Carbon dioxide atmospheric concentration and hydrometeorological disasters

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Abstract
We study the long-run connection between atmospheric carbon dioxide (CO2) concentration and the probability of hydrometeorological disasters using a panel of 193 countries over the period 1970–2016 providing annual disaster projections to the year 2040 for each of these countries. Generating accurate predictions on where hydrometeorological disasters have greater chances to occur, may facilitate preparedness and adaption to such disasters, thus helping to reduce their high human and economic costs. We estimate the probabilities of hydrometeorological disasters at country levels using Bayesian sampling techniques. We decompose the probability of country disaster into the effects of country-specific factors, such as climatological and socio-demographic factors, and factors associated with world climate, which we denote global probability of disaster (GPOD). Finally, we subject these GPOD time paths to a cointegration analysis with CO2 concentration and provide projections to the year 2040 of the GPOD conditional on nine Shared Socioeconomic Pathways scenarios. We detect a stable long-term relation between CO2 accumulation and the GPOD that allows us to determine projections of the latter process conditional on the former. We conclude that readily available statistical data on global atmospheric concentrations of CO2 can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of occurrence of 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 increases in well-mixed greenhouse gas (GHG) concentrations since 1750 are unequivocally caused by human activities and that, as a result of that, it is also unequivocal that human influence has warmed the Earth’s atmosphere, ocean and land (IPCC 2014.

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The IPCC states that oceanic and atmospheric temperatures have risen, the overall sea level is higher and Arctic and Antarctic ice and glaciers have diminished, and that, by the year 2050, global warming may reach 1.5 °C above pre-industrial levels if the current trend holds (IPCC 2019). Anthropogenic greenhouse gas emissions have increased, leading to atmospheric concentrations of CO₂, methane and nitrous oxide that are unprecedented in the last 800,000 years, according to the Keeling Curve measurement series made at the Mauna Loa Observatory in Hawaii (USA National Oceanic Atmospheric Administration (NOAA)). As of 2021, for the first time since accurate measurements began 63 years ago, the monthly average of CO₂ concentration in the atmosphere reached 419 parts per million (ppm), and the rate of increase of atmospheric CO₂ accumulation appears to be accelerating (NOAA 2021, 2019a, b).

Evidence of observed weather extremes such as heatwaves, heavy precipitation, droughts, and tropical cyclones, as well as their attribution to human influence has strengthened since the IPCC’s Fifth Assessment Report of 2014, and it is likely that extreme precipitation events will intensify and become more frequent in many regions (IPCC 2014, 2021; 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 each person in the world will be subject to at least one major disaster per year.

No other kind of natural 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. According to the EM-DAT database, in 2018 floods affected 35.4 million people causing 2.859 deaths while 12.8 million people were affected by storms, which caused 1593 deaths (UNISDR 2019).

To prepare and adapt to hydrometeorological disasters and reduce their high human and economic costs, strategies for managing risks can be developed, including amending land use practices, occupation habits, and economic activities (Ramirez 2011, Herrmann-Lunecke and Villagra 2020; Loebach 2019). A better and more effective use of these strategies could be facilitated by more accurate predictions on where hydrometeorological disasters have greater chances to occur (IPCC 2012; Marvin et al. 2013; Sperling and Szekely 2005; Thomalla et al. 2006; Dore 2003; Cook et al. 2020; Davlasheridze et al. 2017). This explains the large and growing literature attempting to provide better predictions for different climate change induced disasters (Mora et al. 2018; Tan et al. 2019; Wei et al. 2017, 2019; Li and Wang 2018; Pei et al. 2016; Jayawardena 2015, Siverd et al. 2020).

There are several studies predicting characteristics and consequences of future hydrometeorological disasters. However, most of these 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. 2020) or 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). Others have applied climate change models to selected episodes, including extreme events (Lee and Lee 2016; Diffenbaugh
et al. 2015; Easterling et al. 2000; Pall et al. 2000; Schreider et al. 2000). Most of these studies use climatological models based on physical relationships.\(^1\)

The objective of the present work is to study the relationship between atmospheric CO\(_2\) accumulation and hydrometeorological disasters. We study the long-run dynamic and predictive connection between atmospheric CO\(_2\) concentration and the probability of hydrometeorological disasters using a panel of 193 countries over the period 1970–2016. We use a statistical-econometric approach exploiting data evidence for many countries at the same time, an approach which is highly complementary with the more structural and region and/or disaster specific case study approach used by most existing literature. This allows us to: 1. Test the hypothesis that increased atmospheric carbon dioxide accumulation causes more disasters thus giving greater support from a different perspective to the case study literature which has generally found that such causality exists. 2. Provide annual projections of hydrometeorological disasters to the year 2040 for each of the 193 countries that we consider in our analysis. By providing accurate predictions on where hydrometeorological disasters have greater chances to occur, we facilitate preparedness and adaption to such disasters, thus helping to reduce their high human and economic costs.

Some recent works have already used the econometric approach, including López et al. (2016, 2020) and Pretis (2020). We add to this body of work, with an approach partly based in López et al. (2020), by using a more flexible methodology that allows us to capture further nonlinearities by which the link between CO\(_2\) concentration and disaster’s incidence may manifest, allowing for better adjustment and more precise estimations. 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 CO\(_2\). A second contribution consists of a predictive tool for this type of disasters that operates at the global level and takes advantage of the long-term relation. We analyze the relationship between the global disaster trends and CO\(_2\) accumulation and use this information to project annual disaster incidences at the country level for 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 CO\(_2\) global atmospheric concentrations can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of occurrence of hydrometeorological disasters for each of the 193 countries considered.

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. Section 4 provides detailed explanations of the empirical approach and estimation results. In Sect. 5, we test for atmospheric CO\(_2\) 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 data sources and definitions, robustness tests and estimation results in more detail.

\(^1\) Climatological models typically build upon physical principles and laws, fluid mechanics and/or chemistry relations, used for running computer simulations of the earth climate system.
2 Empirical strategy

We focus on analyzing the potential of global atmospheric concentration of CO₂ as a meaningful explanatory and predictive factor for the global probability of disasters (GPOD). The key approach is to use a country panel data of disasters to separate country-specific factors from a global common-to-all-countries factor. It is the effect of the latter factor that we expect to be related with the CO₂ concentration.

We assume that risk exposure manifests itself mainly through three contributing factors, local climatic variance, local exposure/vulnerability conditions, and a global climatic pattern. We hypothesize that there is a long-term relationship between the global climatic pattern and CO₂ concentration in the atmosphere. We use CO₂ concentrations as a predictor for hydrometeorological disasters at the global level. In doing so we use panel country-level data covering most countries in the world over the period 1970–2016. We provide statistically valid predictors of the probability of occurrence of climate change induced hydrometeorological disasters at the country level. These predictors can be used by potentially affected countries to design and implement both appropriate and timely risk managing measures and adapting policies.

As our dependent variable is coded after human losses (see Sect. 3), some considerations are to be taken about the country-specific factors included in the model. Exposure and vulnerability of the population are dependent on country-specific characteristics. To control for and then isolate their effects are crucial steps in the identification of the global effect. The key idea is to use proxies for exposure and vulnerability of the population as control variables in the regression analysis. In addition, the use of random country-specific effects allows us to control for other unobserved country effects. This allows us to isolate the effect of factors associated with atmospheric CO₂ accumulation free from non-climatic country factors, including exposure and vulnerability.

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 as a proxy for population vulnerability. Similarly, we use population density to proxy the exposure of people living in geographic locations prone to be affected by severe hazards. And then, the random country effects control for unobserved country-specific factors.

In addition, separation of the country-specific climate effect variance from the total climate effect allows us to obtain the global carbon effect that we are after. 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 using random effects by country, by region and time.

The empirical strategy used can be resumed in the following steps:

1. We estimate the GPOD using an unbalanced annual data panel of 193 countries for the period 1970–2016. To isolate a global (i.e., common-to-all-countries) trend in disaster probabilities as close 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 iso subregion). We apply Bayesian Markov Chain Monte Carlo (MCMC) techniques to estimate a zero-inflated Poisson count data model and use the posterior distributions for sampling model parameters.

2. Samples of the GPOD trends are constructed using the set of posterior parameters obtained in step 1. For this purpose, we only use the subset of common-to-all-countries time-related parameters (e.g., time trends, time effects).

3. The GPOD samples obtained in step 2 are subjected to a cointegration analysis with the atmospheric $\log(CO_2)$. Two remarks are worth making. First, it is important to investigate if the $\log(CO_2)$ process can be regarded as weakly exogenous in this relationship. 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 disaster occurrences.

4. We implement projections of the GPOD to the year 2040 conditional on $CO_2$ under various SSP scenarios. Having the global probability projections, we get back to country-level probabilities by using in-sample mean differences between the GPOD and the country-specific estimated probabilities.

3 The data

The dependent variable is the annual count of hydrometeorological disasters by country and year, 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). 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. Definition and sources of the data can be found in Appendix A.

4 The count data model for disaster probabilities

Our first 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 subsequently extract the time-related GPOD.

The discrete nature of the dependent variable requires the use of a count data model. One issue we must deal with is the excess of zeros present in the dependent variable. As a

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2 This definition was also adopted by López et al. (2020) and accords with the one by the United Nations Office for Disaster Risk Reduction: “Process or phenomenon of atmospheric, hydrological or oceanographic nature that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage” (UNISDR, 2009).

3 In addition to the EM-DAT coding for the disasters, we also use a more demanding criterion suggested in Thomas et al. (2014) and López et al. (2020) for robustness analysis. Results for this second definition of disasters can be found in Appendix D.
Table 1 Summary statistics of the dataset

| Variable | Statistic | Complete sample | Decade | Year 2016 |
|----------|-----------|-----------------|--------|----------|
|          |           |                 | 1970   | 1980     | 1990     | 2000     | 2010     |            |
| General  |           |                 |        |          |          |          |          |            |
| Observations | Total number of | 7516 | 1127 | 1402 | 1727 | 1930 | 1330 | 180 |
| Dependent Variable | Mean per year/country | 0.64 | 0.241 | 0.394 | 0.555 | 0.964 | 0.874 | 0.922 |
| Global   |           |                 |        |          |          |          |          |            |
| $log(CO_2)$ | Mean | 5.885 | 5.802 | 5.845 | 5.887 | 5.936 | 5.983 | 6.002 |
|         | Standard deviation | 0.064 | 0.011 | 0.014 | 0.013 | 0.016 | 0.013 | – |
| $\Delta log\ (CO_2)(\text{annual }\%)$ | Mean | 0.470 | 0.374 | 0.472 | 0.423 | 0.504 | 0.606 | 0.839 |
|         | Standard deviation | 0.151 | 0.169 | 0.092 | 0.181 | 0.100 | 0.126 | – |
| Local socioeconomic–demographic | Mean per year/country | 2.002 | 2.964 | 0.970 | 1.450 | 2.733 | 1.931 | 1.592 |
|         | Standard deviation | 6.497 | 6.312 | 5.588 | 8.240 | 6.547 | 4.308 | 3.650 |
| Population density growth (annual %) | Mean per year/country | 1.723 | 2.162 | 2.097 | 1.643 | 1.482 | 1.408 | 1.348 |
|         | Standard deviation | 1.590 | 1.326 | 1.619 | 1.565 | 1.740 | 1.399 | 1.091 |
| Local climate | Mean per year/country | –21.141 | –18.994 | –28.801 | –33.130 | –12.407 | –11.993 | –34.491 |
|         | Standard deviation | 185.044 | 150.184 | 169.295 | 191.115 | 181.431 | 220.537 | 179.323 |
| Temperature deviation (°C) | Mean per year/country | 0.208 | –0.043 | 0.105 | 0.216 | 0.278 | 0.416 | 0.544 |
|         | Standard deviation | 0.450 | 0.382 | 0.356 | 0.393 | 0.458 | 0.517 | 0.543 |

Data sources are EM-DATA and own calculations.
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 \( \pi \). Moreover, disaster counts exhibit a Poisson distribution with parameter \( \lambda \). Thus, \( \pi \) corresponds to the structural probability that no disaster occurs, while \( \lambda \) is a parameter associated with the marginal effect of one additional disaster on the estimated probability of disasters. The ZIP model adopted here is structural in the sense that both parameters \( \pi \) and \( \lambda \) depend on covariate information. Let \( y_{it}, i = 1, \ldots, N, t = 1, \ldots, T \), denote the number of disasters in country \( i \) and time \( t \). Then, the probability of a number \( y_{it} \) of disasters to occur is

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

where \( I() \) is an indicator function which equals to one if \( y_{it} = 0 \). The parameters \( \lambda \) and \( \pi \) are determined by the following link functions,

\[
\ln(\lambda_{it}) = c^{(\lambda)} + f_t^\prime \gamma^{(\lambda)} + x_{it}^\prime \beta^{(\lambda)} + \alpha^{(\lambda)}_{1i} + \alpha^{(\lambda)}_{2t},
\]

and

\[
\pi_{it} = \frac{B_{it}}{1 + B_{it}}, \text{ where } B_{it} = \exp \left( c^{(\pi)} + g_t^\prime \gamma^{(\pi)} + z_{it}^\prime \beta^{(\pi)} + \alpha^{(\pi)}_{1i} + \alpha^{(\pi)}_{2t} \right),
\]

where \( c^{(\lambda)} \) and \( c^{(\pi)} \) denote intercept terms, \( f_t \) and \( g_t \) are vectors of time specific variables, namely \( t, t^2 \) and the first differences of \( \log(CO_2) \). The country-specific climatological, demographic, and economic controls enter the linear combinations \( x_{it}^\prime \beta^{(\lambda)} \) and \( z_{it}^\prime \beta^{(\pi)} \). Apart from measurable heterogeneities, the ZIP model comprises random effects in two dimensions, i.e., geography and time, denoted as \( \alpha^{(\lambda)}_{1i}, \alpha^{(\lambda)}_{2t}, \alpha^{(\pi)}_{1i} \) and \( \alpha^{(\pi)}_{2t} \), respectively.\(^4\)

This methodology improves over that in López et al. (2020) in several respects. Firstly, López et al., assume that the global CO\(_2\) concentration affects the probability of disasters only through the parameter of the count distribution (in our case the parameter \( \lambda \)) and not through the Bernoulli distribution parameter \( \pi \). In contrast, our model allows for both parameters to be affected by the GPOD determinants. Secondly, we improve the model adjustment by including linear and quadratic time trends as well as random time effects in two dimensions in both parameter equations, yielding more precise and flexible estimates of the GPOD.

Our methodology, however, implies complex nonlinearities caused by allowing all time-related variables to affect both parameters (\( \lambda \) and \( \pi \)), which make a maximum likelihood estimation approach non-reliable. Following Klein et al. (2015), we estimate the model by means of MCMC\(^5\) methods implemented in the software BayesX (Belitz et al. 2012). We

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\(^4\) Iso-region or iso-subregion are used depending on the selected model and refer to a geographical classification 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.

\(^5\) 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.
performed a total number of 60,000 MCMC iterations. To improve convergence and reduce autocorrelation, we deleted the first 10,000 iterations (burn-in) and stored each 50-th iterate (thinning) leading to a total of 1000 samples. Convergence of the chains has been checked in terms of the sampling paths and autocorrelation plots. We consider effects to be significant if a credibility interval constructed from the posterior 2.5% and 97.5% quantiles of MCMC samples does not include zero.

For model specification and variable selection, we rely mainly on the deviance information criterion (DIC) (Spiegelhalter et al. 2002). We look for the most flexible and DIC-minimizing specification for both parameters, $\lambda_{it}$ and $\pi_{it}$, in the context of geographic and time-related random effects. Table 2 shows the explanatory variables needed to estimate the minimal DIC.

Statistics for the estimated marginal effects on $P(y_{it} > 0)$ (see Eq. (4) below) and the contribution of each covariate are shown in Table 3 (estimated random effects are not reported because they are too numerous). Precipitation difference from long-term average is significant and implies a 5.6% change in the probability of a disaster per standard

### Table 2 Included explanatory variables in the model with minimal DIC

| Parameter  | Linear covariates       | Random effects |
|------------|-------------------------|----------------|
| $\lambda_{it}$ | $f_t$ Trend             | $\alpha_{2t}^{(l)}$ Year |
|             | $Trend^2$               |                |
|             | $\Delta \log(CO_2)$     |                |
| $x_{it}$   | Temperature deviation   | $\alpha_{t}^{(l)}$ Country |
|             | Precipitation deviation |                |
|             | GDP per capita growth   | $\alpha_{2t}^{(l)}$ Year |
|             | Population density growth|               |
| $\pi_{it}$ | $g_t$ Trend             | $\alpha_{2t}^{(r)}$ Year |
|             | $\Delta \log(CO_2)$     |                |
| $Z_{it}$   | Precipitation deviation | $\alpha_{1i}^{(r)}$ Country |

Parameters and symbols refer to the model in (2) and (3)

### Table 3 Estimated marginal effects on disaster probabilities and ZIP parameters

| Variable                        | $P(y_{it} > 0)$ | $\lambda_{it}$ | $\pi_{it}$ |
|---------------------------------|-----------------|---------------|------------|
|                                 | Mean SD Q2.5% Q50% Q97.5% | Mean SD | Mean SD |
| **Country level**               |                 |               |            |
| 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 | – –         |
| **Global**                     |                 |               |            |
| 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 |

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.
deviation. Local temperature deviation appears with insignificant effect. Both the socioeconomic and the demographic controls affect disasters only via the $\lambda$ equation, and neither exerts a significant effect. It is worth mentioning here that all results for the ZIP model are largely robust for a more restrictive definition of disasters (see Appendix D, Table D3).

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

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

where $\hat{\pi}_{it}$ and $\hat{\lambda}_{it}$ are obtained from (2) and (3) using the MCMC parameter estimates and the estimated random effects.

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 Thomas et al. 2014). A dramatic change occurs in the year 2010 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. In other regions, Russia jumps from a probability of 64% in 1970 to 95% in 2010, U.S.A from 42 to 63%, Australia from 44 to 73% and Brazil from 23 to 40%.

6 To put the effect estimates into perspective, consider the descriptive statistics in Table 1 using two country examples. Vietnam had a precipitation deviation of 46.74 mm/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 for -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.

7 As our model selection process favored growth rates instead of log levels for these controls, a direct interpretation of the correlation results in the sense of the ones in Wu et al. (2018), Mora et al. (2018), or López et al (2020) cannot be made here. Taking GDP per capita as an example, 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, Cavallo et al. 2013 and others). Hence, we refrain from making any causal interpretation.
5 The GPOD

We are now in position to build GPOD time paths. For this purpose, the effects of all variables 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 Eq. (4) after replacing \( \hat{\lambda}_t \) and \( \hat{\pi}_t \), respectively, by

\[
\ln ( \hat{\lambda}_t ) = \hat{\zeta}^{(\lambda)} + f_t \hat{\phi}^{(\lambda)} + \hat{\alpha}^{(\lambda)}_{2t} \tag{5}
\]

and

\[
\hat{\pi}_t = \frac{\hat{B}_t}{1 + \hat{B}_t} \quad \text{with} \quad \hat{B}_t = \exp \left( \hat{\zeta}^{(\pi)} + g_t \hat{\phi}^{(\pi)} + \hat{\alpha}^{(\pi)}_{2t} \right). \tag{6}
\]

This exercise results in a set of 1,000 time paths samples of GPOD (paths of \( P(y_t > 0) \)), which we subject to cointegration and predictive analysis with \( \log (CO_2) \).

5.1 Disaster occurrence probabilities and the atmospheric CO\(_2\) concentration

Let \( \tau_t \) and \( q_t \) denote, respectively, the global time component of estimated probabilities of disasters (the GPODs) and \( \log(CO_2) \) in year \( t \). Henceforth we consider \( q_t \) as a potential (weakly exogenous) determinant of \( \tau_t \). We implement the following regressions which are informative about potential long-run linkages between \( \tau_t \) and \( q_t \):

\[
\tau_t = k_1 + \beta_1 q_t + \omega_{1,t} \tag{7}
\]

\[
\Delta \tau_t = k_2 + \alpha_2 \tau_{t-1} + \beta_2 q_{t-1} + \omega_{2,t} \tag{8}
\]

and

\[
\Delta q_t = k_3 + \alpha_3 \tau_{t-1} + \beta_3 q_{t-1} + \omega_{3,t}. \tag{9}
\]

The variables \( \tau_t \) and \( q_t \) may have a meaningful relation if the estimates of \( \beta_1 \) in (7) are positive for a significant fraction of the performed regressions. The regression model (8) allows for error correcting dynamics inherent in the adjustment of disaster probabilities. Under cointegration and weak exogeneity of \( q_t \), the error correction parameter \( \alpha_2 \) must be negative. The regression in (9) is designed to unravel potential violations of weak exogeneity. The process is consistent with weak exogeneity if the parameter \( \alpha_3 \) is not significant.

Parameter estimates for the cointegration analysis are reported in Table 4. The fact that the estimated parameter \( \beta_1 \) is positive and significant, implies the existence of an equilibrium long-run relationship linking the GPOD and \( \log(CO_2) \). 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

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8 See Kremers et al. (1992) for a discussion of single equation cointegration and error-correction models.
the GPOD adjusts to deviations from the long-run equilibrium with the \( \log(CO_2) \).\(^9\) Results from the regression (9) show that \( \alpha_3 \) is not significant. This result is consistent with weak exogeneity of \( \log(CO_2) \). Hence, if one of the two variables deviates from their long-term relation, the GPOD adjusts toward a new equilibrium and not the \( \log(CO_2) \).\(^10\)

### 5.2 Projections to year 2040

Both, the diagnosed weak exogeneity of \( \log(CO_2) \) and the joint dynamics linking the GPOD and the \( \log(CO_2) \) imply a meaningful long term relation between these variables, in which the GPOD values adjust to lagged changes of \( \log(CO_2) \). Although this 'statistic causality' is only an observed phenomena capturing the effect of underlying physical relationships not modeled here, it justifies the use of \( \log(CO_2) \) for projections of the GPOD, provided some stability and accuracy tests are confirmed. We can project the GPOD by means of the set of parameters estimated for the regression model (7), using certain assumptions for the conditioning variable (\( \log(CO_2) \)),

\[
\tau_t = \hat{k}_1 + \hat{\beta}_1 q_t, \tag{10}
\]

where \( \hat{k}_1 \) and \( \hat{\beta}_1 \) are the parameters estimated from Eq. (7), as reported 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, showing model stability and predictive accuracy.

\(^9\) Under the null hypothesis of no cointegration, testing the significance of \( \alpha_3 \) requires non-standard critical values (Kremers et al. 1992). Appendix AB.1 provides the results with these values.

\(^10\) 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 B.2). Hence, for the conditioning of GPOD projections Global Temperature and World GDP per capita lack an essential qualification.
For performing the conditional projections, we use simulated annual series for CO₂ accumulation up to the year 2040, as provided by Meinshausen et al. (2020) for 9 SSP scenarios. SSPs describe alternative possible evolution pathways in the absence of climate change mitigating policies. Families SSP1 and SSP5 envision relatively optimistic trends, family SSP2 scenarios envision a pathway in which trends continue their historical patterns and SSP3 and SSP4 envision more pessimistic developments (O’Neill et al. 2016).

Figure 2 shows GPOD projections to year 2040 by SSP scenario. Except for the more optimistic scenario SSP1-1.9, the rising trend in the GPOD is clear. 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. 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 per annum to occur by country in 2040, we combine the projected GPOD with in-sample country-specific average relations between the estimates of \( P(y_{it} > 0) \) and the GPOD (i.e., \( P(y_i > 0) \)).

Figure 3 displays the estimated country-specific probabilities of having at least one disaster per year for the four Tier 1 priority scenarios (O’Neill et al. 2016) and allows for a

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11 These scenarios include 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 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). For a comprehensive description of the SSPs we refer the reader to the work of Riahi et al. (2016).
direct comparison with results displayed in Fig. 1 (see Appendix E for a detailed documentation). Probabilities of disasters to occur by country are subject to marked increases. For most countries, the probabilities to experience at least one disaster in 2040 are above 50%. Most Asian countries can be expected to experience at least one disaster per year more frequently in 2040 than 2010 under all displayed scenarios. Austria jumps from a 14.5% probability of experiencing at least one disaster in 2010 to 39.7% in 2040 under SSP1-2.6 scenario and to 50.9% under SSP5-8.5 scenario, Congo from 32 to 47% under SSP1-2.6 and 58.3% under SSP5-8.5 scenario, Guinea from 28.6% in 2010 to 56.9% in 2040 under SSP1-2.6 and 68.2% under SSP5-8.5, Lebanon from 5.8% in 2010 to 41.7% in 2040 under SSP5-8.5, Singapore from 46% to 61.9% under SSP1-2.6, United Kingdom from 8.6% to 37.8% under SSP1-2.6, and so on.

These projections by country can be an important input for governments and communities to design and develop adequate strategies to face upcoming hydrometeorological disasters. The complete data set of projected probabilities for any of the countries considered in this analysis, from year 2021 to 2040, for the 9 scenarios, are available upon request from the authors.

6 Conclusion

This study adds to a new literature using the statistics/econometric approach to study the connection between climate change and natural disasters. We have quantitatively studied the long-run dynamic and predictive connection between atmospheric CO2 accumulation and the probability of hydrometeorological disaster occurrence. As stated by the IPCC, other international agencies as well as by numerous authors, this could contribute to a more effective and less costly use of preventive and mitigating instruments to reduce people’s exposure and vulnerability.
To discover the properties of CO$_2$ 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 CO$_2$ levels to assess and check the ability of the trend in global atmospheric CO$_2$ concentration to accurately anticipate the future occurrence of hydrometeorological disasters. Finally, we used this information to forecast disaster incidences at the global level as well as for each of the countries considered in the analysis, using high-priority scenarios as reported by the Sixth Assessment Report of the IPCC.

We show that statistical data on global atmospheric CO$_2$ concentrations can be used as a conceptually meaningful, statistically valid and policy useful predictor of the probability of hydrometeorological disasters. Moreover, we also show that controlling for country-specific characteristics, and conditional on emission scenarios, most countries will be affected by at least one annual disaster with a 50% or higher probability by the year 2040.

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Author contributions Andrés Fortunato involved in data acquisition, software programming, tables and figures, literature review, model description and manuscript co-editing. Helmut Herwartz participated in econometric model designing and result interpretation, model description, text review. Ramón López involved in Initial conception, manuscript editing, text review, result interpretation, and supervision. Eugenio Figueroa B. participated in Research coordination, literature review, and manuscript writing and editing.

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Declarations

Conflicts of interest We declare that there are no competing interests.

Code availability Code files for replicating results can be downloaded from: https://www.dropbox.com/s/mqb7agivkt5yst7/hydro_disasters.rar?dl=0.

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