } B_{it} = \exp\left(c^{(\pi)} + g_t'\gamma^{(\pi)} + z_{it}'\beta^{(\pi)} + \alpha_{1i}^{(\pi)} + \alpha_{2t}^{(\pi)}\right), \quad (3)$$

where $c^{(\lambda)}$ and $c^{(\pi)}$ denote intercepts terms, f_t and g_t are vectors of time specific variables, namely t, t^2 and the first differences of $\log(CO2)$. The country-specific climatological, demographic and economic controls enter the linear combinations $x_{it}'\beta^{(\lambda)}$ and $z_{it}'\beta^{(\pi)}$. Apart from measurable heterogeneities, the

238 ZIP model comprises random effects in two dimensions, i.e. geography and time, denoted as $\alpha_{1i}^{(\lambda)}$, $\alpha_{1i}^{(\pi)}$
239 and $\alpha_{2t}^{(\lambda)}$, $\alpha_{2t}^{(\pi)}$, respectively.⁹

240 Another issue to deal with comes from the complex nonlinearities arising from including all time related
241 variables to affect both parameters (λ and π) in the ZIP model. Klein et al. (2015) find that modelling zero-
242 inflated and over dispersed count data by means of MCMC¹⁰ methods provides valid credible intervals
243 that are difficult to obtain by means of maximum likelihood frequentist approaches. Therefore, we
244 estimate the model by means of MCMC methods implemented in the software BayesX (Belitz et al. 2012).
245 We performed a total number of 60,000 MCMC iterations. To improve convergence and reduce
246 autocorrelation, we deleted the first 10,000 iterations (burn-in) and stored each 50-th iterate (thinning)
247 leading to a total of 1000 samples. Convergence of the chains has been checked in terms of the sampling
248 paths and autocorrelation plots. We consider particular effects to be significant if a credibility interval
249 constructed from the posterior 2.5% and 97.5% quantiles of MCMC samples does not include zero.

250 4.1 Results from the first step estimations

251 For model specification and variable selection, we rely mainly on the deviance information criterion (DIC)
252 (Spiegelhalter et al. 2002). We look for the most flexible and DIC-minimizing specification for both
253 parameters, λ_{it} and π_{it} , in terms of geographic and time related random effects. Table 2 shows the
254 variables that came out of this process.

255

256

⁹ Iso-region or iso-subregion are used depending on the selected model and refer to a geographical classifications of countries. Iso-region corresponds to continent (5 categories total) and iso-subregion to a within continent subdivision (21 categories). For aggregating observations over time we allow for random year and decade effects.

¹⁰ The Metropolis-Hastings (also known as MCMC) algorithm is a recursive method to simulate multivariate distributions. It can be shown that the simulated distribution converges to the target distribution, a detailed description of the algorithm can be found in Chib and Greenberg (1995). BayesX software utilizes a generalized version of the algorithm with distribution specific iteratively weighted least squares proposal densities.

257

Table 2 Included explanatory variables in the model with minimal DIC

Parameter	Linear covariates		Random effects	
λ_{it}	f_t	trend trend ² $\Delta \log(CO_2)$	$\alpha_{2t}^{(\lambda)}$	year decade
	x_{it}	Temperature deviation Precipitation deviation GDP per capita growth Population density growth	$\alpha_{1i}^{(\lambda)}$	country isosubregion
π_{it}	g_t	trend $\Delta \log(CO_2)$	$\alpha_{2t}^{(\pi)}$	year decade
	z_{it}	Precipitation deviation	$\alpha_{1i}^{(\pi)}$	country isosubregion

258 Note: Parameters and symbols refer to the model in (2) and (3).

259 Statistics for the estimated marginal effects on $P(y_{it} > 0)$ (see equation (4) below) and the contribution
 260 of each covariate can be seen in Table 3 (random effects are not reported because they are too
 261 numerous). Out of the country-specific climatic controls, precipitation differences from long-term
 262 averages have more explanatory content for hydrometeorological disasters in comparison with
 263 temperature. It exhibits the most important and significant effect out of all covariates implying a 5.6%
 264 change in the probability of a disaster per standard deviation¹¹. Precipitation also affects the disaster
 265 probability through both channels of the ZIP model. It reduces the probability of no disaster (π_{it}), and
 266 increases the mean of the Poisson distribution for disasters (λ_{it}). Unlike precipitation, temperature only
 267 affects hazards incidence through λ_{it} . A rise in local temperature deviation is associated with a slight and
 268 insignificant reduction of the probability of disasters.

269 Both the socioeconomic and the demographic controls correlate with disasters only via the Poisson
 270 distribution, and neither covariate exerts a significant effect. Population density growth, our proxy for
 271 exposure, has a very small positive effect when compared with the other factors. As our model selection

¹¹ To put the effect estimates into perspective, consider the descriptive statistics in Table 1. Furthermore, as two particular examples, Vietnam had a precipitation deviation of 46.74mm/month in 1990 and -78.13 mm/month in 2010; Zambia -81.82 mm/month in 1990 and 37.64 mm/month in 2010. These changes account to -0.67 (Vietnam) and 0.65 (Zambia) standard deviations. Hence, other things equal this precipitation changes account for a reduction of the probability of at least one disaster by 3.78% for Vietnam, and an increase of 3.62% for Zambia.

process favored growth rates instead of log levels for these controls, a direct interpretation of the correlation results in the sense of Wu et al. (2018), Mora et al. (2018), or López et al (2020) cannot be made here. Taking GDP per capita, we have that on the one hand neoclassical theory suggests conditional higher growth rates for lower income (more vulnerable) countries, while on the other hand growth has been shown to be sensitive to disasters (Loayza et al. 2012, Caballo et al. 2013 and others). Hence, we refrain from making any causal interpretation. For the global effect we have that coefficients of *trend* and *trend*² are both statistically significant, the former affecting disasters through both channels. Interestingly, the negative coefficient attached to *trend*² indicates a reduction in annual growth of disaster probabilities. We expect these covariates to capture partially the GPOD joint with year and decade specific random effects. Annual carbon dioxide emissions ($\Delta \log(CO_2)$) impact only mildly and insignificantly on disaster probabilities. It is worth mentioning here that all results for the ZIP model are largely robust for a more restrictive definition of disasters (see Appendix C, Table C3).

Table 3 Estimated marginal effects on disaster probabilities and ZIP parameters

Variable	$P(y_{it} > 0)$					λ_{it}		π_{it}	
	Mean	SD	Q2.5%	Q50%	Q97.5%	Mean	SD	Mean	SD
<i>Country level</i>									
temperature deviation	-0.005	0.004	-0.012	-0.005	0.003	-0.022	0.018	-	-
precipitation deviation	0.056	0.004	0.047	0.056	0.065	0.167	0.017	-0.074	0.016
GDP per capita growth	0.007	0.004	-0.001	0.007	0.014	0.030	0.018	-	-
population density growth	0.000	0.007	-0.014	0.000	0.013	-0.002	0.031	-	-
<i>Global</i>									
trend	0.163	0.036	0.091	0.165	0.232	0.622	0.165	-0.093	0.044
trend ²	-0.076	0.033	-0.141	-0.074	-0.012	-0.337	0.148	-	-
$\Delta \log(CO_2)$	0.007	0.005	-0.003	0.007	0.016	0.009	0.021	-0.019	0.010

Notes: SD indicates standard deviations. Q2.5%, Q50% and Q97.5% stand for posterior MCMC quantiles. We regard a parameter as significant, if the zero is not included in the Q2.5% - Q97.5% interval.

We can now estimate the probability of at least one disaster to happen in country i and year t as

$$P(y_{it} > 0) = (1 - \hat{\pi}_{it})(1 - e^{-\hat{\lambda}_{it}}), \quad (4)$$

where $\hat{\pi}_{it}$ and $\hat{\lambda}_{it}$ can be obtained from (2) and (3) using the MCMC parameter estimates (see Table 3 for descriptive statistics) and the estimated random effects.

Fig. 1 Mean of estimated $P(y_{it} > 0)$ by country, years 1990 and 2010

Figure 1 displays the posterior MCMC mean of the estimated probabilities of a disaster by country in years 1990 and 2010 (see Appendix D for a detailed documentation). A concentration of disasters in the tropical areas can be observed in 1990, especially in Asia and the Pacific region (see also Thomas et al. 2013 and Thomas et al. 2014). With regard to 2010 a dramatic change obtains for (almost) all regions. Aligning with earlier findings of increasing disaster incidences (see, for example, Stott et al. 2004, Otto et al. 2012, Hoerling et al. 2012, Rahmstorf and Coumou 2011, Smith et al. 2019, López et al. 2020, Mora et al. 2018), some African countries jump from less than 30% to more than 70% probability of experiencing at least one disaster.

5. The GPOD

With estimates for all covariate and random effects at hand, we are in position to build GPOD time paths. For this purpose, all variables (and their effects) that are not explicitly related to time are removed from the computation of the probabilities of interest. Specifically, we construct estimates of $P(y_t > 0)$ from equation (4) after replacing $\hat{\lambda}_{it}$ and $\hat{\pi}_{it}$, respectively, by

$$\ln(\hat{\lambda}_t) = \hat{c}^{(\lambda)} + f_t' \hat{\gamma}^{(\lambda)} + \hat{\alpha}_{2t}^{(\lambda)} \quad (5)$$

$$\text{and } \hat{\pi}_t = \frac{\hat{B}_t}{1 + \hat{B}_t}, \text{ with } \hat{B}_{it} = \exp \left(\hat{c}^{(\pi)} + g_t' \hat{\gamma}^{(\pi)} + \hat{\alpha}_{2t}^{(\pi)} \right). \quad (6)$$

This exercise results in a set of 1,000 time paths of probabilities $P(y_t > 0)$ which we subject to cointegration and predictive analysis.

5.1 Disaster occurrence probabilities and the atmospheric CO2 concentration

Let τ_t and q_t denote, respectively, the global time component of estimated probabilities (the GPODs) and $\log(\text{CO}_2)$ in year t . Henceforth we consider q_t as a potential (weakly exogenous) determinant of τ_t . In coping with issues of cointegration vs. spurious regression, we implement the following regressions which are informative about potential long-run linkages between τ_t and q_t .¹²

$$\tau_t = k_1 + \beta_1 q_t + \omega_{1,t}, \quad (7)$$

$$\Delta \tau_t = k_2 + \alpha_2 \tau_{t-1} + \beta_2 q_{t-1} + \omega_{2,t}, \quad (8)$$

$$\text{and } \Delta q_t = k_3 + \alpha_3 \tau_{t-1} + \beta_3 q_{t-1} + \omega_{3,t}. \quad (9)$$

The variables τ_t and q_t may have a meaningful relation if the estimates of β_1 in (7) are positive for a significant fraction of the performed regressions. The regression model (8) allows for error correcting

¹² See Kremers et al. (1992) for a discussion of single equation cointegration and error-correction models.

dynamics inherent in the adjustment of disaster probabilities. Under cointegration and weak exogeneity of q_t , the error correction parameter α_2 must be negative. The regression in (9) is designed to unravel potential violations of weak exogeneity. Specifically, the $\log(CO2)$ process lacks the property of weak exogeneity if a significant fraction of parameter estimates of α_3 is positive.

Table 4 Estimated parameters for cointegration analysis

Parameter	Mean	SD	Q2.5%	Q50%	Q97.5%
Regression (7)					
k_1	-7.110	1.193	-4.909	-7.016	-9.730
β_1	1.241	0.208	1.700	1.226	0.857
R^2	0.849	0.028	0.897	0.851	0.782
Regression (8)					
k_2	-2.299	0.805	-0.895	-2.239	-4.143
α_2	-0.338	0.092	-0.169	-0.34	-0.528
β_2	0.402	0.14	0.724	0.391	0.157
Regression (9)					
k_3	-0.054	0.019	-0.014	-0.054	-0.091
α_3	0.001	0.003	0.007	0.001	-0.004
β_3	0.010	0.003	0.016	0.010	0.003

Note: See Table 3.

Parameter estimates for the cointegration analysis are reported in Table 4. From regression (7), the cointegration property implies the existence of an equilibrium long-run relationship linking the GPOD and $\log(CO2)$, since β_1 is positive and significant. Hence, according to the Engle-Granger theorem (Engle and Granger 1987) the variables are linked by an error-correction mechanism, and at least one of the variables must adjust to transitory violations of the equilibrium relationship. Results from regression (8) show strong evidence that the GPOD adjusts to deviations from the long run equilibrium with the $\log(CO2)$. Under the null hypothesis of no cointegration, testing the significance of α_2 requires non-standard critical values (Kremers et al. 1992), tests considering this can be found in Appendix A.1. Results from the regression (9) show that adjustments of $\log(CO2)$, i.e. Δq_t , do not correlate with lagged violations of the diagnosed equilibrium among q_t and τ_t (see Table 4). This result underpins weak exogeneity of $\log(CO2)$. Hence, if one of the two variables deviates from their long-term relation, the GPOD adjusts towards a new

equilibrium and not the $\log(CO_2)$. We have also applied these exercises to two other related trending variables as placebo, namely Global Temperature and World GDP per capita. Both variables appear to be also correlated in the long-term with the GPOD, but both trending variables fail to be weakly exogenous (see Appendix A.2). Hence, for the conditioning of GPOD projections Global Temperature and World GDP per capita lack an essential qualification.

5.2 Projections to year 2040

Both, the diagnosed weak exogeneity of $\log(CO_2)$ and the joint dynamics linking the GPOD and the $\log(CO_2)$ qualify the latter factor for conditioning projections of the former. We can project the GPOD by means of the set of model parameters estimated for the regression model (7) and specific assumptions for the conditioning variable,

$$\tau_t = \hat{k}_1 + \hat{\beta}_1 q_t, \quad (10)$$

where $\hat{k}_1$ and $\hat{\beta}_1$ are from the distribution of parameter estimates as documented in Table 4. Test results for parameter stability and out-of-sample forecast exercises using the specification in (10) can be found in Appendix B, and underpin model stability and predictive accuracy.

We use simulated annual series for CO_2 accumulation up to the year 2040, as provided by Meinshausen et al. (2020) for SSP scenarios.¹³ The five high-priority scenarios for the Sixth Assessment report by the IPCC (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5 and SSP1-1.9), the three scenarios that complete the Tier 2

¹³ SSPs describe alternative possible evolution pathways in the absence of climate change mitigating policies. SSP1 and SSP5 envision relatively optimistic trends, SSP2 envisions a pathway in which trends continue their historical patterns, SSP3 and SSP4 envision more pessimistic developments (O'Neill et al. 2016). For a comprehensive description of the SSPs we refer the reader to the work of Riahi et al. (2016).

list suggested by O'Neill et al. (2016) (SSP4-6.0, SSP4-3.4, SSP5-3.4-OS) and a variation of the SSP3-7.0 scenario (Meinshausen et al., 2020). Estimated GPOD projections are shown in Figure 2.

Fig. 2 GPOD projections to year 2040 by scenario with 90% confidence intervals

With the exception of the more optimistic scenario SSP1-1.9, the rising trend in the GPOD is apparent. Comparing results for 2015 and 2040, on average, the time component of global disaster occurrence probabilities can be expected to rise by about 30% or more and by about 20% for the SSP1-1.9 scenario. The trend is clearly significant, since lower bounds of GPOD confidence intervals for the year 2040 are above the mean projections for the year 2015.

While the GPOD projections reflect the global impact of the expected increases of atmospheric CO2 concentration, the projections are not directly informative for country-specific disaster probabilities. Thus, to provide global maps of probabilities of at least one disaster to occur by country in 2040, we combine the projected GPOD with in-sample country-specific average relations between estimates of $P(y_{it} > 0)$ and the GPOD (i.e. $P(y_t > 0)$). Figure 3 displays estimated country-specific probabilities for the four Tier 1 priority scenarios according to O'Neill et al. (2016), and allows for a direct comparison with

results displayed in Figure 1 (see Appendix D for a detailed documentation). Apparently, probabilities of disasters to occur by country are subject to marked increases. For a majority of countries, the probabilities to experience at least one disaster in 2040 are beyond 50%. Comparing in-sample results for 2010 and projections for 2040 shows that, in particular, Asian countries can be expected to experience at least one disaster per year much more frequently under all displayed scenarios. Noting again the value of these projections as input for governments and communities to design and develop adequate strategic capacities to face upcoming hydrometeorological disasters (Simpson 2008, McGuire and Schneck 2010, IPCC 2012, Marvin et al. 2013, Sperling and Szekely 2005, Thomalla et al. 2006, Dore 2003, Cook et al. 2020, Davlasheridze et al. 2017), the complete data set of projected probabilities by country, from year 2021 to 2040 and for the 9 SSP scenarios considered, is available on request.

Fig. 3 Mean of projected $P(y_{it} > 0)$ in year 2040 for Tier 1 scenarios

9. Conclusion

In this work, we have quantitatively studied the long-run dynamic and predictive connection between atmospheric *CO2* accumulation and the probability of hydrometeorological disasters occurrence. As stated by the IPCC, other international agencies and numerous authors, this could contribute to a better and more effective and less costly use of preventive and mitigating instruments to reduce people's exposure and vulnerability.

To unravel and test the properties of *CO2* accumulation measures as a predictive tool for hydrometeorological disasters, we have employed flexible Bayesian MCMC simulation techniques to first obtain a global trend in the probabilities of disaster occurrence conditional on climate, socioeconomic and other country-specific factors. We then analyzed its relationship with *CO2* levels to assess and check the ability of the trend in global atmospheric *CO2* concentration to accurately (with 90% of confidence) anticipate the future occurrence of hydrometeorological disasters. Finally, we used this information to forecast disaster incidences at the global level for nine SSP scenarios, including the five high-priority scenarios for the Sixth Assessment report by the IPCC.

We show that statistical data on global atmospheric *CO2* concentrations can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of hydrometeorological disasters at the global level. Moreover, we also show that controlling for country-specific characteristics, and conditional on emission scenarios, the vast majority of countries will be subject to the occurrence of at least one disaster with at least 50% probability in 2040. A paramount policy implication of having these reliable projections of future hydrometeorological disasters is their usefulness to designing ex-ante mitigation projects and risk managing programs, whose effective returns can be almost twice the returns from ex-post recovery programs from such disasters.

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Figures

Figure 1

Mean of estimated $P(y_{it} > 0)$ by country, years 1990 and 2010. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

GPOD projections to year 2040 by scenario with 90% confidence intervals

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